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Soil organic carbon patterns under different land uses in South India

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A B S T R A C T

Soil organic carbon (SOC) is the largest terrestrial organic carbon pool; thus, there is a growing interest in its spatial distribution and potential for carbon sequestration. However, our knowledge about spatial distribution in different soil depths and under different land uses is still limited in many regions of the world. The aim of this study was to analyse the soil depth and land use specific SOC contents in a small catchment (6.46 km²) located in the tropical monsoon climate of South India and to determine potential auxiliary variables suitable to derive high resolution maps. A soil survey was carried out, taking 112 soil cores representing three soil depth increments each (< 0.2 m, 0.2 - 0.5 m, and 0.5 - 0.9 m, respectively) and a number of spatially distributed auxiliary variables (slope; curvature; elevation above the next potential irrigation source; water erosion; wetness index; mean NDVI) were determined. The interrelationship between SOC contents and these variables and their principal components were analysed with a combination of an ANCOVA, an iterative linear regression and a multivariate non-linear regression procedure. The mean SOC contents of 3.4 g kg^{-1} (upper 0.9 m) are consistent with large scale data. The more detailed analysis of land use specific differences in SOC contents showed that the sampling points of irrigated arable land had the highest mean contents in topsoil and over the whole measured depth. SOC contents under arable land were followed by those under plantations, forests/shrubland and grassland. Within the different land use categories SOC under arable land declines with increasing elevation above the next potential irrigation source, SOC under grassland is positively correlated with mean NDVI, and SOC under forest/shrubland is best described by variables indirectly related to the accessibility of forest areas. Overall, this study indicates that the commonly used relations to estimate spatial distribution of SOC on larger scales might not be adequate for large areas in South India, which are dominated by pronounced dry and wet seasons, intensive irrigation farming and human-induced forest degradation.

1. Introduction

Soil organic carbon (SOC) is the largest terrestrial organic carbon pool. The latest global SOC map based on the Harmonized World Soil Database (FAO, 2009) was derived by Hiederer and Köchy (2011). It reported global SOC contents of 1417 Gt C in the upper meter and 699 Gt C in the top 0.3 m (Hiederer and Köchy, 2011). Hence, small changes in rates of mineralization of this pool due to climate and/or land use and management change will directly affect atmospheric CO_2 concentrations (Stockmann et al., 2013). For both climate mitigation and amelioration of soil quality and fertility, there is a growing interest in adopted agricultural soil management to stabilize or increase soil SOC contents (Lal, 2007; Stockmann et al., 2013). Moreover, considerable efforts to reduce forest degradation, which leads to a decline in SOC stocks (e.g. Chhabra and Dadhwal, 2004), are taken in many parts of the world.

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Despite the improved SOC maps available on the global scale, e.g. Hiederer and Köchy (2011) with a resolution of 30 × 30″, there is still limited knowledge on the small scale SOC patterns in many regions of the world. Today, more detailed SOC maps are mostly available from OECD states where a large number of studies focus on in-field SOC variability (e.g. Bornemann et al., 2010; Dlugoß et al., 2010) or SOC inventories are combined with models to estimate the spatial distribution of SOC in different soil depths (Lacoste et al., 2014; Meersmans et al., 2009). Depending on spatial scale and data availability, different auxiliary variables are used in these studies to estimate the spatial distribution of SOC contents or stocks. On the larger regional to global scale, the spatial distribution of SOC contents (partly stocks) is mostly estimated combining SOC data with typological soil units available in global soil maps (e.g. Hiederer and Köchy, 2011), combinations of soil units with land use information or ecosystem categories (D'Acqui et al., 2007; Don et al., 2011). On smaller scales from single fields to landscape segments, a wide variety of auxiliary variables were successfully tested for 3D SOC mapping. These range from high resolution terrain attributes, geological variables, detailed land use information and soil properties to modeled or measured erosional status (Dlugoß et al., 2010; Lacoste et al., 2014; Minasny et al., 2013; Quine and Van Oost, 2007).

In India, considerable efforts have been made over the last decades to provide modern and homogenous soil maps (Harindranath et al., 1999; Krishnan et al., 1996; Natarajan et al., 1996; Shiva Prasad et al., 1996). Despite the well-known relations between land use and SOC contents, most estimates of SOC contents or stocks available in India are based on relations between soil units or groups of soil units from these maps and SOC data (Bhattacharyya et al., 2000). Regional studies focusing on the spatial distribution of SOC in South India are relatively rare (Krishnan et al., 2007) and mostly limited to differences in SOC stocks under forest with different degradation status (Chhabra and Dadhwal, 2004) or effects of land use change on SOC stocks (Jenny and Raychaudhuri, 1960). Generally, it can be concluded from these land use change studies in India as well as from more extensive meta-analyses in the tropics (Don et al., 2011) that SOC contents or stocks decline from primary forest to grassland and to cropland. Besides these soil degradation studies, which allow addressing some spatial variation in SOC stocks, there is a large number of recent studies from India dealing with SOC contents in different agricultural regions and the potential benefits from SOC sequestration due to adopted agricultural soil management (Brar et al., 2013; FAO, 2004; Pathak et al., 2011; Srinivasarao et al., 2013). However, studies focusing on more small-scale patterns in SOC contents within small catchments with different land uses, which also take different soil depths into account, are to our knowledge missing. Nevertheless, soil depth-specific spatial SOC patterns are of major importance to understand processes of carbon sequestration on the landscape scale affected by the different carbon saturation status of soils (Qin et al., 2013; Wiesmeier et al., 2013).

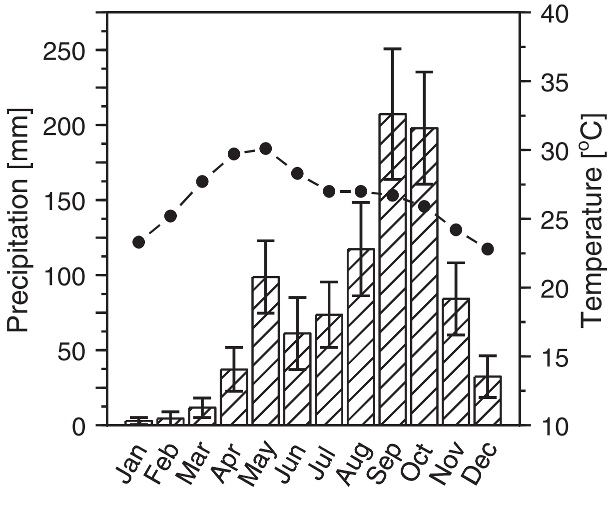

Fig. 2. Long-term (1981–2011) monthly precipitation measured in a distance of 4 km from the test site at the Krishnagiri reservoir; error bars give 95% confidence intervals; mean monthly temperatures taken from climate-data.org (Anon., 2013).

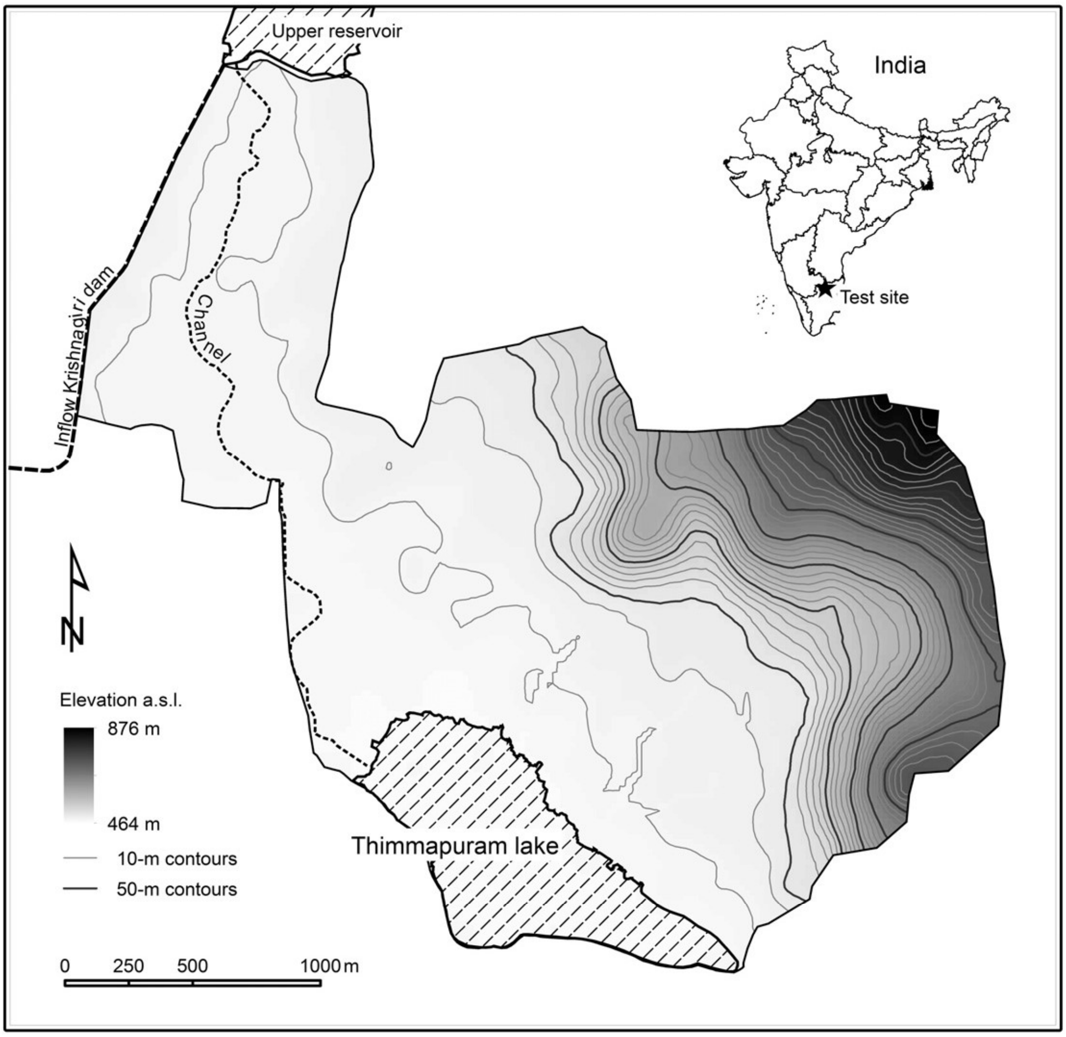

Fig. 1. Computed extent of the test catchment with topography and hydrological situation.

The major objectives of this study are firstly, to determine the soil depth-specific (0 m to 0.2 m, 0.2 m to 0.5 m, and 0.5 m to 0.9 m) distribution of SOC contents in a small, intensively used catchment under monsoon climate typical for South India and secondly, to analyze the drivers of spatial patterns in SOC contents taking land use, topography, erosion and vegetation status into account.

2. Materials and methods

2.1. Test site

The test site is located in the Krishnagiri District in Tamil Nadu, India, about 220 km west of Chennai and 100 km south-east of Bangalore. It covers a small catchment of approximately 6.46 km^2 draining into the Thimmapuram lake with a surface area of about 0.64 km^2. The altitude of the catchment at the lake outlet is 477 m increasing to 876 m above sea level at the peak of a small Inselberg (12.74° N, 78.24° E) in the eastern part (Fig. 1). The landscape is generally characterized by a flat-bottomed valley floor (approx. 70% of catchment area) and partly very steep slopes of the Inselberg with granitoid gneiss rock (Geological Survey of India, 2001). The catchment represents a typical landscape segment of the 'foothills' of the Eastern Ghats.

The climate of the test site is representative for the wet and dry, tropical monsoon climates of South India with a long-term mean annual rainfall of 779 mm (measured 1981–2011 at the Krishnagiri dam located 4 km north-west of the catchment) and a potential evapotranspiration estimated to be 1670 mm a^{-1} in the district (Natarajan et al., 1996). Rainfall has a pronounced seasonality with a first small peak end of May and a main rainy season related to south-west (summer) as well as north-east (winter) monsoon between August and November (Fig. 2). Compared to rainfall, the seasonality of temperature is small (Fig. 2) with an average of about 26.4 °C (Anon., 2013).

Following the 1:500,000 soil map of Tamil Nadu (Natarajan et al., 1996) the soils in the test catchment can be roughly characterized in relation to topographic subdivisions, with moderately deep, well drained, sandy loamy soils in-between rock outcrops at the slopes of an Inselberg, and deep, moderately drained, clayey soils in the gently sloping valley floors. Soils in the catchment are all classified as Inceptisols (suborder: Tropepts; greater group: Ustropepts; subgroup: Typic Ustropepts) following the taxonomy of the US Department of Agriculture (USDA) used by the Indian State Soil Survey (Natarajan et al., 1996). Comparing the location of the two topographic subdivisions from the 1:500,000 map with the topography derived from a 90 × 90 m SRTM DEM (Jarvis et al., 2008) it indicates that the resolution of the soil map is not appropriate to use the drainage classes of the map subdivisions for further statistical analyses. Probably more detailed maps exist but were not available for our study.

Land use in the catchment also follows topography with sparse forests, shrubland and grassland on the steeper slopes in its eastern part and arable land and plantations (e.g. Jasmine) in the mostly flat areas around the lake (Table 1). Generally, the area is dominated by irrigation farming, which allows two crops per season (approximately 90–95% of the arable land in the catchment is irrigated). Depending on water availability, which is governed by the annual variability of monsoon rainfall and the proximity to water sources for irrigation, the cropping intensity varies. In the direct proximity of the lake and along the channel between the upper water tank and the lake (Fig. 1) paddy rice is planted twice per season in most years. Moving upslope from the lake to the Inselberg in the north-eastern part of the catchment, a gradual change from rice dominated cultivation to a combination of rice and vegetables and/or millet, sorghum or bean variations is observed. In case of limited irrigation options due to larger distances to water sources (approximately 5–10% of arable land), mostly millet, sorghum and bean variations are planted. The hydrological situation in the catchment is very complex, dominated by man-made water harvesting structures, channels and groundwater wells intensively used for irrigation, often by pumping water to fields above water level of the irrigation source. From the end of the rainy season in December to approximately April, the catchment gets additional water through the Krishnagiri dam (personnel communication with the dam management), which was established in the late 1950s to store monsoon runoff of the Ponnaiyar river (gross capacity: $47 \cdot 10^6$ m^3). This inflow is transferred via the small reservoir in the north of the catchment (Fig. 1) into the Thimmapuram lake, which itself was built for irrigation purposes and to improve ground water recharge.

Table 1
Land use in the Thimmapuram lake catchment derived from aerial photographs and ground-truth mapping in 2011 and 2012; USLE C factors adapted from studies in South India (Chatterjee et al., 2013; Dabral et al., 2008; Jain and Das, 2010; Vemu and Pinnamaneni, 2011); USLE P factor of arable land (mostly small flood irrigated parcels) was averaged from values reported by Chen et al. (2012) and Yoshikawa et al. (2004).

Land use	Area		USLE factors	
	[ha]	[%]	C	P
Arable land	193.3	29.9	0.37	0.25
Plantations[a]	117.7	18.3	0.2	1
Grassland[b]	70.3	10.9	0.2	1
Shrubland[b]	38.5	6.0	0.2	1
Forest[b]	123.8	19.2	0.03	1
Settlements & infrastructure	31.5	4.9	1	1
Wetland	6.6	1.0	–	–
Lake	64.3	9.9	–	–
Total sum	645.9	100		

[a] Plantations summarize plantations of Mango, Jasmine, Chilly, Palm trees etc. typically planted in the area.
[b] Grassland, shrubland and forest include an area of approx. 10% of rock outcrops.

2.2. Soil sampling and analysis

For an inventory of the soil carbon contents in the catchment a field sampling campaign was carried out in early May 2012. The late dry season was chosen for the sampling campaign as almost all litter is mineralized or consumed via intensive grazing of sheep and goats on all land uses. Overall 112 soil cores were extracted down to a depth of 0.9 m or as deep as possible using a Pürckhauer soil auger (Eijkelkamp, NL; approximately 2 cm diameter). The Pürckhauer was used as it allowed penetrating into hard, dry clayey soils which was not possible with other hand augers with larger diameters. The complete samples from the auger were sub-divided within the field into three depth increments (from 0.0 m to 0.20 m, from 0.20 m to 0.50, and from 0.50 m to 0.90 m, respectively). Subsequently these depth increments are referred to as depth D1, depth D2 and depth D3. Samples were stored in plastic bags to be transported to the laboratory in the dark. Sampling locations were determined to represent typical land uses (Fig. 3) and a potential soil gradient between the lake and the Inselberg. Land use classes (Table 1) were defined as arable land, plantations, grassland, shrubland, and forest. For each of these classes, an area proportional number of sampling locations were randomly chosen from a generic 20 m × 20 m raster covering the eastern part of the catchment where the strongest gradients in slope and erosion potential can be expected. As we hypothesized that soil erosion might be an important driver of SOC patterns, especially in the forest area, an additional number of samples (approx. 12) were taken along a steep thalweg with visual signs of recent erosion and in a downslope flat area where deposition was observed.

The soil samples were oven dried at 105 °C for 24 h. Coarse particles were separated by 2 mm sieving, roots and other undecomposed organic matter particles were removed by hand picking. To determine the coarse soil fraction, both coarse (>2 mm) and fine soil fractions (<2 mm) were weighed. Afterwards the fine soil fractions were grounded with a hand mortar. The total C and N contents were determined by elemental gas-chromatography using a CNHS elemental analyzer (vario MicroCUBE, Elementar, Hanau, Germany). Although the soils in the area are characterized as non-calcareous (Geological Survey of India, 2001)

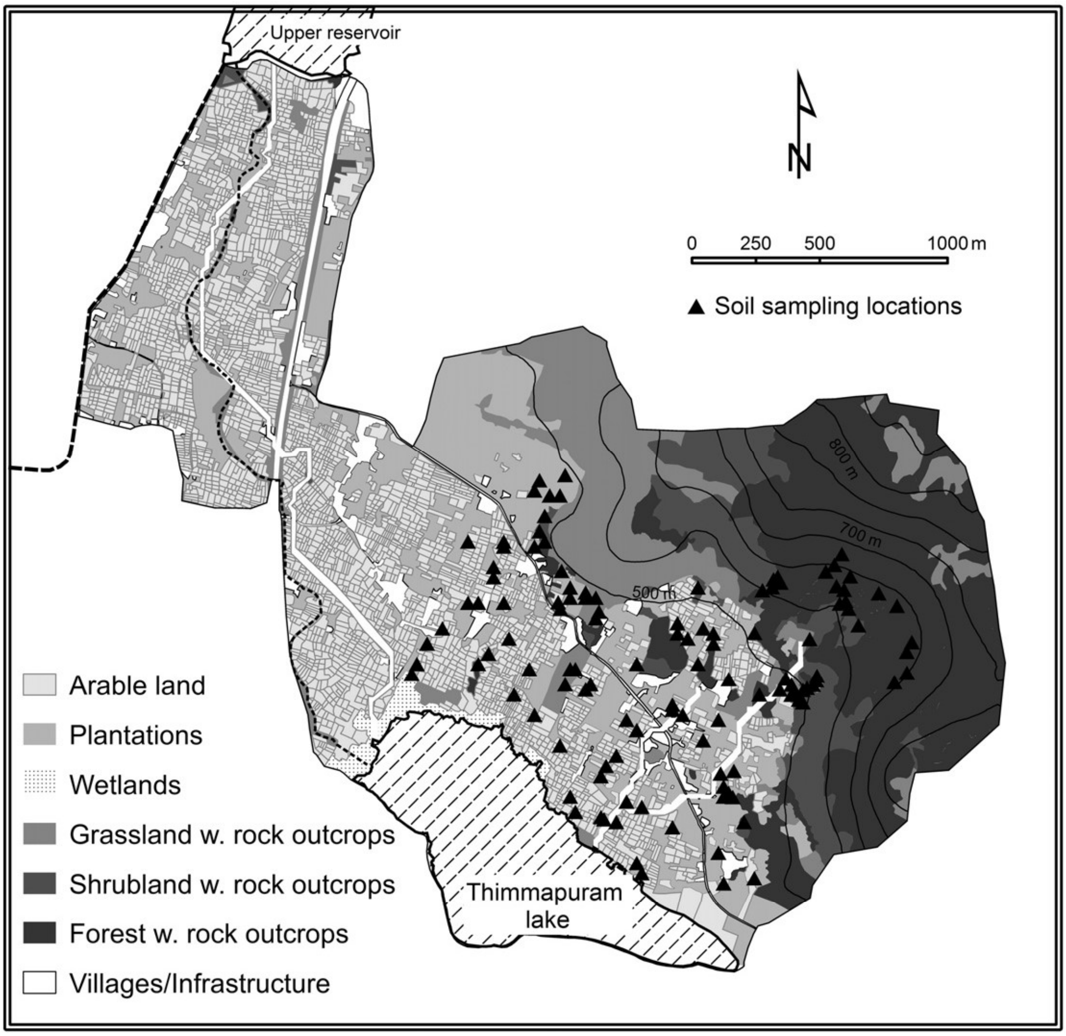

Fig. 3. Land use and sampling locations in the test catchment.

all soil samples were checked for inorganic carbon content with HCl. In the case of any signs of inorganic carbon (approximately 25% of all samples) we determined the total inorganic carbon content (TIC) with a combined total carbon (TC) and TIC analyzer (DIMA-TOC 100, Dimatec, Essen, Germany).

To keep the C content values consistent based on the data from the CNHS elemental analyzer (vario MicroCUBE) we used the ratio of TIC to TC from the DIMA-TOC100 to calculate total organic carbon (TOC) from the TC data of the CNHS elemental analyzer (Eq. (1)). The resulting TOC contents are subsequently referred to as SOC contents.

$$TOC = TC_{CNHS\text{-}analyser} \cdot \left(1 - \frac{TIC_{DIMA\text{-}TOC}}{TC_{DIMA\text{-}TOC}}\right) \quad (1)$$

As the soil sampling campaign was carried out during the dry season the very clayey and dry soils could be hardly sampled for subsoil bulk density. Hence, only regional information regarding subsoil bulk density ($1.6 \cdot 10^3$ kg m^{-3}) was available from global maps (Anon., 2007). To determine top-soil bulk density stainless steel sampling rings with a cutting edge at the bottom (diameter 0.06 m, length 0.07 m) were hammered into the soil and afterwards excavated. The sampled soil was dried at 105 °C in the laboratory and bulk density was calculated from ring volume and dry sample weight. Bulk density samples were taken at 20 locations representing the different land uses. Interestingly, the topsoil bulk densities only slightly varied between the different land uses (Mean ± standard deviation: $(1.40 \pm 0.13) \cdot 10^3$ kg m^{-3}). Unfortunately, the available soil texture and bulk density data did not allow to parameterize any pedo-transfer function (e.g. Meersmans et al., 2009) to calculate bulk density for different soil depths. However, using the available spatially uniform bulk density information and the measured coarse fractions for each sample allowed to at least estimate SOC stocks. As these estimates are associated with a larger uncertainty compared to measured SOC contents, we mostly restrict our spatial analyses to SOC contents. Nevertheless, we partly used the calculated SOC stocks to indicate that the spatial distribution of the coarse fraction does not bias our general findings regarding SOC differences under different land use categories.

2.3. Terrain analysis

A number of primary terrain attributes and one terrain index that might affect the spatial distribution of SOC were calculated. The derivation of these parameters was based on a SRTM DEM (Jarvis et al., 2008) down-scaled to a resolution of 20 m × 20 m. For this downscaling an inverse distance approach was used with a weighting exponent of one to linearly interpolate between the center values of each 90 m × 90 m grid cell of the original SRTM data. The downscaling to 20 m × 20 m was necessary for two reasons: (i) the sediment transport capacity approach implemented in the later on used erosion model WaTEM/SEDEM (Van Oost et al., 2000; Van Rompaey et al., 2001; Verstraeten et al., 2002) is calibrated to this grid size, and (ii) the higher resolution more easily allowed to burn-in the major streams and drainage channels into the

DEM, which connect the steep slopes in the eastern part of the catchment with the Thimmapuram lake.

The following primary terrain attributes were calculated using ArcGIS 10 (ESRI, USA): slope, profile curvature (Curv_prof; orientated in the direction of maximum slope) and plan curvature (Curv_plan; orientated perpendicular to the direction of maximum slope). The latter terrain attributes were chosen as these represent concavities and convexities of slopes, which might be related to lateral soil movement and hence changes in SOC patterns (e.g. Dlugoß et al., 2010). The secondary attribute wetness index (Moore et al., 1991) was used as proxy variable for soil moisture potentially affecting SOC contents:

$$WI = \ln \frac{A_s}{\tan \beta} \quad (2)$$

where A_s is the specific catchment or contributing area ($m^2\ m^{-1}$) orthogonal to the flow direction, calculated as the grid cell specific catchment area divided by the grid length (20 m), and β is the slope.

Another potential driver of spatial variability in SOC is the spatially varying irrigation within the catchment. As it is difficult to get detailed data regarding irrigation amounts, which is the most important driver of crop growth in the region, we tried to identify a commonly available proxy variable valuable to estimate irrigation potential. Generally, there are two irrigation sources typically used in this region of India. On the one hand, there is a long tradition in channel irrigation based on an interconnected system of water harvesting reservoirs/lakes (as the Thimmapuram lake). On the other hand, more and more farmers pump ground or surface water to fields located on elevations above these water sources. Furthermore, the groundwater level around the lake is partly so shallow (if the lake is board full) that it is directly available for plants. Hence, a hypothetical height distance to the next open water source (elevation above surface water, EaW) is calculated, assuming that irrigation water availability is directly related to stream and lake levels (which are assumed to correspond to groundwater levels) extractable from the DEM. To this end, we calculated the specific catchment area of each stream/lake raster cell and associated the height of the respective outlet to these individual catchments. The result is a set of intersecting horizontal plains, each with the elevation of the respective outlet point. The difference between the elevation of the original DEM and the maximum plain elevation at a certain location leads to a raster, which represents EaW.

2.4. Erosion modeling

To account for patterns of water erosion, which should be especially important for SOC patterns in the forest and shrubland located on partly steep slopes, we applied the spatially distributed erosion and sediment delivery model WaTEM/SEDEM. It is a spatially distributed model combining a water and tillage erosion model (WaTEM, Van Oost et al., 2000) and a sediment delivery model (SEDEM, Van Rompaey et al., 2001). WaTEM is an adapted version of the Revised Universal Soil Loss Equation (RUSLE; Renard et al., 1996). The most important adaptation is the replacement of the slope length with the unit contributing area according to Desmet and Govers (1996a).

SEDEM calculates sediment transport and sedimentation. Sediments are routed along the flow pathway using a multiple-flow algorithm (Desmet and Govers, 1996b). Deposition is controlled by grid cell specific transport capacity, which is assumed to be proportional to the potential rill (and ephemeral gully) erosion volume calculated following an approach of Van Rompaey et al. (2001). If the local transport capacity is lower than the sediment flux, deposition is modeled.

WaTEM/SEDEM requires a number of input maps as well as various input parameters which are briefly described in the following: The 20 m × 20 m DEM serves as main basis for the calculations. Aerial photographs were used to delineate single fields and parcels as well as land use and pond distributions (see Fig. 3). A watercourse map (rivers/canals) was calculated from the DEM, in which artificial canals were 'burned in' beforehand. The K factor was calculated from texture (Auerswald et al., 2014) as given in the soil map of Tamil Nadu (Natarajan et al., 1996); it is either 10 kg m^{-2} h MJ^{-1} mm^{-1} or 21 kg m^{-2} h MJ^{-1} mm^{-1}. The R factor [MJ mm ha^{-1} h^{-1} a^{-1}] was calculated from the long-term mean annual precipitation (P_{an}) at the station Krishnagiri using an equation provided by Jain and Das (2010) for South India ($R = 81.5 + 0.38\ P_{an}$; for $340 \leq P_{an} \leq 3500$ mm). A conservation practice factor (P factor) for the arable land, which is dominated by small fields (Fig. 3), mostly used to cultivate paddy rice or other flood-irrigated crops, is not available from standard RUSLE/USLE literature. Hence, we took an average P factor of 0.25 for similar small paddy rice fields averaged from values reported by Chen et al. (2012) for Taiwan and Yoshikawa et al. (2004) for Japan.

The most complex RUSLE/USLE factor is the C factor which originally combines daily erosivity (derived from long-term, high resolution rainfall data) with daily or seasonal soil cover by plants or plant residues (derived from long-term measurements). As both is not available for the test site, the C factors of the main land uses (Table 1) were estimated from other studies carried out in Southern India (Chatterjee et al., 2013; Dabral et al., 2008; Jain and Das, 2010; Vemu and Pinnamaneni, 2011). However, all these studies use rough estimates of the C factors, e.g. calculating it from remote sensing derived Normalized Digitized Vegetation Index (Jain and Das, 2010), or apply tabular data from Wischmeier and Smith (1978) not experimentally tested under conditions comparable to the respective test sites.

Due to the uncertainties associated with applying WaTEM/SEDEM in the case of the small irrigation fields we did not analyze the spatial distribution of erosion and deposition for the arable land and the plantations but focus on the near natural areas not dominated by flood irrigation. Nevertheless, we compared the overall erosion potential within the different land use categories. Erosion and deposition are given as the variable ERO with negative values indicating erosion and positive values indicating deposition.

2.5. Vegetation attributes

To account for the spatial patterns in vegetation density and activity, which are important drivers of spatial SOC patterns in near-natural environments, a multi-temporal remote sensing analysis was performed. A long-term mean Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1973) was calculated utilizing the near infrared (NIR) and red bands of five satellite scenes acquired between 1992 and 2011. The used sensors were Landsat 5 TM (one scene in January 1992), Landsat 7 ETM+ (scenes in November and December 2000), and IRS-P6 LISS III (scenes in March and November 2011).

2.6. Statistical analysis

The following analyses were performed to evaluate the spatial patterns in the land use and soil depth-specific amounts of SOC:

(i) SOC data as well as terrain attributes, soil erosion and NDVI were analyzed for normality using visual interpretation of normal Q–Q-plots. In case it was necessary (and possible) variables were transformed to reach near normality.
(ii) A principal component analysis was performed using all seven explanatory variables (Slope, Curv_plan, Curv_prof, WI, EaW, ERO, NDVI) to derive the most important spatial patterns within these variables which partly exhibit a strong collinearity, e.g. between slope and wetness index.
(iii) To test whether the mean SOC values per land use and soil depth are significantly different, an analysis of variance (ANOVA) was performed. A clear correlation between the different land uses, the principal components (PCs), and the single explanatory variables was given (e.g. forest is mostly located on steeper slopes).

Therefore, land use was taken as categorical explanatory variable together with the continuous explanatory variables in an analysis of covariance (ANCOVA). The ANCOVA allowed estimating intercepts and slopes of land use specific linear regressions between SOC and continuous explanatory variables. In case the model coefficients (intercept and slope) of different land uses were similar, such model could be stepwise simplified to test if specific land uses can be aggregated into a new land use category without losing explanatory power. To test if simplification of a model reduces explanatory power, we used Akaike's Information Criterion (AIC; Akaike, 1974).

(iv) Based on the aggregated land use categories, a soil depth-specific iterative linear regression and a multivariate non-linear regression procedure were performed taking likely interactions between explanatory variables and curvilinear behavior into account (Crawley, 2009). To avoid the problem of collinearity of explanatory variables (terrain, erosion, and vegetation parameters) PCs derived from these variables were also used in the multivariate regression analysis. To test if regression model simplifications are possible without losing explanatory power, again the Akaike's Information Criterion (AIC; Akaike, 1974) was used.

(v) To test the sensitivity of certain relations between soil depth-specific SOC contents and potential auxiliary variables against data from individual sampling points, we used a cross-validation approach. Therefore, one SOC measurement after the other was omitted from the data used to derive the

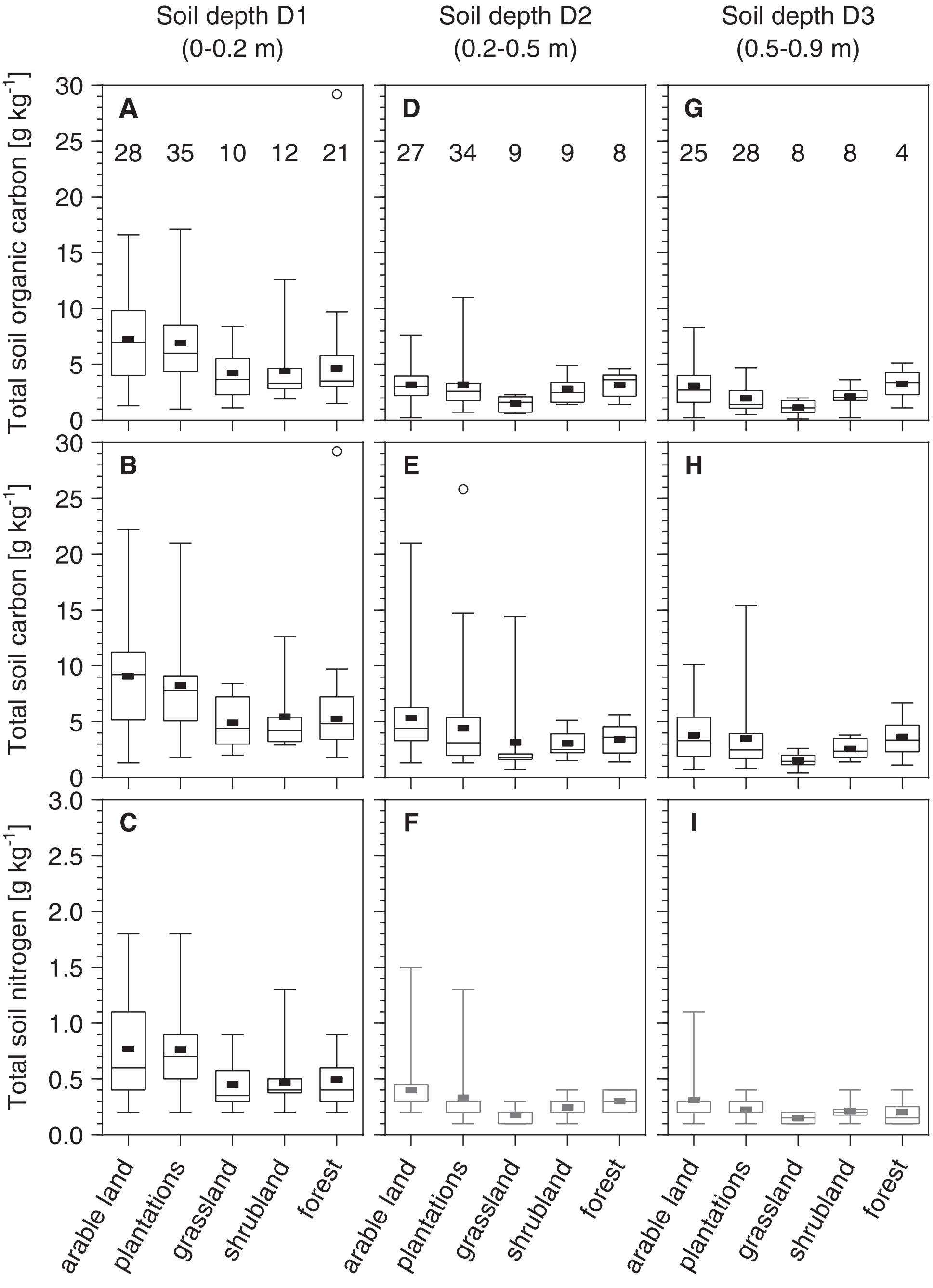

Fig. 4. Box-plots of total soil organic carbon, total soil carbon, and total soil nitrogen in the different soil depths; boxes show the median and the 1. and 3. quartile, while whiskers give the minimum and maximum (excluding outliers as circles); values above boxes in A, D, and G give number of samples; black rectangles represent mean values; the values of N in the two deeper soil layers (>0.2 m) are marked in gray as the mean N values are already at the detection limit of the CNHS analyzer and are therefore associated with large uncertainties.

relations and the missing values were subsequently estimated. As goodness-of-fit parameters, we used the root mean squared error (RMSE) and the model-efficiency coefficient (MEF) of Nash and Sutcliff (Nash and Sutcliffe, 1970):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{3}$$

$$\mathrm{MEF} = 1 - \frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{\sum_{i=1}^{n}(x_i - \overline{x}_i)^2} \tag{4}$$

where n is the number of points, x_i are the observed values, $\hat{x}_i$ are the predicted values, and $\overline{x}$ is the arithmetic mean of the observed values.

3. Results

3.1. Soil depth and land use specific SOC contents

In the topsoil depth increment D1 (0 m to 0.2 m) the SOC contents ranged between 1 g kg^{-1} and 17 g kg^{-1} (excluding one obvious outlier under forest with a SOC content of 29 g kg^{-1}), with a mean SOC content of 6 g kg^{-1} (Fig. 4A). On average about 16% of total soil carbon is inorganic carbon determined in 47% of all topsoil samples via the HCl test and measured with a TC analyzer (DIMA-TOC 100). Under arable land inorganic carbon contents were slightly higher with a mean of about 20% of total carbon (no significant difference). As the geological map (Geological Survey of India, 2001) does not indicate any source of inorganic carbon in the parent material, we assume that this resulted on the one hand from pedogenic carbonates (Durand et al., 2007) and on the other hand from shell-bearing molluscs (*Conchifera*), especially accumulated in the regularly flooded fields (visible remains of mollusc shells have been found in the soil samples during processing). In general, highest SOC contents were found under arable land and plantations, while forest, shrubland, and grassland show substantially smaller SOC contents (Fig. 4A). The difference in SOC between the intensively cultivated irrigated and fertilized land uses and the less intensively used forest, grassland and shrubland was also mirrored in the significantly higher total nitrogen contents under arable land and plantations (Fig. 4C). The ANOVA null hypothesis that mean land use specific SOC contents are equal in soil depth D1 could be rejected ($p = 0.010$), indicating the importance to take land use as major reason of spatial variability in SOC contents into account.

In the second soil depth increment D2 (0.2 m to 0.5 m) the mean SOC content declines significantly compared to D1 ($p < 0.001$) ranging from 0.2 g kg^{-1} to 11 g kg^{-1} (mean 3 g kg^{-1}: Fig. 4D), whereas the lowest measured values were associated with large uncertainty as these are close to or even below the detection limit of the CNHS analyzer. Inorganic carbon contents increased relatively with a mean of 28% of the total carbon content (Fig. 4E). Again, the largest mean proportion of inorganic carbon in total carbon content was found under arable land (mean 41%). As expected, the total nitrogen contents in the second soil depth were much lower than those in the topsoil depth increment, with lowest values under grassland (Fig. 4F). The ANOVA null hypothesis of no land use specific mean SOC content differences could not be rejected ($p = 0.19$).

In the third soil depth increment D3 (0.5 m to 0.9 m) SOC contents are again slightly smaller ranging from 0.1 g kg^{-1} to 8.3 g kg^{-1}, respectively. The mean of D3 (2.3 g kg^{-1}) is significantly smaller than the mean in depth D2 ($p = 0.03$). However, the difference is less pronounced than between depth D1 and D2 (Fig. 4A, D and G) because a clear decline could only be detected under plantations and shrubland. However, it is worth noting that especially under forest the number of samples declined substantially from 21 in D1 to only 4 in D3, as the deeper soil depth could not be sampled due to the shallower soils under forest. The ANOVA null hypothesis of equal mean SOC under all land uses could be rejected for depth D3 ($p = 0.014$).

3.2. Importance of land uses and aggregate new land use categories

Combining land uses as categorical variables with other continuous variables in an ANCOVA potentially allows determining the importance of different land use classes in more detail and also to aggregate single land use classes into categories used for further analysis. For soil depth D1, best ANCOVA results were achieved employing land use, distance above surface water (EaW) and PC7, representing Curv_plan and Curv_prof ($R^2 = 0.25$; $p = 0.001$). Slopes and intercepts in the ANCOVA were similar for forest and shrubland, so we tested for a model simplification aggregating both land uses into a new land use category. The aggregation did not on its own reduce the explanatory power of the ANCOVA, whereas in combination with EaW it did significantly affect the explanatory power of the model. The same was true for the land use categories plantation and arable land.

In soil depth D2, best ANCOVA results were obtained applying land uses and PC4, representing mostly water erosion, as explanatory variables ($R^2 = 0.29$; $p = 0.0013$). Again slopes and intercepts for forest and shrubland were similar and aggregation of these land uses into a new category did not reduce explanatory power of the model. The combination of all land uses with PC4 significantly improved the overall model.

In soil depth D3, best ANCOVA results were received using land uses and Curv_prof as the explanatory variables ($R^2 = 0.27$; $p = 0.014$). Aggregation of forest and shrubland was less clear from the ANCOVA results but it did not reduce the overall power of the model. Only grassland in combination with Curv_prof had a significant explanatory power.

In general, the soil depth-specific ANCOVA resulted in an aggregation of forest and shrubland. Hence, in the following the land use categories arable land, plantation, grassland and forest/shrubland will be analyzed separately.

3.3. Land use category specific explanatory variables for SOC patterns

3.3.1. Linear regression analysis

Under arable land, the principal components derived from all seven explanatory variables (Slope, Curv_plan, Curv_prof, WI, EaW, ERO, and NDVI) or their transformations (log[Slope]) could not explain more of the variation in SOC contents than single original explanatory variables. Most important in soil depth D1 was the elevation above the nearest surface water source (EaW; Table 2). In soil depth D2 no significant correlation with the used explanatory variables could be detected and in soil depth D3 curvature was important (Table 2). However, curvature was a somewhat difficult predictor, since it always exhibited some outliers. Hence, PC1, which was significantly ($p = 0.01$) correlated with curvature, WI and EaW, might be a better predictor.

Under plantations none of the explanatory variables or their PCs was significantly related to SOC content in D1. This might result from the higher diversity of the plantations ranging from young jasmine plantations located in regularly flooded fields to old palm tree stands planted along field borders and in the direct proximity of villages. In soil depth D2, the principal components PC2 and PC5 as well as Curv_prof and EaW had similar explanatory power for the SOC patterns (Table 2). Interestingly, PC2, which represented 25% of the variability in all auxiliary variables, was significantly ($p < 0.001$) correlated not only with EaW and Curv_prof but also with slope.

Under grassland the most important explanatory variables ($p < 0.01$) were PC1, representing 46% of the variability of the auxiliary variables, as well as Curv_plan and NDVI (Table 2). Especially mean NDVI and PC1 seemed to be reasonable predictors for SOC contents in D1 as an average vegetation density should be closely related to potential carbon inputs to

Table 2
Correlation coefficients and significance levels (on bold values) relating soil organic carbon contents of different land use categories and soil depths (D1: 0 m to 0.2 m; D2: 0.2 m to 0.5 m; D3: 0.5 m to 0.9 m) with respective auxiliary variables and their principal components (PC1–PC7); auxiliary variables are: slope, plan curvature (Curv_plan), profile curvature (Curv_prof), wetness index (WI), elevation above next surface water (EaW), modeled water erosion (ERO), and mean normalized difference vegetation index (NDVI).

	Arable land			Plantations			Grassland			Forest & shrubland		
	D1	D2	D3	D1	D2	D3	D1	D2	D3	D1	D2	D3
Variable	Correlation coefficients R and significance levels											
PC1	**−0.47***	−0.20	**−0.34**	−0.22	0.03	0.31	**0.71***	0.08	0.48	0.24	**0.57***	0.27
PC2	0.04	−0.27	−0.30	0.00	**0.39***	−0.05	0.34	−0.20	−0.41	**−0.33**	−0.40	−0.11
PC3	0.14	0.02	−0.20	−0.06	−0.12	0.18	−0.23	−0.35	−0.04	0.12	−0.13	0.12
PC4	0.32	−0.28	0.07	0.01	0.03	**0.35**·	0.28	−0.56	−0.17	−0.22	0.12	−0.40
PC5	0.24	−0.02	**−0.35**	0.22	**0.39***	0.08	0.18	0.24	0.57	0.20	0.36	0.44
PC6	−0.22	0.10	0.20	0.18	−0.20	0.04	−0.35	−0.51	0.30	**−0.39***	−0.36	0.43
PC7	−0.17	0.22	0.14	−0.20	0.05	−0.06	0.22	−0.21	−0.39	−0.29	0.00	0.45
Slope		−0.22	0.02		−0.20	0.13	−0.03	0.08	−0.31	**0.30**	**0.68****	0.26
log(Slope)	0.04			0.15								
Curv_plan	**0.39***	0.31	**−0.49***	−0.14	0.01	−0.08	**0.66***	0.36	**0.67**	−0.28	−0.24	−0.32
Curv_prof	−0.15	−0.29	**0.44***	0.06	**0.38***	−0.17	−0.25	0.03	−0.48	0.03	−0.10	−0.16
WI	−0.10	0.06	0.22	0.23	0.17	−0.09	−0.48	0.36	−0.21	**−0.35***	**−0.54***	−0.26
EaW	**−0.57****	0.04	0.13	0.03	**−0.40***	0.17	−0.54	−0.12	−0.59	**0.34**	**0.49***	0.45
ERO							**−0.61**	−0.19	−0.17	−0.08	0.09	0.02
NDVI	0.29	−0.18	0.23	−0.24	0.08	−0.11	**0.71***	0.02	0.19	0.17	0.43	−0.12

Significance levels: ·, *, **, and *** are $p < 0.1$, $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively; due to the uncertainty with modeling erosion in small flood-irrigated fields erosion as co-variable was not taken into account in areas of arable land and plantations.

soils. For the deeper soil depths D2 and D3 no highly significant ($p < 0.01$) relations were detected to any PC or auxiliary variable.

Under forest/shrubland highly significant relations with PCs or auxiliary variables only occurred in the soil depths D1 and D2, which was probably a consequence of the small number of remaining samples in the deepest soil depth. Apart from different significant correlations with PCs the most important auxiliary variables in both depths were slope, WI and EaW (Table 2). Compared to most other soils under arable land, plantations and grassland all these variables were inversely related to SOC content, as SOC contents increased with slope and EaW and decreased with WI.

3.3.2. Nonlinear multivariate regression analysis

The estimates based on the iterative nonlinear multivariate-regression analysis were used only for the upper two soil depths, as generally the number of available sampling points substantially decreased with depths, whereas the uncertainty associated with the measurements increased due to the small overall carbon contents. As the different PCs as auxiliary variables did not improve the explanatory power of the linear regression models, we used only the original auxiliary variables for this analysis, which are more straightforward to be interpreted.

Significant relations ($p < 0.05$), which explained some of the variability in soil depth and land use category specific SOC contents, were found for D1 under arable land, D2 under plantations, D1 under grassland, and D1 and D2 under forest/shrubland (Table 3). The restriction to only one explanatory variable in each of the regression equations did not reduce the explanatory power. This was confirmed by a stepwise model simplification from using multiple variables to only one explanatory variable, while calculating the AIC values. One exception was D2 under plantations which could be better estimated if EaW would be combined with Curv_prof ($R^2 = 0.36$; $p = 0.003$). However, due to the outlier problem in the distribution of Curv_prof and the missing improvement by using two variables found during the following cross-validation, we omitted Curv_prof from the regression.

As already indicated by the coefficient of determination of the different regression equations, the MEF values obtained by the cross-validation were largest in the case of arable land and grassland in soil depth D1, and in the case of forest/shrubland in soil depth D2 (Table 3; MEF: 0.17–0.33). In the case of soil depth D1 under forest/shrubland and D2 under plantations, respectively, the MEFs are close to zero indicating that instead of using the regression equations the SOC contents could have been equally estimated using the soil depth and land use category specific mean SOC contents. Hence, the only valuable auxiliary variables potentially usable to predict the land use category specific SOC contents are EaW (D1 on arable land), NDVI (D1 on grassland), and slope (D2 in forest/shrubland).

Table 3
Estimates of soil depth (D1 and D2) and land use category specific SOC contents based on linear and non-linear regressions; quality of the derived estimates given in goodness-of-fit-parameters from cross-validation; soil depths D1 and D2 represent soil depths of 0 m to 0.2 m, and 0.2 m to 0.5 m; RMSE is root mean squared error, MEF is the Nash and Sutcliffe (1970) model efficiency coefficient.

	Best SOC content model		Explanatory power of model		Cross-validation of model	
	Equation/Mean SOC (10 g kg^{-1})	Tested range	R^2	p-Value	RMSE of SOC (10 g kg^{-1})	MEF
Arable land						
D1	$2.14 - EaW^{0.18}$	1.3 m < EaW < 32 m	0.35	0.001	0.36	0.17
Plantation						
D2	$0.49 - 0.015 \times EaW$	0.5 m < EaW < 23 m	0.16	0.021	0.26	0.01
Grassland						
D1	$-0.60 + 2.21 \times NDVI$	0.3 < NDVI < 0.6	0.51	0.020	0.20	0.30
Forest & shrubland						
D1	$0.52 - 0.04 \times WI$	−2.3 < WI < 7.8	0.12	0.044	0.26	−0.02
D2	$0.17 + 0.01 \times slope$	0.5% < slope < 26%	0.46	0.003	0.10	0.33

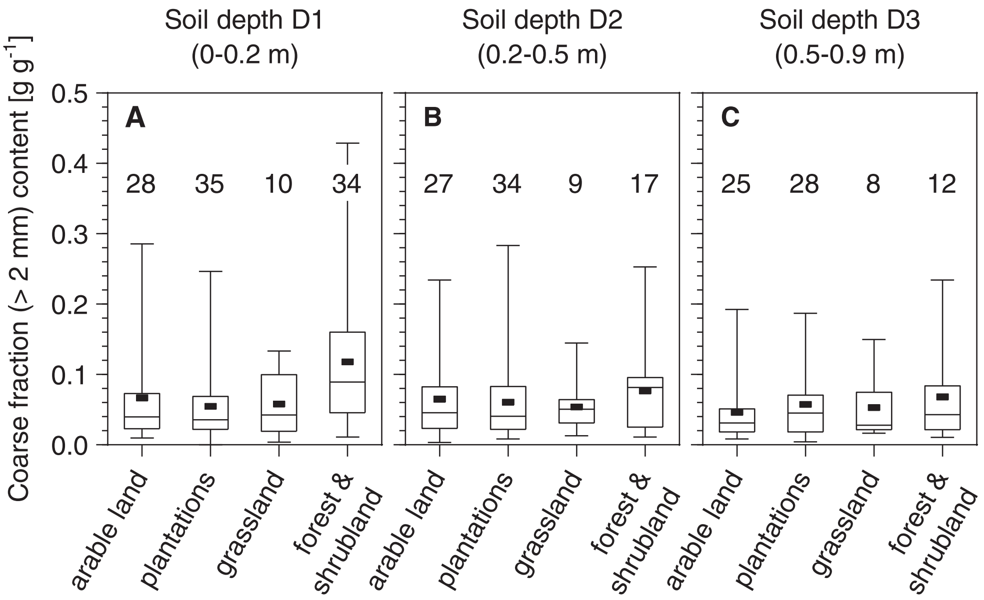

Fig. 5. Box-plots of stone content (>2 mm) of the different soil depths; boxes show the median and the 1. and 3. quartile, while whiskers give minimum and maximum; values above boxes give number of samples; black rectangles represent mean values.

4. Discussion

4.1. SOC contents under different land use categories

Generally, the mean topsoil (0 m to 0.2 m) SOC contents of 6 g kg^{-1} in the Thimmapuram catchment are in the range of SOC contents found in similar soils in southern India, e.g. 4 g kg^{-1} to 8 g kg^{-1} on the peninsular plateau (Bhattacharyya et al., 2000).

The most surprising finding was that we could not confirm the general results from many studies dealing with SOC contents/stocks under different land uses which usually indicate a decrease of SOC from forest to grassland and to cropland (e.g. Powlson et al., 2011). For the tropics this general finding is strongly supported by e.g. Don et al. (2011) who performed a meta-analysis using 385 studies to estimate the effects of land use change (more than five years before sampling) upon SOC stocks. Their study indicated a tremendous decline of SOC stocks if primary tropical forest is converted to grassland or cropland but still a substantial decline of SOC stocks (on average in the upper 32 cm) of (-6.4 ± 2.5)% and (-21.3 ± 4.1)% if secondary forest is converted to grassland and cropland, respectively. It might be argued that our results cannot be compared to the results of Don et al. (2011) as we did not measure bulk densities at all locations and all depths which would be necessary for a more substantial determination of SOC stocks. However, due to the small differences in topsoil bulk density under the different land use categories (mean $(1.4 \pm 0.13) \cdot 10^3$ kg m^{-3}), a combination of a homogenous bulk density with the spatially varying topsoil coarse fraction contents (Fig. 5A) does not weaken but strengthen our topsoil SOC content findings. While the highest SOC contents were found in topsoils under arable land and plantations and lowest under the grassland and forest & shrubland category, the opposite is true for coarse fractions (Fig. 5). Hence, the differences between land use categories should be slightly more pronounce when comparing topsoil SOC stocks instead of SOC contents. This effect is less clear for the subsoil depths as these show smaller differences in coarse fraction contents (Fig. 5), which again might be affected by the decreasing number of samples with increasing soil depth. In general, we assume that our contradicting results compared to Don et al. (2011) originate from the fact that our test site and hence its SOC contents are dominated by (i) the monsoon climate with a pronounced dry period and (ii) the intensive land use either for irrigation farming or forestry.

The difference in mean SOC contents/stocks between arable land and forest/shrubland was most pronounced in the topsoil depth increment (under forest/shrubland −36% and −41% in SOC contents and stocks, resp.). In the subsoil depths D2 and D3, the differences in mean SOC contents/stocks were much smaller comparing arable land with forest/shrubland (−12% and −16%, respectively), while much more pronounced differences were found between arable land and grassland (−55% and −58% for SOC contents and stocks, respectively). The different declines in SOC with depth might be associated to three processes: (i) there is more C input into topsoil due to the smaller rooting depths in case of irrigated crops and grassland compared to forest, (ii) forest under monsoon climate might especially invest in deeper roots to compensate water shortage in the dry period, and (iii) soil organic matter accumulates in topsoils of paddy fields (Lo Seen et al., 2010) due to the reduced mineralization under water logged conditions and a prolonged vegetation period due to irrigation during the first months of the dry period. However, the results regarding the decline of SOC contents with depth might be also a bit misleading, since the number of sampling locations especially under forest/shrubland drastically decreased by 64% between soil depth D1 and D3, while it decreased only by 26% under arable land. The reason for the strong decline of the number of samples with depth under forest/shrubland might result from the shallower soils and/or very hard and dry subsoil (with higher stone contents) hindering a deeper penetration of the soil auger. Generally, the smaller SOC contents found under forest/shrubland and grassland, which are in contrast to other results from India (Saha et al., 2011), have potentially a number of reasons: (i) The forest/shrubland in the region is heavily degraded due to the long-term use as forest pasture, as source of non-wood products and fire wood, as well as its regular burning (Saha, 2002; Schmerbeck and Seeland, 2007). (ii) Forest/shrubland is located on the steepest parts of the catchment (mean slope at sampling locations: (13.6 ± 7.6)%) while arable land is located on mostly flat areas (mean slope at sampling locations: (2.1 ± 1.9)%) near the lake shore, which are subject to intensive irrigation and thus accumulation of soil organic matter (Krishnan et al., 2007; Lo Seen et al., 2010). (iii) The grassland is heavily used for grazing of a large number of livestock which leaves the soil more or less bare during the dry period. Moreover, cattle dung is/was typically used as cooking fuel instead of fertilizing the grassland (Lal, 2007).

The general relation that increasing soil erosion is associated with decreasing SOC stocks is already underlined through other studies in India (Krishnan et al., 2007; Saha et al., 2011). Accounting only for those sampling points where erosion is modeled (neglecting depositional sites), there is an obvious difference between arable land and forest/shrubland regarding erosion intensity (0.46 t ha^{-1} a^{-1} vs. 14.0 t ha^{-1} a^{-1}).

4.2. Land use category specific explanatory variables for SOC patterns

Focusing on the SOC patterns within the different land use categories, we found interesting results which highlight the importance of human impacts on SOC contents in the region. Under arable land, the variability of SOC content is best explained by EaW (Tables 2 and 3). Assuming that EaW is a valuable proxy variable for potential irrigation, this seemed to be consistent with earlier studies. E.g. Krishnan et al. (2007) found that topsoil (<0.3 m) under irrigated cropland in India had significantly higher SOC stocks than rainfed cropland (4.8 kg m^{-2} and 3.6 kg m^{-2}, respectively). In general, there are no data available on irrigation amounts and spatial distribution of irrigation over the last decades potentially affecting SOC contents in the region. Best estimates of overall irrigation within districts or within meso-scale catchments result from agricultural statistics (Indian Ministry of Agriculture, 2014) or hydrological models solving the water balance (Wagner et al., 2011). However, such data cannot be applied to derive spatial variability of irrigation in different fields within a small catchment. Hence, such a robust variable as EaW, which can be easily derived from a DEM and which at least has some relation to channel and well irrigation, seemed to be a useful proxy in data scarce regions dominated by irrigation farming.

In the case of grassland, the most important predictor of topsoil SOC content is the mean NDVI representing the vegetation status (density and viability) during the last decades (Tables 2 and 3). This seemed to be consistent with general findings about the positive relations between above ground biomass and SOC contents as used in many SOC turnover models (e.g. Dlugoß et al., 2012).

Focusing on forest/shrubland the results are somewhat counterintuitive. First of all it is surprising that no relation between SOC patterns and modeled erosion was found, which was expected due to the steep slopes and the degradation of forest and understory canopy, especially at the beginning of the monsoon season after several dry months. These results hold even true for areas with obvious signs of erosion along a thalweg and its footslope where sedimentation occurred. The reason that depositional sites do not show higher SOC contents within the upper 0.9 m compared to erosional sites might result from the deposition of already SOC depleted soils coming from the erosional sites and the preferential loss of fines and the associated carbon (Schiettecatte et al., 2008). One could speculate that at depositional sites SOC stocks are higher compared to erosional sites as SOC might be buried in depths below 0.9 m, but this could not be unraveled with our data. Other studies that have been conducted in India compared not eroded sites with heavily degraded sites (e.g. Saha et al., 2011) and found that high erosion rates imply low SOC contents. Our results indicate that this finding cannot be easily transferred to a single land use with internal patterns of erosion and deposition.

Apart from the counterintuitive behavior regarding erosion, it is also somewhat surprising that forest/shrubland areas with large WI (representing the wettest conditions) show smallest SOC contents (Table 2), although best growing conditions and hence highest C inputs could be expected. However, even more puzzling is the fact that the most strongly related co-variable slope is positively related to SOC contents (Tables 2 and 3), implying that the steepest slopes show the highest SOC contents. As at our test site as well as generally in the region the most remote and steepest slopes carry the densest forest and shrub vegetation, it can be assumed that the resulting SOC patterns in forest/shrubland are not directly resulting from topography or topography driven natural processes (erosion, water availability) but are interrelated to human and/or livestock accessibility of these slopes. If the assumption holds true that SOC contents under forest/shrubland are highest on steepest slopes because these areas exhibit the densest vegetation, it could have been expected that the mean NDVI is also a good predictor. However, this was not the case at the sampling locations (Table 2). Based on our field surveys, we often found the densest forest on steepest slopes alternating with rock outcrops on a scale of several meters. Hence, it can be considered a fact that the 30 m × 30 m NDVI products do not show the density of these forests correctly, as pixels always include a mixture of the reflectance of vegetation and rock.

5. Conclusions

Based on 112 soil cores, the soil depth and land use specific SOC contents (partly SOC stocks) were analyzed in a small catchment in the tropical south of India, which is in general dominated by an intensive human use for irrigation farming, pasturing and forestry. Within the different land use categories SOC was related to a number of auxiliary variables (slope; curvature; elevation above next surface water; water erosion; wetness index; mean NDVI). Our key findings are: (i) In contradiction to most studies evaluating SOC contents or stocks under different land uses we find the highest SOC contents/stocks under arable land, followed by forest/shrubland and grassland. This counterintuitive behavior in the relation of SOC contents/stocks under arable land and forest/shrubland is most probably a result of the prolonged carbon assimilation, higher N inputs and retarded C mineralization due to regular/permanent flooding of arable land during the vegetation period compared to the intensive use of forest biomass leading to soil and vegetation degradation. (ii) SOC content of topsoil under arable land declines with elevation above the next surface water, a proxy variable for the proximity to the next potential irrigation source. (iii) SOC content of topsoil under grassland is positively correlated with mean NDVI. (iv) SOC content under forest/shrubland is best described by variables indirectly related to the accessibility of forest areas (positive correlation with slope and elevation above next surface water). Interestingly, no significant correlation between SOC content under forest and erosion/deposition could be found. Overall, this study indicates that the commonly used relations to estimate spatial distribution of SOC on larger scales might not be adequate for large areas in South India dominated by pronounced dry and wet seasons, intensive irrigation farming and human induced grassland and forest degradation.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version, at http://dx.doi.org/10.1016/j.geodrs.2014.10.005. These data include Google map of the most import areas described in this article.

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