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Quantification of the effects of long-term straw return on soil organic matter spatiotemporal variation: A case study in typical black soil region

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Abstract. The straw return practice is essential to soil organic matter (SOM) accumulation in the black soil area with high carbon sequestration potential. However, due to lacking accurate spatial distribution of straw return, few studies took straw return as a variable to carry out rigorous research on the impact of straw return on SOM variation on a regional scale. Based on soil samples and 16 environmental covariates including a 10-meter-resolution straw return amount, the study mapped the spatial distributions of SOM in 2006 and 2018 by random forest (RF) and evaluated the effects of the interaction of soil properties, land use and straw return on SOM spatial-temporal variation. The results show that in the context of the straw returning, the mean SOM content increased from 18.93 g kg^{-1} to 20.84 g kg^{-1} during 2006–2018. And 74.49 % of the region had a significant increase (maximum: 24.41 g kg^{-1}) of SOM. The severest SOM loss occurred in the northwest due to the light texture and the transition from paddy fields to dryland. Nevertheless, for areas from paddy fields to dryland, the SOM loss decreased with the increased amount of straw return. The SOM even increased by 1.84 g kg^{-1} when the straw return amount reached 60–100 %. In addition, soil with higher initial SOM and sand content had a lower response to straw return. The study revealed that straw return is beneficial to carbon sink in farmland and is a better way to prevent a carbon source caused by the change of paddy field to dryland.

1 Introduction

Soil organic matter (SOM) profoundly impacts carbon contents, cationic exchange capacity, water holding capacity, soil fertility, microorganisms, and soil structure (Ciais et al., 2011). Therefore, the SOM/ soil organic carbon (SOC) contents spatial-temporal variation was significant to global warming, soil quality, and ecosystem health (Ciais et al., 2011; Viscarra Rossel et al., 2014; Ondrasek et al., 2019), especially in black soil with rich SOM (Lugato et al., 2014; Amelung et al., 2020b). Recently, poor management practices have resulted in SOM loss in the black soil area. Previous studies have reported that soil fertility decreased in the black soil area in North America and Eastern Europe (Russell et al., 2005; Fabrizzi

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et al., 2003). Meanwhile, a similar decline trend occurred in the black soil area in Northeast China (Wang et al., 2018). Therefore, rapidly and accurately quantifying the heterogeneity of SOM in the black soil region is necessary.

Conventional mapping involves data collection, field investigation, interpretation, field inspection, calibration, and mapping. It is time-consuming and laborious and thus cannot satisfy the growing demand for the latest soil spatial information. Jenny (1994) described the soil as follows: $soil = f\ (climate, organism, relief, parent\ material, age)$ (Jenny, 1994). McBratney et al. (2003) proposed the $SCORPAN$ function model and described the soil as follows: $soil = f(prior\ soil\ information, climate, organism, relief, parent\ material, age, location)$ (Mcbratney et al., 2003). Based on the soil-forming theory, digital soil mapping (DSM) offers a promising solution for predicting soil properties with high precision and tremendous speed (Hengl et al., 2015; Dou et al., 2019; Liang et al., 2019; Schulze and Schütte, 2020). Thus, the DSM method with environmental factors can accurately quantify the SOM spatial-temporal variation and measure the relationship between environment covariates and SOM variation on a regional scale (Schillaci et al., 2017; Song et al., 2018; Zhou et al., 2019).

Nowadays, SOM variation under different land-use change and management practices has attracted increasing attention (Pan et al., 2010; Muñoz-Rojas et al., 2015). Some studies proposed to reduce SOC loss through straw return (West and Post, 2002; Liu et al., 2014; Wang et al., 2015; Amelung et al., 2020b). Conversely, previous scholars have reported the influence of straw return on the SOM accumulation is non-significant (Pittelkow et al., 2015; Poeplau et al., 2015; Powlson et al., 2011). The opposite result may be due to the various study areas with different soil properties, initial carbon content, land-use change, and straw return. In addition, these studies were mainly conducted on a field scale. On a regional scale, it is mostly through literature citation and policy enumeration to analyze the impact of straw return on SOM variation (Han et al., 2016; Zheng et al., 2015). However, few studies took the straw return amount as a variable to implement rigorous research on the effect of straw return on SOM variation due to lacking accurate spatial distribution of straw return.

In the study, the overall objective was to take a typical black soil area with long-term straw return demonstration as a case to quantify the relationship between SOM accumulation and straw return on a regional scale. The specific objectives were of three folds, which include: a) evaluate the performance of RF models with different groups of factors to develop the most robust model; b) analyze the spatial-temporal variation of SOM during 2006–2018; c) discuss the effects of straw return on SOM variation under different soil types, soil texture and land-use change.

2 Materials and methods

2.1 Study region

The study was conducted in Lishu County, Jilin Province. The average elevation is 160 m (Fig. 1). The annual mean precipitation and annual mean temperature are 6.5 ℃ and 553.5 mm, respectively. The mean annual sunshine duration is 2,541.4 hours. The region's climate is classified as a semi-humid temperature. The soil parent material in Lishu County gradually changes from most weathered rocks and red sediments in the east to the loess-like sediment and loessal sub-sandy

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soil in the west, resulting in the regularity of soil type distribution. Arenosols, Anthrosols, Phaezems, Luvisols, Cambisols, and Chernozems are the main soil types (World Reference Base for Soil Resources). Rainfall is the only source of water for crops growing in this region. In addition, a research base was established in Lishu County, Jilin Province, China, in 2007, and the straw return technology was popularized continually.

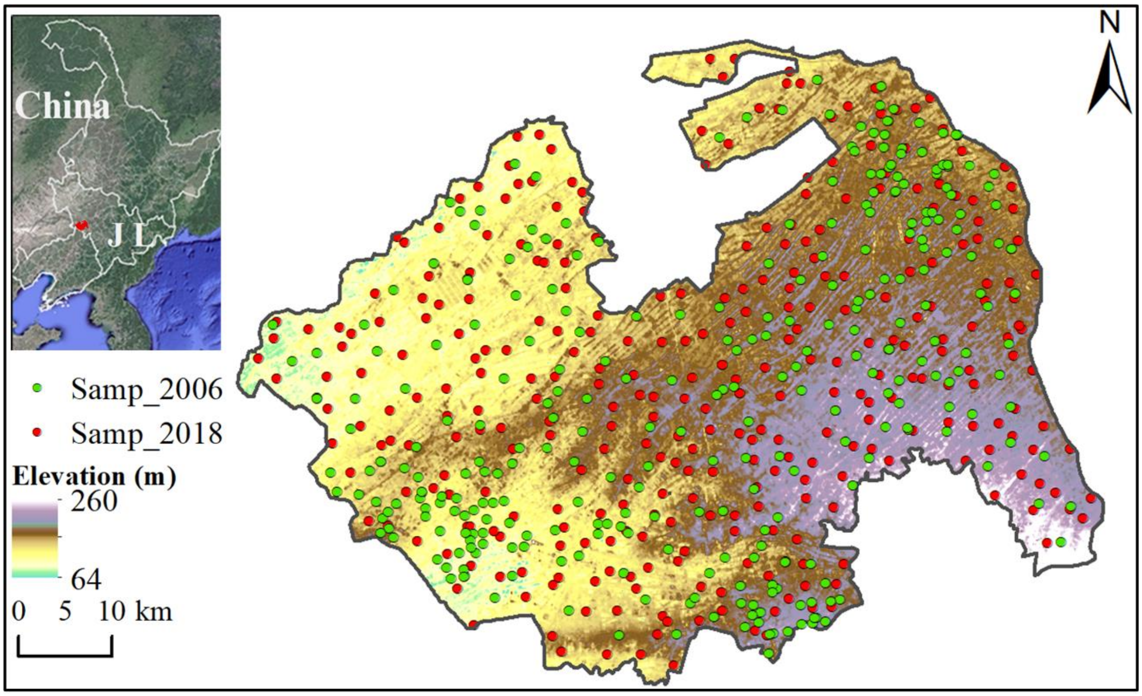

Figure 1: Schematic diagram of the geographical position of the study area and sampling sites. The background is from © Google Earth and the distribution of elevation was derived from the Resource and Environment Data Could Platform.

2.2 Soil data

The straw return measure has been implemented in Lishu County since 2007, so the SOM in 2006 and 2018 were selected to quantify the SOM change under the straw return background. The local landform and soil type determined the sampling locations. The surface (0–20 cm) soil samples were collected, and the corresponding longitude and latitude were also documented. The prediction error caused by the differences in sampling designs for the years 2006 and 2018 was not considered to make full use of legacy soil data (Ou et al., 2017; Sun et al., 2017; Nguemezi et al., 2021).

A portion of 3 kg of soil at each sampling site was air-dried. During the process of air drying, the soil samples were frequently turned over and the intrusions outside the soil were removed. Sun exposure, acid, alkali, and dust pollution were strictly prohibited. After air drying and grinding, the soil samples were thoroughly mixed and passed through a 0.25 mm mesh to determine SOM concentration with the wet oxidation method (Liu et al., 1996).

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2.3 Environmental covariates

We collect the available grids on the website as factors. A 30 m resolution digital elevation model (DEM) was derived from the Resource and Environment Data Could Platform. Other terrain variables were calculated from DEM in the SAGA GIS software (Conrad et al., 2015), including terrain relief (TR), topographic wetness index (TWI), slope, aspect, profile curvature (PRC), multi-resolution valley bottom flatness (MrVBF) and plan curvature (PLC). Landsat 5 TM and Landsat 8 TM were used to calculate the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) in 2006 and 2018. Huang et al. (2020) offered crop residue coverage (CRC) at a 10 m resolution in 2018 (Huang et al., 2020). The study used the Normalized difference tillage Index (NDTI) and Simple Tillage index (STI) extracted from Sentinel-2A images and observed data to predict CRC. The accuracy R^2 of the model is 0.84. Lishu County has implemented the straw return policy since 2007. Therefore, the amount of straw return in 2006 can be regarded as 0.

The resolution of land-use types in 2005 and 2018 is 30 m. The land-use types in 2005 and 2018 are consistent with six major classes and 25 subclasses. An electronic version of soil type map in Lishu County, offered by the Agricultural Extension Station in Lishu County, was digitized and delineated for this study. The map for soil clay content at 250 m resolution was obtained from SoilGrids250m products (Hengl et al., 2015) in International Soil Reference and Information Center.

The National Earth System Science Data Center, National Science & Technology Infrastructure of China provided annual mean precipitation (AMP) in 2006 and 2018. After multivariate regression analysis of 16 variables (Table 1) and SOM content, the Variance Inflation Factor (VIF) of independent variables were less than five, indicating multicollinearity did not exist among independent variables.

These environmental covariates (Table 1) were resampled to 30 m using the bilinear method in ArcGIS 10.2.

Table 1 Environmental covariates used for predicting soil organic matter (SOM).

Theme	Environmental factors	Original resolution	Source
Geographical coordinate	Y	30 m	
Terrain	DEM, m	30 m	http://www.resdc.cn/
	Slope	30 m	Calculated from DEM
	Aspect	30 m	Calculated from DEM
	TR	30 m	Calculated from DEM
	TWI	30 m	Calculated from DEM
	PLC	30 m	Calculated from DEM
	PRC	30 m	Calculated from DEM
	MrVBF	30 m	Calculated from DEM

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Vegetation	NDVI	30 m	Landsat 5 and Landsat 8
	EVI	30 m	Landsat 5 and Landsat 8
	CRC (2018)	30 m	Liu et al., (2020)
Soil	Land-use types 2005	30 m	http://www.resdc.cn/
	Land-use types 2018	30 m	http://www.resdc.cn/
	Soil type	1:100, 000	the Second National Soil Survey
	Soil clay content, %	250 m	https://soilgrids.org/
Climate	AMP, mm	1000 m	http://www.geodata.cn/

Notes: Y, latitude; DEM, digital elevation model, m; TR, terrain relief index; TWI, topographic wetness index; PLC, plan curvature; PRC: profile curvature; MrVBF, multi-resolution valley bottom flatness; NDVI, normalized difference vegetation index; EVI, enhanced vegetation Index; CRC, crop residue coverage; AMP, annual mean precipitation, mm.

2.4 Spatial predictive modeling

2.4.1 Random Forest

Many studies successfully predicted various soil nutrient content by using RF model (Wiesmeier et al., 2011; Guo et al., 2015; Zhang et al., 2017). First proposed by Breiman in 2001, RF (Breiman, 2001) is a tree-based ensemble model. Combined with the idea of feature selection, the approach can increase the diversity of individual decision trees and improve the generalization ability of the final RF model. We used ten-fold cross-validation to optimize the parameters of RF. The study took SOM content and various environmental factors (Table 1) as the dependent and independent variables to build two RF models: consider all the variables as predictors (RF-all); consider the environment variables without latitude as predictors (RF- (all-Y)).

2.4.2 Geographical detector (GE)

GE (Wang and Xu, 2017) is effective to quantify the spatial heterogeneity of attributes between layers. The method includes factor, interaction, risk, and ecological detector. We used the factor and interaction detector to explore the driving factors for SOM prediction in the study. In the factor detector, the q value (from 0 to 1) and whether it passes the significance test was given. The q value is proportional to the effect of the independent variable on the dependent variable. The interaction detector obtained five different results by comparing the q values ($q1$, $q2$) for each of two factors with the q value ($q3$) of the two factors interaction, as presented in Table 2.

Table 2 Interaction judgment in Geographical detector.

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Judgment	Interaction
$q3$<Min ($q1$, $q2$)	Nonlinear weakening
Min($q1$, $q2$)<$q3$<Max($q1$)	Single factor nonlinear weakening
$q3$>Max ($q1$, $q2$)	Double factor enhancement
$q3$=$q1$+$q2$	Independent
$q3$>$q1$+$q2$	Nonlinear enhancement

2.4.3 Model assessment

Independent verification was used to evaluate the performance of the model. The Lins' Concordance Correlation Coefficient (CC) and the root mean squared error (RMSE) were as evaluation metrics. The data was first randomly divided into a modelling set and a validation set according to the 7:3 ratio. In the modelling set, ten-fold cross-validation was used to obtain the best parameters of the model through RMSE as an index. The calculation of RMSE and CC is as follows:

$$RMSE = (1/n \times \sum_{i=1}^{n}(p_i - o_i)^2)^{1/2} , \quad (1)$$

$$CC = 2r\sigma_p\sigma_o/\left(\sigma_p^2 + \sigma_o^2 + (\hat{p}_i - \hat{o}_i)^2\right) , \quad (2)$$

where p_i and o_i are the predicted value and observed value, respectively. $\hat{p}_i$ and $\hat{o}_i$ are the average value of all predictions and observations, respectively. n is the number of soil samples. σ_p^2 is the variances of predicted values and σ_o^2 is the variances of measured values. r is the correlation coefficient of predictions and observations. Model evaluation, descriptive analysis, and variance analysis were realized in R 4.0.2 (R Core Team, 2020).

3 Results and discussion

3.1 Descriptive Statistics of SOM data

As shown in Table 3, from 2006 to 2018, the average SOM content increased from 18.93 g kg^{-1} to 20.84 g kg^{-1} and the coefficient of variations (CV) rose slightly from 0.33 to 0.38. The CVs indicated moderate variation (Cambardella et al., 1994). The ascending CV could be attributed to more active human activities, such as popularized straw return technology in Lishu County, which is consistent with recent studies (Fan et al., 2020; Hu et al., 2014).

Table 3 Statistical description of SOM in 2006 and 2018 in Lishu County.

	Year	Mean	SD	Min	Max	Skew	Kurtosis	CV
SOM	2006	18.93	6.20	6.40	39.50	0.29	−0.45	0.33
(g kg^{-1})	2018	20.84	7.82	2.10	64.26	0.29	1.29	0.38

Notes: SOM, soil organic matter, g kg^{-1}; SD, standard deviation; CV, coefficient of variation.

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3.2 Model performance

Table 4 shows that the RF-all (CC = 0.59, RMSE = 4.54 g kg^{-1}, took 2006 as example) (Fig. 2) performed better than RF-(all-Y) did (CC = 0.55, RMSE = 4.63 g kg^{-1}). The result indicated geographical coordinates were significant for SOM mapping. Compared with a RF-all model to predict nematode worm distribution, Ploton et al. (2020) obtained similar results
145 by using a RF-XY model because the RF-all model mainly depends on geographic proximity (Van Den Hoogen et al., 2019). However, studies seldom took geographic coordinates as variables for SOM prediction. Further research should consider the importance of geographic coordinates in DSM.

Table 4 The performance of the random forest model.

Methods		2006		2018	
		CC	RMSE (g kg^{-1})	CC	RMSE (g kg^{-1})
RF-all	Calibration	0.55	5.04	0.44	6.99
	Validation	0.59	4.54	0.54	5.38
RF- (all-Y)	Calibration	0.50	5.22	0.38	7.18
	Validation	0.55	4.63	0.47	5.55

Notes: RF-all: consider all the variables as predictors; RF- (all-Y), consider the environment variables without latitude as
150 predictors; CC, Lins' Concordance Correlation Coefficient; RMSE, root mean squared error.

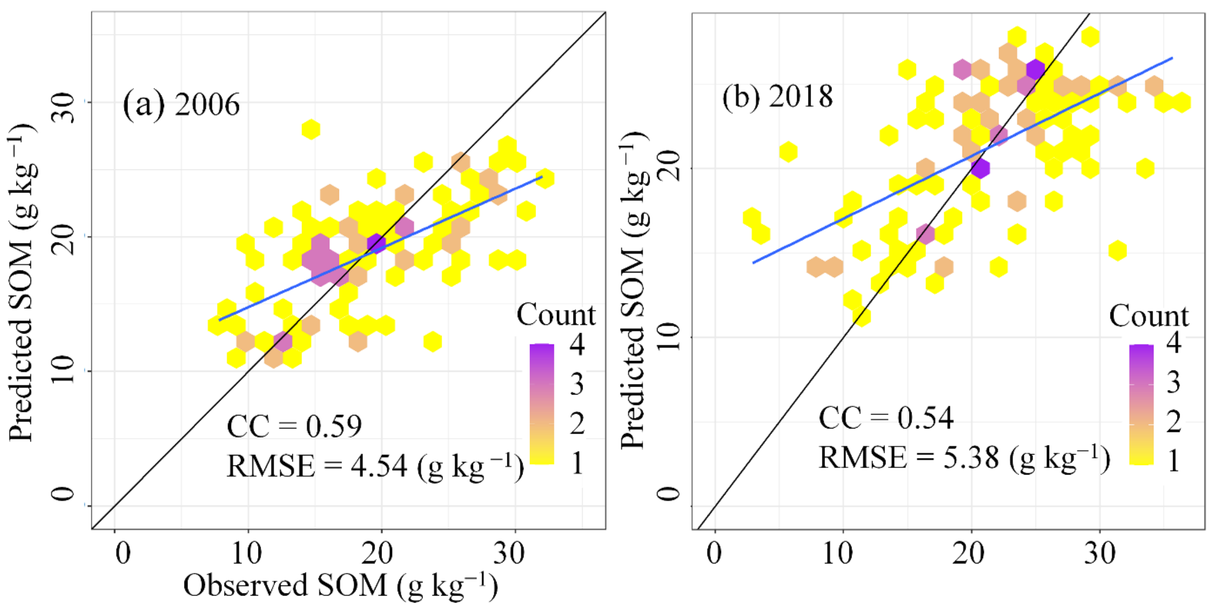

Figure 2: Performances of the random forest with all environmental covariates (RF-all) on validation data in 2006 (a) and 2018 (b). RMSE, root mean squared error; CC, Lins' Concordance Correlation Coefficient; SOM, soil organic matter.

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3.3 Importance of driving factors on SOM spatial distribution

As Fig. 3a and c prevented, the relative importance of environmental factors obtained from the RF and GE methods was comparable, proving the feasibility of the two methods. The geographical coordinates, soil type, precipitation, clay content, DEM, and MrVBF play key roles in SOM prediction (the relative importance > 10 %). The relative importance of the other factors was almost less than 5 %. Moreover, straw return was an essential factor in SOM spatial distribution.

As Fig. 3b and d presented, the explanatory strength of 16 variables' interaction in pairs was stronger than that of the single factor through nonlinear enhancement or double factor enhancement (Enhancement, bi). This finding proved that the complex interaction among different influencing factors led to the spatial distribution pattern of SOM. Fig. 3b and d also proved that y, AMP, DEM, MrVBF, Soil type, and Clay have the greatest influence on SOM.

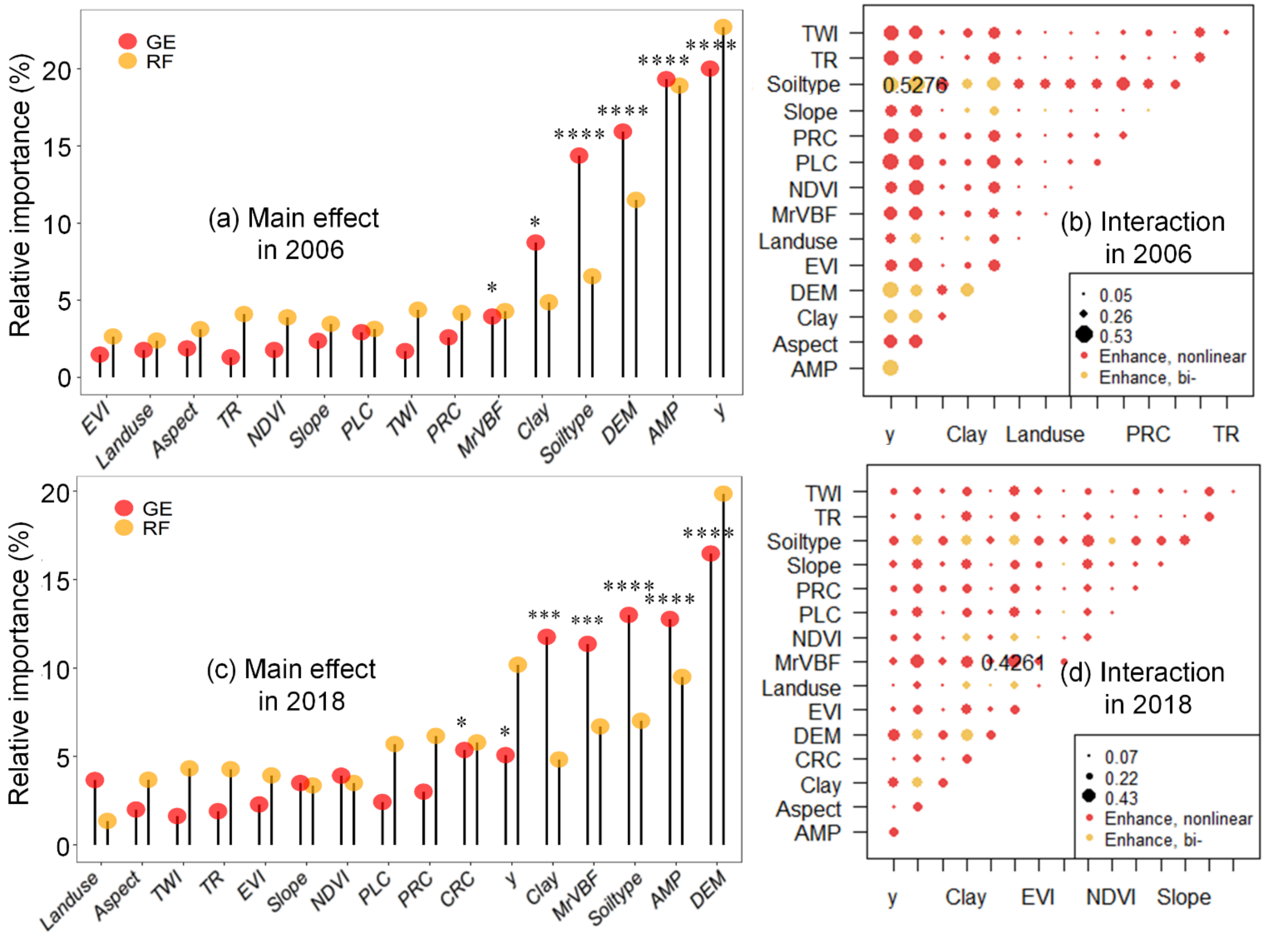

Figure 3: Relative Variables importance (a), (c) and interaction (b), (d) derived from the random forest and geographic detectors (GE) for soil organic matter (SOM) in 2006 and 2018. Notes: y, latitude; DEM, digital elevation model, m; TR,

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terrain relief index; TWI, topographic wetness index; PLC, plan curvature; PRC: profile curvature; MrVBF, multi-resolution valley bottom flatness; NDVI, normalized difference vegetation index; EVI, enhanced vegetation Index; CRC, crop residue coverage; AMP, annual mean precipitation, mm.

3.4 Spatial variation of SOM over time

Fig. 4 presents the spatial distributions of SOM (30 m resolution) in 2006 and 2018. The general spatial pattern was clear: the SOM decreased from southeast to northwest in Lishu County each year. In 2006, SOM concentration was highest in the south of Lishu County (22–28 g kg^{-1}) and lowest in the western part (under 12 g kg^{-1}). The highest SOM content was concentrated in the middle and east of the study area in 2018, while low SOM content (0–12 g kg^{-1}) occupied a tiny area.

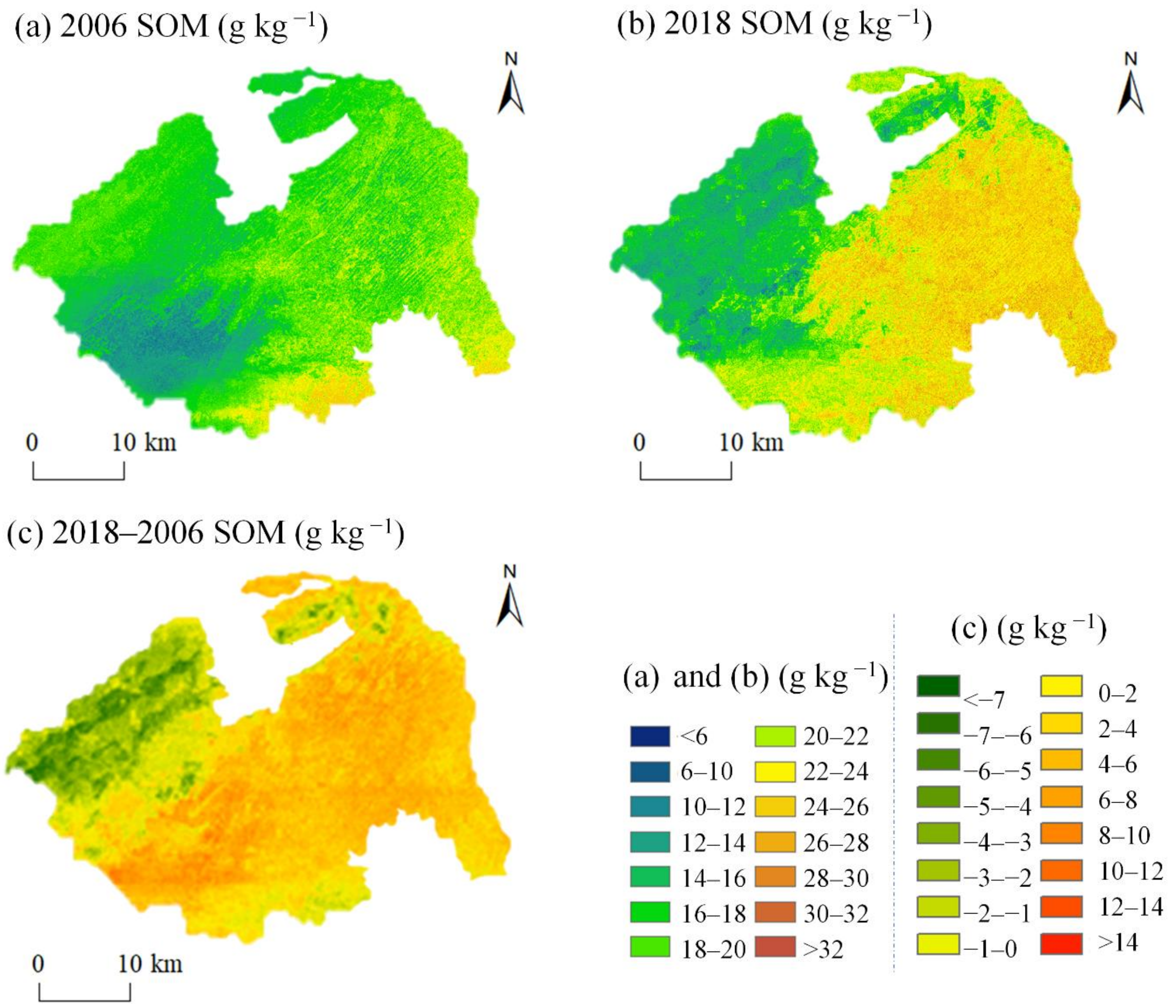

Figure 4: Prediction map of soil organic matter (SOM) in 2006 (a), 2018 (b), and the change (c) over the same period in the study area.

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The overall trend of SOM content was on the rise from 2006 to 2018. Consistent with the distribution of high straw return amount (0.3–1) (Fig. 5a), the SOM content in 74.49 % areas of Lishu County displayed a significant increasing trend, especially in the eastern part of the county (Fig. 4c) with a maximum increase of 24.41 g kg^{-1}. Many studies have revealed that straw return contributes to carbon sink due to increased microbial biomass and biological activity (Han et al., 2016; Amelung et al., 2020a; Berhane et al., 2020).

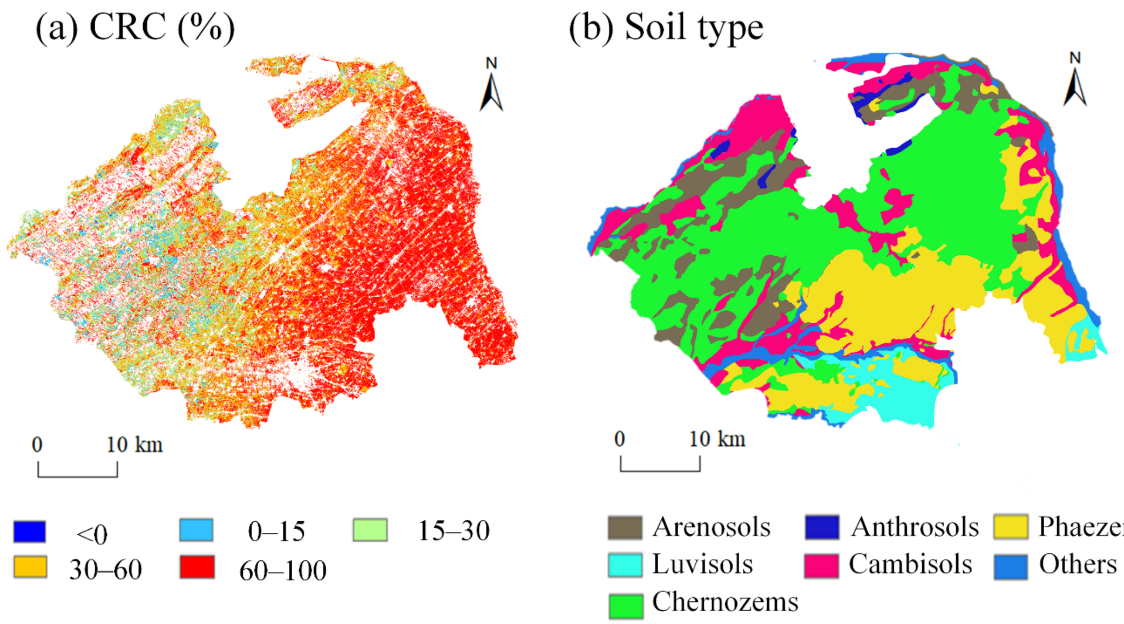

Figure 5: The variation of straw returning content (CRC) during 2006–2018 (a) and soil type (b) in the study area.

The decrease of SOM mainly occurred in the northwest and south of Lishu County. The SOM reduction in southern Lishu County happened to be the area with the high initial SOM concentration (2006) (Fig. 4c). Consistent with previous research, the reduction was severe in areas with initial higher concentrations of SOC (Zhou et al., 2019). In the northwest corner, the decrease of SOM was mainly distributed on the Arenosols and Anthrosols with a marked decline of 12.70 g kg^{-1} (Figs. 4c, 5b). The phenomenon may be related to the small amount of straw return, light-texture soil, and the change that paddy land to dryland.

3.5 Effects of straw return on SOM variation

Fig. 6 presents SOM increased by 0.76, 1.99, 2.66, and 3.08 g kg^{-1} when the straw return amount was 0–15 %, 15–30 %, 30–60 %, and 60–100 %, respectively. This result proved the SOM increment was proportional to the straw return amount. Previous study revealed that the effect of straw return on SOM content was closely linked to soil properties, initial SOM content, land-use change, and the straw return amount (Berhane et al., 2020). Therefore, variance analysis was conducted to explore the effects of straw return on SOM variation under different land-use change, soil types, and soil texture.

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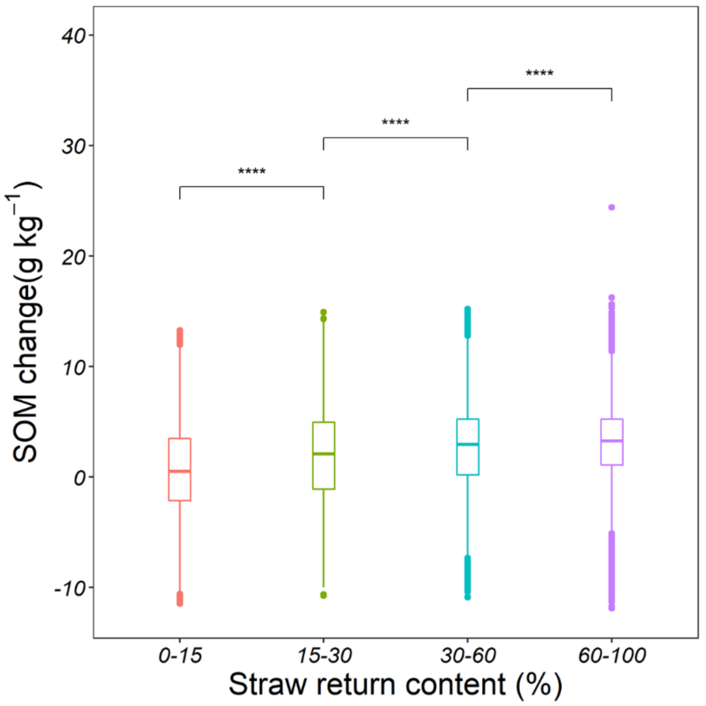

Figure 6: The soil organic matter (SOM) change for different straw returning content.

3.5.1 Effects of the straw return on SOM variation under different soil types

According to Fig. 7, for Anthrosols, Cambisols, and Chernozems, SOM increment was proportionate to the straw return amount. For Luvisols and Phaezems, SOM variation showed a decreasing trend with the boosted straw return amount. This phenomenon is relevant to the initial SOM contents. As displayed in Fig. 8, the initial SOM contents were lower in Anthrosols, Cambisols, and Chernozems and higher in Luvisols, and Phaezems. Berhane et al. (2020) claimed that regardless of the soil type, the higher the initial SOC content, the lower the response of SOC change to carbon input. Li et al. (2018) concluded that Phaezems with the highest initial SOM content had the lowest response rate to fertilization (Li et al., 2018). A possible explanation for this might be that soils with low initial SOM are far away from their saturation levels and thus have a greater potential for carbon sequestration. Except for the SOM loss that occurred in Arenosols and Anthrosols, the changes of SOM under other soil types were almost positive (Fig. 7). The result verified that the degradation of Arenosols and Anthrosols resulted in the SOM reduction due to the light-texture soil and land-use change from the paddy land to dryland, respectively.

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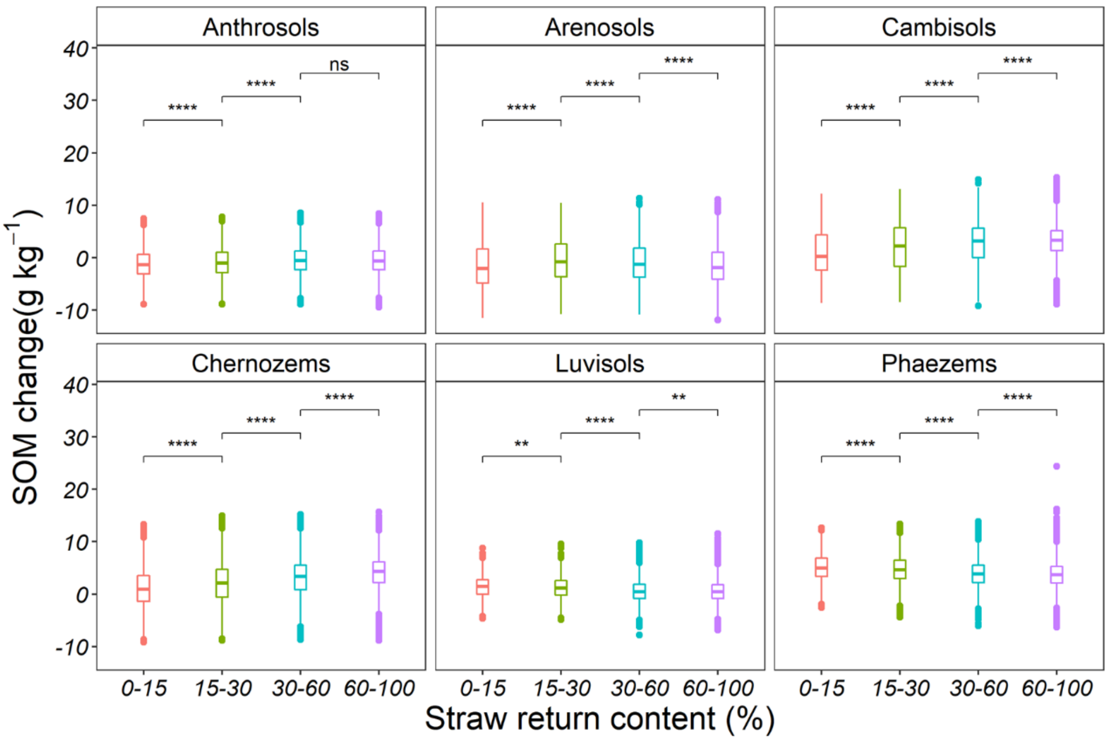

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Figure 7: The soil organic matter (SOM) change for different straw returning content under soil type

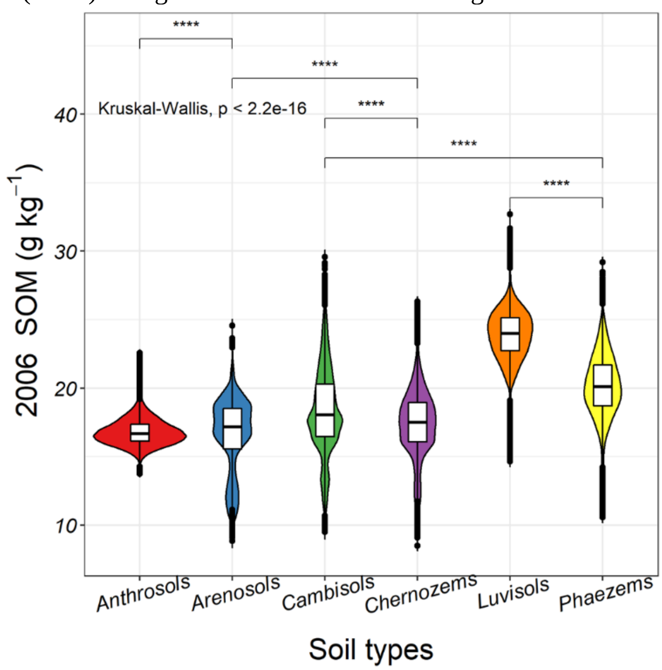

Figure 8: Initial soil organic matter (SOM) content (2006) for soil type

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3.5.2 Effects of straw return on SOM variation under different soil texture

With the straw return amount increasing, SOM first increased and then decreased for soil with low clay content (Fig. 9). Nevertheless, SOM increases with the boosted straw return amount in soils with high and medium clay contents (Fig. 9), indicating that clay content was directly proportional to the response of SOM increment to straw return. The findings are consistent with previous studies that straw return leads to the highest carbon chelation under the high clay content (Xia et al., 2018). One possible explanation for this observation was soils with higher clay content have greater potential to store organic carbon (Li et al., 2020), so the SOM accumulation in clayey soils is more responsive to straw return. Moreover, the SOM increment under sandy soil declined when the straw return amount was 60–100 %, which was because sandy soil cannot be protected by mineral particles (Xia et al., 2018) and is more susceptible to the influence of microorganisms.

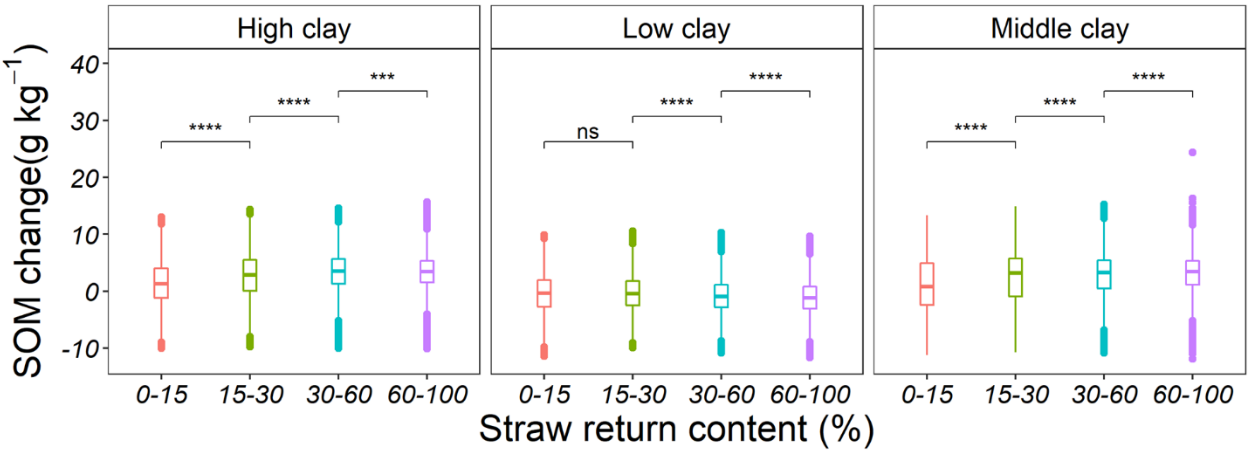

Figure 9: The soil organic matter (SOM) change for different straw returning content under soil texture.

3.5.3 Effects of straw return on SOM variation under different land-use change

The study considered only two kinds of land-use change: a) the change from dryland to paddy land; b) the change from paddy land to dryland because the crop area accounted for over 70 % of the total sown area in Lishu County and all the samples were taken from farmland. Variance analysis was carried out for the SOM variation in the two kinds of land-use change under different straw return amounts. As shown in Fig. 10, the SOM increment increases with the boosted straw return amount under the change from dryland to paddy field. From paddy to dry land, the SOM dropped by 0.59 g kg^{-1} when the straw return amount was 0–15 %. However, with the increase in the straw return amount, the SOM loss gradually decreased. Even the SOM increased by 1.84 g kg^{-1} when the straw return amount was 60–100 %, indicating that straw return can reverse the carbon loss caused by the transformation of paddy to dryland. Previous studies have found that due to the transformation from anaerobic to aerobic, the conversion of paddy to dry land will cause carbon loss (Wang et al., 2014; Nishimura et al., 2008; Li et al., 2016). Some research pointed that we can reduce the carbon loss by rewetting (Driessen et al., 2000) or cultivation of paddy fields continuously (Chen et al., 2017). The study pointed out that straw return is a way to

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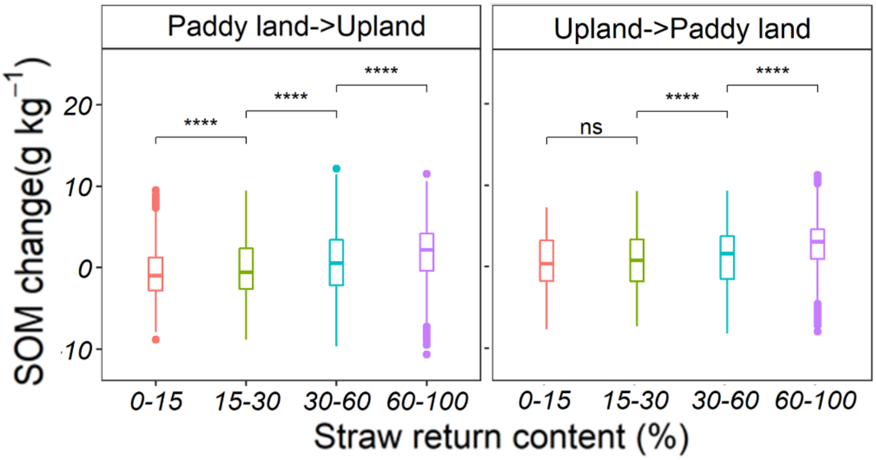
prevent a C source caused by the change of the paddy field to dryland and can be carried out after that paddy is converted to dryland or when paddy is fallow.



240 Figure 10: The soil organic matter (SOM) change for different straw returning content when paddy land change to dryland.

4 Conclusion

The study estimated the surface SOM content and SOM variation between 2006 and 2018 by the RF model, quantified the spatial relationship between measured SOM and predictors and further explored the effect of the interaction of soil properties, land use and straw return on SOM change. The results of the study were as follows:

245 (1) The RF model with all predictors (CC = 0.59, RMSE = 4.54 g kg^{-1} in 2006) performed better than that with all predictors except for geographical coordinates did (CC = 0.55, RMSE = 4.63 g kg^{-1}) in both 2006 and 2018. The result indicated geographical coordinates were significant for SOM mapping.

(2) The SOM contents for both periods decreased from the southeast to the northwest. For temporal variation, the SOM in 74.49 % of areas of Lishu County existed an apparent upward trend, especially in the eastern of the county with a maximum 250 increase of 24.41 g kg^{-1}. The northwest and south corners of the study area aggregated the SOM loss, especially in the northwest with a significant decline of 12.70 g kg^{-1}.

(3) Straw return played the main role in SOM variation. SOM increased by 0.76, 1.99, 2.66, and 3.08 g kg^{-1} with straw return amount of 0–15 %, 15–30 %, 30–60 %, and 60–100 %. The response rate of SOM to the amount of straw return was inversely proportional to the initial SOM and the sand contents.

255 The study revealed that straw return is beneficial to carbon sink in farmland. This article can provide a significant reference for conservation tillage to be extended to the entire black soil region.

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Data availability

The data that support the findings of this study are available on request from the corresponding author.

Author contributions

Conceptualization, Wenjun Ji and Yang Yan; data curation, Guiman Wang and Zhong Liu; methodology, Wenjun Ji and Yang Yan; writing-original draft preparation, Yang Yan; writing-review and editing, Wenjun Ji, Songchao Chen and Dehai Zhu; supervision, Wenjun Ji and Baoguo Li; project administration, Wenjun Ji and Baoguo Li; funding acquisition, Wenjun Ji.

Competing interests

The authors declare that they have no conflict of interest.

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