Effects of land use and cover change on soil organic carbon and total nitrogen in southwest China Karst region: A Meta-analysis

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Abstract

The vast Karst area in southwestern China is ecologically fragile region, where both soil organic carbon (SOC) and total nitrogen (TN) are evidently sensitive to LUCC. However, there has not been any comprehensive study to analyze the effects of LUCC on SOC/TN in this region based on large data ensembles. In this paper, the response of SOC and TN storage to LUCC (i.e., deforestation and land restoration) in the Karst region of southwestern China was investigated by meta-analysis, which was found to be controlled by a series of impact factors, such as the type of LUCC, sampling depth, calculation methods and environmental factors. Based on 471 sets of SOC data and 468 sets of TN data, Firstly, we evaluated the calculation methods (i.e., fixed-depth method, the main deviation from the two methods was that the FD procedure neglected the heterogeneity of soil bulk density, which may underestimate the loss of SOC and TN after deforestation but overestimate the benefits of land restoration to SOC and TN. Secondly, we found that when woodland and grassland were converted to cultivated land or other land types, SOC and TN losses were greater; while other LUCCs had less impact. Similarly, land restoration increased the SOC and TN, especially the restoration from farmland to forests. Also, we demonstrated that increasing the soil sampling depth could significantly alter the response of SOC and TN to LUCC. Finally, the environmental factors affecting SOC storage (such as soil properties, geographic and climatic factors and duration) were discussed.

1. INTRODUCTION

Land use and land cover change (LUCC) plays a crucial role in global carbon (C) and nitrogen (N) cycles by modifying soil C and N turnover, storages, and soil erosion (Post and Kwon, 2000; Watson et al., 2000; Lal, 2004; Ding et al., 2013; Han et al., 2019). After cultivating the native forests, soil organic carbon (SOC) may be rapidly decreased owing to degradation and erosion through human-disturbed activities (Harris et al., 2012; Mukhopadhyay et al., 2016; Wiesmeier et al., 2016). On the contrary, shifting from cropland to perennial vegetation was reported to increase SOC accumulation by transforming more atmospheric C into the soil and simultaneously decrease C loss from decomposition and erosion (Post and Kwon, 2000; Guo and Gifford, 2002; Berthrong et al., 2009; Laganiere et al., 2010; Duan et al., 2018; Nave et al., 2018). As another key factor in maintaining soil quality, total nitrogen (TN) and SOC generally exhibit similar responses to LUCCs by changing the microbial conditions and litter inputs in ecosystems (Xie et al., 2004; Luo et al., 2009; Xu et al., 2019), hydrothermal conditions at the land surface (Luo et al., 2009; Jerome et al., 2010; Fei et al., 2015) and plant species (Nie et al., 2014; Pan et al., 2015), which, if considering the impact of human activities (Xiao et al., 2009; Deng and Shangguan, 2017), jointly determined the changes in TN storage. Thus, appropriate land-use management practices (e.g., reforestation and land restoration) have been considered as one of the major strategies for mitigating climate change (Richard et al., 2006; Song et al., 2014; Hu et al., 2018).

The SOC and TN are important factors affecting ecosystem productivity and various physiological processes (Reich et al., 1997; Vitousek, 2005). Since the beginning of the 21st century, much attention has been paid to the effects of LUCC on SOC and TN storage (Post and Kwon, 2000; Guo and Gifford, 2002; Don et al., 2011; Poeplau et al., 2011; Van et al., 2015; Nave et al., 2018), specifically, leading to contradictive discussions. Previous studies have found that deforestation (DF) could cause SOC and TN losses, which depends on land use patterns (Guo and Gifford, 2002; Lal, 2005; Shirvani et al., 2010; Gamboa and Galicia, 2011; Van et al., 2015; Nyawira et al., 2016). In contrast, land restoration (LR) could increase SOC and TN storage (Guo and Gifford, 2002; Song et al., 2014; Deng et al., 2016; Hu et al., 2018; Nave et al., 2018). Overall, the obvious SOC and TN loss/gain were found to be sensitive to LUCC.

The fixed-depth method (FD) is widely used to calculate SOC and TN storages, which is simply multiplied by soil bulk density (BD), depth and SOC and TN concentrations (Lee et al., 2009). Nevertheless, the calculated SOC and TN storages under different LUCC patterns using the FD may induce errors (Lee et al., 2009; VandenBygaart et al., 2010; Palm et al., 2014; Du et al., 2017; Hu et al., 2018). Instead, the equivalent soil mass method (ESM) could more accurately quantify SOC and TN storages by calibrating soil mass per unit area among different treatments (Ellert and Bettany, 1995; Gifford and Roderick, 2003; Du et al., 2017). Since both the LUCC and soil depth may lead to soil BD changes, more precise methods (such as the ESM) need to be utilized in practice.

Karst landform is known to be one of the most ecologically fragile regions in China (together with the Loess Plateau) and the total area in southwest China is about $4.3 \times 10^4 km^2$. In particular, this fragile ecosystem is extremely sensitive to LUCC, which has become major ecological and environmental problems in the Karst areas. Since the late 1990s, China had launched the Returning Farmland to Forest Program in the southwest Karst region. The subsequent land use and cover changes (i.e., deforestation and land restoration) have potentially interfered the local ecosystems and induced severe environmental stress (Wang et al., 2010; Hu et al., 2018). Therefore, investigating the responses of SOC and TN storage to LUCC may provide some insights into the interactions between local ecosystems and human activities, and eventually provide scientific evidences to support policy making for stakeholders.

In the recent decades, the meta-analysis approach has been considerably utilized to evaluate the changes in SOC and TN storages responsive to LUCC (Virto et al., 2012; Powlson et al., 2016; Shi et al., 2016). Despite variations in sampling methods and experiment conditions, the meta-analysis could provide a comprehensive way by obtaining a large amount of data, which is helpful to explain the overall trend of SOC and TN storage in responses to LUCC. To our best knowledge, such systematic analyses have not been carried out to analyze the impact of LUCC on SOC and TN storage in southwest China Karst region. This study aimed to (1) assess the uncertainties of calculation methods (the FD vs. ESM) on SOC and TN storages, (2) quantitatively analyze the effects of specific land use and cover and soil layers on SOC and TN storages the in Karst areas, and (3) reveal the controlling factors that affect SOC storage.

2. MATERIALS AND METHODS

2.1 Data collection

For the datasets used by meta-analysis, we selected peer-reviewed literature on the effects of LUCC on SOC and TN storage in southwest China from 1990 to 2018 by searching major academic databases, e.g., CNKI, CAB Abstracts, Elsevier, China Knowledge Resource Integrated Database, and by sorting the reference lists. The keywords and phrases used for the literature search were: 'Karst area of China', 'land use/land cover change', 'soil organic carbon', 'total nitrogen', 'soil quality' in title, abstract, or keywords. In addition, each study was further screened for integrity, relevance and scientific merits based on the following steps: (1) Select an appropriate classification for each study: defined as the experimental group and the control group. In the vegetation destruction mode, the land use mode with the minimum human disturbance intensity was selected as the control group (usually forest land and grassland). In the model of returning farmland to forest and grass, farmland was selected as the control group; (2) Ensure that each study was independent and published after 1990. We excluded studies before 1990 because land use patterns did not change much before that year; (3) Make sure the soil sampling depth was more than 10 cm (the minimum soil stratification in this study), and the same study cannot be classified as both vegetation destruction and conversion of farmland to forest and grass (unless clearly stated in the study); (4) Make sure all publications specified the results of SOC or TN concentrations. If the data was graphically represented, the GetData Graph Digitizer (Russian Federation version 2.22) was utilized to obtain the data.

In total, 89 published papers and 939 sets of data were included, consisting of 471 sets of SOC data and 468 sets of TN data (SOC or TN concentration and storage, and soil mass). More specifically, 253 sets of SOC data and 240 sets of TN data belonged to deforestation; 218 groups SOC data and 228 groups TN data belonged to land restoration. According to the land use status classification criteria issued by the Ministry of Land and Resources on November 1, 2017 (GB/T21010-2017), the land cover in the Karst area was categorized into native forest, grassland (including natural grassland, artificial grassland and abandoned farmland), secondary forest, shrubby land, cropland (including dry land and paddy fields), plantation and fruit tree. It is noted that DF-others mainly refers to the transformation of grassland into farmland, while LR-others mainly refers to the transformation of grassland into woodland. Spatial distribution of the study sites where the datasets were collected is shown in Fig. 1.

In this study, we classified the collected data into three categories: (1) different patterns of LUCCs (vegetation destruction; returning farmland to forest and grass); (2) SOC and TN storages accumulated in different soil layers (0-20, 20-30, 30-40, 40-60, and 60-100 cm) in response to LUCCs; (3) four specific impact factors as: climate factors (annual average temperature and annual precipitation), geographical factors (slope and elevation), the duration of LUCCs, soil physicochemical properties (initial SOC/TN storage, BD, TN, total phosphorus, total potassium and pH, clay and water content), which were selected in order to further explain the cumulative SOC/TN storage changes affected by LUCC.

Insert Fig. 1

2.2 SOC and TN storage estimation and statistical analysis

SOC and TN storage were calculated using the FD and ESM methods respectively. The lightest soil mass was referred as the equivalent soil mass (Lee et al., 2009):

$$\text{FDstock}_{\text{SOC or TN}} = \text{Con}_{\text{SOC or TN}} * \text{Soil}_{\text{BD}} * h * 10^{-1} (1)$$

$$\text{ESMstock}_{\text{SOC or TN}} = \text{FDstock}_{\text{SOC or TN}} - M_{\text{ex}} * \frac{C_{\text{sn}}}{1000} \quad (2)$$

$$\text{M}_{\text{ex}} = \sum_1^n \text{Soil}_{\text{BD}} * 100 - M_{\text{ref}} (3)$$

where $\text{FDstock}_{\text{SOC or TN}}$ and$\text{ESMstock}_{\text{SOC or TN}}$ represent the SOC or TN storage estimated based on the FD and ESM methods, respectively;$\text{Con}_{\text{SOC or TN}}$ indicates the concentration of SOC or TN; Soil_{BD} and h represent soil bulk density and sample depths, respectively; M_{ref} is the reference soil mass (the lightest soil mass), and M_{ex} is the excess soil mass. All the constants in Eqs. (1)-(3) are unit conversion factors.

Due to unavailable soil BD data in some studies, the following non-linear equations were used to estimate the BD (Song et al., 2005):

$$\text{Soil}_{\text{BD}} = 1.3770 * Exp\left(-0.0048 * \text{Con}_{\text{SOC}}\right) \quad (4)$$

where BD is soil bulk density (Mg m-3) with a given concentration of SOC (g kg^{-1}). In addition, 1.3770 and -0.0048 are empirical coefficients.

Different soil depths were sampled within this study (0-20, 20-30, 30-40, 40-60, 60-100 cm). In order to make comparable estimates of SOC or TN changes to the same depth and to include more experimental results from particular regions (southwest China), the storage changes with irregular sample depths (h, cm) were adjusted to those of the top 20 cm of the soil sample using following equations (Yang et al., 2011):

$$Y = 1 - \beta^h (5)\backslash n \qquad \text{C}_{20} = \frac{1-\beta^{20}}{1-\beta^h} * C_h (6)$$

where Y is the cumulative proportion of the SOC or TN storage from the surface to a specific depth h (cm); β is the relative rate of decrease in the SOC or TN storage at specific depth (0.9786 for SOC and 0.9831 for TN, respectively) (Jobbágy and Jackson, 2000; 2001). C_{20} is the expected SOC or TN storage adjusted to the top 20 cm soil layer at a specific site; h is the sample depths available in each study (cm); C_h is measured SOC or TN storage at sample depth h (cm) at a specific site.

We used the mean (Mean), standard deviation (SD), sample size (n), standard error (SE) and 95% confidence interval (95%CI) to characterize the variations of selected datasets. The SE and 95%CI were calculated as follows:

$SE = SD/\sqrt{n}$ (7)

If the SD data was missing, we would convert the coefficient of variation of the entire database (Geisseler and Scow, 2014).

The natural logarithm of the response ratio (RR) was employed to quantify the effect (Hedges et al., 1999):

$$lnRR = \ln\left(\mathrm{RR}_d/\mathrm{RR}_c\right) = ln\mathrm{RR}_d - lnRR_C (8)$$

where RR_d and RR_c are the values of the control and experimental groups.

The statistical distribution of the lnRR calculated in this way was found to be nearly normal, and only minor biases were detected (Hedges et al., 1999). The variances (V) were calculated by:

$$V = \frac{\mathrm{SD}_d^2}{n_d M_d^2} + \frac{\mathrm{SD}_c^2}{n_c M_c^2}(9)$$

where SD_d and SD_c represent the standard deviation of the control group and the experimental group, respectively. In general, the land use pattern (native forest) with the least degree of damage is the control group in deforestation, and the cropland with the greatest intensity of activity disturbance is the land restoration control group; $\mathrm{n_d}$ and $\mathrm{n_c}$ are the numbers of control and experimental groups; M_d is the average of SOC or TN storage in the control group, and M_{c} is the average of the SOC or TN storage corresponding to the experimental group.

The reciprocal of the variance was used as the weight (W) for each lnRR:

$$W = 1/V(10)$$

The overall mean response ratio (lnRR_{++}) and the SE of lnRR_{++} were then calculated as:

$$\mathrm{lnRR}_{++} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{k} W_{\mathrm{ij}R_{\mathrm{ij}}}}{\sum_{i=1}^{m}\sum_{j=1}^{k} W_{\mathrm{ij}}}(11)\backslash n \qquad SE\left(\mathrm{lnRR}_{++}\right) = 1/\sqrt{\sum_{i=1}^{m}\sum_{j=1}^{k} W_{\mathrm{ij}}}(12)$$

The lnRR_{++} and 95%CI can be converted by [EXP (lnRR_{++}) - 1] $\times$ 100%. We defined that if the 95%CI is larger than zero, the effect of the treatment is considered as significant.

Statistical analyses were performed with IBM SPSS 20.0 (SPSS Inc., Chicago, USA). The normality of the data was tested by using the Shapiro-Wilk test (Stephens,1975). Because some datasets failed to meet the assumptions underlying parametric statistical tests, nonparametric procedures were applied to conduct further analysis. Correlation analysis was applied to examine relationships of response change of SOC and TN storage (only for cumulative SOC/TN storage on ESM basis) with other impact factors: climate factors, and geographical factors, the duration of LUCCs, and soil physicochemical properties. All differences discussed are significant at the $P < 0.05$ probability level unless otherwise stated.

3. RESULTS

3.1 General dataset information

We established a SOC and TN database from different sampling depths and corresponding to different LUCCs. A more detailed data description is presented in Table 1. Obviously, the deeper the soil, the smaller the sample size (number of samples collected) in our meta-analysis. Therefore, appropriate adjustments were made: when the soil depth was greater than 30 cm, the sample size of shrub land was greatly reduced, so it was incorporated into the secondary forest. Similarly, when the soil depth reached 100 cm, secondary forests, plantation and fruit trees were collectively referred as other woodlands.

Insert Table 1

3.2 Effects of deforestation and land restoration on SOC, TN storage and soil bulk density

The mean response ratio (*lnRR*) was weighted by the mean value and standard deviation of each sample. Before meta-analysis, we tested the data normality using the Shapiro-Wilk test (Shapiro and Wilk, 1965). Overall, the *lnRR* of SOC, TN storages and soil mass were normally distributed (Table 2), regardless of deforestation or land restoration. The data showed that LUCC had remarkable influence on SOC, TN storage and soil mass ($P < 0.05$). On the one hand, deforestation had negative effects on SOC and TN storages (*lnRR*< 0; $P < 0.5$), indicating that deforestation caused huge SOC and TN losses. Specifically, the *lnRR* of SOC and TN storage were -0.66 and -0.62, respectively, which means that deforestation caused a loss of 48.3% for SOC and 46.2% for TN respectively. On the other hand, after land restoration, the *lnRR*of SOC and TN storage were 0.27 and 0.19, which indicates that land restoration increased SOC and TN storage by 31% and 20.9% in the Karst areas. In addition, the *lnRR* of soil mass after deforestation was 0.09, and the *lnRR* after land restoration was -0.04, demonstrating that both deforestation and land restoration had great impacts on soil bulk density (Table 2).

Insert Table 2

3.3 SOC and TN storage calculated using the FD and ESM methods

In recent years, uncertainties from the methods estimating SOC/TN caused by BD change have attracted more attention (Lee et al., 2009; Toledo et al., 2013). This study compared SOC and TN storage between two estimation methods (i.e., FD, Fig. 2a; ESM, Fig. 2b).

Not surprisingly, the *lnRR* of SOC after deforestation was -0.43 (*95%CI* : [-0.48, -0.38], $P < 0.05$) based on the FD and -0.66 (*95%CI* : [-0.74, -0.58], $P< 0.05$) based on the ESM. This means that deforestation calculated by the FD caused 34.8% carbon loss, while the ESM results showed that the SOC loss was as high as 48.2%. Similarly, the*lnRR* of TN storage estimated by the FD and ESM were -0.29 (*95%CI* : [-0.38, -0.21], $P < 0.05$) and -0.62 (*95%CI* : [-0.78, -0.46], $P < 0.05$), respectively. The loss efficiency of TN storage was 25.4% and 46.0%. Obviously, there were notable variations in the estimation of SOC and TN storage if using alternative methods (Fig. 2a, paired t-test: $P< 0.01$). On the other hand, the FD and ESM calculations showed that land restoration could significantly increase SOC and TN storage (Fig. 2b). The *lnRR* of SOC and TN storage calculated by the FD and ESM were 0.23 (95%CI: [0.17, 0.28], $P < 0.05$), 0.25 (*95%CI* : [0.17, 0.32], $P < 0.05$), 0.16 (*95%CI* : [0.10, 0.21], $P < 0.05$), and 0.23 (*95%CI* : [0.14, 0.31], $P < 0.05$), respectively. The FD and ESM evidently provided different estimations (Fig. 2b, paired t-test:$P < 0.01$), which led to uncertainties in estimating SOC and TN storage. Thus, we should carefully select the estimation method when calculating the SOC and/ or TN storages.

Insert Fig. 2

The SOC and TN storages calculated by the FD and ESM methods showed significant variations (Fig. 2). The deviations should be caused by the inequal soil mass that induced by variations of soil BD (Vandenbygaart and Angers, 2006; Wiesmeier et al., 2016). In this study, large sample statistics were carried out on BD, and the results showed that BD increased significantly after deforestation (Fig. 2c,*lnRR* $= 0.09$, $P < 0.05$), and decreased significantly after land restoration (Fig. 2c, *lnRR* $=$ -0.02,$P < 0.05$). Therefore, when LUCC increased soil mass (i.e., higher soil BD), the FD underestimated the loss of SOC/TN storage. By contrast, when LUCC decreased soil mass, the FD overestimated the SOC/TN storage. Thus, the ESM were found to be more accurate in capturing SOC/TN storage changes and we only adopted the ESM for the following analysis.

3.4 Response ratio of SOC and TN storage under specific LUCC types

We further explored the response of SOC and TN storage to different types of the deforestation and land restoration Regardless of different types of LUCCs, deforestation caused loss of SOC and TN (Fig. 2, Fig. 3a-b, $P< 0.05$), whereas SOC and TN showed gains after land restoration (Fig. 2, Fig. 3c-d, $P < 0.05$).

Insert Fig. 3

Obviously, deforestation has resulted in the loss of SOC and TN storage ($lnRR < 0$, $P < 0.05$, Fig. 3a-b). The lost SOC was mainly found in the grassland, cropland, fruit trees and other fields (grassland mainly turned into farmland), with the loss efficiency more than 50.0%. Even the farmland with the lowest loss efficiency reached 34.4%. We observed slight difference between LUCCs after deforestation ($P = 0.09$), and instead the response of TN storage varied greatly in different LUCCs ($P = 0.02$). When native forest was converted to secondary forest, the TN storage loss was highest (57.5%), while the lowest loss was noticed in the cropland (29.0%) originating from native forest. When native forest was converted to plantation and grassland, the reduction was 34.2% and 49.7%, respectively. Undoubtedly, deforestation greatly contributed to the loss of SOC and TN in the Karst areas of southwest China.

In contrast to the effect magnitude of deforestation, land restoration benefited for SOC and TN gain to some extent (Fig. 3c-d, $P< 0.01$). The increased SOC storage was 87.7%, 64.3% and 55.0%, respectively when the cropland was recovered to grassland, native forest and others (mainly refers to the conversion of grassland to native forest). Interestingly, insignificant gain was observed upon reverting cropland to grassland ($lnRR = 0.11$, $P> 0.05$) and fruit trees ($lnRR = 0.10$, $P> 0.05$), and even slight loss after the converting from cropland to plantation ($lnRR = - 0.12$, $P > 0.05$). The TN had similar trend as SOC, showing variations among specific LUCCs (Fig. 3, d, $P < 0.01$). Specifically, the TN storage increased by 109.2% ($lnRR = 0.74$, $P< 0.05$) and 94.8% ($lnRR = 0.10$, $P < 0.05$), respectively after restoring from cropland to native forest and other LUCCs (mainly grassland to native forest). Shifting from cropland to the grassland ecosystem slightly increased the TN storage ($lnRR = 0.01$, $P > 0.05$). Additionally, we observed the lost TN storage when cropland was converted to fruit trees ($lnRR = -0.09$, $P > 0.05$) and plantations ($lnRR = -0.04$, $P > 0.05$).

3.5 Response ratio of SOC and TN storage due to specific LUCCs at different sampling depths

In addition to the differences in overall response and estimation methods of SOC and TN storage to LUCCs, it is noteworthy that soil depth is another key factor affecting SOC and TN effects. Therefore, we focused on the response of SOC and TN storage to LUCCs at different sampling depths (Table 3; Fig. 4 a-b; Fig. 5 a-b).

Insert Table 3

The response of SOC and TN storage to LUCCs varied greatly among sampling depths (Table 3). Generally, the deforestation decreased the SOC and TN storage within the 0-100 cm profiles, with the SOC loss ranging from -0.69 to -0.36 from shallow to deep sampling. The SOC loss efficiencys in the 0-20 and 0-30 cm layers were much higher than those in deeper soil layers, with a loss of 49.8% and 53.7% respectively. The effect magnitude of SOC loss gradually decreased with the sampling depth.

Insert Fig. 4

The response of TN storage to specific LUCCs sampled at different depths exhibited similar pattern. The shallow sampling led to a higher loss efficiency of TN and TN storage loss efficiency gradually decreased with deeper sampling. TN loss efficiencys were 43.5%, 42.3%, 38.1%, 34.3% and 33.6%, respectively for the 0-20, 0-30, 0-40, 0-60 and 0-100 cm profiles. Land restoration increased the SOC and TN storages, and these gains occurred in these selected five sampling depths. Specifically, the gained SOC storage was 49.2% in the 0-20 cm soil layer, while the increased SOC was 10.5%, 19.7% and 20.9% respectively, in the 0-30, 0-40 and 0-60 cm profiles and the revered SOC lost was observed in the 0-100 cm profile. Thus, sampling depth significantly influenced the SOC and TN storages in response to LUCC.

Insert Fig. 5

Importantly, there were still variations when considering specific LUCCs. This variation was observed in different LUCCs within the same soil layer and in different layers within specific LUCC (Fig. 4, Fig. 5). On the one hand, all specific LUCCs showed significant SOC loss at different sampling depths after deforestation, except for the 0-40 cm ($lnRR$ = 0.21, $95\%CI$: [-0.49, 0.14]) and 0-60 cm profiles ($lnRR$ = -0.13, $95\%CI$: [-0.50, 0.46]) under the grassland transformed from the native forest (Fig. 3a). On the other hand, the response SOC storage to specific LUCC varied with the sampling depths. Generally, the lost SOC in shallow sampling (0-20 and 0-30 cm) was higher than that of deeper sampling (Fig.4 and Table 3). Overall, the lost SOC nearly 50.0% in shallow sampling (i.e., 0-20 cm, 0-30 cm) after deforestation, and less than 40.0% in deeper sampling (i.e., 0-40 cm, 0-60 cm, 0-100 cm). Similarly, there was no apparent loss of TN storage for the 0-40 cm profile after transforming from native forest to grassland. Other specific LUCCs resulted in significant lost TN storage at all sampling depths. On average, the loss efficiency of TN storage were 43.5%, 42.3%, 38.1%, 34.3% and 33.7% respectively, in the 0-20, 0-30, 0-40 and 0-60 cm profiles, showing a clear decreasing trend with depths. Therefore, these data implied that the response of SOC and TN to deforestation was pronounced in the surface layers.

In our study, we found that land restoration benefited for SOC and TN gains (Table 3, Fig. 5), but the effect magnitude showed large variation between LUCCs. Except for the slight loss after recovering from farmland to plantation, other LUCCs increased the SOC storage. Notably, the restoration from cropland to native forest significantly increased SOC for all sampling depths (Fig. 3) and the gained effect of other LUCCs decreased with sampling depths. Similarly, the increased TN storage by land restoration differed among different LUCCs. The increased of TN storage from cropland to native forest and other types (mainly indicating that grassland to native forest) was satisfactory.

4. DISCUSSION

4.1. Response ratio of SOC and TN storage due to deforestation

The soil organic matter (SOM), carbon and nutrients are deemed as key attributes to soil fertility, providing ecosystem services, environmental quality and sustainable land use (Kucharik et al., 2001; Lal, 2016). The increased SOC storage is also viewed to be a potential source to offset the enhanced global atmospheric CO_2 concentration (Smith, 2016). In this study, significant losses of SOC and TN storage happened after deforestation (Fig. 2, Fig. 3, Table 3, Fig. 4), which has become an urgent issue to improve the fragile ecological environment in Karst areas (Hu et al., 2018). Similar results were found in the Loess Plateau, another ecologically fragile region in the northwest China (Zhang et al., 2014). The decreased SOC and TN are probably due to deforestation that destroyed soil structure (i.e., aggregation) leading to releasing the previously protected organic matter (Jiang et al., 2005; Xiao et al., 2009) and reduced terrestrial litter inputs (Xie et al., 2004; Luo et al., 2009). On the other hand, the changed vegetation types may influence soil moisture and temperature conditions and thus accelerate SOM decomposition (Luo et al., 2009; Fei et al., 2015). Besides, because of the fragile land scape and soil properties in the Karst areas, deforestation may greatly aggravate soil erosion, resulting in massive loss of soil nutrients (e.g., C, N). When native forests are converted to plantations, they are also affected by tree species and human management (Zhu et al., 2004).

Overall, our meta-analysis revealed the greatly reduced SOC and TN storages due to deforestation. This depleted SOM may hamper soil quality and subsequent serious ecological and environmental problems, posing big challenges under global climate context. We should propose some effective ecological measures to restore SOM in this fragile Karst areas.

4.2. Response ratio of SOC and TN storage due to land restoration

Our meta-analysis demonstrated that land restoration could increase overall SOC and TN storages by 27.9% and 25.7% respectively (based on ESM calculation, Fig. 2). It should be noted that the SOC and TN gains have large variations within specific LUCCs and sampling depths (Fig. 3, Fig. 5, and Table 3). Our data and other studies have confirmed that the lost SOC and TN could be reversed by adopting land restoration strategy (especially conversion from farmland to grassland or forest) (Hu et al., 2018; Deng et al. 2016). The underlying reasons may be attributed to the increased quantity and quality of litter inputs (Deng and

Shangguan, 2017) and the maintained soil moisture after vegetation coverage and land restoration, thereby reducing the decomposition of SOM (Jerome et al., 2010).

In our study, the SOC and TN storages did not significantly increase upon restoring from the cropland to other types, such as grassland, fruit trees and plantations (Fig. 3). This case may be associated with the depleted SOM from these land-use types previously subjected to intense human disturbance (e.g., mowing, fertilization and tillage, etc.) are unable to recover in short term (Post and Kwon, 2000). In addition, the positive effect of land restoration on SOC and TN gains showed spatial heterogeneity among different LUCCs (Fig. 3, Fig. 5). When the cropland returned to the natural forest and shrub, higher SOC and TN accumulated, which may be due to higher species diversity and litter detritus (Wei et al., 2009; Hu et al. 2018). A study in the Loess Plateau of northwest China by Jin et al. (2014) found that natural vegetation restoration benefited for soil surface C sequestration than tree plantation. On the one hand, lower fertilizer input may result in less carbon sequestration after converting from farmland to plantation (Jiang, 2006). Secondly, the planted trees (e.g., eucalyptus) are harvested regularly (once every five years), which probably limit C input in the soils.

Our data have implications that to protect and improve the fragile ecological environment in the Karst area of southwest China, we should urgently implement ecosystem restoration project. Further, we should fully consider the variations of SOM stabilization mechanisms under different land use patterns in future study.

4.3 Effect of sampling depth on the SOC and TN storage

Our meta-analysis showed that the deforestation could lead to SOC and TN losses, whereas land restoration had reverse trend gains (Fig. 2). However, the changes of SOC and TN storages varied with sampling depths (Table 3, Fig. 4, and Fig. 5). With the increasing sampling depth, the response of SOC and TN to LUCC gradually decreased. From shallow sampling depths (< 30 cm) to deep sampling depths (> 30 cm), the corresponding SOC and TN storages under deforestation ranged from - 0.77 to - 0.36, from - 0.57 to - 0.46; the corresponding SOC and TN under land restoration ranged from 0.40 to 0.1, from 0.44 to 0.11, respectively.

The effect of LUCC on the SOC and TN storages in the shallow depth (< 30 cm) were more sensitive than that in the deep sampling (> 30 cm). The results are supported by others (Olson and Al Kaisi, 2015). Till now, shallow sampling (i.e., up to 20 or 30 cm) procedure is still popular in China (Liao et al., 2014). This would undoubtedly produce uncertainties and biases even lead to incomplete conclusions. To accurately assess the impact of LUCC on SOC and TN storage, we should choose deeper sampling method. As such, Lal (2009) recommended that sampling depth should be at least 1 m or 2 m to accurately assess SOC due to land-use changes. Our study highlights that more attention should be paid to the uncertainty of sampling depth in future research. Otherwise, the response of SOC and TN to LUCC would be biased if soil samples were collected only at shallow depth.

4.4 Effect of calculation methods on the SOC and TN storage

Our meta-analysis showed that calculation methods (the FD and ESM) have unavoidable impacts on SOC and TN Storage estimation (Fig. 2). After deforestation, the response values of SOC storage calculated by the FD and ESM were - 0.43 and - 0.66, and that of TN storage were - 0.29 and - 0.62, respectively. There was a significant difference between the two calculated methods (Fig. 2a, $P < 0.01$). In addition, the responses of SOC and TN storages calculated by the FD and ESM to land restoration were 0.23, 0.25, 0.16 and 0.23, respectively.

The results clearly indicated that the FD method overestimated SOC and TN storage due to the increased soil BD after deforestation. Instead, the FD underestimated the SOC and TN storage after land restoration, likely owing to the reduced soil BD (Fig. 2). Therefore, the FD method may produce greater variations and even lead to wrong judgement (Don et al., 2011; Du et al., 2017; Hu et al., 2016). The variation between the two methods may be mainly due to the changed BD in the collected soil profile (Fig. 2c). In recent years, SOC estimation bias from soil BD has received more attention (Lee et al., 2010; Schrempf et al., 2011;

Toledo et al., 2013; Gulab et al., 2019). Therefore, it is critical important to select the accurately method (e.g., ESM) to estimate soil carbon and nitrogen storage in future study.

4.5 The effect land-use changes and pedo-climatic factors on the response ratio of SOC storage

In addition to the potential method uncertainties (i.e., sample depths and calculation methods), there are still some uncertainties in estimating SOC and TN storages (Fig. 6). In our meta-analysis, all available data are integrated and analyzed to study the relationship between their factors and SOC response to LUCC (we only discussed SOC). The uncertainties were mainly raised from four aspects: soil physicochemical characteristics (BD, TN, pH, TP, TK, clay content, soil water content), topographic factors (slope, altitude), climatic factors (average temperature, average rainfall) and the year of land-use change.

In this study, there was a significant correlation between soil characteristics and soil SOC storage (Fig. 6). Except for the soil BD, other factors were positively correlated with SOC storage in the deforestation (Fig. 6). Soil pH (r = 0.50, $P < 0.01$,$n = 93$) and total N storage (r = 0.80, $P < 0.01$,$n = 69$) were positively correlated with SOC storage. Taken together, we highlight that soil properties have strong effects on SOC storage based on the collected database.

We focused on two topographic variables, altitude and slope. It is generally believed that elevation could induce temperature changes and thus the SOC and TN storage, showing a positive correlation with SOC storage (Tashi et al., 2016). Recent studies have shown that the contribution of elevation to different vegetation systems may be due to rock exposure or human activities (Hu et al., 2018). On the other hand, the effect of slope on the distribution of SOC storage may be associated with soil erosion, microbial biomass and activity, evaporation and infiltration (Moffet et al., 2005). Different vegetation types will be formed with the combination of altitude and climate factors, resulting in different types and quantities of plant residues entering the soil, making SOC estimation more uncertain (Oskar et al., 2017). Temperature and precipitation are another main climatic variable considered in this study. These two variables not only affect the net primary productivity, but also the soil microbial properties, and thus the SOC and TN dynamics (Sotta et al., 2010). Besides, duration of LUCC is another important factor impacting SOC storage. In the early stage of LUCC, the changes of SOC is relatively higher, and gradually decreased with times (Morris and Sven, 2007; Wang et al., 2016;)

Taken together, it is a challenge to quantify the contribution of environmental factors to estimating SOC and TN storage. To reduce the estimated bias of SOC/TN storage, the interaction between human activities and climatic factors should be comprehensively considered in future work.

Insert Fig.6

5. CONCLUSION

We conclude that it may be valuable to pay attention to LUCCs as a strategy to relieve climate pressure in some cases, but its impact shows great variation (i.e., showing positive and negative SOC / TN gains). Besides the LUCCs (reforestation and land restoration), the future research should include more extensive depth sampling and appropriate accounting methods. In addition, the results of meta-analysis indicate that there is a high degree of variation in SOC / TN storage, and it may be unwise to estimate the benefits / losses of SOC / TN storage from a specific soil depth. To quantify the storage of SOC and TN in response to LUCCs, the increased depths of the soil profile Finally, we suggest that environmental factors (i.e., geography, climate, soil properties and time factors) should be considered as potential predictors to assess of SOC accumulation under the concession station and land restoration in Karst A comprehensive and accurate understanding of SOC / TN storage response to LUCCs is a strong support for climate change mitigation and food security strategies.

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DECLARATION OF CONFLICT OF INTERESTS

The authors declare no conflicts of interest.

References

Deng, L., Wang, G.L., Liu, G.B., ShangGuan, Z.P., (2016). Effect of age and land-use changes on soil carbon and nitrogen sequestrations following cropland abandonment on the Loess Plateau, China.*Ecological Engineering,* **90** , 105–112. https://doi.org/10.1016/j.ecoleng.2016.01.086

Deng, L., ShangGuan Z.P., (2017). Afforestation drives soil carbon and nitrogen changes in China. *Land Degradation & Development,***28** *,* 151-165. https://doi.org/ 10.1002/ldr.2537

Ding, F., Hu, Y.L., Li, L.J., Li, A., Shi, S.W., Lian, P.Y., Zeng, D.H., (2013). Changes in soil organic carbon and total nitrogen storage after conversion of meadow to cropland in Northeast China. *Plant Soil* ,**373** , 659-672. https://doi.org/ 10.1007/s11104-013-1827-5

Don, A., Schumacher, J., Freibauer, A., (2011). Impact of tropical land use change on soil organic carbon storage-a meta-analysis, *Global change biology* , **17** , 1658–1670. https://doi.org/ 10.1111/j.1365-2486.2010.02336.x

Du, Z.L., Angers, D.A., Ren, T.S., Zhang, Q., Li, G., (2017). The effect of no-till on organic C storage in Chinese soils should not be overemphasized: A meta-analysis. *Agriculture, Ecosystems & Environment,* **236** , 1-11. http://dx.doi.org/10.1016/j.agee.2016.11.007

Duan, Y.F., Wang, K.L., Feng, D., et al., (2018). Response of the spatial pattern of soil organic carbon and total nitrogen to vegetation restoration in a typical small karst catchment. *Acta Ecologica Sinica* , **38** (5). 1560-1568. (In Chinese with English abstract) https://doi.org/10.5846/stxb201701220184

Ellert, B.H., Bettany, J.R., (1995). Calculation of organic matter and nutrients stored in soils under contrasting management regimes.*Canadian Journal of Soil Science,* **75,** 529-538. https://doi.org/10.4141/cjss95-075

Fei, L.I., Juan, L.I., Long, J., Liao, H.K., Liu, L.F., Zhang, W.J., (2015). Effects of vegetation Types on Soil Organic Carbon and Nitrogen in Typical Karst Mountainous Areas. *Chinese Journal of Ecology,***34** , 3374-3381. (In Chinese with English abstract)

Gao, G., Li, Z., Chang, R., et al., (2019). Effects of plantation age and precipitation gradient on soil carbon and nitrogen changes following afforestation in the Chinese Loess Plateau. *Land Degradation & Development* , **45** , 1-13.

Geisseler,D., Scow, K.M., (2014). Long-term effects of mineral fertilizers on soil microorganisms-A review. *Soil Biology and Biochemistry* , **75** , 54-63. https://doi.org/10.1016/j.soilbio.2014.03.023

Gifford, R.M., Roderick, M.L., (2003). Soil carbon storage and bulk density: spatial or cumulative mass coordinates as a basis of expression? *Global Change Biology* , **9** , 1507-1514.

Gulab, Singh, Yawav, et al., (2019). Long-Term Effects of Different Passages of Vehicular Traffic on Soil Properties and Carbon Storage of a Crosby Silt Loam in USA.*Pedosphere* , **29** (02):16-26. https://doi.org/10.1016/S1002-0160(19)60796-4

Guo, L.B., Gifford, R.M., (2002). Soil carbon storage and land use change: A meta-analysis. *Global Change Biology* , **8** , 345–360.

Harris, N.L., Brown, S., Hagen, S.C., Saatchi, S.S., Petrova, S., Salas, W., Hansen, M.C., Potapov, P.V., Lotsch, A., (2012). Baseline map of carbon emissions from deforestation in tropical region. *Science* ,**336** , 1573–1576. https://doi.org/ 10.1126/science.1217962

Hedges, L.V., Gurevitch, J., Curtis, P.S., (1999). The meta-analysis of response ration in experimental ecology. *Ecology,* **80** , 1150-1156. https://doi.org/

Hu, P.L., Liu, S.J., Ye, Y.Y., Zhang, W., Wang, K.L., Su, Y.R., (2018). Effects of environmental factors on soil organic carbon under natural or managed vegetation restoration. *Land Degradation & Development* ,**29** (3): 387-397. https://doi.org/ 10.1002/ldr.2876

Hu, Y.C., Zheng, F.Y., Xu, S., (2017). Assessment of Immigration Effect of Ecological Immigrants in Immigration Areas of Guangxi.*Transactions of the Chinese Society of Agricultural Engineering* ,**33** , 264-270. (In Chinese with English abstract) https://doi.org/

Inglima, I., Alberti, G., Bertolini, T., Vaccari, F.P., Gioli, B., Miglietta, F., Cotrufo, M.F., Peressotti, A., (2009). Precipitation pulses enhance respiration of Mediterranean ecosystems: the balance between organic and inorganic components of increased soil CO2 efflux.*Global Change Biology* , **15** , 1289–1301. https://doi.org/ 10.1111/j.1365-2486.2008.01793.x

JeRoMe, L.R., Denisa, A., David, P., (2010). Carbon accumulation in agricultural soils after afforestation: a meta-analysis. *Global Change Biology* , **16** , 439-453. https://doi.org/ 10.1111/j.1365-2486.2009.01930.x

Jiang, Y.J., (2006). The impact of land use on soil properties in a Karst agricultural region of Southwest China: A case study of Xiaojiang watershed, Yunnan.*Journal of Geographical Sciences* **16** , 69-77. (In Chinese with English abstract)

Jin, Z., Dong, Y.S., Wang, Y.Q., Wei, X.R., Wang, Y.F., Cui, B.L., Zhou, W.J., (2014). Natural vegetation restoration is more beneficial to soil surface organic and inorganic carbon sequestration than tree plantation on the Loess Plateau of China. *Science of the Total Environment* , **485** , 615–623.

Jobbágy, E.G., Jackson, R.B., (2000). The vertical distribution of soil organic carbon and its relation to climate and vegetation,*Ecological Applications* , **10** , 423–436. https://doi.org/10.1890/1051-0761(2000)010[0423:TVDOSO]2.0.CO;2

Jobbágy, E.G., Jackson, R.B., (2001). The distribution of soil nutrients with depth: global patterns and the imprint of plants.*Biogeochemistry* , 53 , 51–77.

Kucharik, C.J., Brye, K.R., Norman, J.M., Foley, J.A., Bundy, G.L.G., (2001). Measurements and Modeling of Carbon and Nitrogen Cycling in Agroecosystems of Southern Wisconsin: Potential for SOC Sequestration during the Next 50 Years. *Ecosystems* , **4** , 237-258. https://doi.org/10.2307/3658956

Lal, R., (2004). Soil carbon sequestration impacts on global climate change and foodsecurity. *Science* , 304 , 1623–1627. https://doi.org/ 10.1126/science.1097396

Lal, R., (2009). Challenges and opportunities in soil organic matter research. European *Journal of Soil Science,* **60** ,*158–169. https://doi.org/10.1111/j.1365-* 2389.2008.01114.x

Lal, R., (2016). Feeding 11 billion on 0.5 billion hectare of area under cereal crops. *Food and Energy Security* , **5** , 239-251. https://doi.org/10.1002/fes3.99

Lee, J., Hopmans, J.W., Rolston, D.E., Baer, S.G., Six, J., (2009). Determining soil carbon storage changes: simple bulk density corrections fail. *Agr Ecosyst Environ* , **134** , 251-256. https://doi.org/10.1016/j.agee.2009.07.006

Liao H K, Li J, Long J, Zhang, W.J., Liu,L.F., (2014). Effects of Land use and conversion of farmland on soil active Organic carbon in Karst Mountains. *Environmental Science* , **35** , 240-247.

Luo, H.B., Liu, F., Liu, Y.S., He, T.B., Su, Y.G., (2009). Soil organic carbon changes under different vegetation communities in Karst rocky desertification area. *Scientia Silvae Sinicae,* **45** , 24-28. (In Chinese with English abstract)

Moffet, C.A., Zartman, R.E., Wester, D.B., et al., (2005). Surface biosolids application: Effects on infiltration, erosion, and soil organic carbon in Chihuahuan Desert grasslands and shrublands. *Journal of Environment Quality* ,**34** (1):299-311.

Morris, S.J., Sven, B., Shawel, H.M., Paul, E.A., (2007). Evaluation of carbon accrual in afforested agricultural soils. *Global Change Biology* , **13** , 1145-1156. https://doi.org/ 10.1111/j.1365-2486.2007.01359.x

Mukhopadhyay, S., Masto, R.E., Cerdà, A., Ram, L.C., (2016). Rhizosphere soil indicators for carbon sequestration in a reclaimed coal mine spoil.*Catena* **141** , 100–108. https://doi.org/ 10.1016/j.catena.2016.02.023

Nave, L.E., Domke, G.M., Hofmeister, K.L., Mishra, U., Perry, C.H., Walters, B.F., Swanston, C.W., (2018). Reforestation can sequester two petagrams of carbon in US top soils in a century. *Proceedings of the National Academy of Sciences* , **115** (11), 201719685. https://doi.org/10.1073/pnas.1719685115

Nie, Y.P., Chen, H.S., Wang, K.L., Ding, Y.L., (2014). Rooting characteristics of two widely distributed woody plant species growing in different Karst habitats of Southwest China. *Plant Ecology***215** , 1099–1109. https://doi.org/10.1007/s11258-014-0369-0

Olson, K.R., Al-Kaisi, M.M., (2015). The importance of soil sampling depth for accurate account of soil organic carbon sequestration, storage, retention and loss. *Catena* **125** , 33–37. https://doi.org/10.1016/j.catena.2014.10.004

Oskar, B., Cezary, K., Ukasz, M., et al., (2017). Labile and stabile soil organic carbon fractions in surface horizons of mountain soils-relationships with vegetation and altitude. *Journal of Mountain Science* . **14** (012): 2391-2405. https://doi.org/10.1007/s11629-017-4449-1

Palm, C., Blanco-Canqui, H., DeClerck, F., Gatere, L., Grace, P., (2014). Conservation agriculture and ecosystem services: an overview.*Agriculture, Ecosystems & Environment* , **187** , 87–105. https://doi.org/ 10.1016/j.agee.2013.10.010

Pan, F.J., Zhang, W., Liu, S.J., Li,D.J., Wang, K.L., (2015). Leaf N: P stoichiometry across plant functional groups in the Karst region of southwestern China. *Trees* , **29** , 883–892. https://doi.org/ 10.1007/s00468-015-1170-y

Poeplau, C., Don, A., Vesterdal, L., Leifeld, J., Wesemael, B.V., Schumacher, J., Gensior, A., (2011). Temporal dynamics of soil organic carbon after land-use change in the temperate zone - carbon response functions as a model approach. *Global Change Biology* ,**17** , 2415–2427. https://doi.org/ 10.1111/j.1365-2486.2011.02408.x

Post, W.M., Kwon, K.C., (2000). Soil carbon sequestration and land-use change: processes and potential. *Global Change Biology* ,**6** , 317–327. https://doi.org/ 10.1046/j.1365-2486.2000.00308.x

Powlson, D.S., Stirling, C.M., Thierfelder, C., White, R.P., Jat, M.L., (2016). Does conservation agriculture deliver climate change mitigation through soil carbon sequestration in tropical agro-ecosystems?*Agriculture, Ecosystems & Environment* , **220** , 164–174. https://doi.org/ 10.1016/j.agee.2016.01.005

Reich, P.B., Grigal, D.F., Aber, J.D., Gower, S.T., (1997). Nitrogen mineralization and productivity in 50 hardwood and conifer stands on diverse soils. *Ecology* , **78** , 335–347. https://doi.org/ 10.2307/2266011

Richard, B., Kurt, P., Alan, L., (2006). Forest Carbon Management in the United States. *Journal of environmet quality,* **35** , 1461-1469. https://doi.org/ 10.2134/jeq2005.0162

Schrumpf, M., Schulze, E.D., Kaiser, K., Schumacher, J., (2011). How accurately can soil organic carbon storage and storage changes be quantified by soil inventories? *Biogeosciences* , **8** , 1193–1212. https://doi.org/ 10.5194/bgd-8-723-2011

Shapiro, S.S., Wilk, M.B., (1965). An analysis of variance test for normality (complete

samples). *Biometrika*, 591–611. https://doi.org/10.2307/2333709

Shi, S.W., Peng, C.H., Meng, W., Zhu, Q., Gang, Y., Yang, Y.Z., Xi, T.T., Zhang, T.L., (2016). A global meta-analysis of changes in soil carbon, nitrogen, phosphorus and sulfur, and stoichiometric shifts after forestation. *Plant Soil* , **407** , 1-18. https://doi.org/ 10.1007/s11104-016-2889-y

Shi, W.Y., Tateno, R., Zhang, J.G., Wang, Y.L., Yamanaka, N., Du, S., (2011). Response of soil respiration to precipitation during the dry season in two typical forest stands in the forest-grassland transition zone of the Loess Plateau. *Agricultural and Forest Meteorology* ,**151** , 854-863. https://doi.org/10.1016/j.agrformet.2011.02.003

Song, X., Peng, C., Zhou, G., Jiang, H., Wang, W., (2014). Chinese Grain for Green Program led to highly increased soil organic gcarbon levels: A meta-analysis. *Scientific reports* , **4** :4460. https://doi.org/10.1038/srep04460

Sotta, E.D., Meir, P., Malhi, Y., Nobre, A.D., Grace, J., (2010). Soil CO2 efflux in a tropical forest in the central Amazon. *Global Change Biology* , **10** , 601-617. https://doi.org/ 10.1111/j.1529-8817.2003.00761.x

Stephens, M.A., (1975). An analysis of variance test for normality (complete samples). *Publications of the American Statistical Association* , **67** , 215-216.

Tashi, S., Singh, B., Keitel, C., Adams, M., (2016). Soil carbon and nitrogen stocks in forests along an altitudinal gradient in the eastern Himalayas and a meta-analysis of global data. *Global Change Biology* , **22** , 2255-2268. https://doi.org/ 10.1111/gcb.13234

Toledo, D.M., Galantini, J.A., Dalurzo, H.C., Vazquez, S., Bollero, G., (2013). Methods for assessing the effects of land use changes on carbon storage of subtropical oxisols. *Soil Science Society of America Journal* , **77** , 1542-1552. https://doi.org/ 10.2136/sssaj2013.03.0087

Van Straaten O., Marife D, C., Wolf, K., Tchienkoua, M., Cuellar. E., Robin B, M., Veldkamp, E., (2015). Conversion of lowland tropical forests to tree cash crop plantations loses up to one-half of stored soil organic carbon. *Proceedings of the National Academy of Sciences* , **112** , 9956-9960. https://doi.org/10.1073/pnas.1504628112

Van Lent, J., Hergoualc, H.K., Verchot, L.V., (2015). Soil N_2O and NO emissions from land use and land-use change in the tropics and subtropics: a meta-analysis. *Biogeosciences* ,**12** , 7299-7313. https://doi.org/10.5194/bg-12-7299-2015

Vandenbygaart, A.J., Angers, D.A., (2006). Towards accurate measurements of soil organic carbon storage change in agroecosystems. *Canadian Journal of Soil Science* , **86** , 465-471. https://doi.org/ 10.4141/S05-106

Vandenbygaart, A.J., Bremer, E., Mcconkey, B.G., Janzen, H.H., Angers, D.A., Carter, M.R., Drury, C.F., Lafond, G.P., Mckenzie, R.H., (2010). Soil organic carbon storage on long-term agroecosystem experiments in Canada. *Canadian Journal of Soil Science* , **90** , 543-550. https://doi.org/ 10.4141/cjss10028

Virto, I., Pierre, B., Aurélien, B., Claire, C., (2012). Carbon input differences as the main factor explaining the variability in soil organic C storage in no-tilled compared to inversion tilled agrosystems.*Biogeochemistry* , **108** , 17–26. https://doi.org/ 10.1007/s10533-011-9600-4

Vitousek, P.M., (2005). Nutrient cycling and limitation: Hawaii as a model system. *Princeton University Press* , Princeton. https://doi.org/10.1111/j.1442-9993.2005.01458.x

Wang, S.J., Liu, Q.M., Zhang, D.F., (2010). Karst Rocky Desertification in Southwestern China: Geomorphology, Land use, Impact and Rehabilitation. *Land Degradation & Development* , **15** , 115-121. https://doi.org/10.1002/ldr.592

Wang, S.Q., Li, T.X., Zheng, Z.C., (2016). Effect of tea plantation age on the distribution of soil organic carbon and nutrient within micro-aggregates in the hilly region of western Sichuan, China.*Ecological Engineering* , **90** :113-119.

Wiesmeier, M., Lützow, M.V., Spörlein, P., Geuß, U., Hangen, E., Reischl, A., Schilling, B., Kögel-Knabner, I., (2016). Land use effects on organic carbon storage in soils of Bavaria: the importance of soil types. *Soil and Tillage Research* , **146** , 296–302. https://doi.org/10.1016/j.still.2014.10.003

Xiao S.S., Dong, Y.S., Qi, Y.C., Peng, Q., He, Y.T., Yang, Z.J., (2009). Advance in responses of soil organic carbon pool of grassland ecosystem to human effects and global changes. *Advances in Earth Science* **24** , 1138-1148. https://doi.org/ 10.11867/j.issn.1001-8166.2009.10.1138

Xie, X.L., Sun, B., Zhou, H.Z., Li, P.Z., (2004). Storage and influencing factors of soil organic carbon in China under different vegetation conditions. *Acta Pedologica Sinica* , **41** , 687-699. (In Chinese with English abstract)

Xu, L., He, N.P., Yu, G.R., (2016). Methods of evaluating soil bulk density: Impact on estimating large scale soil organic carbon storage. *Catena* , **144** , 94-101. https://doi.org/10.1016/j.catena.2016.05.001

Xu, J.X., Li, X.M., Sun, G.X., et al., (2019). The fate of labile organic carbon in paddy soil is regulated by microbial ferric iron reduction. *Environmental science & technology* , **53** (15), 8533-8542. https://doi.org/10.1021/acs.est.9b01323

Yang, Y.H., Fang, J.Y., Tang, Y.H., Ji, C.J., Zheng, C.Y., He, J.S., Zhu, B., (2008). Storage, patterns and controls of soil organic carbon in the Tibetan grasslands. *Global Change Biology* , **14** , 1592-1599. https://doi.org/10.1111/j.1365-2486.2008.01591.x

Yang, Y.H., Luo, Y.Q., Finzi, A.C., (2011). Carbon and nitrogen dynamics during forest stand development: a global synthesis. *New Phytologist* , **190** , 977-991. https://doi.org/10.1111/j.1469-8137.2011.03645.x

Zhang, S., Xu, M., Zhang, Y., Wang, C., Chen, G., (2014). Effects of land use change on soil organic carbon storage in the hilly Loess Plateau. *Acta Scientiae Circumstantiate* **34,** 3094-3101. (In Chinese with English abstract)

Zhu, Y.L., Han, J.G., Wu J S, (2004). Effect of agricultural practices on soil organic carbon dynamics. *Chinese Journal of Soil Science* **35** , 648-651. (In Chinese with English abstract)

Table 1 SOC and TN database in the Karst region of southwest China.

Types	Depth (cm)	sample size *SOC*	sample size *TN*	*SOC*	sample size *SOC*	sample size *TN*
LR	0-20	116	92	NF-GL	64	74
	20-30	67	84	NF-SF	45	48
	30-40	38	38	NF-SL	20	-
	40-60	30	26	NF-CL	57	69
	60-100	1	5	NF-PL	22	38
				NF-FT	33	-
				Others	5	-
LR	0-20	89	87	CP-GL	70	68
	20-30	57	69	CP-FT	49	35
	30-40	44	49	CP-SL	19	-
	40-60	28	14	CP-PL	34	43
	60-100	8	-	CP-NF	44	33
				Others	10	40

Note: NF: Native forest, GL: grassland, SF: secondary forest, SL: Shrub land, CL: cropland, PL: Plantation land, FT: Fruit trees, DF-others: Grassland reclamation is the main field of farmland, LR-others: Grassland restoration to forestland and similarly hereinafter. The OF in the following indicates other forest land, which are collections of PL, FT and SL.

Table 2 *lnRR* distribution of SOC and TN storage and soil mass.

Different treatment	*Mean*	*SD*	*n*	*P*
SOC storage on DF	-0.66	0.56	253	< 0.05
SOC storage on LR	0.27	0.57	218	< 0.05
TN storage on DF	-0.62	0.99	240	< 0.05
TN storage on LR	0.31	0.77	228	< 0.05
soil mass on DF	0.09	0.09	257	< 0.05
soil mass on LR	-0.04	0.1	231	< 0.05

*Mean represents the average value of SOC, TN and soil BD; SD is the standard deviation of Mean; n and *P* represent sample size and significance, respectively.

Table 3 The mean and 95% confidence interval of response ratio (*lnRR*) for the SOC and TN storage from different sampling depths under deforestation and land restoration conditions.

LUCC Type	Soil depth (cm)	SOC storage	SOC storage	SOC storage	SOC storage	TN storage	TN storage	T
		n	*lnRR*	95%CI	*P*	n	*lnRR*	9
DF	0-20	116	-0.69	[-0.81, -0.58]	0.43	92	-0.57	[-
	0-30	67	-0.77	[-0.96, -0.58]		84	-0.55	[-
	0-40	38	-0.51	[-0.68, -0.35]		38	-0.48	[-
	0-60	30	-0.50	[-0.71, -0.30]		26	-0.42	[-
	0-100	1	-0.36	[-0.47, -0.25]		5	-0.41	[-
LR	0-20	89	0.40	[0.19,0.61]	< 0.01	87	0.30	[0
	0-30	57	0.10	[-0.18,0.39]		69	0.18	[0
	0-40	44	0.18	[-0.13,0.49]		49	0.11	[-
	0-60	28	0.19	[-0.20,0.58]		12	0.44	[0
	0-100	8	-0.43	[-1.27,0.40]		-	-	-

**P* represents the significance of SOC and TN at each sampling depth level.

Figures captions

Fig. 1. Spatial distribution of the land use/land cover change study sites in the southwest China Karst region.

Fig. 2. The response ratio (*lnRR*) for SOC and TN storage calculating by FD and ESM methods under (a) deforestation and (b) land restoration conditions. The response ratio for (c) soil mass due to land-use changes. DF indicates DF, LR indicates land restoration. The point is the mean value of *lnRR* ; the bars show the 95%CI.

Fig. 3. SOC/TN storage in response to DF (a, b) and land restoration (c, d). The point is the mean value of *lnRR* , the bars show the 95%CI, P indicates the difference between the types of land.

Fig. 4. The changes of SOC (a) and TN (b) storage after deforestation at different sampling depth; the point is the mean value of *lnRR* , the bars show the mean and 95%CI.

Fig. 5. The changes of SOC (a) and TN (b) storage after land restoration at different sampling depth; the point is the mean value of*lnRR* , the bars show the mean and 95%CI.

Fig. 6. Linear regression results of possible influential factors affect RRSOC under Deforestation and land restoration. R is the correlation coefficient (* and ** are the significant levels of $P < 0.05$ and $P < 0.01$, respectively); n represents number of samples; BD is soil bulk density; TN and TK represent total nitrogen and total potassium, respectively; Clay, Percentage content of clay content in soil; Water is soil moisture

content; Year is the time of LUCC; Slope and Altitude represent the slope and elevation of the experimental sample points, respectively; MAT, mean annual temperature; MAP, mean annual precipitation.

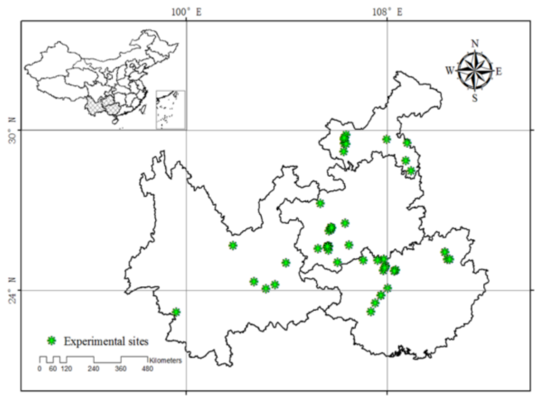
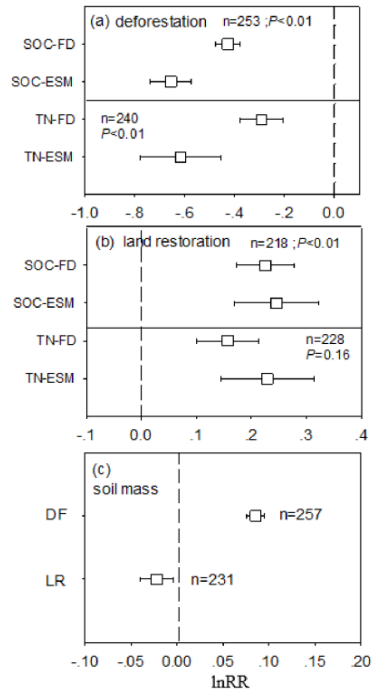
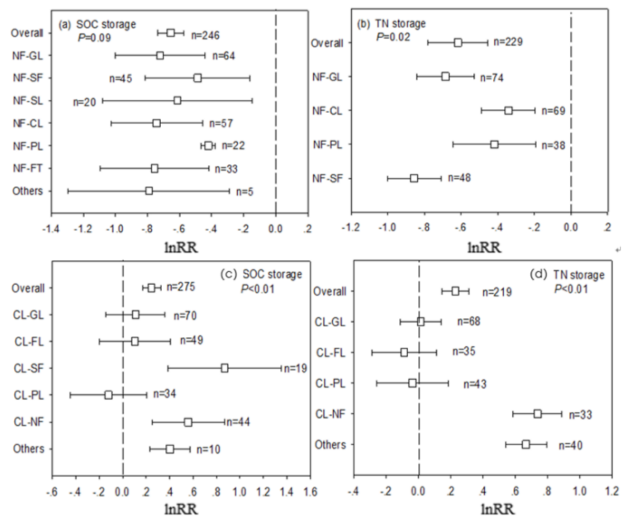
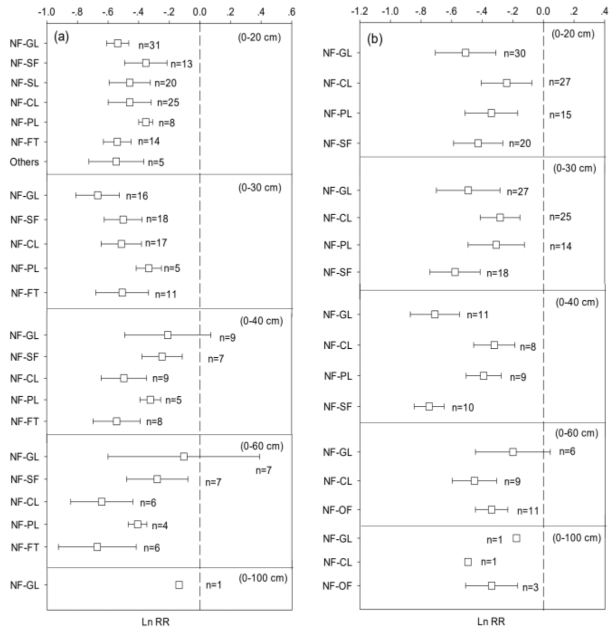
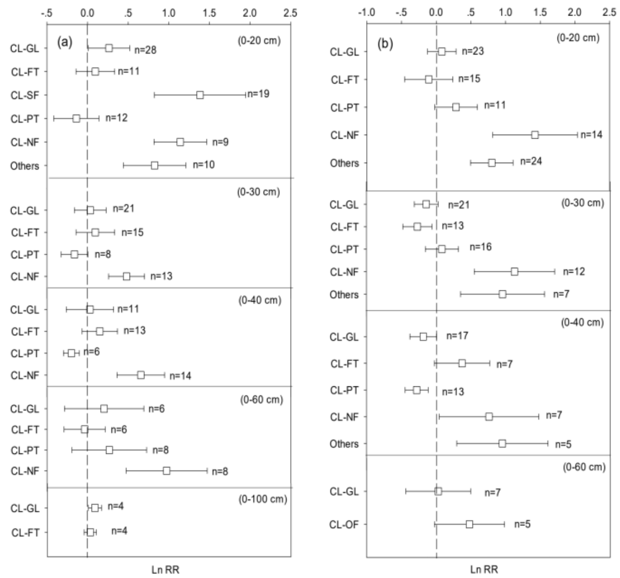


Fig. 1

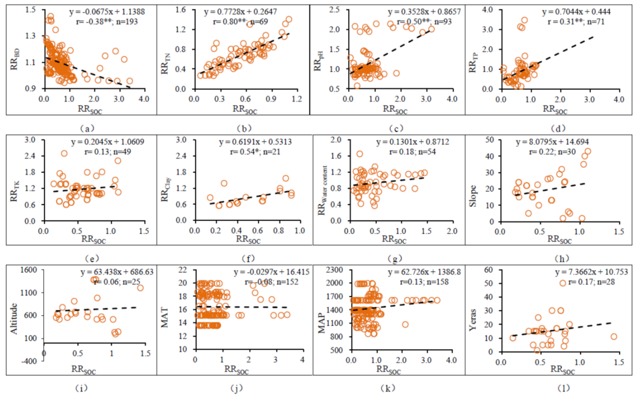

(a) deforestation
n=253 ; P<0.01
SOC-FD
SOC-ESM
TN-FD
TN-ESM
n=240
P<0.01
-1.0 -.8 -.6 -.4 -.2 0.0
(b) land restoration
n=218 ; P<0.01
SOC-FD
SOC-ESM
TN-FD
TN-ESM
n=228
P=0.16
-.1 0.0 .1 .2 .3 .4
(c)
soil mass
DF
n=257
LR
n=231
-.10 -.05 0.00 .05 .10 .15 .20
lnRR


(a) SOC storage
P=0.09
Overall
NF-GL
NF-SF
NF-SL
NF-CL
NF-PL
NF-FT
Others
n=246
n=64
n=45
n=20
n=57
n=22
n=33
n=5
lnRR
(b) TN storage
P=0.02
Overall
NF-GL
NF-CL
NF-PL
NF-SF
n=229
n=74
n=69
n=38
n=48
lnRR
(c) SOC storage
P<0.01
Overall
CL-GL
CL-FL
CL-SF
CL-PL
CL-NF
Others
n=275
n=70
n=49
n=19
n=34
n=44
n=10
lnRR
(d) TN storage
P<0.01
Overall
CL-GL
CL-FL
CL-PL
CL-NF
Others
n=219
n=68
n=35
n=43
n=33
n=40
lnRR


(a)
(0-20 cm)
NF-GL n=31
NF-SF n=13
NF-SL n=20
NF-CL n=25
NF-PL n=8
NF-FT n=14
Others n=5
(0-30 cm)
NF-GL n=16
NF-SF n=18
NF-CL n=17
NF-PL n=5
NF-FT n=11
(0-40 cm)
NF-GL n=9
NF-SF n=7
NF-CL n=9
NF-PL n=5
NF-FT n=8
(0-60 cm)
NF-GL n=7
NF-SF n=7
NF-CL n=6
NF-PL n=4
NF-FT n=6
(0-100 cm)
NF-GL n=1
Ln RR
(b)
(0-20 cm)
NF-GL n=30
NF-CL n=27
NF-PL n=15
NF-SF n=20
(0-30 cm)
NF-GL n=27
NF-CL n=25
NF-PL n=14
NF-SF n=18
(0-40 cm)
NF-GL n=11
NF-CL n=8
NF-PL n=9
NF-SF n=10
(0-60 cm)
NF-GL n=6
NF-CL n=9
NF-OF n=11
(0-100 cm)
NF-GL n=1
NF-CL n=1
NF-OF n=3
Ln RR



(a)
(0-20 cm)
CL-GL n=28
CL-FT n=11
CL-SF n=19
CL-PT n=12
CL-NF n=9
Others n=10
(0-30 cm)
CL-GL n=21
CL-FT n=15
CL-PT n=8
CL-NF n=13
(0-40 cm)
CL-GL n=11
CL-FT n=13
CL-PT n=6
CL-NF n=14
(0-60 cm)
CL-GL n=6
CL-FT n=6
CL-PT n=8
CL-NF n=8
(0-100 cm)
CL-GL n=4
CL-FT n=4
Ln RR
(b)
(0-20 cm)
CL-GL n=23
CL-FT n=15
CL-PT n=11
CL-NF n=14
Others n=24
(0-30 cm)
CL-GL n=21
CL-FT n=13
CL-PT n=16
CL-NF n=12
Others n=7
(0-40 cm)
CL-GL n=17
CL-FT n=7
CL-PT n=13
CL-NF n=7
Others n=5
(0-60 cm)
CL-GL n=7
CL-OF n=5
Ln RR

1 
y = -0.0675x + 1.1388
r= -0.38**; n=193
y = 0.7728x + 0.2647
r= 0.80**; n=69
y = 0.3528x + 0.8657
r= 0.50**; n=93
y = 0.7044x + 0.444
r = 0.31**; n=71
y = 0.2045x + 1.0609
r= 0.13; n=49
y = 0.6191x + 0.5313
r= 0.54*; n=21
y = 0.1301x + 0.8712
r= 0.18; n=54
y = 8.0795x + 14.694
r= 0.22; n=30
y = 63.438x + 686.63
r= 0.06; n=25
y = -0.0297x + 16.415
r= 0.08; n=152
y = 62.726x + 1386.8
r= 0.13; n=158
y = 7.3662x + 10.753
r= 0.17; n=28
RRSOC
Altitude
MAT
MAP
Slope
Yeras
(a) (b) (c) (d)
(e) (f) (g) (h)
(i) (j) (k) (l)