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Prediction and digital mapping of soil carbon storage in the Lower Namoi Valley

Budiman Minasny[A,D], *Alex. B. McBratney*[A], *M. L. Mendonça-Santos*[B], *I. O. A. Odeh*[A], *and Brice Guyon*[C]

[A]Faculty of Agriculture, Food & Natural Resources, The University of Sydney, JRA McMillan Building A05, NSW 2006, Australia.
[B]EMBRAPA-Centro Nacional de Pesquisa de Solos, Rua Jardim Botânico 1024, 22.460-000 Rio de Janeiro-RJ, Brazil.
[C]Ecole Nationale d'Ingenieurs des Travaux Agricoles de Bordeaux, 1 cours du general de Gaulle, B.P. 201, 33175 Gradignan, Cedex, France.
[D]Corresponding author. Email: b.minasny@usyd.edu.au

Abstract. Estimation and mapping carbon storage in the soil is currently an important topic; thus, the knowledge of the distribution of carbon content with depth is essential. This paper examines the use of a negative exponential profile depth function to describe the soil carbon data at different depths, and its integral to represent the carbon storage. A novel method is then proposed for mapping the soil carbon storage in the Lower Namoi Valley, NSW. This involves deriving pedotransfer functions to predict soil organic carbon and bulk density, fitting the exponential depth function to the carbon profile data, deriving a neural network model to predict parameters of the exponential function from environmental data, and mapping the organic carbon storage. The exponential depth function is shown to fit the soil carbon data adequately, and the parameters also reflect the influence of soil order. The parameters of the exponential depth function were predicted from land use, radiometric K, and terrain attributes. Using the estimated parameters we map the carbon storage of the area from surface to a depth of 1 m. The organic carbon storage map shows the high influence of land use on the predicted storage. Values of 15–22 kg/m^2 were predicted for the forested area and 2–6 kg/m^2 in the cultivated area in the plains.

Additional keywords: soil information system, neural networks, carbon stock, carbon sequestration, organic carbon, Vertosol, digital soil mapping.

Introduction

Estimation and mapping of carbon storage in the soil is currently an important topic; carbon stored in the soil to a given depth has been estimated for the whole world (Batjes 1996), for the continent (Jones *et al*. 2005), countries (Bellamy *et al.* 2005; Bernoux *et al*. 2002; Mikhailova and Post 2006), and regionally (Knowles and Singh 2003). Soil can hold more than twice as much carbon as held in vegetation or the atmosphere (Batjes 1996). The amount of carbon stored in the soil per unit of land area is highly variable depending on the land use, annual input, soil type, and the degradation rate. A global average of 16–20 kg/m^2 is estimated for carbon stored up to 1 m in tropical forests and 11 kg/m^2 for cropping area (Jobbágy and Jackson 2000).

The distribution of carbon content with depth is essential information for estimating soil carbon storage. Conventionally, carbon storage (also called the carbon stock, carbon pool or carbon density), i.e. carbon mass per unit area for a given depth, is calculated by summing the C density of soil layers 1, 2, . . . , *N*:

$$C_I = \sum_{j=1}^{N} (C_m \times \rho_j) \times \text{thick}_j \quad (1)$$

where C_I is carbon density (kg/m^2), C_m is carbon content in mass basis (kg/kg), ρ is soil bulk density (kg/m^3), and thick is the thickness of the layer (m).

Alternatively, a profile depth function can be defined and fitted to the soil carbon data, where carbon content at different depths can be estimated, and the integral of the function represents the carbon storage. This is useful where it is necessary to estimate the carbon storage down to certain depths. Expressing carbon content as a depth function is also advantageous when dealing with soil databases where the

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depths are not sampled completely and uniformly (Arrouays and Pélissier 1994).

The advantage of using a depth function (such as a negative exponential) is that we are able to derive empirical functions to predict the parameters of the function using more easily measured or more widely available data. In the pedotransfer function (PTF) context, these are called parametric PTFs (McBratney *et al*. 2002), allowing us to predict the carbon depth function from more easily measured soil properties. In a larger context, for digital mapping (McBratney *et al*. 2003) we can map the parameters for the area of interest using spatial interpolation or predictive functions using environmental variables.

Zinn *et al*. (2005) analysed the profile organic carbon content of 3 highly weathered Brazilian Cerrado soils that were sampled at 7 depths from the surface to a depth of 1 m. The organic carbon content was found to be linearly correlated with the (clay + silt) content for all depths:

$$\mathrm{C} = a + b\,(\mathrm{clay} + \mathrm{silt}) \tag{2}$$

The intercept (a) and slope (b) of these linear relations decreased with depth following exponential and logarithmic functions. They then formulate the intercept and slope as functions of depth:

$$\begin{aligned} a &= a_1 \exp(-a_2\, z) + a_3 \exp(-a_4\, z) \\ b &= b_1 + b_2 \log(z) \end{aligned} \tag{3}$$

where a_1, a_2, a_3, b_1, and b_2 are empirical parameters, and z is depth.

In digital soil mapping, soil carbon storage is conventionally estimated by using PTFs or rules based on either soil groups or basic soil properties. Soil carbon storage is then estimated by applying these pedotransfer rules to a soil map of the area of interest (Batjes 1996; Jones *et al*. 2005). Barson *et al*. (2004) compiled a database of soil profiles to estimate the size of the Australian soil carbon pool. A linearised version of the negative depth exponential function was fitted to the soil profile data. Parameters of the exponential function were then predicted from environmental variables. These predictive equations were combined with continental data layers of bulk density, clay content, pH, elevation, and climatic parameters to predict organic C stored at different depths for each 5-km grid cell across the Australian continent.

McBratney and Lagacherie (2004) defined digital soil mapping as the creation and population of spatial soil information systems by the use of field and laboratory observational methods coupled with spatial and non-spatial soil inference systems. From this definition, it is clear that the main aspect of digital soil mapping is not the production of a map but mainly the organisation of soil and environmental information in order to produce knowledge on soil in space and time.

This paper proposes a novel method for digital soil mapping of soil carbon storage. This is achieved in several stages:

(i) Derive pedotransfer functions to predict soil organic carbon, and bulk density;
(ii) Fit the exponential decay function to carbon profile data;
(iii) Derive a neural network model to predict parameters of the exponential function from environmental data;
(iv) Map the organic carbon storage.

Theory

Soil carbon depth function

Soil carbon has been observed to decline rapidly with depth (Spain *et al*. 1983); the concentration of carbon with depth is usually expressed as an exponential decay function.

Russell and Moore (1968) found the organic matter content from 63 profiles from Australia could be expressed as:

$$\mathrm{C} = \mathrm{C}_0 \exp(-k\, z) \tag{4}$$

where C_0 is the C concentration at the soil surface, k is the rate of decrease, and z is depth. They reasoned that this function is chosen because of its mathematical simplicity and its apparent similarity to the profile depth changes found for biological and related properties. Bennema (1974) analysed the soil carbon profile data of Oxisols from Brazil and suggested that a power function can be used to describe the carbon profile:

$$\mathrm{C} = a\, z^b \tag{5}$$

where C is the carbon content at depth z, and a and b are empirical parameters. Ogawa *et al.* (1961) found that the organic carbon and nitrogen content from the forest soils in Thailand declined exponentially with depth and can be expressed as Eqn 4. This is followed by Nakane (1976) who presented an alternative form of the exponential function to describe the carbon content with depth:

$$\mathrm{C} = \mathrm{C}_0 \exp\left[-\left(\frac{1}{(Az + B)} + a\right)z\right] \tag{6}$$

with empirical parameters A, B, and a. Arrouays and Pélissier (1994) suggested an exponential function for modelling the profile distribution of carbon in temperate humic loamy soils in France:

$$\frac{\mathrm{C} - \mathrm{C}_2}{\mathrm{C}_1 - \mathrm{C}_2} = \frac{\exp[-k\, z] - \exp[-k\, z_2]}{\exp[-k\, z_1] - \exp[-k\, z_2]} \tag{7}$$

where C_1 and C_2 is the carbon content at fixed upper depth z_1 and lower depth z_2. Bernoux *et al*. (1998) compared the power (Eqn 5) and exponential (Eqn 7) functions to describe the profile soil carbon in the Amazon forest soils, and they found the exponential model fits best. Jobbágy and Jackson (2000) compared different log–log models to fit the organic

carbon profile data from global soil databases. They found that the log form of Eqn 5 fits best:

$$\log \mathrm{C} = b \log\, z + a \tag{8}$$

It appears that the exponential C depth model is the most widely accepted model. It has also been used in Belgium (Mestdagh *et al*. 2004) and Russia (Mikhailova and Post 2006).

The negative exponential depth function has also been adapted in different numerical models. Elzein and Balesdent (1995) developed a mechanistic model for organic matter decomposition incorporating within-profile transport; the depth function is expressed as an exponential distribution. Rosenbloom *et al*. (2001) also used an exponential function to extrapolate carbon at depth in a mechanistic soil–landscape erosion model. Hilinski (2001) employed the negative exponential depth function for the soil organic matter CENTURY model.

A disadvantage of using the negative depth exponential function is that any local variation in the soil profile affects the quality of fit everywhere else in the profile (Webster 1978). Consequently, they lack flexibility in fitting depth functions and the quality of fit may be quite varied. Webster (1978) showed that the spline interpolators are better for some organic matter profiles of British soils, especially the Podzols where the exponential decrease assumption is inappropriate. As an alternative, Ponce-Hernandez *et al*. (1986) proposed a non-parametric depth function, involving a variation of the spline function, called an equal-area spline to model soil attribute depth functions. Bishop *et al*. (1999) tested the ability of equal-area spline to predict soil depth functions based on bulk horizon data of 3 soil profiles. The soil attributes that were measured includes organic carbon content. The results clearly indicated the superiority of equal-area splines in predicting depth functions.

Nevertheless the exponential function has the advantage that it can summarise the profile data in 3 parameters (which cannot be done with the spline). This permits us to derive empirical relationships to predict the parameters using more easily measured or more widely available data. This is of course based on the assumptions that C decreases exponentially with depth and there is no buried surface horizons.

The negative exponential depth model

Organic carbon content can be expressed on a mass basis $\mathrm{C_m}$ (kg/kg) or a volume basis C (kg/m^3). The relationship is derived from soil bulk density ρ:

$$\mathrm{C\ (kg\ C/m^3\ soil)} = \mathrm{C_m(kg/kg)} \times \rho\mathrm{(kg/m^3)} \tag{9}$$

The distribution of C with depth can be expressed as a negative exponential depth function:

$$\mathrm{C} = \mathrm{C}_a \exp(-k\, z) + \mathrm{C}_b \tag{10}$$

with conditions C_a, C_b, $k \geq 0$, where: C is organic carbon (C) content in volume basis (kg/m^3), z is the absolute value of depth from the soil surface (m), C_a is the difference in C content between the surface and the lowest depth, $(\mathrm{C}_a + \mathrm{C}_b)$ kg/m^3 is C content at the soil surface, C_b is C content at the bottom of the profile, and k (m^{-1}) is the rate of C decrease with depth. The variation of C over depth with different values of k is illustrated in Fig. 1.

The integral represents C density or C storage to depth z:

$$\mathrm{C}_I = \int_0^z \mathrm{C}_a \exp(-k\, z) + \mathrm{C}_b\, dz \tag{11}$$

where C_I is in kg/m^2 or amount of organic C stored per unit land area. Integrating Eqn 11, the storage from the soil surface to depth z is given by:

$$\mathrm{C}_I = \frac{\mathrm{C}_a}{k}[1 - \exp(-k\, z)] + \mathrm{C}_b\, z \tag{12}$$

Mapping the parameters of the exponential depth function

For mapping purposes, we wish to predict parameters C_a, C_b, and k of the exponential function Eqn 10. Predicting the parameters enables us to calculate the C distribution over the profile and also the storage of C. We can either interpolate the parameters individually or predict them using environmental variables. Since they are parameters of a function, there are correlations among the parameters and we cannot interpolate them separately using spatial interpolator (e.g. kriging).

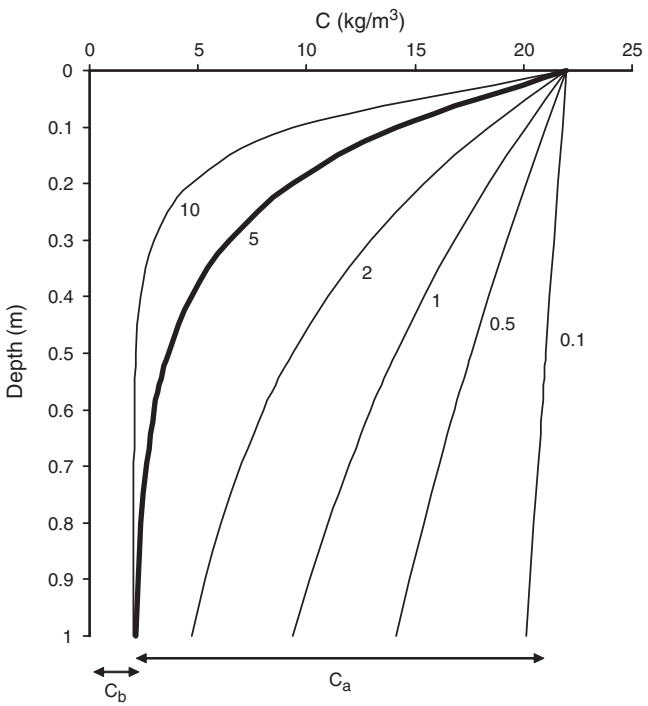

Fig. 1. The negative exponential depth function for soil carbon content.

An alternative solution is to interpolate the parameters simultaneously using co-kriging (Chilès and Delfiner 1999). The procedure in co-kriging is slightly complicated and mapping them in large areas with few observations tends to over-smooth the reality.

A common way to predict the parameters of a function is by forming empirical relationships between basic soil properties and parameters:

$$\hat{\beta} = f(x) \tag{13}$$

where $\hat{\beta}$ is the predicted parameter vector [C_a, C_b, k] from environmental variables x. Regression using environmental variables is formed with an objective function to minimise the difference between observed and predicted parameter values, in the least squares sense:

$$O = \sum_{i=1}^{Ns} \left(\hat{\beta}_i (x_i) - \beta_i \right)^2 \tag{14}$$

where Ns is the number of soil observations. As the parameters are estimated from observations that are subjected to errors, and are highly correlated, they may not be directly related to other soil properties. Therefore, many studies have reported small correlation between the predictors and the parameters (e.g. Barson *et al*. 2004; Van den Berg *et al*. 1997).

Since the aim is to be able to predict the C content as a function of depth, it is more practical to predict parameter β that minimises the difference between the observed and predicted C content.

$$O = \sum_{i=1}^{Ns} \sum_{j=1}^{Nz} \left[\hat{C}_{ij} \left(z_j, \hat{\beta}_i(x_i) \right) - C_{ij}(z_j) \right]^2 \tag{15}$$

where $i = 1, 2, \ldots, Ns$ represents the number of observations, and $j = 1, \ldots, Nz$ is the number of soil depths, and C_{ij} is carbon content of profile i at depth z_j. Minasny and McBratney (2002) used neural networks to predict the parameters of a water retention function, where the networks are trained with an objective function that minimises the difference between observed and predicted dependent variable, rather than minimising the parameter values (Eqn 14). They called it the *neuro-m* method; more details can be found in Minasny and McBratney (2002). We will adapt this method for prediction of parameters of the exponential function from environmental data.

Methods

The soil data

The soil data used in this study came from the Edgeroi area, near Narrabri, NSW, Australia (Fig. 2). The area is about 1500 km^2. It is a typical part of the North-western Slopes and Plains of New South Wales as described by Ward (1999). The soil dataset consists of 341 soil profiles, from which 210 are arranged on a systematic, equilateral triangular grid with approximately 2.8 km spacing between sites (McGarry *et al*. 1989), and 131 are distributed more irregularly or on transects (Ward 1999). Soil attributes (both field morphological and laboratory analytical data), vegetation and landform information were recorded. Soil samples were taken from the profiles at depths: 0–0.1, 0.1–0.2, 0.3–0.4, 0.7–0.8, 1.2–1.3, and 2.5–2.6 m, from which the soil physical and chemical analyses were conducted, (for details see McGarry *et al*. 1989). Soil organic C was calculated as the difference between total C determined by combustion using a Leco furnace and carbonate carbon. The distribution of soil organic C with depth of the soil profiles is shown in Fig. 3.

The soil profiles were classified according to the Australian Soil Classification system (Isbell 1996). The distribution of the Soil Orders in the area is given in Table 1; the area is dominated by Vertosols.

McBratney *et al*. (2003) proposed an empirical formula for describing the relationships between soil and other spatially referenced factors (or environmental predictors) which are used here as soil spatial prediction functions. The McBratney *scorpan* model can be defined as follows:

$$S = f(s, c, o, r, p, a, n)$$

where S is soil properties or soil classes, s refers to soil information either from a prior map or from remote or proximal sensing or expert knowledge, c refers to climate, o refers to organisms, r refers to relief, p refers to parent materials, a refers to age or time, and n refers to spatial position. The sources of data, the methods to estimate f, and the *scorpan* framework are discussed in McBratney *et al*. (2003).

We wish to map the carbon storage for the area with resolution (pixel size) of 25 m. In order to predict soil carbon for the purpose of digital soil mapping, the following environmental factors were used:

(i) Landsat 7 ETM+ images from 2003: band #1 (blue), #2 (green), #3 (red), #4 (Near infrared), #5 (middle infrared) and #7 (Thermal infrared). The Landsat bands were used to estimate the land cover.
(ii) Gamma-radiometric survey, which measured naturally occurring gamma radiation emitted from the ground surface. The measurement is from airborne survey in the spectral windows for ^{40}K, ^{238}U, and ^{232}Th.
(iii) Digital elevation model and its derivatives (slope, aspect, and wetness index).

The variations in gamma radiation corresponded to the distribution of soil-forming materials over the landscape, and were used to distinguish between highly weathered residuum and fresh material from granitic outcrops (Cook *et al*. 1996). Radiometric K is the gamma radiation of natural radioactive isotope ^{40}K (Wong and Harper 1999). Wong and Harper (1999) showed a strong relationship between radiometric K and organic C content. Slope is the gradient or rate of change of elevation, while aspect is the azimuth of slope (Gallant and Wilson 2000). Slope may be thought of as the first derivative of the elevation surface down the slope, or perpendicular to the contours, and aspect as the first derivative of the elevation surface across the slope, or parallel to the contours (Gallant and Wilson 2000). Wetness index is defined as:

$$\mathrm{TWI} = \ln\left(\frac{A_s}{\tan \beta} \right) \tag{16}$$

where A_s is specific catchment area, and β is slope. It is originated from studies in hydrological modelling, Large TWI values indicate an

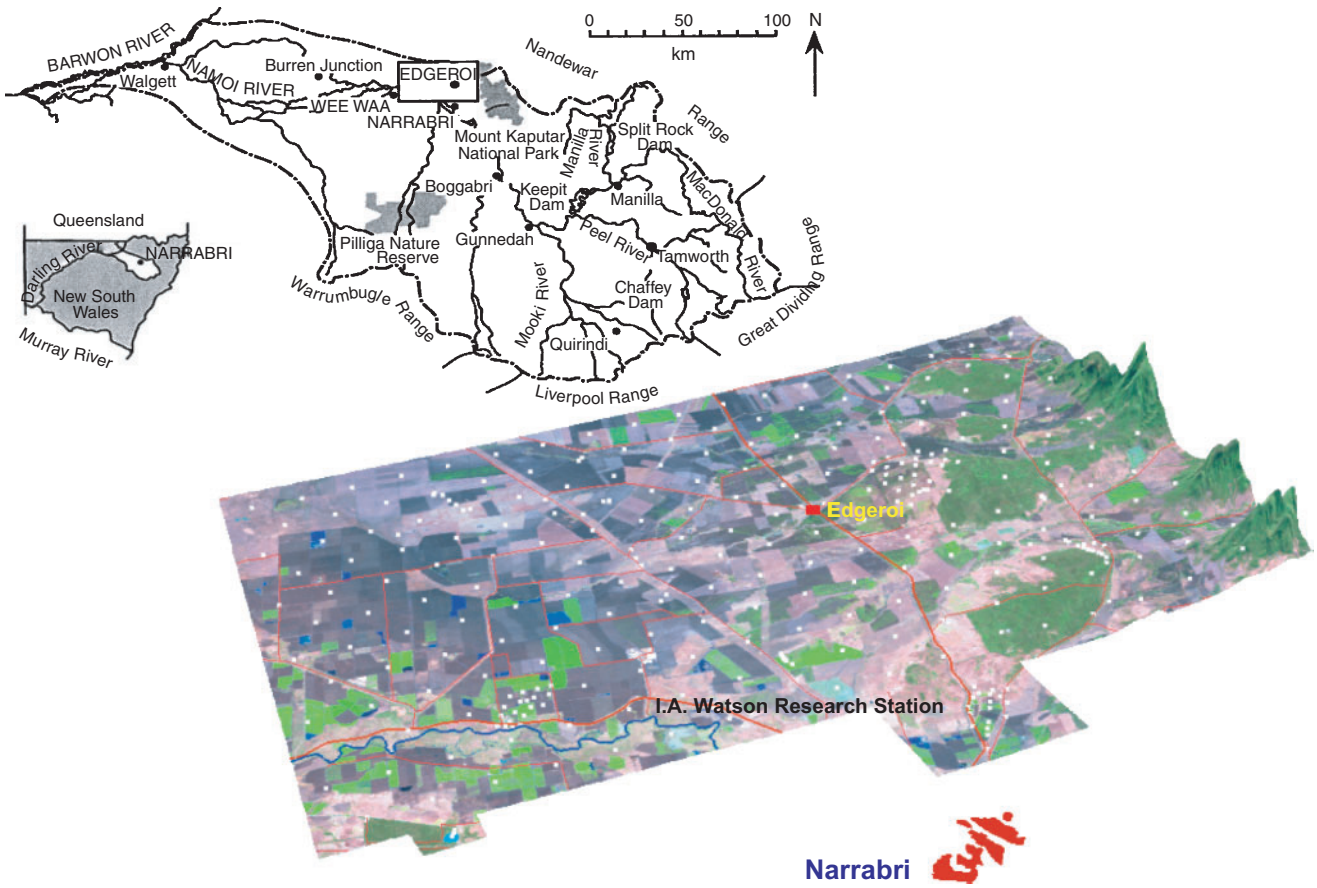

Fig. 2. The Edgeroi study area.

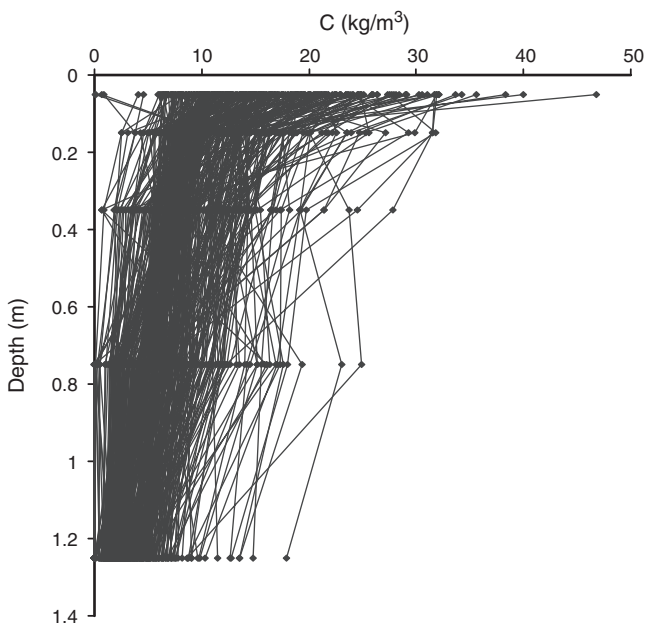

Fig. 3. Distribution of soil organic C with depth for the study area.

increased likelihood of saturated conditions; the larger values are usually found in the lower parts of watersheds and convergent hollow areas associated with soils with small hydraulic conductivity or areas of small slope (Beven and Wood 1983).

All environmental variables were recorded for the whole area on a grid of 25 m. These data represents the *scorpan* factors: *s* (radiometrics), *o* (land cover), *r* (terrain attributes), *p* (gamma radiometrics). Climate is an important factor but does not vary significantly within the study area.

Data analysis and modelling

This study is divided into several steps; the details will be provided in the Results section. The steps are:

(*i*) Developing PTFs to predict soil organic carbon from particle-size analysis and soil colour;
(*ii*) Developing PTF to predict bulk density from particle-size analysis, incorporating depth;
(*iii*) Modelling organic C distribution with depth, which involves fitting Eqn 10 to individual soil profiles;
(*iv*) Predicting parameters of the C exponential depth function with environmental variables using a neural network model;
(*v*) Mapping parameters of the negative exponential depth function and its integral, the C storage.

Table 1. Distribution of soil order in the Edgeroi area

Soil Order	No. of profiles	Percentage
Calcarosol	16	4.7
Chromosol	13	3.8
Dermosol	50	14.7
Kandosol	13	3.8
Kurosol	5	1.5
Rudosol	8	2.3
Sodosol	21	6.2
Tenosol	4	1.2
Vertosol	211	61.9

Results

PTF to predict organic carbon from particle-size distribution and soil colour

From the Edgeroi soil database, 320 soil profiles have complete laboratory analysis; the other 21 only have morphological properties decribed. To utilise all the data, we predicted organic C for the missing laboratory values from soil texture and soil colour.

Soil colour was recorded using the Munsell soil colour chart under wet condition (hue, value, and chroma). The Munsell values were also translated into the CIE colour system (L, u*, v*) with Colosol 2.0 software (Viscarra Rossel *et al*. 2006). For profiles without particle-size analysis, the sand, silt, and clay content was predicted from the field texture class.

As we have postulated that soil organic carbon decreases exponentially with depth, we tried different linear models to predict log(C) from soil texture and colour.

Using stepwise regression, we found that the influential predictors are Munsell value, clay and silt content, and depth z. The resulting PTF is:

$$OC = \exp[0.777 - 1.327\,z - 0.275\,\text{value} + 0.004\,(\text{clay} + \text{silt}) + 0.012 \times (\text{clay} + \text{silt} - 60) \times (z - 0.5)] \quad (R^2 = 0.46,\ \text{RMSE} = 0.52\ \text{dag/kg},\ n = 1579) \tag{17}$$

where OC is percent mass of organic C (dag/kg), clay is clay content (particles $<2\,\mu$m) (dag/kg), silt is silt content (particles 2–20 μm) (dag/kg), z is depth from the soil surface (m), value is Munsell value which indicates the lightness of the soil colour, and RMSE is the root mean squared error of the prediction. The Munsell value in this dataset ranges from 2 (dark) to 8 (light). Viscarra Rossel *et al*. (2006) also found that carbon content decreases with increasing CIE v* (which is the same as Munsell value).

Figure 4 shows the response of the Munsell value for a soil with (clay + silt) content of 65 dag/kg. The change in colour value from 2 (dark) to 8 (light) represents an 81% decrease in organic C. This model is then applied to the samples with no laboratory measurement.

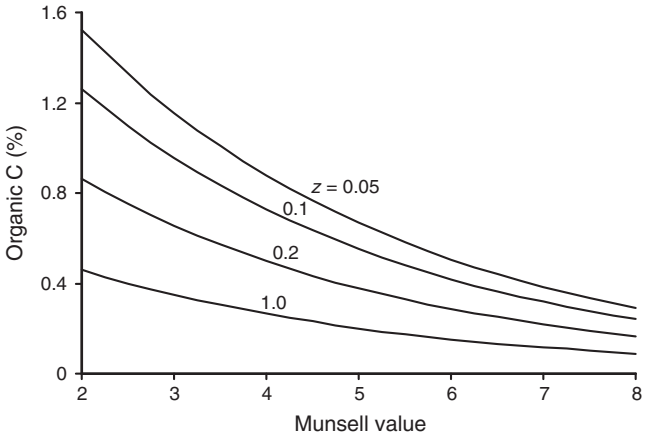

Fig. 4. Effect of Munsell value on soil organic C content at different depths. Numbers beside the curves represent soil depth from the surface (in m).

Bulk density PTF

The first step to calculate C on a volume basis is the requirement of an estimate of soil bulk density. The data used in this paper are derived from various studies in Australia (Minasny and McBratney 2002) where profile bulk density at several depths is complemented with particle-size analysis. Bulk density is observed generally to increase with depth, mainly due to an overburden effect; thus, we are able to derive the following linear relationship. The mineral soil bulk density is calculated as:

$$\rho_M(\text{kg/m}^3) = 1813.6 + 111.27\log(z) - 4.949\,(\text{clay} + \text{silt}) \quad (R^2 = 0.48,\ \text{RMSE} = 156.7\ \text{kg/m}^3,\ n = 295) \tag{18}$$

The fit and response function is shown in Fig. 5.

The influence of organic C on soil bulk density (ρ) is included using the relationship (Adams 1973):

$$\rho = \left(\frac{OM}{\rho_{OM}} + \frac{1 - OM}{\rho_M}\right)^{-1} \tag{19}$$

where OM is the organic matter content in the soil (kg/kg), ρ_{OM} is the average organic matter bulk density (224 kg/m^3). Organic matter is estimated from organic C using the conversion factor of 1.724.

Modelling soil organic C with depth

Using bulk density PTFs (Eqns 18 and 19), organic C on a mass basis is transformed to a volume basis, and the distribution with depth for all the profiles is shown in Fig. 5. Carbon content is shown to vary from 5 to 50 kg/m^3 in the surface and decreases exponentially to 0–20 kg/m^3 at depth of 1.3 m. The exponential function Eqn 10 was fitted to individual soil profile at 5 depths (0–0.1, 0.1–0.2, 0.3–0.4, 0.7–0.8, 1.2–1.3 m) using nonlinear least-squares.

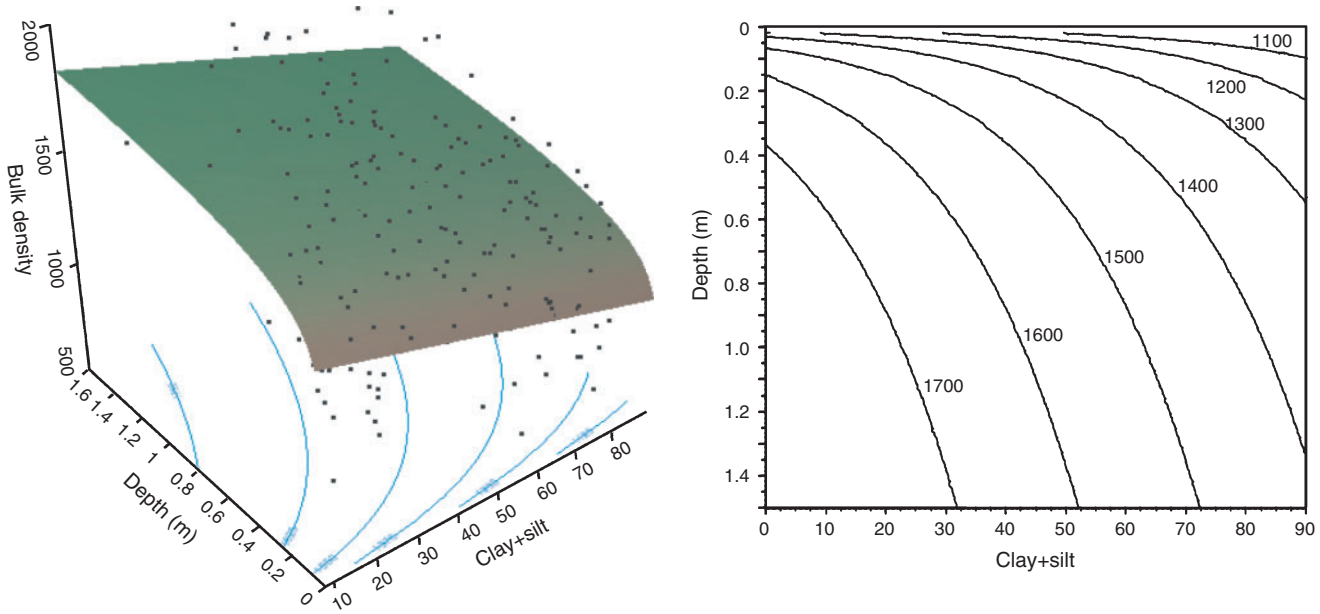

Fig. 5. Response function of bulk density as a function of soil depth and clay + silt content. Dots represent measured data.

The results showed that the exponential model fits the data very well with mean RMSE for all the profiles of 1.22 ± 1.21 kg/m^3 and $R^2 = 0.88 \pm 0.18$. (see Fig. 6). We are able to estimate the C storage in the profile by the conventional method, by summing the C storage at every 0.10-m-thickness layer from the surface to the depth of 1 m. Layers with missing observations were interpolated using the exponential function.

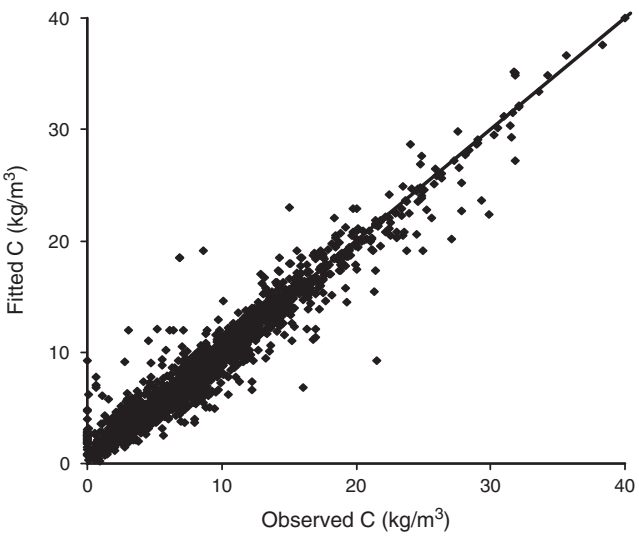

Fig. 6. Measured and exponential depth function fitted organic carbon content.

Variation of profile C with soil class

Organic carbon profile has been shown to vary with soil classes, climate, and land use (Spain *et al.* 1983; Spain 1990). The average profile organic C with soil order is shown in Fig. 7. Rudosols are shown to have the highest organic C content, these are mainly alluvials with suborder Stratic and Lutic, and under native vegetation and forests. All other soil classes have similar C content at the surface of around 1.4 kg/m^3. The C content in Vertosol can be seen to decline relatively slowly with depth compared with other soil. Further analysis confirms this trend. Figure 8 shows the distribution of the log(k) parameter as a function of soil class. Analysis of variance (Fig. 8, Table 2) showed that both log(k) and C_a were significantly lower for Vertosols than for other soil classes. Low k value refers to low decrease in C with depth (see Fig. 1), and C_a represents the difference in C content between the surface and the lowest depth. This is in accord with the observation of Spain *et al.* (1983) that the grassland black earths have a relatively slow decline in organic carbon with depth compared with other soil types such as the Krasnozems. The analysis here confirms that the Vertosols have a relatively uniform C content. However, the carbon storage to a depth of 1 m (C_1) for the Vertosols (8.4 ± 0.8 kg/m^2) is not significantly different from Calcarosols, Dermosols, and Kandosols, whereas it is higher than Sodosols and Chromosols (6.5 kg/m^2), and lower than Rudosols (15 ± 1).

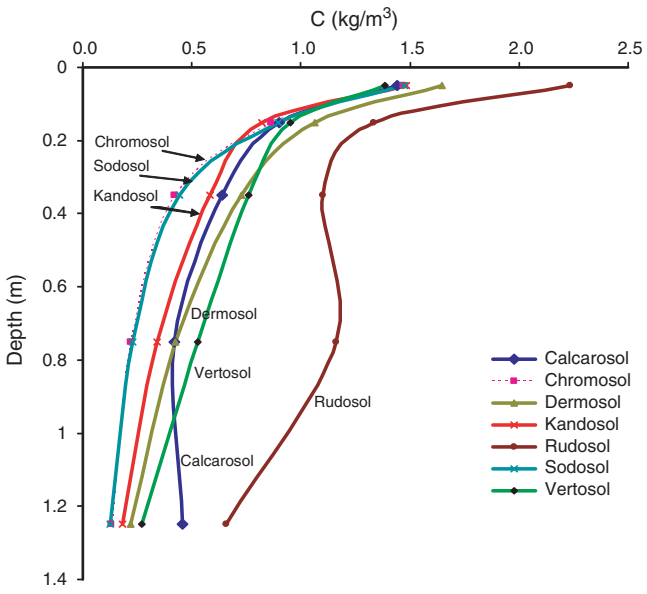

Fig. 7. Mean profile of carbon content according to Soil Order.

Prediction of exponential parameters using environmental variables

We used neural networks to predict parameters C_a, C_b, and k using the following environmental variables: radiometric K; elevation, slope, aspect, and topographic wetness index (TWI); land cover (4 main classes: forest, cultivated, cultivated dark soil, saline).

The dataset (341 profiles) was divided into a training set (256 profiles) and a test set (85 profiles). We used the feed forward neural network with single hidden layer and 3 hidden units. The neural network model is trained to predict parameter C_a, C_b, and k using environmental variables with the objective function given in Eqn 15. Details on neural networks are given in Minasny and McBratney (2002). The algorithm is implemented in Matlab (Mathworks 2005); the codes are available from the authors' website.

The predicted carbon content at different depths using the neural network model is given in Fig. 9. The model predicts reasonably well with $R^2 = 0.59$ and RMSE of 4.0 kg/m^3 for the prediction set (256 profiles). When tested on the test set (85 profiles) the R^2 is slightly less (0.50) and RMSE 4.6 kg/m^3.

Using the predicted parameters we calculated carbon storage from soil surface to the depth of 0.1, 0.2, 0.5, 0.8 and 1.0 m using Eqn 12 and compared it with measured values (Table 3). The R^2 values range from 0.26 to 0.4 with better prediction near the surface. This demonstrates error propagation in the model and also suggests that the model predicts better for surface condition.

Mapping soil carbon storage

Finally we mapped the carbon storage to depth of 1 m (Fig. 10). The map shows the large influence of land cover on carbon storage, thus indicating the dominant influence of land use. The forested area on the west has a large storage of 15–22 kg/m^2, and the area that has been cleared and cultivated area in the plains has much smaller storage of 3–6 kg/m^2.

We highlight some limitations and possible improvement to our model. We use the land-use derived from the Landsat image acquired in 2003. Thus, our map here is under the

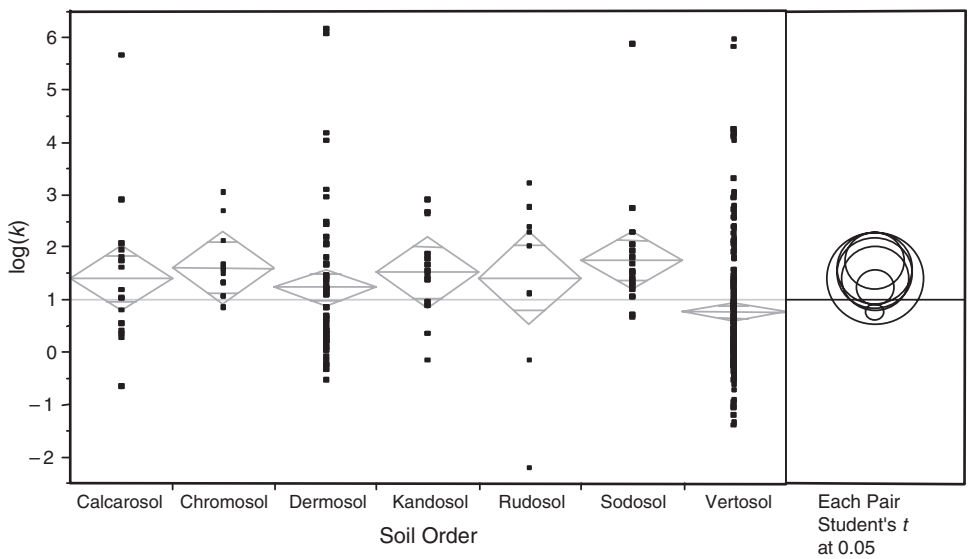

Fig. 8. Analysis of variance and *t*-test for parameter log(k) according to Soil Order. The line across each diamond represents the Soil Order mean. The vertical span of each diamond represents the 95% confidence interval for each Order. The comparison circles (on the right) tell whether group means are significantly different. Circles for means that are significantly different either do not intersect or intersect slightly.

Table 2. Mean and standard error of parameters of the negative exponential function, and carbon storage as grouped by Soil Order

Within columns, means followed by the same letter are not significantly different at $P = 0.05$

Soil Order	No. of samples	C_a (kg/m^3) Mean	s.e.	log (k) (log/m) Mean	s.e.	C_I (kg/m^2) Mean	s.e.
Calcarosol	16	18.08ab	2.99	1.421ab	0.313	8.41bcd	0.78
Chromosol	13	22.26a	3.32	1.626a	0.347	6.45cd	0.87
Dermosol	50	20.93a	1.69	1.254a	0.177	8.36bd	0.44
Kandosol	13	20.02ab	3.32	1.537a	0.347	7.25bcd	0.87
Rudosol	8	22.97ab	4.23	1.428ab	0.443	14.67a	1.10
Sodosol	21	20.81a	2.61	1.764a	0.273	6.56c	0.68
Vertosol	211	14.91b	0.82	0.788b	0.086	8.41b	0.21

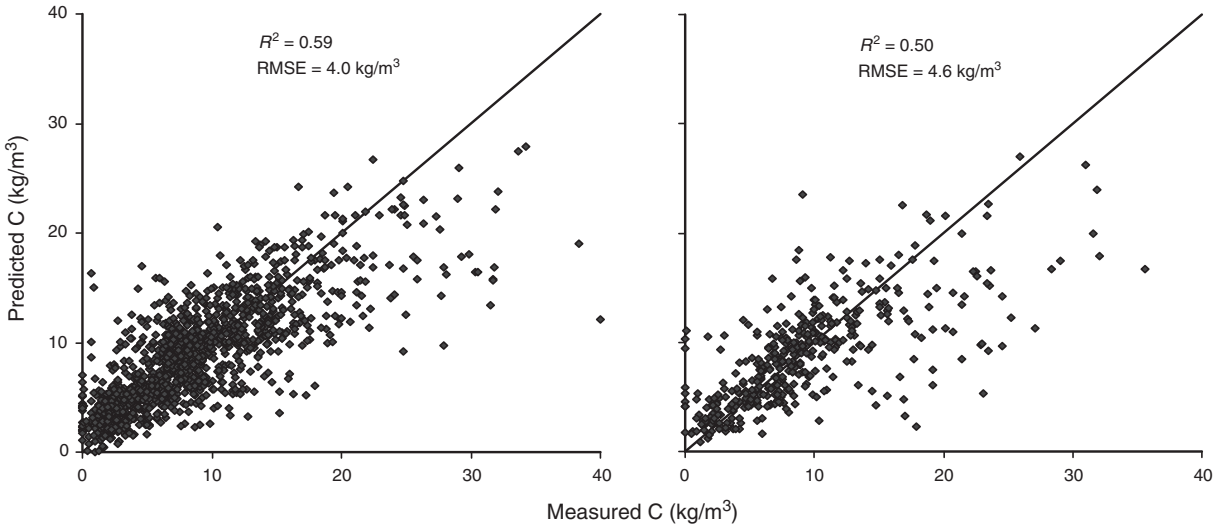

Fig. 9. Measured and predicted carbon content for the prediction set (left) and test set (right).

Table 3. Performance of the neural network model in predicting carbon storage at different depths

	0–0.1 m	0–0.2 m	0–0.5 m	0–0.8 m	0–1.0 m
RMSE (kg/m^2)	0.563	0.836	1.427	2.390	2.803
R^2	0.357	0.412	0.364	0.281	0.255

assumption that the land-use has not varied significantly. The soil samples in this study were taken in 1985–1987; therefore, the predicted map reflects carbon storage about 2 decades ago. Recent research has shown a rapid decrease in soil carbon content with land use changes in the study area (Odeh *et al*. 2003). Based on extensive field survey in the Lower Namoi valley to test the hypothesis that the cotton production systems have led to decrease in organic carbon stored in the soil (Fig. 11), Odeh *et al*. (2003) reported topsoil (0–0.10 m) carbon decline of up to 65% after 10 years of clearance or conversion from the original average values of 1.5–1.0 dag/kg under native vegetation. Their model also indicates a steady-state soil organic carbon at about 0.7–0.8 dag/kg, about half the original values under the native vegetation. Bellamy *et al*. (2005) found that the relative rate of carbon loss in the top 0.15 m increased with soil carbon content in England and Wales, and the rate of carbon loss is irrespective of land use, suggesting a link to climate change.

A second limitation to the map produced in this paper is that we used the environmental variables (Landsat, gamma radiometrics) that mainly reflect the surface condition to predict the carbon storage to depth of 1 m. It is the main reason for predictability (prediction quality in terms of RMSE and R^2) decreasing with depth (Table 3), with the best prediction at a depth of 0.2 m. Nevertheless we are able to give a good representation of the carbon status of the area highlighting the effect of land use on the declining carbon storage.

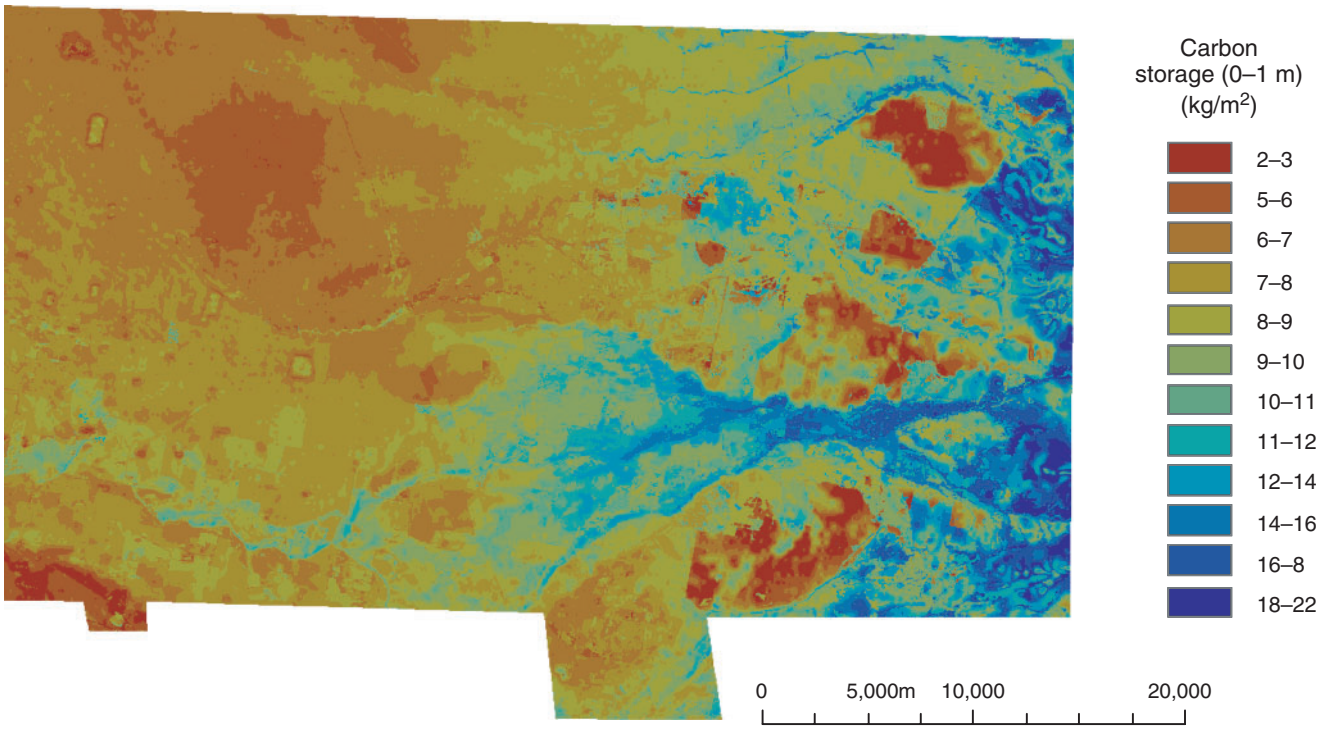

Fig. 10. Map of carbon content storage at 0–1 m for the Edgeroi area.

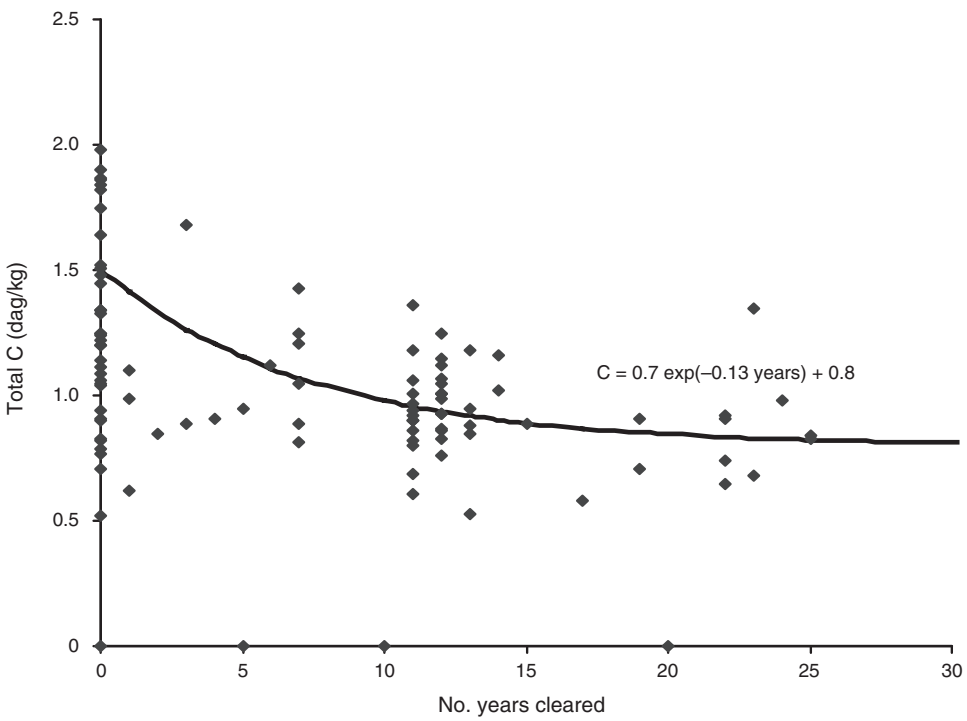

Fig. 11. The evolution of soil carbon as a function of the number of years since land clearance.

Conclusion

We demonstrated the process of digital soil mapping of soil profile carbon. Predicting parameters of an exponential function allow us to map carbon content and storage at different depths. Some highlights and limitations were outlined.

This is the first map which may be expanded to partially dynamic 'scenario' soil maps (McBratney *et al*. 2003). It has become increasingly important for environmental reasons to know not just the carbon storage at particular time also the changes or trend with time. A first approach is to run a soil organic matter model over the area (e.g. Walter *et al*. 2003) to project the evolution of soil carbon storage. Alternatively, McBratney *et al*. (2003) postulated that if we know any of the partial differentials of the *scorpan* model, $\partial s/\partial t$, $\partial c/\partial t$, $\partial o/\partial t$, the last one perhaps being the most important, we can project the existing soil map forward by some time u by calculating most simply, say, $o + u\partial o/\partial t$ for all points and running the new o layer(s) through the prediction function. This approach has limitations compared with a dynamic soil organic matter simulation model, such as lack of feed-back and possible extrapolation problems. Nevertheless, we still have a relatively quick and easy way to produce first-cut 'scenario' soil maps.

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