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Effects of tillage intensities on spatial soil variability and site-specific management in early growth of *Eucalyptus grandis*

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ABSTRACT

Soil tillage is one of the most common and important site preparation managements in forestry. However, in highly variable soils, uniform management practices might not be the best alternative. Site-specific management on the other hand, allows an optimal resource management as well as decreased environmental impact. However, the choice of a suitable strategy to manage areas with high soil variability is still a challenge. Our goal was to compare strategies that use soil characteristics to improve the comparison of tillage managements on *Eucalyptus grandis* growth. Specifically, we aimed to: compare strategies that incorporate soil characteristics into the models to compare tillage treatments; to determine the most useful soil characteristics for zone management delineation; and to compare tillage methods for site-specific management. We compared tillage intensities in contrasting soil types in a randomized complete block design with four and five replications. Tillage treatments included pit-planting, disc harrowing, and subsoiler. Experimental units consisted of three rows of fifteen trees each. Soil characteristics as well as plant height and diameter were evaluated periodically during the first 30 month after implantation. Intra-plot variability was described with multivariate geostatistical models. Using soil properties as covariates in the model to compare tillage treatments improved model fit. When root development is limited by soil conditions and electroconductivity is high, tillage intensity makes a difference in plant growth; subsoiler is the best treatment when electroconductivity is high, while disc harrowing is the best when electroconductivity is low. However, when root development is not limited by soil conditions, no differences were found between subsoiler and disc harrowing. We show how the use of soil characterization is a tool that provides better comparisons among treatments when high intra-plot variability is present. Additionally, the use of soil characterization either directly into the model or to determine zones provides useful information for site-specific management. Site-specific management could therefore easily be implemented to decrease the environmental impact of soil tillage as well as to increase wood production in forestry.

1. Introduction

The *Eucalyptus* genus has more than 500 species used for afforestation and is the single most important genus in terms of rapid-growth species (Flynn, 2005). Specifically, *Eucalyptus grandis* is one of the species with the largest area of afforestation having a sustained area expansion since the 1990s (Gonçálvez et al., 2004). Afforestation is generally established in low fertility or degraded soils and therefore, a general consensus exists in the literature about tillage benefits. Tillage is beneficial for weed control (McLaughlin et al., 2000; Wetzel and Burgess, 2001; Villalba et al., 2010), and improving soil physical conditions for root (Smith, 1998) and plant growth (Worrell and Hampson, 1997; Querejeta et al., 2001). On the other hand, it is not well established whether low or high intensity tillage systems are more beneficial. The reports regarding the effect of tillage intensities on tree growth parameters are not consistent and may be site-specific (Carnerio et al., 2008; Graham et al., 2009).

Tillage systems used for forest plantations range from intensive tillage such as subsoilers (Schönau et al., 1981) to reduced tillage systems such as disking (Norris and Stuart, 1994; Madeira et al., 1999; Du Toit, 2008). Some studies found a benefit of tillage systems when compared to no-till systems, but no improvement in increasing tillage intensity (Morris and Lowery, 1988; Madeira et al., 1999; Lowery and Gjerstad, 1991; Garcia Préchac et al., 2001). However other studies found a clear advantage on more intense tillage systems such as subsoilers (Schönau et al., 1981;

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Gatto et al., 2003). Specifically, Smith et al., 2005 indicated that the improvements of subsoiler were strongly affected by soil type, soil condition, and soil water content at the time of site preparation. On the other hand, the most intensive tillage system such as subsoiler increases the amount of bare soil until canopy closure and therefore increases soil erosion risk (Worrell and Hampson, 1997; Baptista and Levien, 2010). Therefore, it is necessary to establish soil tillage systems with high production levels for each soil condition, while minimizing negative environmental impacts (Binkley et al., 2004; du Toit and Dovey, 2005).

Furthermore, experimental designs for studying tillage intensity are generally underpowered due to the requirement of large experimental units to capture treatment effects with the consequence of having experimental units with large heterogeneity within (Joyce et al., 2002; Zas, 2006). Appropriately capturing local heterogeneity in experimental design is challenging. The most widely used experimental designs for studying tillage effect are randomized complete blocks. With this design, local heterogeneity might not be properly captured (Grondona et al., 1996) due to non-linear patterns found in soil heterogeneity (Cressie, 1993). Furthermore, since large experimental units are required in tillage experiments of forest species in order to properly evaluate the treatment effects, an unintended increase of experimental unit variability occurs. Additionally, when abrupt changes in soil type and unevenness of terrain are present, poor estimation of treatment effects is obtained (Dutkowski et al., 2002). One alternative to characterize soil heterogeneity is the use of soil electroconductivity and soil properties (Rhoades et al., 1999; Corwin and Lesch, 2003). Soil electroconductivity and other soil properties have been used in classic geostatistical models for variogram construction and kriging prediction (Matern, 1960; Ripley, 1981; Diggle, 1988), to model the residuals error variance–covariance structure in mixed models (Gleeson and Cullis, 1987; Cullis and McGilchrist, 1990; Cullis et al., 1991; Smith et al., 2005), and for curve smoothing (Hutchinson y Gessler, 1994). Another alternative is to use soil properties to delineate management zones through cluster analysis (Yan et al., 2007) and to evaluate treatments within zones. Soil properties such as fertility, electroconductivity, organic matter, and texture, satellite images, topographic factors, as well as yield monitor maps have successfully been used for zone delimitation and management in agriculture (Franzen et al., 2002; Schepers et al., 2000, 2004). Therefore, spatial information from soil properties could be used in experiments to model within experimental unit heterogeneity. However, the best way to incorporate spatial variability into the models is not clear.

Precision forestry is therefore one of the tools that could be successfully used to determine optimal site-specific management (van Schilfgaarde, 1999). However, it is not evident which models would better capture the spatial variability. The goal of this study was to compare statistical tools that incorporate soil properties into the analysis of forest experiments with large intra-plot variability to control soil spatial heterogeneity. Specifically, we compared different strategies to incorporate soil characteristics to improve treatment estimation efficiency in forest experiments with large experimental units. We proposed a method to identify the most useful variables for zone delimitation to be used in site-specific management, and we evaluated the use of zone management for tillage intensities in forest experiments.

2. Materials and methods

2.1. Site description and experimental design

The experimental site was located in ‘‘Mellizos’’, Rio Negro Department, Uruguay (32°37′49″S; 57°10′07″W). Uruguay has a temperate climate with four clearly distinguished seasons and an isohydric precipitation regime. Yearly mean average temperature is 17.9 °C with a minimum average temperature of 12.2 °C and a maximum average temperature of 23.8 °C (Fig. 1). Average annual precipitation is 1200 mm and air relative humidity is 73%. The experiment was established in two contrasting soil types separated 500 m approximately (E_1 and E_2, Fig. 2). Dominant soils are Lithic Dystrudepts in one experiment (E_1) and Typic Argiudoll in the other experiment (E_2) (Table 1). The *E. grandis* commercial clone *X2334* was used. Both experiments were planted on April 4, 2011. The previous land use at the experimental site was native grasses. Disc harrowing and subsoiler were applied on January 14 and February 10, 2011, on E_1 and E_2 respectively. Pits were prepared for plantation on March 23, 2011.

A randomized complete block experimental design with three tillage intensity treatments was used. Tillage treatments were: pit-planting (P), subsoiler on the planting row (F), and disc harrowing on the planting row (R). Subsoiler was chosen as one of the treatments because it is used for forestry producers when soils have potential physical limitations for tree roots growth, yet it is

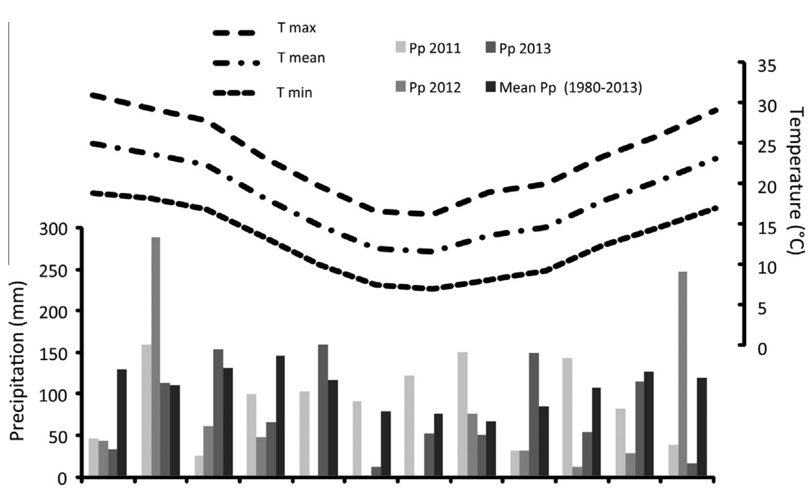

Fig. 1. Environmental conditions during the experimental growing seasons. Monthly accumulated precipitation for all years (Pp 2011, Pp 2012, Pp 2013), historical average accumulated precipitation (Pp from 1980 to 2013) and average minimum, mean and maximum temperature (Tmin, Tmean, Tmax).

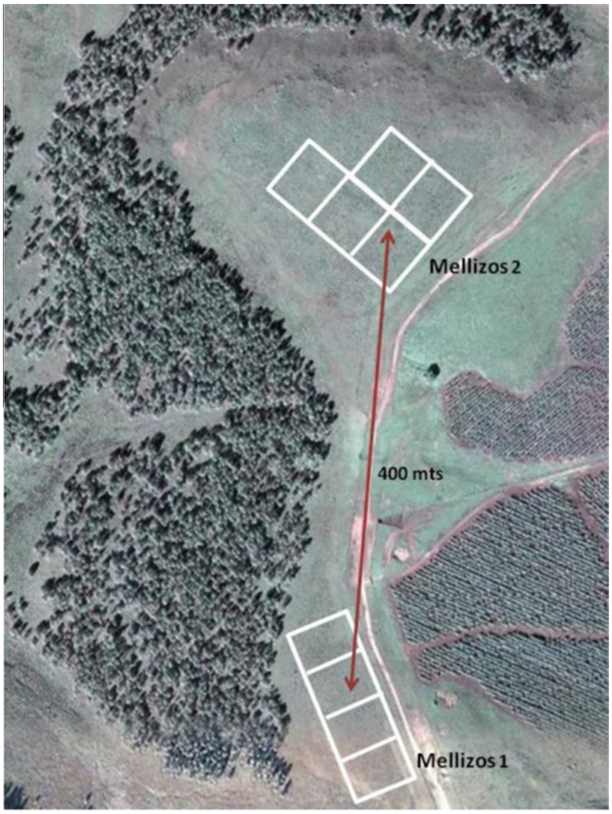

Fig. 2. Experimental site, Mellizos 1 (E_1) and Mellizos (E_2).

Table 1
Physical and chemical characteristics of soil horizons for both experimental sites (E_1 and E_2).

Experiment	Horizon	Depth (cm)	Soil texture			pH	CEC	OM
			Sand	Silt	Clay			
E_1	A	0–10	71.0	15.0	14.0	5.6	6.8	2.0
	R	+10	–	–	–	–	–	–
E_2	A	0–7	67.7	19.9	16.4	5.5	7.9	4.6
	A–B	7–43	63.8	14.7	21.5	5.8	12.2	2.1

CEC: Cation exchange capacity; OM: Organic matter.

an expensive practice in energy terms. Disc harrowing and pit planting were chosen as alternative treatments that reduce energy costs and soil erosion risk while maintaining forest productivity. Four blocks were used in E_1 and five blocks in E_2. Experimental units consisted of three rows with 12–15 trees per row. Planting density was 1150 plants per hectare, having 3.5 m between rows and 2.5 m between trees.

2.2. Soil and plant evaluation

The experiment was measured every four month from November 2011 (seven-month-old trees) until October 2013 (2.5-year-old trees). Plant height (h) and diameter at breast height (dbh) were recorded for each tree at every evaluation time (Table 2). Tree volume was calculated as

$$\text{Volume } (\text{m}^3\text{tree}^{-1}) = \text{Heigth} * \text{dbh} * 0.45$$

where 0.45 is used as a shape factor for *Eucalyptus* (Perdomo et al., 2007).

Table 2
Evaluation points (in months after planting) for all plant and soil properties variables in experiments E_1 and E_2.

Measurement[a]	E_1						E_2					
	7	12	16	20	25	30	7	12	16	20	25	30
h	■	■	■	■	■	■	■	■	■	■	■	■
dbh				■	■	■				■	■	■
EC		■			■	■		■			■	■
Res								■				■
w												■

[a]h, plant height; dbh, diameter at breast height; EC, soil electroconductivity; Res, soil penetration resistance; w, gravimetric soil water content.

Table 3
Pearson's correlation matrix between soil properties for experiment E_2 evaluated 30 month after planting. The lower diagonal shows Pearson correlation coefficients while p-values are shown in the upper diagonal.

Soil property[a]	EC_h	EC_v	Res_{10}	Res_{20}	Hum
EC_h (mS m^{-1})	1.00	<0.01	0.35	0.26	0.04
EC_v (mS m^{-1})	0.98	1.00	0.29	0.19	0.05
Res_{10} (kPa)	−0.08	−0.09	1.00	<0.01	0.07
Res_{20} (kPa)	−0.13	−0.15	0.58	1.00	0.09
Hum (%)	−0.20	−0.18	0.17	0.21	1.00

[a] EC_h: dipole horizontal electroconductivity; EC_v: dipole vertical electroconductivity; Res_{10}: penetration resistance at 10 cm; Res_{20}: penetration resistance at 20 cm; Hum: gravimetric humidity.

Table 4
Pearson's correlation matrix between soil properties for experiment E_2 evaluated 30 month after planting. The lower diagonal shows Pearson correlation coefficients while p-values are shown in the upper diagonal.

Soil property[a]	EC_h	EC_v	Res_{10}	Res_{20}	Hum
EC_h (mS m^{-1})	1.00	<0.01	0.35	0.26	0.04
EC_v (mS m^{-1})	0.98	1.00	0.29	0.19	0.05
Res_{10} (kPa)	-0.08	-0.09	1.00	<0.01	0.07
Res_{20} (kPa)	-0.13	-0.15	0.58	1.00	0.09
Hum (%)	-0.20	-0.18	0.17	0.21	1.00

[a] EC_h: dipole horizontal electroconductivity; EC_v: dipole vertical electroconductivity; Res_{10}: penetration resistance at 10 cm; Res_{20}: penetration resistance at 20 cm; Hum: gravimetric humidity.

Soil properties were measured on a systematic grid in the inter-row. However, due to environmental limitations, not all soil properties were recorded at all measurements (Table 2). Soil electroconductivity was evaluated with a horizontal (EC_h) and vertical (EC_v) dipole using an EM38 electroconductive (Geonics limited, 1998). The theoretical depths of evaluation of EC_v and EC_h were 1.5 m and 0.75 m respectively (McNeill, 1990). Soil penetration resistance was evaluated at depths of 10 (Res_{10}) and 20 (Res_{20}) cm with a digital penetrometer (Topp and Ferré, 2002). Gravimetric soil water content (w) was evaluated at 15 cm depth.

2.3. Statistical analysis

2.3.1. Summary descriptive analysis of soil properties

Descriptive statistics as well as correlation among soil properties were studied.

2.3.2. Geostatistical analysis

Spatial characterization of all individual soil variables was conducted with semivariograms and regression models. Additionally, soil and plant characteristics were combined in a multivariate analysis using a spatially weighted principal component analysis

(MULTISPA-PCA) in E_2. We only conducted a multivariate approach in E_2 because that is the only site where all soil properties were evaluated at the same time. An empiric semivariogram for each soil variable and for the first principal component axis (PC_1) was fitted. Spheric, exponential, and Gaussian models were fitted, and the best model was selected based on the root mean squared error (RMSE). Best model in each situation was used with ordinary kriging to generate maps and predict values for each tree. All of the analyses and map construction were conducted on R statistical software.

Predicted values from kriging were then used as covariates in a linear model to compare tillage treatments as follows:

$$Y_{ijk} = \mu + \tau_i + \beta_j + \varepsilon_{ij} + \alpha X_{ijk} + \alpha_i X_{ijk} + \delta_{ijk}$$

where Y_{ijk} is the response variable (i.e. *h*, dbh, volume) of the *k*-th tree in the *i*-th tillage treatment and the *j*-th block, μ is the overall mean, τ_i is the effect of the *i*-th tillage treatment, β_j is the effect of the *j*-th block, ε_{ij} is the experimental error of the *i*-th tillage treatment and the *j*-th block, α is the global regression coefficient associated with the soil covariate of interest (i.e. EC, Res, *w*, and PC_1), α_i is the regression coefficient of the *i*-th tillage treatment, X_{ijk} is the value of the soil covariate of interest (i.e. EC, Res, *w*, PC_1) at the *k*-th tree, and δ_{ijk} is the sub-sampling error associated with the *i*-th tillage treatment, the *j*-th block, and the *k*-th tree, and ε_{ij} and δ_{ijk} are random variables with $\varepsilon_{ij} \sim N(0, \sigma^2{}_e)$ and $\delta_{ijk} \sim N(0, \sigma^2{}_s)$. The covariates used for E_1 were EC_h and EC_v, while the covariates used for E_2 were EC_h, EC_v, Res_{10}, Res_{20}, *w* and PC_1. We first fitted the model with the response variable and the covariate from the same evaluation time. Later, the model was fitted for each response variable using the covariate evaluated at 30 months after planting. The models with different soil covariates were compared based on AIC and the best model was selected. The analyses were conducted on SAS Statistical Software (SAS Institute, 2005) with the PROC MIXED procedure.

2.3.3. Management zones and site-specific management

A non-supervised clustering algorithm that accounts for spatial patterns was used to delineate management zones. First, the fuzzy c-means partitioning algorithm was used to partition individuals into groups. Then, the optimal number of zones was determined based on the Fuzziness Performance Index (FPI) and the Normalized Classification Entropy (NCE) (Fridgen et al., 2004). The FPI indicates the degree of distance between individuals while the NCE is a measurement of the level of aggregation between groups. The analyses were performed with the Management Zone Analyst (MZA) Software (Fridgen et al., 2004).

A linear model using the management zone as factor was used to evaluate the interaction between management zone and tillage treatment as follows:

$$Y_{ijkl} = \mu + \tau_i + \beta_j + \gamma_k + \tau\gamma_{ik} + \varepsilon_{ijk} + \delta_{ijkl}$$

where Y_{ijkl} is the response variable (*h*, dbh or volume) of the *l*-th tree in the *i*-th tillage treatment of the *j*-th block belonging to the *k*-th management zone, μ is the overall mean, τ_i is the *i*-th tillage treatment effect, β_j is the *j*-th block effect, γ_k is the *k*-th management zone effect, $\tau\gamma_{ik}$ is the tillage by zone interaction, ε_{ijk} is the residual error associated with the *i*-th tillage treatment, the *j*-th

Table 5
Model fit (root mean squared error) for the semivariograms for each soil property evaluated 30 month after planting in experiments E_1 and E_2. Best model for each variable in each experiment is underlined.

Soil property[a]	E_1			E_2		
	Spheric	Exponential	Gaussian	Spheric	Exponential	Gaussian
EC_h (mS m^{-1})	<u>44.08</u>	49.23	45.12	<u>225.14</u>	235.72	274.26
EC_v (mS m^{-1})	35.78	40.17	<u>33.80</u>	106.03	<u>97.82</u>	145.61
Res_{10} (kPa)	–	–	–	340.03	<u>322.72</u>	5282.85
Res_{20} (kPa)	–	–	–	46.09	46.61	<u>42.54</u>
w (%)	–	–	–	<u>37.47</u>	42.49	38.94

[a] EC_h: dipole horizontal soil electroconductivity; EC_v: dipole vertical soil electroconductivity; Res_{10}: soil penetration resistance at 10 cm; Res_{20}: soil penetration resistance at 20 cm; *w*: gravimetric soil water content.

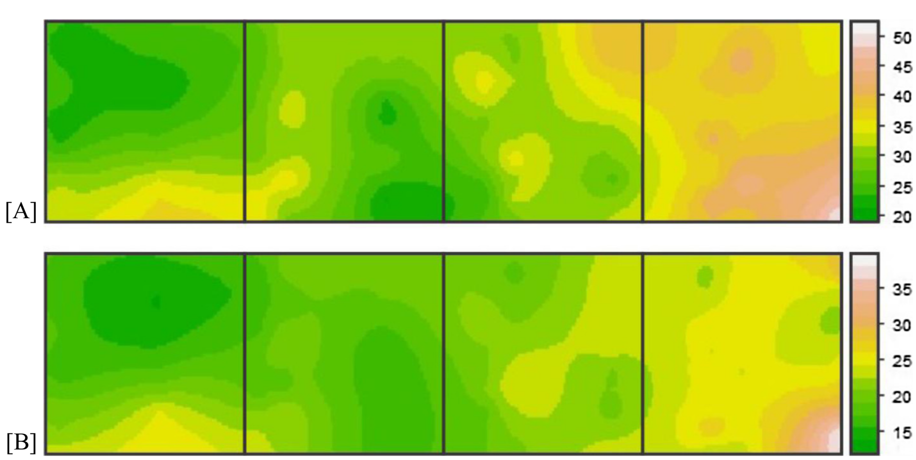

Fig. 3. Map of interpolated values for electroconductivity in experiment E_1 evaluated at 30 months after planting. [A] EC_h; [B] EC_v. *EC_h: dipole horizontal electroconductivity; EC_v: dipole vertical electroconductivity.

block, and the k-th management zone, and δ_{ijkl} is the sub-sampling error associated with the i-th tillage treatment, j-th block, k-th management zone, and l-th tree, and ε_{ijk} and δ_{ijkl} are random variables with $\varepsilon_{ijk} \sim N(0, \sigma^2{}_e)$ and $\delta_{ijkl} \sim N(0, \sigma^2{}_s)$. The management zone is considered here as a post-blocking, existing for all of the experimental units but having a restriction in the randomization. All the statistical analyses were performed in SAS Statistical Software (SAS Institute, 2005) with the PROC MIXED procedure.

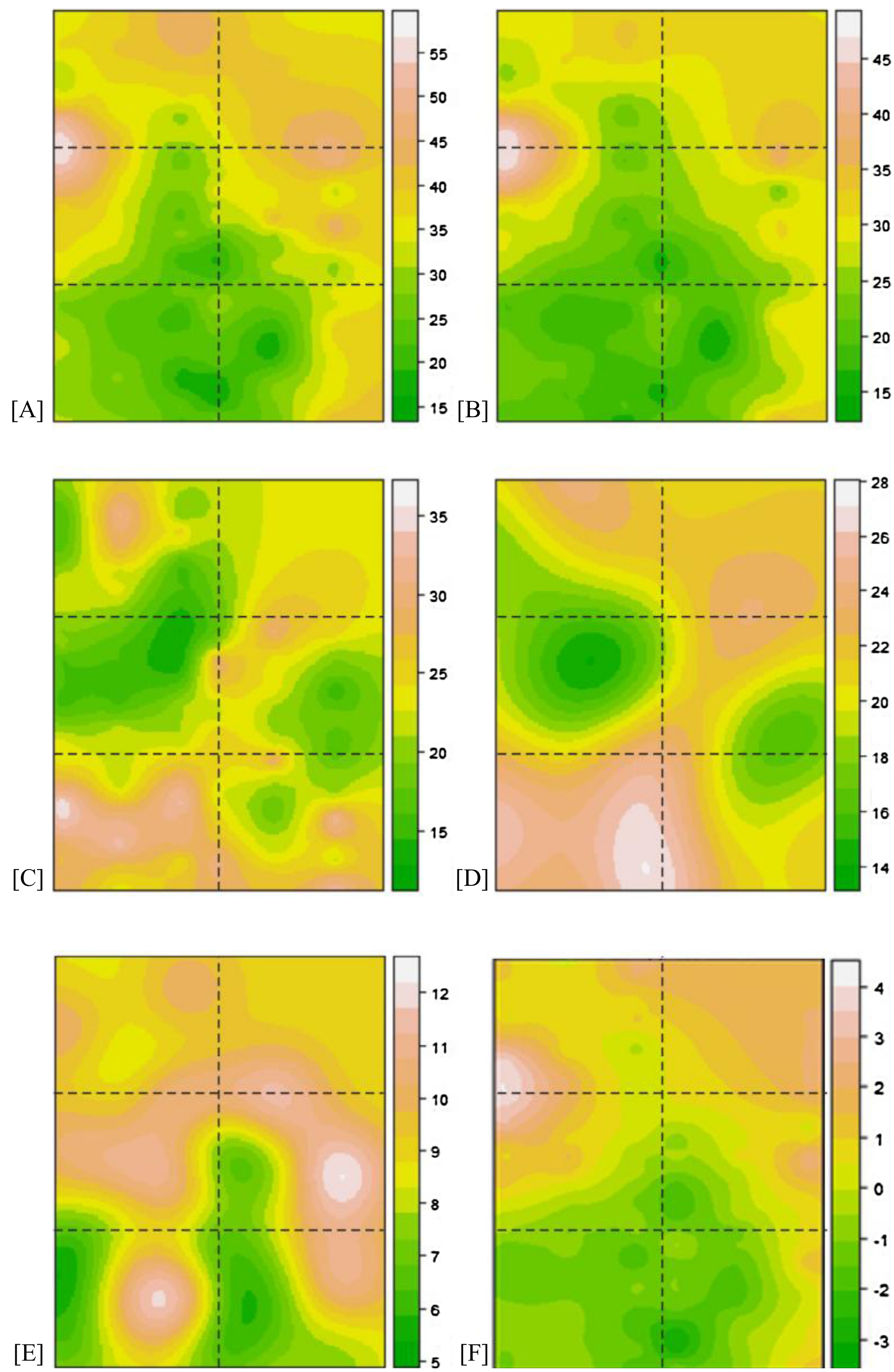

Fig. 4. Map of interpolated values for soil properties in experiment E_2 evaluated at 30 months after planting. [A]: EC_h; [B]: EC_v; [C]: Res_{10}; [D]: Res_{20}; [E]: Hum; [F]: PC1. *EC_h: dipole horizontal electroconductivity; EC_v: dipole vertical electroconductivity; Res_{10}: penetration resistance at 10 cm; Res_{20}: penetration resistance at 20 cm; Hum: gravimetric humidity; PC_1: first axis of the principal component including all soil properties.

3. Results

3.1. Soil characterization

The EC_h values were larger than EC_v in all the experiments, having a similar variance (Table 3). The Res_{10} values were larger than the Res_{20} values having also similar variances. This is attributed to the fact that at 10 cm depth exists a stone line above the B horizon that increases soil penetration resistance in E_2, while in E_1 the A horizon has gravels. The w values were 8.8% on average with a minimum of 2.0% and a maximum of 24.8%. There is a significant correlation ($P < 0.05$) between EC_h and EC_v, Res_{10} and Res_{20}, and EC_h and w (Table 4).

Table 6
Model fit (AIC) for models using soil covariates evaluated either at the same date as the response variable or at 30 month after planting for experiments E_1 and E_2. Best model for each date is underlined.

Experiment	Date R[b]	Date C	Soil covariate[a]						
			Without	EC_h	EC_v	Res_{10}	Res_{20}	w	PC_1
E_1	25	25	4037.3	4027.7	4041.4	–	–	–	–
	30	30	4078.2	4058.5	4059.2	–	–	–	–
	5	30	3078.2	3067.3	3067.8	–	–	–	–
	12	30	4122.9	4126.4	4127.3	–	–	–	–
	16	30	4141.5	4140.6	4144.0	–	–	–	–
	20	30	4034.2	4019.1	4019.0	–	–	–	–
	25	30	4037.3	4016.3	4014.5	–	–	–	–
	30	30	4078.2	4058.5	4059.2	–	–	–	–
E_2	12	12	5445.6	5444.7	5446.3	5428.4	5449.4	–	–
	25	25	5198.2	5191.4	5190.6	–	–	–	–
	30	30	5185.2	5187.1	5187.3	5187.1	5187.0	5191.0	5185.1
	5	30	4555.6	4549.9	4548.9	4545.5	4550.0	4541.7	4555.1
	12	30	5445.6	5448.4	5445.5	5442.0	5441.1	5446.8	5449.2
	16	30	5516.2	5512.6	5509.5	5509.7	5512.5	5518.3	5515.1
	20	30	4915.0	4906.0	4905.5	4910.7	4917.8	4917.1	4912.1
	25	30	5198.2	5198.2	5196.9	5201.2	5202.3	5202.4	5197.7
	30	30	5185.2	5187.1	5187.3	5187.1	5187.0	5191.0	5185.1

[a] EC_h: dipole horizontal soil electroconductivity; EC_v: dipole vertical soil electroconductivity; Res_{10}: soil penetration resistance at 10 cm; Res_{20}: soil penetration resistance at 20 cm; w: gravimetric soil water content; PC1: first axis of the principal component including all soil properties.
[b] Date R: evaluation date of the response variable; Date C: evaluation date of the covariate.

Table 7
Estimated slopes for plant height for the interaction between tillage treatment and soil covariate for experiments E_1 and E_2.

Exp.	Covariate[a]	Tillage	Date (months after plantation)					
			5	12	16	20	25	30
E_1	EC_h (mS m^{-1})	Pit-planting	-0.15^{c}	−2.60	-3.02^{b}	-2.28^{b}	-1.99^{b}	-0.44^{b}
		Disc harrowing	0.17^{b}	−1.87	-3.55^{c}	-5.80^{c}	-5.35^{c}	-4.30^{c}
		Subsoiler	0.81^{a}	−1.03	-0.82^{a}	-1.17^{a}	0.66^{a}	2.73^{a}
	EC_v (mS m^{-1})	Pit-planting	-0.05^{b}	−3.38	-5.09^{b}	-3.56^{a}	-5.18^{b}	-2.01^{b}
		Disc harrowing	0.38^{b}	−1.77	-3.71^{b}	-6.99^{b}	-7.58^{c}	-6.08^{c}
		Subsoiler	1.35^{a}	−1.55	-2.10^{a}	-2.66^{a}	-0.88^{a}	2.73^{a}
E_2	EC_h (mS m^{-1})	Pit-planting	−0.55	−0.24	−0.95	−1.67	−0.19	−0.53
		Disc harrowing	−0.95	-0.97	−1.93	−2.02	−1.63	−1.30
		Subsoiler	−0.37	−1.26	−1.81	−2.62	−2.27	−2.05
	EC_v (mS m^{-1})	Pit-planting	−0.45	0.21	-0.64^{a}	−1.50	−0.29	−0.58
		Disc harrowing	−1.62	−1.94	-3.30^{a}	−3.02	−2.70	−2.21
		Subsoiler	−0.65	−2.05	-2.89^{a}	−3.65	−3.10	−2.30
	Res_{10} (kPa)	Pit-planting	−1.12	−3.74	−4.33	−1.67	−1.76	−1.37
		Disc harrowing	−1.50	−1.87	−1.32	−2.02	0.29	2.15
		Subsoiler	−1.70	−1.07	−1.56	−1.85	1.51	1.57
	Res_{20} (kPa)	Pit-planting	−1.08	−4.91	−4.86	−3.23	−1.52	0.70
		Disc harrowing	−0.21	−2.44	−2.22	-1.53	2.03	4.91
		Subsoiler	−2.40	−2.75	−3.32	−1.46	1.24	3.15
	w (%)	Pit-planting	2.05^{a}	2.24	2.34	2.82	4.10	−0.54
		Disc harrowing	2.91^{a}	−0.71	−1.09	−2.05	1.74	1.78
		Subsoiler	-4.07^{b}	−6.19	−6.27	−5.40	−4.07	0.69
	PC_1	Pit-planting	2.04	−1.99	2.36	6.51	2.30	4.59
		Disc harrowing	5.13	4.42	10.25	10.09	11.52	12.54
		Subsoiler	0.94	5.89	9.02	13.04	13.44	13.08

Different letters indicate significant differences ($P < 0.05$).
[a] EC_h: dipole horizontal soil electroconductivity; EC_v: dipole vertical soil electroconductivity; Res_{10}: soil penetration resistance at 10 cm; Res_{20}: soil penetration resistance at 20 cm; w: gravimetric soil water content; PC1: first axis of the principal component including all soil properties.

3.2. Geostatistical analysis

There is not a single best variogram model for the soil characteristics (Table 5). Best model for EC_h was Spheric while for EC_v was Gaussian in E_1 and Exponential in E_2. In E_2, the best model for Res_{10} was Exponential, for Res_{20} was Gaussian, and for w was Spheric.

Soil spatial variability was properly modeled with the variograms, having adequate standard error of the prediction throughout the field (data not shown). Spatial variability in E_1 represented by EC indicated four areas in the field: two low EC areas, an intermediate EC area, and a large EC area (Fig. 3). Spatial variability in E_2 showed similar patterns for EC_h and EC_v (Fig. 4A and B). Similar patterns were also found for Res_{10} and Res_{20} but showing stronger differences (Fig. 4C and D). The variable w showed a homogeneous pattern in the field with some differences between blocks (Fig. 4E). The PC_1 was able to describe the patterns found for all the variables (Fig. 4F).

3.3. Spatial modeling of soil properties as covariates

For both the E_1 and the E_2 experiments, using soil properties as covariates improved the model fit in comparison with modeling just the experimental design (Table 6). For the E_1 experiment using *per se* (i.e. soil properties from the same date as the response variable) EC_h as covariate improved the model fit. Using EC_h or EC_v from the final measurement (30 months after planting) improved the model fit in all instances except for 12 months after planting where the no-soil-covariate model was best. For the E_2 experiment using Res_{10}, EC_v or PC_1 as *per se* covariates and Hum, Res_{20}, EC_v and PC_1 as covariates from 30 months after planting showed the best fit.

Experiment E_1 showed a significant tillage treatment by soil covariate interaction for all the evaluation dates, except for 12 months after planting indicating that the best treatment depends on the level of the soil property in the area (Table 7). For E_2, we did not find a significant interaction between tillage treatment and soil covariate for any of the dates or covariates except for w at seven months after planting. In general, the best tillage treatment is consistent across the field in E_2.

3.4. Management zones and site-specific tillage

3.4.1. Management zone characterization

The optimal number of zones was two for E_1. The optimal number of zones ranged from two (EC_h y PC_1), to four (EC_v) in E_2. We therefore decided to use two management zones for both experiments. In E_1, most of the trees belonged to Zone 2 (85%), but all the treatments were represented in both zones (Table 8). Zone 1 had larger values of EC_h and EC_v than Zone 2 in E_1. In E_2, both zones were equally represented and contained all treatments (Table 8). Zone 1 had lower values of EC_h and EC_v, and larger Res and w values than Zone 2 in E_2.

A significant interaction between management zone and tillage treatment was found for E_1 for all dates except seven months after planting (Table 9). In general, in Zone 1 of E_1 with larger values of EC, the subsoiler tillage treatment was the best treatment for both plant height and volume. In Zone 2 in E_1 the best treatment was the disc harrowing. On the other hand, we did not find a significant interaction between tillage treatment and management zone for plant height and volume in E_2 (Table 9). The single best treatment was subsoiler. However, no significant differences were found between subsoiler and disc harrowing in E_2.

Table 8
Management zones description: number of trees included in each zone and average values of the soil properties in each zone for experiments E_1 and E_2.

Experiment	E_1		E_2	
Zone	1	2	1	2
Number of points	68	472	309	366
EC_h[a] ($mS\ m^{-1}$)	47.7 (5.1)	30.8 (5.2)	25.9 (3.6)	36.7 (4.7)
EC_v ($mS\ m^{-1}$)	33.7 (4.1)	20.4 (3.2)	20.4 (1.8)	28.8 (4.1)
Res_{10} (kPa)	–	–	25.1 (3.6)	20.4 (4.1)
Res_{20} (kPa)	–	–	22.7 (2.7)	18.9 (2.3)
w (%)	–	–	8.2 (1.4)	9.9 (0.9)
PC_1	–	–	1.1 (0.5)	−1.0 (0.7)

[a] EC_h: dipole horizontal soil electroconductivity; EC_v: dipole vertical soil electroconductivity; Res_{10}: soil penetration resistance at 10 cm; Res_{20}: soil penetration resistance at 20 cm; w: gravimetric soil water content; PC_1: first axis of the principal component including all soil properties.

4. Discussion

This study evaluated the effect of tillage intensity on plant growth in afforestation with Eucalyptus. We compared procedures to improve mean comparison among treatments and statistical approaches for delineating site-specific management in soils with large spatial variability. Spatial variability was characterized with several soil properties. Smaller values of resistance to the penetration were found deeper in the soil in E_2. This is probably explained by gravel on the top 15 cm of the horizon that reduces root penetration. After 15 cm, where the presence of grave is decreased, smaller values of resistance to the penetration were found. However, there is still a gradual increase in resistance to the penetration from 15 to 30 cm. Soil electroconductivity showed high values in general. Higher values of electroconductivity are expected with larger values of soil water content and further away from the parent rock. Additionally, coefficients of variation were small in comparison with other studies (Cetin and Kirda, 2003; Yan et al., 2007). This could be explained by the size of the studied area, where we used a relatively small area (0.9 hectares). The EC_h and EC_v showed a strong spatial structure with a high correlation. This pattern is not unexpected due to EC_h and EC_v being the same variable evaluated across different sections of the soil (Corwin and Lesch, 2005).

Incorporating spatial information from soil properties improved the model fit. The gain achieved by incorporating spatial information has been addressed in agricultural experiments with small plots (Brownie et al., 1993; Casler, 1999; Qiao et al., 2000; Smith and Casler, 2004) as well as in forest experiments with experimental units consisting of single trees (Anekonda y Libby, 1996; Mummery et al., 1999; Costa e Silva et al., 2001). However, most of these studies model between-plots spatial variation while our main effort was to account for within-plot spatial variation. Strong spatial patterns occurring in short distances within large plots are usually not considered in classic analysis (Dutkowski et al., 2002). Soil electroconductivity was the best soil covariate for E_1. This indicates that there is a gain in model comparison by using soil covariates. However, since we did not study other soil covariates at that site, it is not possible for us to generalize this pattern. On the other hand, in E_2 where a thorough soil characterization was conducted, a multivariate approach was optimal. This is similar to what other authors found for the multivariate approach (Officer et al., 2004; Moral et al., 2010; Córdoba et al., 2012).

The date in which the soil properties are evaluated does not have a significant impact on the ability to improve the model fit. This indicates a stable pattern of these soil properties in time. Spatial stability of soil electroconductivity was evaluated in other studies finding similar results (Hartsock et al., 2000; Farahani y Buchleiter, 2004). Therefore, a single soil covariate is enough to

Table 9
Adjusted means of plant height and volume for each treatment in each management zone for all evaluation dates. Best treatment is underlined for each date in each trait and experiment. Z1 and Z2 indicate the site-specific management zone.

Trait	Exp.	Soil covariate	Tillage	5			12			16			20			25			30		
				Z1	Z2	Mean[a]	Z1	Z2	Mean	Z1	Z2	Mean	Z1	Z2	Mean	Z1	Z2	Mean	Z1	Z2	Mean
Plant height (m)	E_1	EC_v ($mS\ m^{-1}$)	Disc harrowing	56.6	50.6	53.6	301.4	305.8	303.6	390.3	411.1	400.7	554.4	611.7	583.1	788.7	858.1	823.4	874.1	931.1	902.9
			Pit-planting	36.4	41.1	38.8	152.7	199.7	199.7	225.7	287.3	265.5	436.7	500.1	468.4	703.3	762.3	733.1	789.8	854.3	822.1
			Subsoiler	48.0	41.3	44.7	373.7	268.5	271.1	374.7	366.7	370.7	582.1	586.7	584.4	845.6	837.9	841.9	931.7	917.7	924.7
	E_2	PC_1	Disc harrowing	80.4	70.6	75.6	334.9	320.3	327.6	440.4	417.4	428.9	658.5	636.2	647.4	905.6	881.5	893.6	1001	977.5	989.2
			Pit-planting	52.2	46.7	46.8	238.6	238.5	228.3	328.1	305.8	316.4	556.0	531.8	543.8	813.9	799.8	806.9	911.2	985.2	903.2
			Subsoiler	80.2	83.6	83.6	351.7	339.1	345.4	451.9	439.9	445.9	658.7	640.9	649.8	914.2	885.8	900	998.4	970.2	994.3
Volume ($m^3\ ha^{-1}$)	E_1	EC_v	Disc harrowing	–	–	–	–	–	–	–	–	–	22.8	27.1	24.9	42.3	48.4	45.4	50.4	56.8	53.6
			Pit-planting	–	–	–	–	–	–	–	–	–	13.9	16.6	15.3	30.6	35.6	30.1	41.1	46.12	43.6
			Subsoiler	–	–	–	–	–	–	–	–	–	24.8	23.9	24.4	49.3	45.1	47.2	58.8	54.1	56.3
	E_2	PC_1	Disc harrowing	–	–	–	–	–	–	–	–	–	32.6	30.3	31.4	55.5	52.8	54.2	65.8	64.2	65.1
			Pit-planting	–	–	–	–	–	–	–	–	–	21.9	19.6	20.8	43.0	40.6	41.8	55.8	52.0	53.9
			Subsoiler	–	–	–	–	–	–	–	–	–	35.5	30.5	31.6	55.8	54.0	54.9	65.7	64.2	65.7

The covariate used in the model is indicated: EC_v: dipole vertical electroconductivity; PC_1: first axis of the principal component including all soil properties.
[a] If the tillage treatment by management zone is significantly different from zero, the best treatment in each zone is indicated. Otherwise, the overall best treatment is indicated.

correct for soil spatial variability at a given site. We found a significant tillage treatment by either soil covariate or management zone interaction in E_1. Both, our covariate model and our zone-management model indicate that subsoiler was the best tillage treatment when EC was high like in E_1. On the other hand, no interaction was found in E_2. In summary, site characterization should focus on evaluating thoroughly the most relevant variables in a single date and use them to improve model fit. Multivariate analysis seems to perform better than using single variables one at a time.

Management zone delimitation by the fuzzy-c criterion has been successful in other studies with agricultural species (Fridgen et al., 2004; Reyniers et al., 2006; Kyaw et al., 2008), but no forestry studies were found. Specifically, the multivariate clustering algorithms have been used in other studies (Morari et al., 2009; Xin-Zhong et al., 2009). We found a significant tillage treatment by management zone in E_1 for both plant height and volume indicating that the best tillage treatment was different for the two zones; subsoiler was the best tillage treatment in Zone 1 while disc harrowing was the best tillage treatment in Zone 2. Additionally, Zone 1 was associated with larger values of soil electroconductivity. This is probably the reason why the subsoiler tillage treatment was optimal in this zone. The experiment E_1 was located on a shallow soil with a considerable amount of gravels in horizon *A*; therefore we think it is probable that the use of subsoiler was beneficial because it loosened the soil favoring tree performance. In experiment E_2 where soil conditions are more appropriate for forest plantation and root development, no significant tillage treatment by management zone interaction was found. Even though the subsoiler treatment was superior in this experiment, non-significant differences were found between subsoiler and disc harrowing tillage treatments.

The use of statistical tools to define management zones within the experimental site was assessed positively. It allowed us to detect differences among treatments in terms of wood production. Our results showed that under limiting soil physical conditions for root growth the use of subsoiling shows significant improvement in the wood volume produced (E_1). However, for soil conditions such as E_2, tillage practices with disc harrowing are preferred due to their lower operating costs, lower environmental impact and yields obtained (García Préchac et al., 2001; Baptista and Levien, 2010). However, due to the presence of a Bt horizon, and a stone line in these soils, it is important to further evaluate these experiments in the medium and long term. It would be interesting to explore changes in mortality or growth dynamics of neighboring trees, as well as wood production. Some previous research shows differences on timber production among tillage systems at harvest time under non-limiting soil physical conditions for root growth (González et al., 2012).

Most of the tillage experiments are conducted on specific soil types (Gonçálvez et al., 2004) and therefore, drawing general recommendations for site-specific management is hard. Holz et al. (1999) proposed that in general, any type of tillage produces benefit except where soils are well drained and structured. Our results indicate that pit-planting seems to be the worst treatment regardless of the soil characteristics. Soils with low aptitude for tree growth and establishment require a soil characterization and site description to determine zone-specific management. On the other hand, with better soils, less intensive treatments could be implemented to reduce costs and soil erosion risk (Gonçalves et al., 2002).

5. Conclusions

Site characterization using a multivariate approach is a useful tool to characterize within plot spatial variability, improve treatment comparison, and delineate management zones to conduct site-specific management. Zones with better conditions did not show differences between subsoiler and disc harrowing treatments. Disc harrowing is recommended for these areas because in addition to being equally good in terms of plant height and wood production, lower costs, erosion risks, and environmental impacts are expected from less intensive tillage systems. The use of zone management delimitation is specifically useful when soil conditions restrict plant growth. Site-specific management gives the optimal micro-environmental conditions to each plant. Therefore we propose that zone management should be used when strong soil variability is present in order to have sustainable soil management practices.

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