



# The impact of agroforestry combined with water harvesting on soil carbon and nitrogen stocks in central Chile evaluated using the ICBM/N model

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## ABSTRACT

Soil organic carbon (SOC) and total nitrogen (N) stocks in an agroforestry system with water harvesting were analysed in a field experiment and the results compared with those of other crop management systems in the Mediterranean zone of central Chile. Agroforestry with water harvesting showed higher positive effects on N stocks, mainly in the upper soil layer, than the other crop management systems. However, soil analysis revealed a lack of differences between treatments, a fact that might be related mainly to the short study time (12 years) and the high spatial variability in these soil properties at the experimental site. In addition, the Introductory Carbon Balance Model that simulates N processes (ICBM/N) was evaluated for simulating trends in SOC and N stocks in the field experiment. Soil data collected between 1996 and 2008 in the field experiment and primarily literature data sets were used to test ICBM/N and its performance was evaluated by considering uncertainty in model inputs using Generalised Likelihood Uncertainty Estimation (GLUE) methodology. The GLUE estimates (5% and 95%) and measured SOC and N stocks were in satisfactory agreement. The observed SOC and N stocks were bracketed by the uncertainty bands in 70% and 80% of the simulations, respectively. Sensitivity analysis showed the model to be most sensitive to C parameters, such as the humification coefficient ( $h$ ). The results of this study show that ICBM/N can be an effective tool for estimating SOC and N stocks from agroforestry combined with water harvesting systems in the Mediterranean zone of central Chile over the medium term. However, they also indicate that additional data sets are needed to redefine the parameter distributions in the model and thus to predict trends in SOC and N stocks in the future.

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## 1. Introduction

Considering that soils contain a stock of organic carbon (SOC) that is about twice that in the atmosphere and about three times that in vegetation, small losses from this large pool could have significant impacts on future atmospheric carbon dioxide (CO<sub>2</sub>) concentrations, so the response of soils to global warming is of critical importance when assessing climate carbon cycle feedbacks (Smith et al., 2008a). Soil degradation is particularly important in drylands of the world, where desertification is one of most pressing environmental problems (UNEP, 1992). Although SOC stocks are not high in drylands and total potential SOC losses per unit area are low, these regions cover large areas. Lal (2004) estimated that historical losses of soil SOC due to desertification and degradation amount to about 20–30 petagram (Pg) for a total 241 Pg pool in drylands.

Extensive areas of Chile are degraded and partly desertified. Arid and semi-arid zones contribute 50% and 32% of the total degraded area, respectively (Pérez and González, 2001). Accelerated soil degradation in Chile is due to land uses that lead to soil compaction and loss of soil structure and SOC (Ellies, 2000).

Most of the inner rainfed zone of central Chile has a common natural agroecosystem named 'Espinal', where the dominant vegetation is *Acacia caven* (Mol) trees with a spring-grass cover rich in annual plants named 'Mediterranean annual prairie' (Silva and Lozano, 1986; Ovalle and Squella, 1988). In this area of Chile, Ovalle et al. (1990) found that inappropriate agricultural methods, excessive woodcutting and systematic overgrazing have led to serious environmental degradation and economic depression.

On the other hand, land use changes through their effects on the plant community and soil conditions may have important effects on the size of the SOC pool and directly affect the atmospheric concentration of greenhouse gases, such as CO<sub>2</sub> (Batjes, 1996). Thus rigorous quantification of the effects of changing land use on SOC storage is considered a critical area for future research (Schimel, 2006). Extensive research has shown that various changes in land use and/or land management practices can be used for potential

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SOC sequestration in different regions, such as soil amendment with organic matter additions, reducing tillage intensity and frequency or conversion to no-till agriculture, reducing bare fallow, conversion of highly erodible land to grassland, increased use of cover crops in annual cropping systems, and natural woodland regeneration (Paustian et al., 1997; Smith et al., 2000; Sperow et al., 2003; Hutchinson et al., 2007). It is important to note that land management practices that increase SOC may also have a positive impact on food security while mitigating climate change and improving the environment (Lal, 2009).

Lal (2003) noted that the global potential for SOC sequestration and restoration of degraded/desertified soils ranged from 0.6 to 1.2 Pg C year<sup>-1</sup> for about 50 years, with a cumulative sink capacity of 30–60 Pg. However, to increase SOC sequestration in desertified drylands, sustainable diversification of agriculture is needed there. One possible approach is the implementation of agroforestry systems, which allow direct near-term C storage (decades to centuries) in trees and soil (Dixon, 1995). Agroforestry systems have been also suggested as a solution to the farming problems experienced on degraded soils because of their secondary environmental benefits, such as promoting ecological diversity and economic stability (Pandey, 2002). In particular, agroforestry has proved to be a land use system of high productivity, improving the economy of the impoverished farmers who live in the inner rainfed zone of central Chile (Ovalle et al., 2000).

In desertified drylands, land use and/or land management practices that can help to increase the SOC pool are assisted by improving water use efficiency and the implementation of supplemental irrigation techniques (Lal, 2001). This is particularly important for rainfed zones, where the components of agroforestry systems represent competition rather than complementation as regards water use (Le Roux et al., 1995; Kho, 2000). Based on their results, various authors suggest that agroforestry combined with runoff water harvesting in drylands can be a viable solution (Lövenstein et al., 1991; Abdelkadir and Schultz, 2005). In agroforestry in the Mediterranean rainfed zone of central Chile, Ovalle et al. (2002) also reported strong competition for water in the upper soil profile between the trees and the associated herbaceous strata. Runoff water harvesting has been used for supplemental irrigation of agroforestry systems in rainfed areas, helping both to increase and to sustain food production in these regions (Tabor, 1995; Li et al., 2000; Droppelmann and Berliner, 2003; Rabia et al., 2008).

Determining the direction and rate of change in SOC and N pools when vegetation and soil management practices are changed is a complex task because many factors and processes are involved (Post and Kwon, 2000). The development of computer simulation models has provided methods to explain how land use and management practices affect the SOC and N pools. A number of models are available to predict SOC and N dynamics, ranging from simple regression models to complex processes-based models such as those presented in comprehensive reviews by Molina and Smith (1996) and Shibu et al. (2006). One of these models is the Introductory Carbon Balance Model (ICBM), which was developed by Andrén and Kätterer (1997) to calculate SOC balances for medium-term predictions (30-year). The ICBM model has been successfully tested under a wide range of soil, crop and climatological conditions (Kätterer and Andrén, 1999; Bolinder et al., 2006; Andrén et al., 2007). Since its inception, ICBM has been updated to further extend its capabilities, e.g. with ICBM/N, which simulates N processes (Kätterer and Andrén, 2001).

Soil organic C and N models are demanding in terms of input data. Some estimations are needed when there is a lack of inputs, which incorporates uncertainties that are propagated in each step of the calculations. In SOC and N modelling, the number of unknown parameters and initial values is usually large enough with respect to the experimental data to ensure that calibration will find a set

of values to provide a good fit (Molina and Smith, 1996). In this sense, the equifinality concept recognises that under the limited measurements available in any application of an environmental model, it should be accepted that there are many different model structures and parameter sets that can be used in simulating the available data (Beven and Freer, 2001). Based on the equifinality concept, Beven and Binley (1992) proposed the Generalised Likelihood Uncertainty Estimation (GLUE) methodology for calibration and uncertainty estimation of models. Although the GLUE methodology has mainly been used to calibrate and perform uncertainty analysis on a variety of hydrological models (Beven, 2008), it has also been used in a wide range of environmental modelling applications (e.g. Schulz and Beven, 2003; Piñol et al., 2005; Cameron, 2006).

The aim of this paper was (i) to investigate the effects of agroforestry combined with water harvesting on SOC and N stocks and (ii) to evaluate the performance of the ICBM/N model for simulating trends in these SOC and N stocks in a Mediterranean zone in the inner rainfed zone of central Chile. The model was tested by comparing simulated results with measured SOC and N mass from agroforestry combined with runoff water harvesting plots, using three sets of measurements made between 1996 and 2008. The performance of the model was evaluated by considering the uncertainties in model inputs using the GLUE methodology. In addition, a sensitivity analysis was carried out using the GLUE results.

## 2. Materials and methods

### 2.1. Site description

The simulations used data from a field experiment site established in 1996 in an inner rainfed area of central Chile, 20 km from Santiago (33°28'South, 70°50'West, altitude 470 m a.s.l.). The field experiment is located at the Germán Greve Silva Experimental Station, which belongs to the Faculty of Agronomic Sciences at the University of Chile. A detailed description of the area, measurements and management practices in the field experiment is presented in Salazar (2003) and Salazar et al. (2006).

The soil is a sandy loam up to 100 cm depth, resting on a colluvial substratum (gravel and stones) with a sandy clay loam matrix. The gravel content in the 0–40 cm layer ranges from 3% to 7%. The soil is located in a piedmont position in a slightly inclined plain (slope 7–10%) and has a colluvial origin but with alluvial influence (Luzio et al., 2010). It belongs to the Cuesta Barriga Soil Series and is classified as a Typic Haploxeroll with a thermic soil temperature regime and xeric soil moisture regime (CIREN, 1996). The soil is well drained, with moderately slow internal drainage and rapid external drainage.

The climate in the study area is classified according to the Köppen–Geiger system as temperate with dry and warm summer seasons, corresponding to Csb (Peel et al., 2007). The site has a mean annual air temperature of 14.2 °C and mean annual precipitation of 317 mm (using 1960–2003 data from a meteorological station at the Germán Greve Silva Experimental Station), and is characterised by a strong seasonal rainfall distribution with 75% falling in the winter months.

### 2.2. Experimental design and treatments

Fifteen plots were installed in a randomised block design (Blocks 1–3). The treatments were two crop management systems, two water management systems and a control, with three replications per treatment. The plot size was 15 m × 11 m. The water harvesting plots consisted of a runoff catchment area of 10 m × 11 m and a growing area of 5 m × 11 m. The crop management systems were

**Table 1**

Description of the treatments (P: annual prairie; A: agroforestry; AR: agroforestry with water harvesting; W: woody perennial; WR: woody perennial with water harvesting).

Treatment		Species	
		1996	1997–2008
P	Control	Annual prairie	Annual prairie
A	Agroforestry	Acacia, oats and annual prairie	Acacia and annual prairie
AR	Agroforestry with water harvesting	Acacia, oats and annual prairie	Acacia and annual prairie
W	Woody perennial	Acacia and annual prairie	Acacia and annual prairie
WR	Woody perennial with water harvesting	Acacia and annual prairie	Acacia and annual prairie

agroforestry and woody perennials. *Acacia saligna* (Labill.) H. Wendl was used as the woody perennial component. All plots were covered by native Mediterranean annual prairie. The annual crop was oats (*Avena sativa* L.), which was only sown in the first year after ploughing to a depth of 10 cm. Therefore, after the second year there were two vegetal components: annual prairie and *A. saligna* trees (Table 1).

### 2.3. Soil sampling, measurements and statistical analysis

An initial soil sampling at 0–15 cm was carried out in the field experiment in 1996 for baseline soil chemical analyses. After that, three soil samplings were carried out in all treatments in 2000, 2004 and 2008, with four soil sampling depths of 0–10 cm, 10–20 cm, 20–30 cm and 30–40 cm. These soil samples were used in soil chemical and physical analyses.

Soil organic carbon (SOC) content was determined according to the Walkley–Black method. However, the Walkley–Black method recover just readily oxidizable SOC and a standard conversion factor of 1.33 was used to convert Walkley–Black carbon to the total organic-C content (Batjes, 1996). Total nitrogen was determined by the Kjeldahl method. Bulk density of soil was determined by the clod method.

These soil measurements were used to calculate the SOC and N at 0–40 cm for each individual treatment with four soil sampling depths (sd) by volume according to Batjes (1996) as:

$$\text{SOC}_{(0-40\text{ cm})} = \sum_{d=1}^{d=4} \rho_d C\%_d D_d (1 - S_d) \quad (1)$$

where  $\text{SOC}_{(0-40\text{ cm})}$  is the total amount of carbon ( $\text{kg m}^{-2}$ ) in the 0–40 cm layer,  $\rho$  is the bulk density ( $\text{Mg m}^{-3}$ ) of soil layer  $d$ ,  $C\%$  is C concentration ( $\text{g kg}^{-1}$ ),  $D_d$  is the layer thickness (0.10 m), and  $S_d$  is the volume fraction of gravel and stones (>2 mm). Soil nitrogen stocks were calculated accordingly.

To determine the plant development of *A. saligna* trees, the trunk basal perimeter (BP) was measured at 10 cm above the ground line. Biomass production of the Mediterranean annual prairie was determined according to the point quadrat method.

Analysis of variance (ANOVA) at  $p < 0.05$  using a randomised complete block design was used to test the significance of differences among treatments on SOC and N stocks. Additionally, SOC and N stocks measured in 2000 and 2008 were compared using the Student's  $t$ -test at  $p < 0.05$  to test the significance of differences between years. All data from soil analyses were statistically explored using Minitab Version 15.0 Software.

### 2.4. ICBM/N description

The ICBM/N model, which is a companion to the ICBM model, has been developed for predictions of SOC and N fluxes in agricultural soils. A detailed description of the model logic can be found in Andr n and K tterer (1997) and K tterer and Andr n (2001). ICBM/N is a two-component model, which considers two SOC pools: 'Young' (Y) and 'Old' (O). The model has four initial values and nine parameters for simulating C and N dynamics. For SOC simulations, two initial SOC pool sizes are included:  $Y_0$  and  $O_0$ , whereas for N simulations two initial N pool sizes are included:  $Y_{0N}$  and  $O_{0N}$ . To simulate SOC dynamics five parameters are used: the mean annual C input to the soil ( $i$ ); the decomposition rate constants for the Y and O pools, which are denoted as  $k_Y$  and  $k_O$ , respectively; the parameter  $r_e$ , which condenses external factors such as climate, soil type, cultivation, etc. and affects the decomposition rates of Y and O equally; and the humification coefficient ( $h$ ), which represents the fraction of the outflux from Y that enters O. To simulate N dynamics four parameters are used: the yield efficiency of the soil organism community  $e_Y$ , which represents the fraction of the outflux from Y converted into biomass growth at each time step; and the C/N ratios of input, soil organism biomass and humification, which are denoted  $q_i$ ,  $q_b$ , and  $q_h$ , respectively. Then the differential equations describing the dynamics of SOC (Eqs. (2) and (3)) and N (Eqs. (4) and (5)) are:

$$\frac{dY}{dt} = i - k_Y r_e Y \quad (2)$$

$$\frac{dO}{dt} = h k_Y r_e Y - k_O r_e O \quad (3)$$

$$\frac{dY_N}{dt} = \frac{i}{q_i} + k_Y r_e \left( \frac{e_Y (1-h)}{q_b (1-e_Y)} - \frac{h}{q_h} \right) Y - k_Y r_e \frac{1-h}{1-e_Y} Y_N \quad (4)$$

$$\frac{dO_N}{dt} = k_Y r_e h \frac{Y}{q_h} - k_O r_e O_N \quad (5)$$

### 2.5. Model parametisation

The ICBM/N inputs used in this simulation were based on field measurements in the study area reported by Salazar (2003), Leiva (2005) and Villarroel (2010), and on ranges published in the literature. The model was initiated with total initial SOC ( $Y_0 + O_0$ ) and N ( $Y_{0N} + O_{0N}$ ) stocks measured over 0–40 cm in all treatments in 2000.

In the A, AR, W and WR treatments, the size of labile fractions for SOC ( $Y_0$ ) and N ( $Y_{0N}$ ) were based on results reported by Stolpe et al. (2008), who determined the fractions of SOC and N in soils of the Espinal agroecosystem of Central Chile and found that the labile fraction (young fraction) for SOC ranged from 12% to 21% and for N from 6% to 16% at a soil depth of 0–40 cm. In contrast, in the control treatment (P) the  $Y_0$  and  $Y_{0N}$  pools were assumed to be at steady state, where the labile fraction for SOC was 12% and for N was 6% at a soil depth of 0–40 cm.

The range of values for annual SOC input to soil ( $i$ ) and the C:N ratio of the input ( $q_i$ ) were considered using the following assumptions: (a) the C input to soil from above- and below-ground biomass of Mediterranean annual prairie was estimated from measured biomass production in the different treatments at the Germ n Greve Silva Experimental Station site and from values published in the literature (Saggar et al., 1997; Kuzakov et al., 2001); (b) the annual N input from above- and below-ground biomass of Mediterranean annual prairie was estimated from results presented by Guo et al. (2008) in a study of C and N stocks in a native pasture in Australia; and (c) the annual C and N input from above- and below-ground litter of *A. saligna* was calculated based on ranges published in the literature for leguminous trees in drylands (Sandhu et al.,

**Table 2**  
Range of values for annual carbon (C) and nitrogen (N) inputs from above- and below-ground biomass, annual SOC input to soil ( $i$ ), and C:N ratio of the input ( $q_i$ ).

Treatment <sup>a</sup>	Annual prairie		Acacia saligna	$i$ (kg C m <sup>-2</sup> year <sup>-1</sup> )	$q_i$
	Above (kg m <sup>-2</sup> year <sup>-1</sup> )	Below (kg m <sup>-2</sup> year <sup>-1</sup> )	Above-below (kg m <sup>-2</sup> year <sup>-1</sup> )		
P					
C	0.016–0.041	0.150–250	–	0.17–0.29	29.1–153.2
N	0.0003–0.0009	0.0016–0.0048	–		
A and W					
C	0.025–0.058	0.150–250	0.20–0.60	0.38–0.91	14.0–57.1
N	0.0003–0.0009	0.0016–0.0048	0.014–0.021		
AR and WR					
C	0.024–0.049	0.150–250	0.24–0.72	0.41–1.02	14.4–60.3
N	0.0003–0.0009	0.0016–0.0048	0.015–0.23		

<sup>a</sup> P: annual prairie; A: agroforestry; AR: agroforestry with water harvesting; W: woody perennial; WR: woody perennial with water harvesting.

1990; Witkowski, 1991; Lehmann and Zech, 1998; Bryan, 2000; Geesing et al., 2000; Cortina and Maestre, 2005). The SOC and N soil input estimated from ranges published in the literature were approximated for a 0–40 cm soil layer. The range of values used for  $i$  and  $q_i$  are shown in Table 2.

The decomposition rate constant for the 'Young' pool ( $k_Y$ ), the decomposition rate constant for the 'Old' pool ( $k_O$ ) and the humification coefficient ( $h$ ) were set according to previous ICBM model parameterisations (Andrén and Kätterer, 1997; Kätterer and Andrén, 1999).

The parameter  $r_e$  was estimated based on linear regression analysis from the climate data (annual mean temperature and annual precipitation sum) presented by Andrén et al. (2007) for Sweden and five African countries, which used previously calculated  $r_e$  values as independent variables. To consider the effect of higher water supply in the water harvesting treatment, the annual precipitation sum was increased by 12–27% according to the size of the runoff area and previous runoff measurements made by Joel et al. (2002) in the same area.

The C:N ratio of humification ( $q_h$ ) and the fraction of C flux from  $Y$  allocated to organism growth ( $e_Y$ ) were estimated from data presented by Kätterer and Andrén (2001). The C:N ratio of soil organism biomass ( $q_b$ ) was assumed to range from 4 to 10, which includes the most common C:N ratios for bacteria and fungi groups in the soil.

## 2.6. Model calibration and uncertainty estimation

In this study the GLUE procedure was used to calibrate and quantify the uncertainty in total soil organic C and N mass predictions

over 0–40 cm during the study period (2000–2008). GLUE estimates were compared with the C and N mass measurements carried out in 2004 and 2008. The GLUE methodology was applied separately to the five treatments (see Table 1).

The general requirements of the GLUE procedure can be summarised as follows: (a) a formal definition of a likelihood measure; (b) an appropriate definition of the prior parameter distribution; (c) a procedure for using likelihood weights in uncertainty estimation; and (d) a procedure for updating likelihood weights recursively as new data become available.

### 2.6.1. Definition of a likelihood measure

The normalised sum of squared errors (NSSE) was selected as likelihood function (Smith et al., 2008b), given by:

$$NSSE = 1.0 - \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n O_i^2} \quad (6)$$

where  $O$  is the observed value,  $O'$  is the mean observed value,  $S$  is the simulated value and  $n$  is the number of paired observed-simulated values. The NSSE is expressed in terms of the variance of the residuals ( $S^2_{O-S}$ ), which is used to summarise differences in the variability of  $O$  and  $S$  as well the similarity of their pattern. The value of NSSE ranges from minus infinity to 1.0, with an NSSE of 1.0 representing a perfect prediction and lower values indicating less accurate agreement between model simulations and observations.

Beven (2008) indicated that the likelihood threshold for a model to be considered behavioural is site-specific and should consider the main objectives of each modelling project. In this study, three criteria of acceptability were tested for SOC and N simulations:  $NSSE > 0.55$ ,  $NSSE > 0.75$  and  $NSSE > 0.95$ , to determine the thresh-

**Table 3**  
Parameter ranges used in Monte Carlo simulations for the ICBM/N model.

Parameter	Unit	Description	Minimum value	Maximum value
$Y_0$	kg C m <sup>-2</sup>	Initial C mass of the 'Young' pool for A, AR, W and WR treatments	1.11	1.95
$Y_{0N}$	kg N m <sup>-2</sup>	Initial N mass of the 'Young' pool for A, AR, W and WR treatments	0.027	0.071
$i$	kg C m <sup>-2</sup> year <sup>-1</sup>	Annual C input to soil in control treatment (P)	0.17	0.29
		Annual C input to soil in A and W treatments	0.38	0.91
		Annual C input to soil in water harvesting treatments (AR and WR)	0.41	1.02
$k_Y$	year <sup>-1</sup>	Decomposition rate constant for the 'Young' pool	0.2	1.2
		Decomposition rate constant for the 'Old' pool	0.003	0.015
$h$	Dimensionless	Humification coefficient; fraction of 'Young' outflux that enters 'Old'	0.1	1.0
$r_e$	Dimensionless	External response factor that affects outflux from 'Young' and 'Old' for treatments without water harvesting (P, A and W)	0.7	2.3
		External response factor that affects outflux from 'Young' and 'Old' for treatments with water harvesting (AR and WR)	0.8	2.6
$q_i$	Dimensionless	Quality, C/N ratio of input, $i$ in control treatment (P)	29.1	153.2
		Quality, C/N ratio of input, $i$ in A and W treatments	14.0	57.1
		Quality, C/N ratio of input, $i$ in water harvesting treatments (AR and WR)	14.4	60.3
$q_b$	Dimensionless	C/N ratio of soil organism biomass	4.0	10.0
$q_h$	Dimensionless	C/N ratio of humification; the influx to $O$	1	30
$e_Y$	Dimensionless	Efficiency, i.e. the fraction of C flux from $Y$ allocated to organism growth	0.5	0.9

**Table 4**

Soil organic carbon concentration ( $\pm$ standard deviations;  $n=3$ ) in annual prairie (P), agroforestry (A), agroforestry with water harvesting (AR), woody perennial (W) and woody perennial with water harvesting (WR).

Year	Depth (cm)	Treatment <sup>a</sup>				
		P (kg m <sup>-2</sup> )	A (kg m <sup>-2</sup> )	AR (kg m <sup>-2</sup> )	W (kg m <sup>-2</sup> )	WR (kg m <sup>-2</sup> )
2000	0–10	4.81 $\pm$ 0.77	4.01 $\pm$ 0.74	3.22 $\pm$ 1.85	5.23 $\pm$ 1.12	4.53 $\pm$ 0.98
	10–20	1.59 $\pm$ 0.20	2.12 $\pm$ 0.72	2.95 $\pm$ 1.39	1.75 $\pm$ 0.64	2.24 $\pm$ 0.70
	20–30	1.63 $\pm$ 0.22	1.83 $\pm$ 0.37	1.93 $\pm$ 0.15	1.59 $\pm$ 0.48	1.95 $\pm$ 0.10
	30–40	1.45 $\pm$ 0.36	1.59 $\pm$ 0.13	1.94 $\pm$ 0.72	1.28 $\pm$ 0.53	1.22 $\pm$ 0.45
2004	0–40	9.48 $\pm$ 1.54	9.55 $\pm$ 1.88	10.04 $\pm$ 3.70	9.85 $\pm$ 2.73	9.94 $\pm$ 1.53
	0–10	3.53 $\pm$ 0.93	3.77 $\pm$ 0.58	4.27 $\pm$ 1.15	4.39 $\pm$ 0.82	4.33 $\pm$ 0.81
	10–20	2.60 $\pm$ 1.16	2.91 $\pm$ 0.66	2.82 $\pm$ 0.95	2.69 $\pm$ 1.01	2.80 $\pm$ 0.71
	20–30	2.25 $\pm$ 1.32	2.12 $\pm$ 0.48	2.40 $\pm$ 1.11	2.03 $\pm$ 0.82	2.40 $\pm$ 0.76
2008	30–40	1.97 $\pm$ 1.37	2.00 $\pm$ 0.50	2.35 $\pm$ 1.06	1.69 $\pm$ 0.75	1.90 $\pm$ 0.46
	0–40	10.35 $\pm$ 4.78	10.81 $\pm$ 2.00	11.84 $\pm$ 4.23	10.79 $\pm$ 3.33	11.43 $\pm$ 2.41
	0–10	3.55 $\pm$ 0.56	5.52 $\pm$ 2.28	4.94 $\pm$ 1.99	4.86 $\pm$ 0.43	5.10 $\pm$ 0.87
	10–20	2.30 $\pm$ 1.12	2.86 $\pm$ 0.50	2.57 $\pm$ 0.78	2.83 $\pm$ 0.85	2.75 $\pm$ 0.51
	20–30	2.01 $\pm$ 0.97	2.15 $\pm$ 0.48	1.93 $\pm$ 0.60	1.74 $\pm$ 0.43	2.27 $\pm$ 0.28
	30–40	1.56 $\pm$ 0.78	2.35 $\pm$ 0.34	2.27 $\pm$ 0.50	1.94 $\pm$ 0.30	2.25 $\pm$ 0.40
	0–40	9.41 $\pm$ 3.35	12.88 $\pm$ 3.15	11.71 $\pm$ 3.85	11.37 $\pm$ 1.81	12.36 $\pm$ 1.37

<sup>a</sup> Treatment effects were not significant at  $p < 0.05$  according to ANOVA for each row.

old guaranteed to bracket at least 70% of the observations. The 70% threshold was defined to retain a significant number of model runs that may be considered fit for the purpose of this study. Thus all the simulations with an NSSE value equal to or greater than the chosen threshold were retained for making predictions in SOC and N stocks, which were classified as behavioural simulations. In contrast, all the simulations with an NSSE value lower than the chosen threshold were classified as non-behavioural simulations and given a likelihood of zero. In addition, to avoid negative fluxes in the model, a given parameter set was considered behavioural if all the following criteria were met for C predictions:

- (i)  $0 \leq h \leq 1$   
and for N predictions:
- (ii)  $0 < e_Y \leq 1$
- (iii)  $h < e_Y$
- (iv)  $h/q_h < e_Y/q_b$ .

### 2.6.2. Definition of a prior parameter distribution

In this study two initial values and nine parameters of the ICBM/N model were calibrated using the GLUE methodology (Table 3). In the control treatment (P), the  $Y_0$  and  $Y_{0N}$  pools were not considered in the GLUE procedure. The annual C input to soil ( $i$ ) and the quality C/N ratio of input  $i$  ( $q_i$ ) included three replicates according to the different inputs from the treatments P, A–W and AR–WR (see Table 2). The parameter  $r_e$  included two replicates to consider the effect of water harvesting.

The distribution of parameter values to be considered was defined on the basis of some prior knowledge about the system, which included measured and estimated values (see parameterisation section). When there is little prior knowledge about a parameter (i.e.  $k_Y$ ,  $k_O$ ,  $q_h$  and  $e_Y$ ), Beven and Binley (1992) recommend using a uniform parameter distribution with a wide range, which can be refined by comparison with the predicted response for defining a suitable reference prior distribution. For the simulation period (2000–2008), 20,000 random sets of parameters were generated from uniform distributions across the specified ranges shown in Table 3 and the ICBM/N model was run for the 15 plots according to the characteristics of each plot.

### 2.6.3. Procedure for using likelihood weights in uncertainty estimation

The NSSE values were scaled such that the sum of all the NSSE values equalled 1, resulting in a distribution function for the parameter sets. To calculate a cumulative distribution of the predictions,

the predicted SOC and N stocks for each sample model run were ranked in order of magnitude, using the likelihood weights associated with each simulation. For the present study, the 5% and 95% percentiles of the cumulative likelihood distribution were chosen as the uncertainty limits of the predictions.

### 2.6.4. Procedure for updating likelihood weights recursively as new data become available

Driving N parameters of ICBM/N are based on the output of the SOC model ICBM. Consequently, ICBM performance is expected to have a direct impact on the performance of ICBM/N. In this sense, the NSSE contains a form of learning process that may consider this cumulative effect in the N predictions. Thus when more data are added the posterior likelihood distribution of parameter sets derived for NSSE appears to learn about these (Smith et al., 2008b). In this study the NSSE values associated with SOC simulations and estimated uncertainties were defined as the prior likelihood distribution of parameter sets, which was updated when N simulations were assimilated into the analysis using the Bayes equation in the form:

$$L_p(\Theta|y) = L_y(\Theta|y) \times L_0(\Theta) \quad (7)$$

where  $L_p(\Theta|y)$  is the posterior likelihood distribution of parameter sets for NSSE values of N simulations,  $L_y(\Theta|y)$  is the calculated likelihood function of the parameter sets given the assimilation for NSSE values of N simulations,  $y$ ,  $L_0(\Theta)$  is the prior likelihood distribution of the parameter sets for NSSE values of SOC simulations and  $\Theta$  is a set of parameters.

### 2.7. Sensitivity analysis

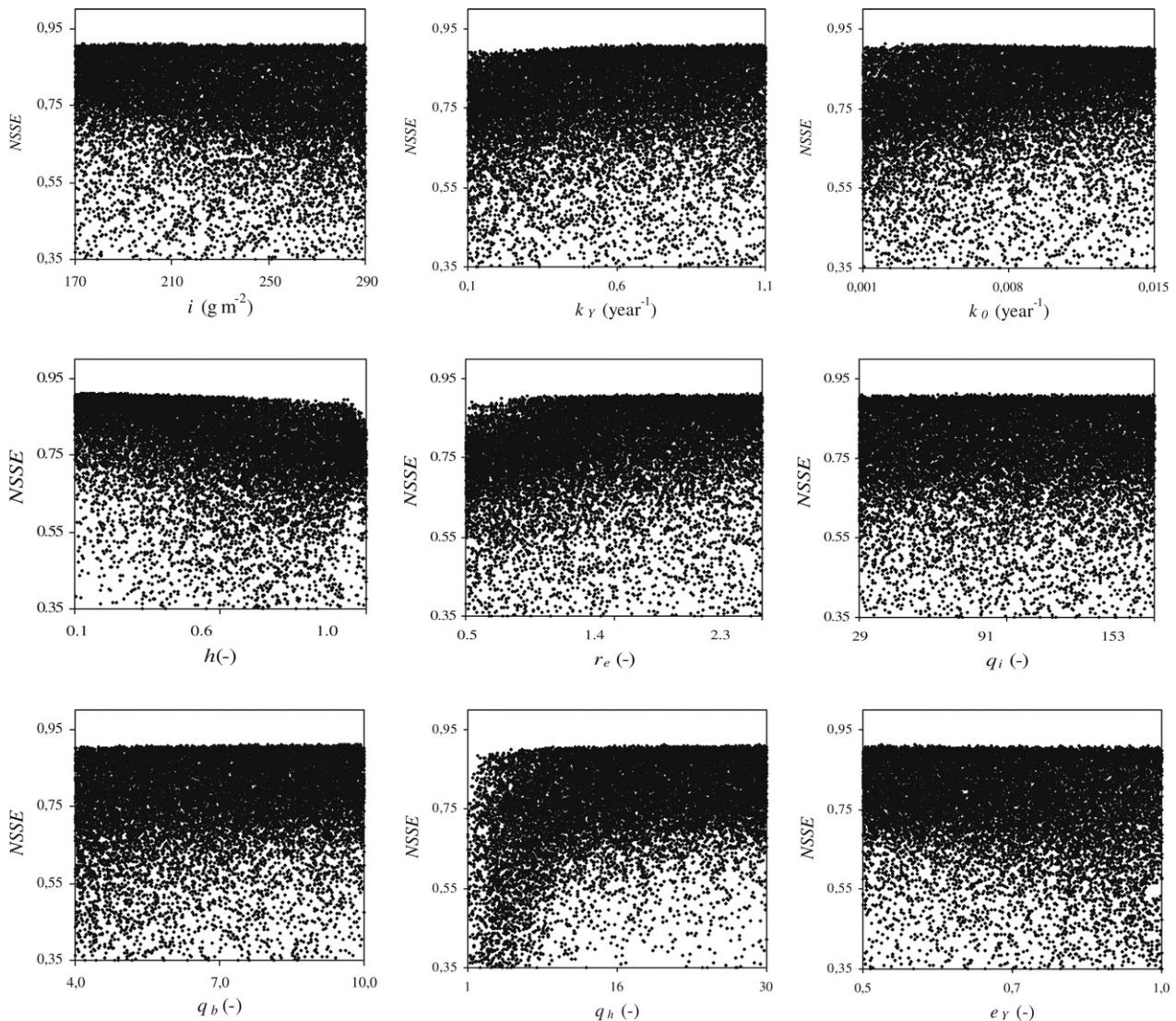
A sensitivity analysis was carried out for two initial values and nine parameters of the ICBM/N model selected in the Monte Carlo simulations (Table 3) using the GLUE results. This methodology considers the likelihood weights for the behavioural simulations (Beven, 2008). In the present study, the sensitivity analysis was performed by comparison of the cumulative distribution for the posterior behavioural simulations of N simulations after the Bayesian updating of likelihood weights and non-behavioural simulations of N simulations. The parameters that showed a strong deviation between behavioural and non-behavioural cumulative distributions across the same parameter range were considered the most sensitive. In contrast, parameters that were uniformly distributed were considered less sensitive to changes in parameter values. In addition, the non-parametric Kolmogorov–Smirnov

**Table 5**  
Soil nitrogen concentration ( $\pm$ standard deviations;  $n = 3$ ) in annual prairie (P), agroforestry (A), agroforestry with water harvesting (AR), woody perennial (W) and woody perennial with water harvesting (WR).

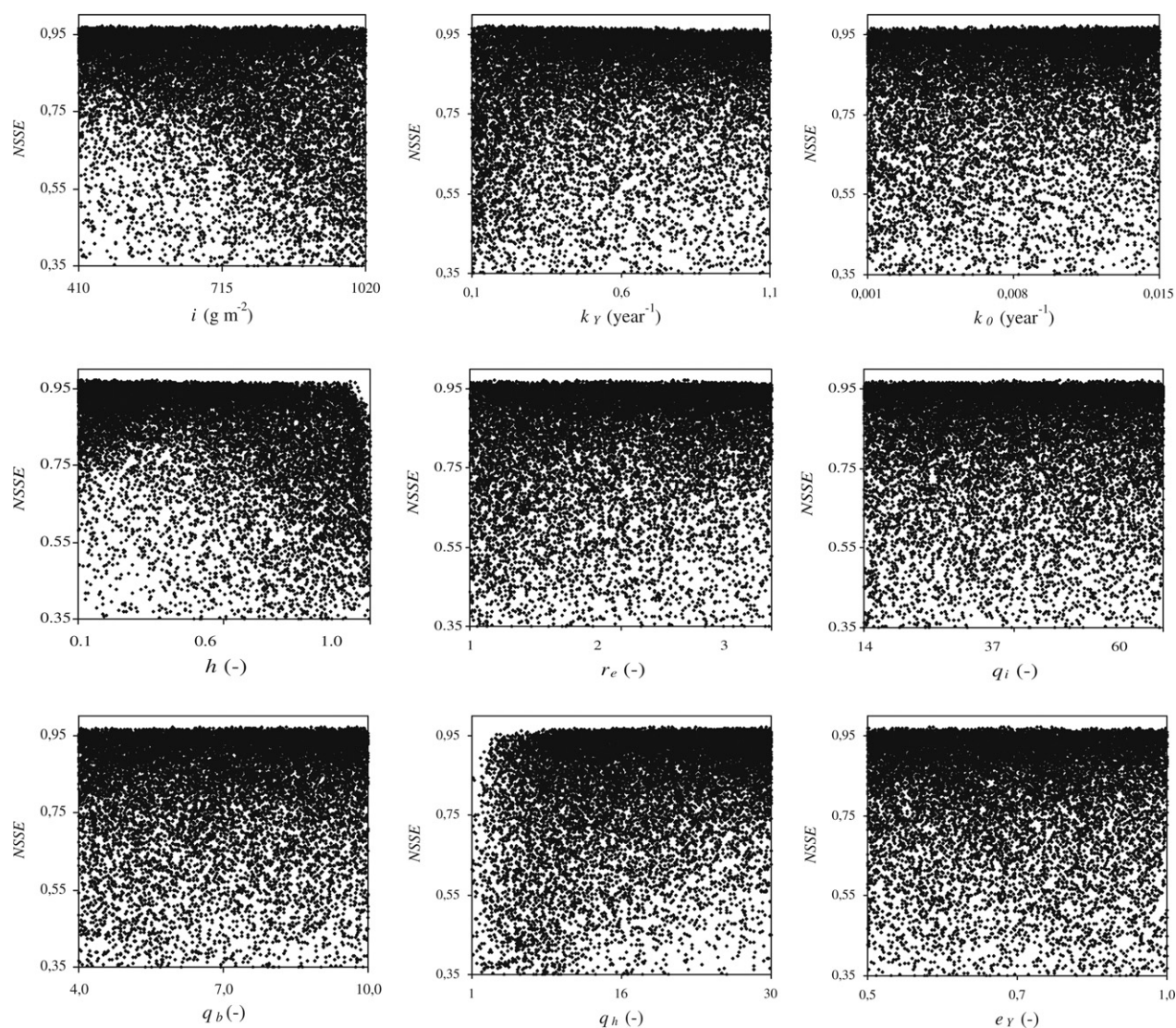
Year	Depth (cm)	Treatment <sup>a</sup>				
		P ( $\text{kg m}^{-2}$ )	A ( $\text{kg m}^{-2}$ )	AR ( $\text{kg m}^{-2}$ )	W ( $\text{kg m}^{-2}$ )	WR ( $\text{kg m}^{-2}$ )
2000	0–10	0.24 $\pm$ 0.06a	0.21 $\pm$ 0.02a	0.17 $\pm$ 0.10a	0.28 $\pm$ 0.02a	0.25 $\pm$ 0.06a
	10–20	0.09 $\pm$ 0.04a	0.10 $\pm$ 0.05a	0.13 $\pm$ 0.04a	0.09 $\pm$ 0.01a	0.11 $\pm$ 0.03a
	20–30	0.07 $\pm$ 0.03a	0.07 $\pm$ 0.03a	0.10 $\pm$ 0.03a	0.08 $\pm$ 0.01a	0.10 $\pm$ 0.01a
	30–40	0.07 $\pm$ 0.01a	0.07 $\pm$ 0.03a	0.10 $\pm$ 0.01a	0.07 $\pm$ 0.02a	0.08 $\pm$ 0.01a
2004	0–40	0.47 $\pm$ 0.13a	0.46 $\pm$ 0.13a	0.51 $\pm$ 0.16a	0.53 $\pm$ 0.06a	0.54 $\pm$ 0.07a
	0–10	0.22 $\pm$ 0.05a	0.22 $\pm$ 0.03a	0.21 $\pm$ 0.05a	0.27 $\pm$ 0.05a	0.28 $\pm$ 0.02a
	10–20	0.14 $\pm$ 0.06a	0.17 $\pm$ 0.03a	0.16 $\pm$ 0.04a	0.16 $\pm$ 0.05a	0.15 $\pm$ 0.03a
	20–30	0.14 $\pm$ 0.06a	0.13 $\pm$ 0.02a	0.14 $\pm$ 0.04a	0.13 $\pm$ 0.04a	0.13 $\pm$ 0.02a
2008	30–40	0.13 $\pm$ 0.08a	0.12 $\pm$ 0.03a	0.15 $\pm$ 0.05a	0.11 $\pm$ 0.03a	0.11 $\pm$ 0.02a
	0–40	0.63 $\pm$ 0.24a	0.65 $\pm$ 0.10a	0.66 $\pm$ 0.16a	0.67 $\pm$ 0.17a	0.66 $\pm$ 0.06a
	0–10	0.21 $\pm$ 0.03b	0.24 $\pm$ 0.04b	0.31 $\pm$ 0.12ab	0.29 $\pm$ 0.05ab	0.38 $\pm$ 0.11a
	10–20	0.19 $\pm$ 0.04a	0.23 $\pm$ 0.04a*	0.17 $\pm$ 0.04a	0.20 $\pm$ 0.03a*	0.15 $\pm$ 0.03a
	20–30	0.14 $\pm$ 0.05a	0.17 $\pm$ 0.02a*	0.16 $\pm$ 0.06a	0.13 $\pm$ 0.03a	0.16 $\pm$ 0.03a
	30–40	0.12 $\pm$ 0.03a	0.12 $\pm$ 0.02a	0.18 $\pm$ 0.09a	0.12 $\pm$ 0.05a	0.14 $\pm$ 0.05a
	0–40	0.66 $\pm$ 0.11a	0.75 $\pm$ 0.07a	0.82 $\pm$ 0.28a	0.74 $\pm$ 0.15a	0.83 $\pm$ 0.14a

<sup>a</sup> Different letters within a row indicate significant differences at  $p < 0.05$  (from ANOVA,  $n = 3$ ; means and standard deviations).

\* Indicates significant differences at  $p < 0.05$  from values in 2000 at corresponding depth according to Student's  $t$ -test for paired samples;  $n = 3$ .



**Fig. 1.** Dotty plots of the normalised sum of squared errors (NSSE) resulting from Monte Carlo realisations for N predictions in the treatment control (P) in Block 3 relative to the nine parameters of the ICBM/N model (see Table 4 for parameter descriptions).



**Fig. 2.** Dotty plots of the normalised sum of squared errors (NSSE) resulting from Monte Carlo realisations for N predictions in the treatment woody perennial with water harvesting (WR) in Block 3 relative to the nine parameters of the ICBM/N model (see Table 4 for parameter descriptions).

$d$ -statistic ( $d_{K-S}$ ) was used as a measure of the sensitivity (Beven, 2008). The  $d_{K-S}$  calculates the maximum distance between the behavioural and the non-behavioural cumulative distributions. The value of  $d_{K-S}$  ranges from 0 to 1, where a parameter with  $d_{K-S} = 1$  indicates a high sensitivity, whereas a parameter with  $d_{K-S} = 0$  indicates non-sensitivity.

### 3. Results and discussion

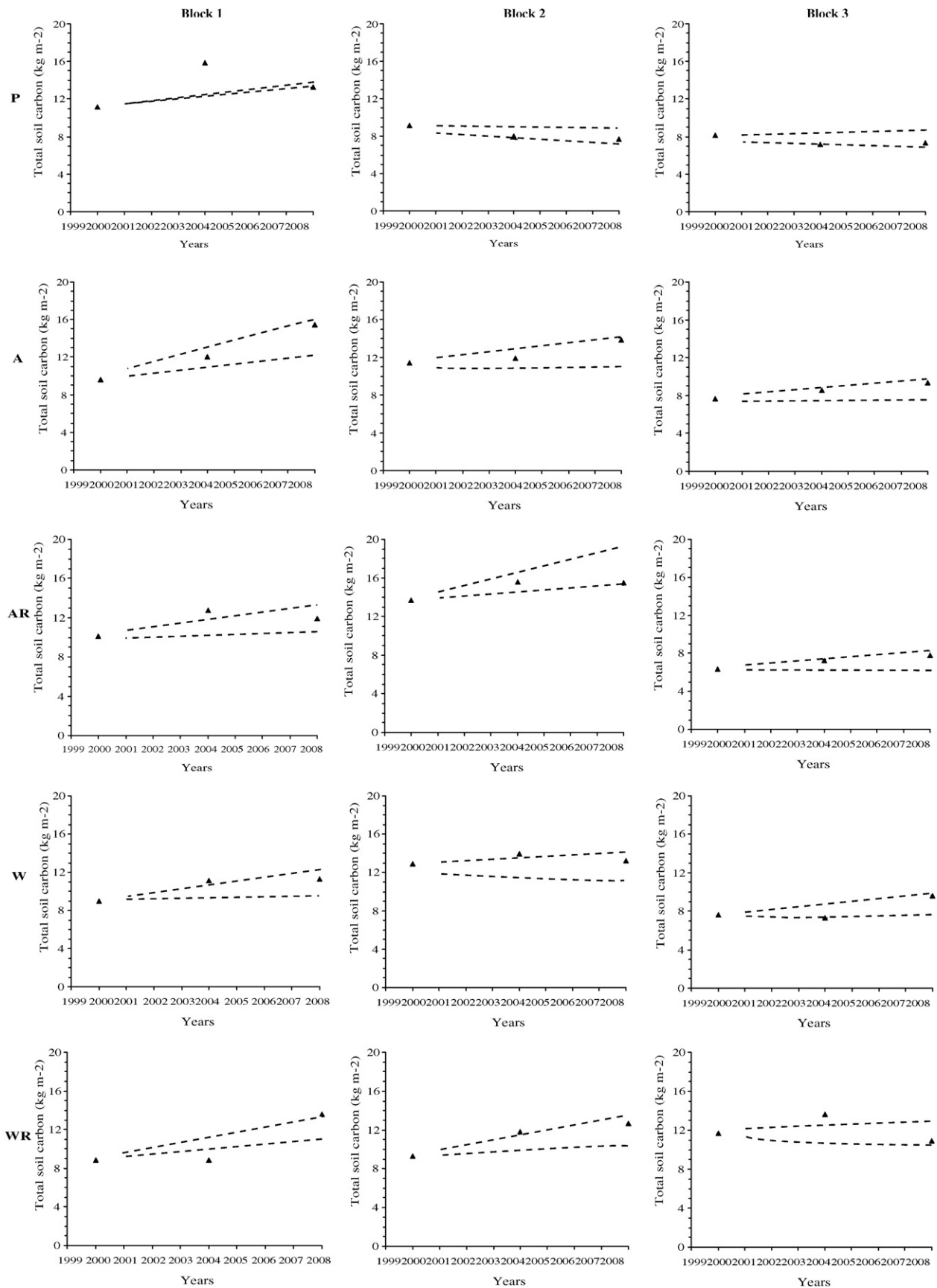
#### 3.1. SOC and N stocks

In 2008, treatments with *A. saligna* trees (A, AR, W and WR) showed higher SOC stocks than the control (P), with treatments A and WR showing the highest contents (Table 4). However, the differences were not statistically significant. In P there was a slight trend for decreasing SOC over time (mainly at the surface layer 0–10 cm) which may indicate a negative SOC balance in the degraded Mediterranean annual prairie system with low C inputs in the long term (Table 4). Unlike treatment P, the treatments with *A. saligna* increased C stocks, probably due to higher litter inputs, but this increase was not statistically significant.

In general, the treatments with *A. saligna* showed higher N stocks than P in 2008 (Table 5). However, there were few significant treat-

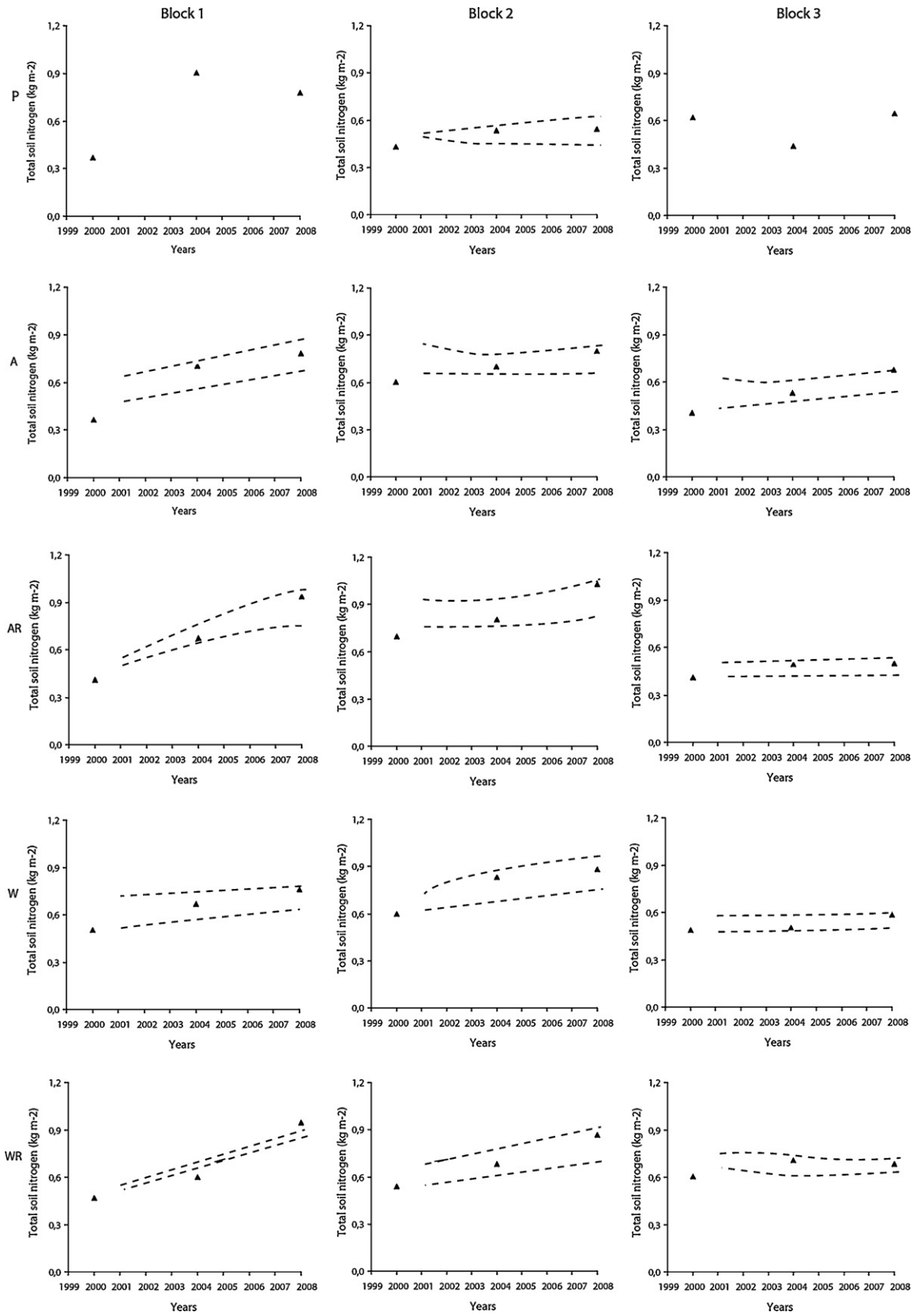
ment effects on N stocks. In the 0–10 layer, the water harvesting treatment WR had the highest content,  $0.38 \text{ kg m}^{-2}$ . This was significantly different from treatment P, which had the lowest content,  $0.21 \text{ kg m}^{-2}$ . This suggests that the WR practice had positive effects in improving the water content in the soil and thus stimulating biomass production and root turnover in the upper layer, probably due to increased  $\text{N}_2$  fixation. This higher biomass production of *A. saligna* in WR was reflected in the highest values of trunk basal perimeter (for details see Salazar, 2003), a biometric parameter directly related to high biomass production of *A. saligna* (Stewart and Salazar, 1992; Lövenstein and Berliner, 1993; Drippelmann and Berliner, 2000). Similarly, in the 0–40 layer the treatments with water harvesting (AR and WR) showed the highest N contents, but this was not statistically significant. Comparing N stocks measured in 2000 and 2008, there was a trend for increasing N content in all plots. However, only treatment A in the 10–20 and 20–30 layers and treatment W in the 10–20 layer showed statistically significant evidence of increased N stocks over time.

The measured SOC and N stocks showed a high variability within treatments (Tables 4 and 5). A possible explanation for this is the conditions before the start of the experiment in 1996, when the area was covered by a degraded Mediterranean annual prairie probably including native *A. caven* trees in some patches. In a study at

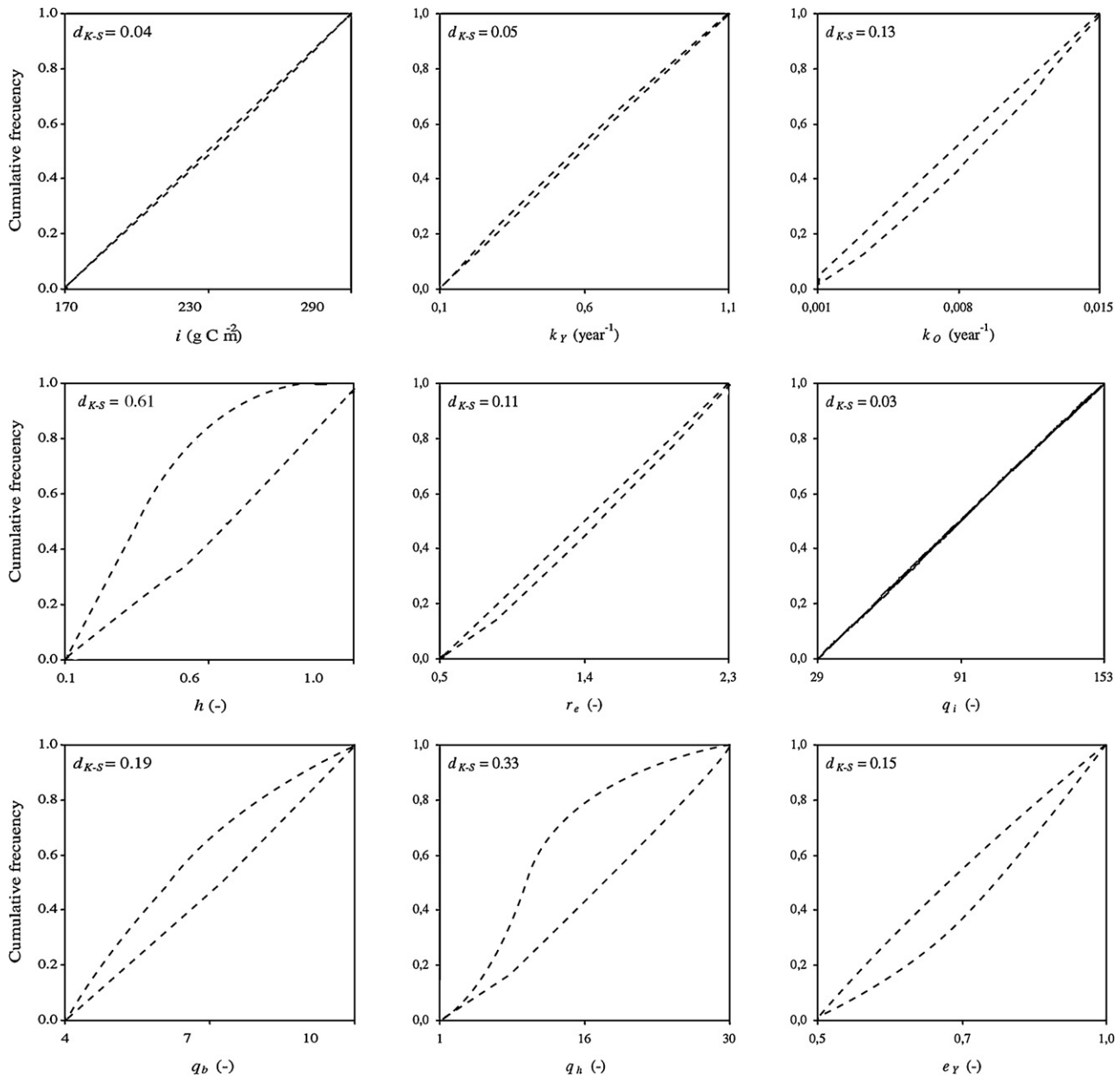


**Fig. 3.** Prior likelihood distribution of the parameter sets with NSSE > 0.95 for results of total soil carbon (0–40 cm) from treatments: control (P), agroforestry (A), agroforestry with water harvesting (AR), woody perennial (W) and woody perennial with water harvesting (WR) in Blocks 1–3. Triangles indicate observed total soil carbon, dashed lines indicate 5% and 95% simulation limits.





**Fig. 4.** Posterior likelihood distribution of the parameter sets with NSSE > 0.95 for results of total soil nitrogen (0–40 cm) from treatments: control (P), agroforestry (A), agroforestry with water harvesting (AR), woody perennial (W) and woody perennial with water harvesting (WR) in Blocks 1–3. Triangles indicate observed total soil nitrogen, dashed lines indicate 5% and 95% simulation limits.



**Fig. 5.** Sensitivity plots for all parameters included in the GLUE procedure (see Table 3) for N predictions in the treatment control (P) in Block 2. Solid lines indicate behavioural parameter distributions (NSSE > 0.95) and dashed lines indicate non-behavioural parameter distributions (NSSE ≤ 0.95).  $d_{K-S}$  is the Kolmogorov–Smirnov test.

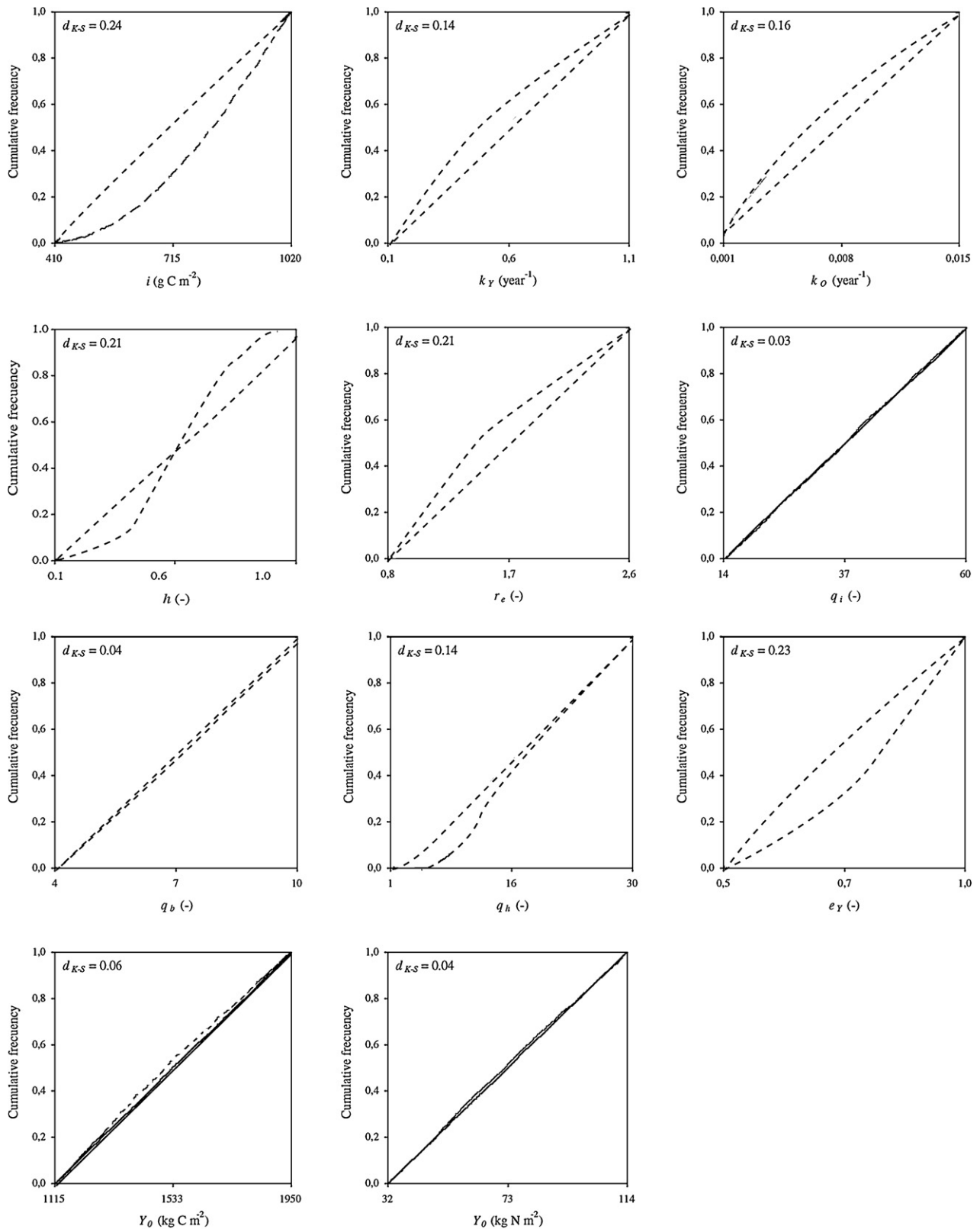
the same experimental site, Olivares et al. (1988) reported greater amounts of SOC and N stocks beneath *A. caven* canopy than in open grassland, which may explain the higher spatial variability in soil properties in the Mediterranean annual prairie. Similarly, Muñoz et al. (2007) in a study in the ‘Espinal’ Chilean agroecosystem found that *A. caven* canopy increased SOC stocks in the 0–40 cm layer by 25% compared with intercanopy. Other studies have noted that tree legumes in semi-arid areas can contribute to the microvariability in soil properties by creating islands of fertility (Buresh and Tian, 1998; Geesing et al., 2000; Traoré et al., 2007).

Agroforestry with water harvesting showed a lack of significant differences at 5% level compared with the other treatments. This might be due to the fact that our study was of short duration (12 years) and therefore its potential contributions towards improving soil properties may not have been fully realised. Similar situations in other agroforestry trials were reported by Power et al. (2003) in New Zealand and Takimoto et al. (2009) in Mali, after 9 and 8 years respectively. In addition, Nair et al. (1995) noted that in agro-

forestry, the potential long-term benefits of soil improvement, such as increases in SOC and N stocks, are often not manifested in the short-term. It is important to note that other studies in semi-arid environments have shown that to increase SOC stocks it is necessary to incorporate large amounts of organic material into soil over a long period of time due to the high rates of decomposition in these regions (de Ridder and van Keulen, 1990; Breman and Kessler, 1997). Although only few treatment differences were significant after 12 years, there was some evidence that differences are starting to occur.

### 3.2. Model calibration and uncertainty estimation

In this study, 20,000 simulations with randomly chosen values of the parameters were performed for each plot. The NSSE results were plotted against individual parameters to get an idea of how ICBM/N performance varied through the parameter space, in which each dot represented one run of the model. Dot plot results from



**Fig. 6.** Sensitivity plots for all parameters included in the GLUE procedure (see Table 3) for N predictions in the treatment woody perennial with water harvesting (WR) in Block 2. Solid lines indicate behavioural parameter distributions (NSSE > 0.95) and dashed lines indicate non-behavioural parameter distributions (NSSE ≤ 0.95).  $d_{K-S}$  is the Kolmogorov–Smirnov test.

Block 3 are shown because these represent the general trends of IBCM/N parameters in the treatments. These dot plots showed very good and very poor results over the whole of the chosen parameter range, with only the humification coefficient ( $h$ ) and the C:N

ratio of humification ( $q_h$ ) showing a slight tendency for more likely values to be seen in one part of the chosen parameter range, e.g. for treatments P and WR in Block 3 in Figs. 1 and 2, respectively. The other parameters showed a clear indication of equifinality due

to the possibility of having the same maximum likelihood despite the parameter value, which might indicate prediction insensitivity to parameters or a close interaction between some parameters in producing behavioural simulations.

The GLUE procedure described above was performed to measure the uncertainty in ICBM/N predictions of SOC and N stocks. It is important to note that the results of the GLUE analysis depend on the choice of likelihood measure used to evaluate the sample of models and the choice of limits of acceptability (Beven, 2008). In this study all SOC and N simulations with normalised sum of squared errors (NSSE) values greater than 0.95 and that met all the requirements defined in Section 2.6.1 were accepted as behavioural, which resulted in at least 70% of the observed SOC and N stocks being bracketed by the 5% and 95% uncertainty bands as shown in Figs. 3 and 4, respectively.

The trend of GLUE estimates predicted by the model was in good agreement with observed SOC values in the different treatments, with most of the observed SOC values in 2004 and 2008 (70%) being bracketed within the GLUE estimates (Fig. 3). In addition, after the calibration of ICBM/N for SOC simulations in all treatments, the prior likelihood distribution of the parameter sets for NSSE values included a range from 1% to 76% of the SOC simulations as behavioural (NSSE > 0.95).

When the model was used for N predictions, the GLUE estimates and the observed soil N values in 2004 and 2008 showed similar performance to those obtained during the SOC simulations, with around 80% of the observed N values being included in the GLUE estimates (Fig. 4). For the N simulations, the range of simulations accepted as behavioural with a threshold of NSSE > 0.95 comparing simulated and observed values was lower for the posterior likelihood distribution for N simulations (range 0–23%) than the prior likelihood distribution for SOC simulations.

In treatment P in Blocks 1 and 3, no behavioural model runs were found within the threshold of NSSE > 0.95 for N simulations (Fig. 4). In these plots, the measured N stocks did not show a clear tendency over time, with the model being unable to replicate breaks in the N trends. This might also indicate that in treatment P initial conditions were far from steady-state.

The uncertainty in SOC stock predictions increased over time (Fig. 3), whereas the uncertainty in N simulations showed no clear increasing or decreasing pattern over time (Fig. 4). These results may indicate that additional data sets are needed to redefine the parameter distributions in the model and thus to predict the trends in SOC and N stocks in the future.

### 3.3. Sensitivity analysis

The sensitivity analysis only included GLUE results from Block 2, because in treatment P in Blocks 1 and 3 no behavioural simulations were found. Comparing results from the sensitivity plots for treatment P, the humification coefficient ( $h$ ) showed a strong deviation between behavioural (NSSE > 0.95) and non-behavioural (NSSE ≤ 0.95) cumulative distributions, for instance as shown in Fig. 5. Similarly, in treatment P the Kolmogorov–Smirnov  $d$ -statistic ( $d_{K-S}$ ) indicated that  $h$  had the highest sensitivity, with a value of 0.61. In treatment P, the C/N ratio of humification ( $q_h$ ) also showed a wide spread of distributions, with a  $d_{K-S}$  value of 0.33.

For the treatments A, AR, W and WR, the parameter  $h$  also showed a distinct difference between behavioural (NSSE > 0.95) and non-behavioural (NSSE ≤ 0.95) cumulative distributions (e.g. treatment WR in Block 2, Fig. 6), but with lower  $d_{K-S}$  values (around 0.21) than in treatment P. In addition, three other parameters: annual SOC input to soil ( $i$ ), the external response factor affecting outflux from 'Young' and 'Old' pools ( $r_e$ ) and the fraction of SOC flux from 'Young' allocated to organism growth ( $e_v$ ) showed sensitivity, with the highest  $d_{K-S}$  value for the  $i$  parameter (around 0.24).

The parameter  $i$  was particularly important in the treatments with *A. saligna* (A, AR, W and WR), because higher amounts of C than in the control (P) treatment were incorporated from tree roots or shoot litter. The high sensitivity to the parameter  $h$  in all treatments reflects the role of the net carbon outfluxes from the young to the old C pool, which is positively correlated with the N stocks. Similarly, Sindhøj et al. (2006) noted that in the ICBM model the SOC dynamics within a given climate are mainly controlled by  $h$ . The sensitivity analysis showed that N predictions depended mainly on C parameters, such as  $h$  and  $i$ , which confirms that SOC simulation performance is expected to have a direct impact on the performance of N simulations. Thus we recommend that in future ICBM/N evaluations, the model should be sequentially calibrated for the SOC and N components.

It is important to recognise that this was an incomplete test of the ICBM/N model since it relied primarily on literature data sets to parameterise the model. To improve model performance as regards SOC and N simulations, the model needs to be tested on the basis of field measurements, particularly of  $h$  and  $i$  parameters. Although additional measurements may help to improve the understanding of these processes and reduce uncertainty, they cannot completely eliminate the uncertainty in model predictions.

## 4. Conclusions

SOC and most N analyses revealed a lack of significant differences between treatments, probably due mainly to the short duration of the present study. Another possible cause of the lack of differences was the high spatial variability in these soil properties at the experimental site. Despite that, agroforestry combined with water harvesting showed some evidence that differences may be starting to occur, for instance treatment woody perennial with water harvesting (WR) showed higher N stocks than the control (P) in the upper soil layer.

The ICBM/N model was calibrated and uncertainties estimated using data sets from this water harvesting field experiment. The temporal trend and magnitude of measured SOC and N stocks were generally well predicted. The observed SOC stocks were bracketed by the uncertainty bands (5% and 95%) for 70% of the time and the observed N stocks for 80% of the time. The sensitivity analysis showed that N predictions were most sensitive to C parameters, which suggests that ICBM/N should be sequentially calibrated for the SOC and N components.

The results indicate that the ICBM/N model can be an effective tool for describing SOC and N fluxes from agroforestry combined with runoff water harvesting systems in the Mediterranean zone of central Chile over the medium term. Although the model showed good performance in the study area, this was an incomplete test of the model since it relied primarily on literature data sets to parameterise the model. Additional data sets are needed for more general projections of SOC and N stock trends into the future.

The results of this pilot field experiment suggest that the use of water harvesting combined with agroforestry systems in the central zone of Chile can be beneficial for increasing SOC and N stocks, which indicates that these land management practices can be used for restoration of degraded soils and potential SOC sequestration in this region.

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## References

- Abdelkadir, A., Schultz, R.C., 2005. Water harvesting in a 'runoff-catchment' agroforestry system in the dry lands of Ethiopia. *Agroforest Forum* 63, 291–298.
- Andr n, A., K tterer, T., 1997. ICBM: the introductory carbon balance model for exploration of soil carbon balances. *Ecol. Appl.* 7, 1226–1236.
- Andr n, O., Kihara, J., Bationo, A., Vanlauwe, B., K tterer, T., 2007. Soil climate and decomposer activity in sub-saharan africa estimated from standard weather station data: a simple climate index for soil carbon balance calculations. *Ambio* 36, 379–386.
- Batjes, N.H., 1996. Total carbon and nitrogen in the soils of the world. *Eur. J. Soil Sci.* 47, 151–163.
- Beven, K., 2008. *Environmental Modelling: An Uncertain Future?* Routledge, London, UK.
- Beven, K., Binley, A., 1992. The future of distributed models: model calibration and uncertainty prediction. *Hydrol. Process.* 6, 279–298.
- Beven, K., Freer, J., 2001. Equifinality, data assimilation, and uncertainty estimation in mechanistic modeling of complex environmental systems using the GLUE methodology. *J. Hydrol.* 249, 11–29.
- Bolinder, M.A., Vandenbygaert, A.J., Gregorich, E.G., Angers, D.A., Janzen, H.H., 2006. Modelling soil organic carbon stock change for estimating whole-farm greenhouse gas emissions. *Can. J. Soil Sci.* 86, 419–429.
- Breman, H., Kessler, J.J., 1997. The potential benefits of agroforestry in the Sahel and other semi-arid regions. *Eur. J. Agron.* 7, 25–33.
- Bryan, J.A., 2000. Nitrogen-fixing leguminous trees and shrubs: a basic resource of agroforestry. In: Ashton, M.S., Montagnini, F. (Eds.), *The Silvicultural Basis for Agroforestry Systems*. CRC, Boca Raton, pp. 41–60.
- Buresh, R.J., Tian, G., 1998. Soil improvement by trees in sub-Saharan Africa. *Agroforest. Syst.* 38, 51–76.
- Cameron, D., 2006. An application of the UKCIP02 climate change scenarios to flood estimation by continuous simulation for a gauged catchment in the northeast of Scotland, UK (with uncertainty). *J. Hydrol.* 328, 212–226.
- CIREN, 1996. Estudio agrol gico de la Regi n Metropolitana. Centro de Informaci n de Recursos Naturales (CIREN). Publicaci n No. 115. 425p. (in Spanish).
- Cortina, J., Maestre, F.T., 2005. Plant effects on soils in drylands: implications for community dynamics and ecosystem restoration. In: Binkley, D., Menyailo, O. (Eds.), *Tree Species Effects on Soils: Implications for Global Change*. Springer, The Netherlands, pp. 85–118.
- de Ridder, N., van Keulen, H., 1990. Some aspects of the role of organic matter in sustainable intensified arable farming systems in the West-African semi-arid-tropics (SAT). *Fert. Res.* 26, 299–310.
- Dixon, R.K., 1995. Agroforestry systems: sources or sinks of greenhouse gases? *Agroforest. Syst.* 31, 99–116.
- Droppelmann, K., Berliner, P., 2000. Biometric relationships and growth of pruned and non-pruned *Acacia saligna* under runoff irrigation in northern Kenya. *Forest Ecol. Manag.* 126, 349–359.
- Droppelmann, K., Berliner, P., 2003. Runoff agroforestry—a technique to secure the livelihood of pastoralists in the Middle East. *J. Arid Environ.* 54, 571–577.
- Ellies, A., 2000. Soil erosion and its control in Chile—an overview. *Acta Geol. Hisp.* 35, 279–284.
- Geesing, D., Felker, P., Bingham, R.L., 2000. Influence of mesquite (*Prosopis glandulosa*) on soil nitrogen and carbon development: implications for global carbon sequestration. *J. Arid Environ.* 46, 157–180.
- Guo, L.B., Cowie, A.L., Montagu, K.D., Gifford, R.M., 2008. Carbon and nitrogen stocks in a native pasture and an adjacent 16-year-old *Pinus radiata* D. Don. plantation in Australia. *Agricult. Ecosys. Environ.* 124, 205–218.
- Hutchinson, J.J., Campbell, C.A., Desjardins, R.L., 2007. Some perspectives on carbon sequestration in agriculture. *Agr. Forest. Meteorol.* 142, 288–302.
- Joel, A., Messing, I., Seguel, O., Casanova, M., 2002. Measurement of surface water runoff from plots of two different sizes. *Hydrol. Process.* 16, 1467–1478.
- K tterer, T., Andr n, A., 1999. Long-term agricultural field experiments in Northern Europe: analysis of the influence of management on soil carbon stocks using the ICBM model. *Agr. Ecosys. Environ.* 72, 165–179.
- K tterer, T., Andr n, A., 2001. The ICBM family of analytically solved models of soil, carbon, nitrogen and microbial biomass dynamics—descriptions and application examples. *Ecol. Model.* 136, 191–207.
- Kho, R.M., 2000. A general tree-environment-crop interaction equation for predictive understanding of agroforestry Systems. *Agr. Ecosyst. Environ.* 80, 87–100.
- Kuzyakov, Y., Ehrensberger, H., Stahr, K., 2001. Carbon partitioning and below-ground translocation by *Lolium perenne*. *Soil Biol. Biochem.* 33, 61–74.
- Lal, R., 2001. Potential of desertification control to sequester carbon and mitigate the greenhouse effect. *Climatic Change* 51, 35–72.
- Lal, R., 2003. Global potential of soil carbon sequestration to mitigate the greenhouse effect. *Crit. Rev. Plant Sci.* 22, 151–184.
- Lal, R., 2004. Carbon sequestration in dryland ecosystems. *Environ. Manage.* 33, 528–544.
- Lal, R., 2009. Sequestering atmospheric carbon dioxide. *Crit. Rev. Plant Sci.* 28, 90–96.
- Le Roux, X., Bariac, T., Mariotti, A., 1995. Spatial partitioning of the soil water resource between grass and shrubs components in a West African humid savanna. *Oecologia* 104, 147–155.
- Lehmann, J., Zech, W., 1998. Fine root turnover of irrigated hedgerow intercropping in Northern Kenya. *Plant Soil* 198, 19–31.
- Leiva, C., 2005. Evaluaci n en el tiempo de las propiedades qu micas de un suelo con manejo agroforestal y cosecha de agua en el secano interior de la zona central de Chile. Tesis Ingeniero Agr nomo, Universidad de Chile (in Spanish with English summary).
- Li, F.R., Cook, S., Geballe, G.T., Burch, W.R., 2000. Rainwater harvesting agriculture: an integrated system for water management on rainfed land in China's semiarid areas. *Ambio* 29, 477–483.
- L venstein, H.M., Berliner, P.R., 1993. Biometric relationships for non-destructive above ground biomass estimations in young plantations of *Acacia salicina* Lindl. and *Eucalyptus occidentalis* Endl. *New Forest* 7, 255–273.
- L venstein, H.M., Berliner, P.R., van Keulen, H., 1991. Runoff agroforestry in arid lands. *Forest. Ecol. Manag.* 45, 59–70.
- Luzio, W., Seguel, O., Casanova, M., 2010. Suelos de la zona Mediterr nea  rida (Soils of the arid Mediterranean zone). In: Luzio, W. (Ed.), *Suelos de Chile (Soils of Chile)*. Universidad de Chile, Santiago, pp. 125–194 (in Spanish).
- Molina, J.A.E., Smith, P., 1996. Modelling carbon and nitrogen processes in soils. *Adv. Agron.* 62, 253–298.
- Mu oz, C., Ovalle, C., Zagal, E., 2007. Distribuci n del carbono org nico del suelo almacenado en el perfil de un Alfisol en ecosistemas Mediterr neos de Chile. R. C. Suelo Nutr. Veg. 7, 15–27 (in Spanish with English summary).
- Nair, P.K.R., Kang, B.T., Kass, D.C.L., 1995. Nutrient cycling and soil-erosion control in agroforestry systems. In: Joo, A.S.R., Freed, R.D. (Eds.), *Agriculture and Environment: Bridging Food Production and Environmental Protection in Developing Countries*, ASA Spec. Publ. 60. ASA, Madison, WI, pp. 117–138.
- Olivares, A., Castillo, M.H., Polzenius, G., 1988. Modificaciones de las caracter sticas microambientales provocadas por la presencia de *Acacia caven* (Mol.) Mol. II. Influencia de la estrata herb cea. *Avances en Producci n Animal* 13, 41–48 (In Spanish with English summary).
- Ovalle, C., Squella, F., 1988. Terrenos de pastoreo con praderas anuales en el  rea de influencia clim tica mediterr nea. In: Ruiz, I. (Ed.), *Praderas para Chile*. INIA, Santiago, Chile, pp. 369–410 (in Spanish).
- Ovalle, C., Aronson, J., del Pozo, A., Avenda o, J., 1990. The espinal: agroforestry Systems of the Mediterranean-type climate region of Chile. *Agroforest. Syst.* 10, 213–239.
- Ovalle, C., Aronson, J., Avenda o, J., del Pozo, A., 2000. Alternativas de praderas y sistemas agroforestales en relaci n con el manejo sostenible de los suelos en el secano interior de la zona central de Chile. *Bolet n INIA* No. 42. Santiago, Chile (in Spanish).
- Ovalle, C., Zagal, E., Fraga, A., Avenda o, J., Aronson, J., Manzanares, P., 2002. Nutrient cycling and water balance in agroforestry Systems with legume trees in Mediterranean central Chile. In: Gamini Keerthisinghe (Ed.), *Report of the Second Research Coordinating Meeting of the FAO/IAEA Coordinated Research Project held in Kuala Lumpur, Malaysia, 7–11 May, 2001*.
- Pandey, D.N., 2002. Carbon sequestration in agroforestry systems. *Climate Policy* 2, 367–377.
- Paustian, K., Andr n, O., Janzen, H.H., Lal, R., Smith, P., Tian, G., Tiessen, H., Van Noordwijk, M., Woerner, P.L., 1997. Agricultural soils as a sink to mitigate CO<sub>2</sub> emissions. *Soil Use Manage.* 13, 230–244.
- Peel, M.C., Finlayson, B.L., McMahon, T.A., 2007. Updated world map of the K ppen-Geiger climate classification. *Hydrol. Earth Syst. Sci.* 11, 1633–1644.
- P rez, C., Gonz lez, J., 2001. Diagn stico sobre el estado de degradaci n del recurso suelo en el pa s. CRI-Quilmapu, INIA, Chill n, Chile (in Spanish).
- Pi ol, J., Beven, K., Viegas, D.X., 2005. Modelling the effect of fire-exclusion and prescribed fire on wildfire size in Mediterranean ecosystems. *Ecol. Model.* 183, 397–409.
- Post, W.M., Kwon, C., 2000. Soil carbon sequestration and land-use change: processes and potential. *Glob. Change Biol.* 6, 317–327.
- Power, I.L., Thorrold, B.S., Balks, M.R., 2003. Soil properties and nitrogen availability in silvopastoral plantings of *Acacia melanoxylon* in North Island, New Zealand. *Agroforest. Syst.* 57, 225–237.
- Rabia, K.A., Solowey, E., Leu, S., 2008. Environmental and economic potential of Bedouin dryland agriculture: a case study in the northern Negev, Israel. *Manage. Environ. Qual.* 19, 353–366.
- Saggar, S., Hedley, C., Mackay, A.D., 1997. Partitioning and translocation of photo-synthetically fixed <sup>14</sup>C in grazed hill pastures. *Biol. Fertil. Soils* 25, 152–158.
- Salazar, O., 2003. Agroforestry combined with water harvesting in the central zone of Chile: soil properties and biomass production. MSc Dissertation, Swedish University of Agricultural Sciences.
- Salazar, O., Casanova, M., Benavides, C., Luzio, W., Vera, W., 2006. Propiedades qu micas de un suelo bajo agroforesteria y cosecha de agua en el secano interior de la zona central de Chile. *TERRA Latinoamericana* 24, 471–476 (in Spanish with English summary).
- Sandhu, J., Sinha, M., Ambasht, R.S., 1990. Nitrogen release from decomposing litter of *Leucaena leucocephala* in the dry tropics. *Soil Biol. Biochem.* 22, 859–863.
- Schimel, D.S., 2006. Terrestrial ecosystems and the carbon cycle. *Glob. Change Biol.* 1, 77–91.
- Schulz, K., Beven, K., 2003. Data-supported robust parameterisations in land surface-atmosphere flux predictions: towards a top-down approach. *Hydrol. Process.* 17, 2259–2277.
- Shibu, M.E., Leffelaar, P.A., Van Keulen, H., Aggarwal, P.K., 2006. Quantitative description of soil organic matter dynamics—A review of approaches with reference to rice-based cropping systems. *Geoderma* 137, 1–18.
- Silva, M., Lozano, U., 1986. Descripci n de las principales especies forrajeras entre la zona mediterr nea  rida y la zona de las lluvias. Universidad de Chile, Fac. Cs. Agrarias y Forestales, Departamento de Producci n Animal. Publicaci n docente No. 9. Santiago, Chile (in Spanish).
- Sindh j, E., Andr n, O., K tterer, T., Gunnarsson, S., Pettersson, R., 2006. Projections of 30-year soil carbon balances for a semi-natural grassland under elevated CO<sub>2</sub> based on measured root decomposability. *Agr. Ecosyst. Environ.* 114, 360–368.

- Smith, P., Powlson, D.S., Smith, J.U., Falloon, P., Coleman, K., 2000. Meeting Europe's climate change commitments: quantitative estimates of the potential for carbon mitigation by agriculture. *Glob. Change Biol.* 6, 525–539.
- Smith, P., Fang, C., Dawson, J., Moncrieff, J., 2008a. Impact of global warming on soil organic carbon. *Adv. Agron.* 97, 1–43.
- Smith, P., Beven, K., Tawn, J.A., 2008b. Informal likelihood measures in model assessment: theoretic development and investigation. *Adv. Water Resour.* 31, 1087–1100.
- Sperow, M., Eve, M., Paustian, K., 2003. Potential soil C sequestration on U.S. agricultural soils. *Climatic Change* 57, 319–339.
- Stewart, J.L., Salazar, R., 1992. A review of measurement options for multipurpose trees. *Agroforest. Syst.* 19, 173–183.
- Stolpe, N., Muñoz, C., Zagal, E., Ovalle, C., 2008. Modeling soil carbon storage in the 'espinal' agroecosystem of central Chile. *Arid Land Res. Manage.* 22, 148–158.
- Tabor, J.A., 1995. Improving crop yields in the Sahel by means of water-harvesting. *J. Arid Environ.* 30, 83–106.
- Takimoto, A., Nair, V.D., Nair, P.K.R., 2009. Contributions of trees to soil carbon sequestration under agroforestry systems in the West African Sahel. *Agroforest. Syst.* 76, 11–25.
- Traoré, S., Thiombiano, L., Millogo, J.R., Guinko, S., 2007. Carbon and nitrogen enhancement in Cambisols and Vertisols by *Acacia spp.* in eastern Burkina Faso: relation to soil respiration and microbial biomass. *Appl. Soil Ecol.* 35, 660–669.
- UNEP., 1992. World Atlas of Desertification. Edward Arnold, Seven Oaks, Nairobi, Kenya.
- Villarroel, R., 2010. Propiedades químicas de un suelo bajo agroforestería asociada a cosecha de aguas, a doce años de su establecimiento: secano central interior de Chile Memoria Ingeniero Agrónomo, Universidad de Chile (in Spanish with English summary).
- Witkowski, E.T.F., 1991. Effects of invasive alien acacias on nutrient cycling in the coastal lowlands on the cape Fynbos. *J. Appl. Ecol.* 28, 1–15.