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Research Article

Ecosystem-dependent two-stage changes in soil organic carbon stock across the contiguous United States from 1970 to 2014

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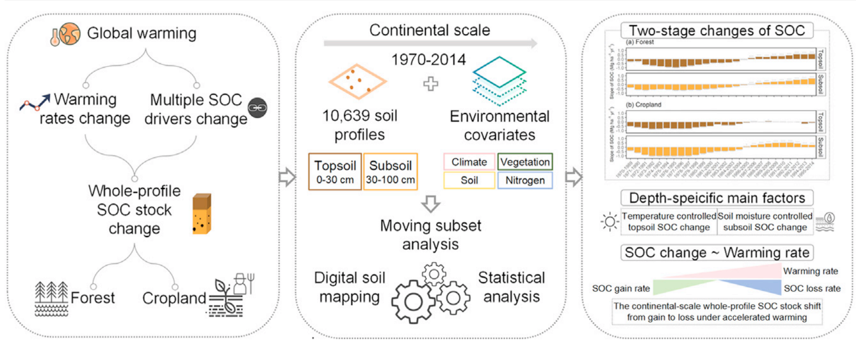
HIGHLIGHTS

- Two-stage SOC changes in the CONUS were strongly associated with changes in warming rates.
- Rising temperatures predominantly coincided with reduced topsoil SOC stock.
- Soil water content emerged as the strongest negative relationship with subsoil SOC dynamics.
- A threshold effect of warming rates on SOC loss was observed at the ecosystem scale.

GRAPHICAL ABSTRACT



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ABSTRACT

Temporal dynamics in soil organic carbon (SOC) play a crucial role in the global carbon cycle. How warming affects SOC change has been widely studied at the site scale, mainly through short-term manipulative experiments. Decades-long SOC dynamics in ecosystems can be complicated, particularly as real-world warming rates varied on decade-scale. However, the lack of long-term repeated observations on whole-profile SOC limits our understanding of SOC dynamics across large regions. Herein, we reconstructed 45 years of SOC dynamics (1970–2014) in topsoil (0–30 cm) and subsoil (30–100 cm) using 10,639 soil profiles from forest and cropland across the contiguous United States, and investigated their relations with key dynamic environments (e.g., climate, vegetation and nitrogen). We further examined the spatial pattern of SOC stock changes at a finer scale (~2 km) using machine learning techniques. Our results revealed ecosystem-dependent, two-stage changes of SOC stock, characterized by continental-scale halts in SOC loss following warming deceleration since the late 1990s. This shift led to an overall increase in SOC stock of 1.41 % in forest and 1.14 % in cropland within the top 1-meter over 45 years. Temperature was the primary factor related to topsoil SOC losses, whereas soil water content may primarily control subsoil SOC change. Notably, a threshold effect of warming rates on SOC loss was identified in both topsoil and subsoil. These findings provide new insights into long-term whole-profile SOC dynamics at a large scale, offering valuable implications for carbon sequestration to support sustainable development in different ecosystems.

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1. Introduction

The top one meter of the global ice-free land stores approximately 1,500 Gt of soil organic carbon (SOC), larger than the combined carbon storage in the atmosphere and terrestrial vegetation (Jobbágy and Jackson, 2000; Köchy et al., 2015). The SOC pool plays an important role in the global carbon cycle through carbon exchange with the atmosphere. Even minor changes in the SOC pool can significantly impact atmospheric CO_2 levels (Bossio et al., 2020). Over the past few decades, climate change has emerged as a non-negligible external force affecting SOC dynamics (Davidson et al., 2000; García-Palacios et al., 2021). Although studies on short-term SOC response to warming have been increasingly carried out, how warming affects decades-long SOC dynamics, a more complex process (Melillo et al., 2017), is still controversial over regions due to the limitation of long-term observations, especially in deep soil layers (Smith et al., 2020; Yang et al., 2022). Uncertainties would arise when extrapolating site-level and short-term results to larger and longer scales (Luo et al., 2016; Hollister, 2024). Particularly, in the real world, temperature changes at decade-scale often exhibit fluctuations rather than linear trends (Marotzke and Forster, 2015), thus global warming rates exhibit inconsistency. For instance, previous studies have reported that global warming accelerated after the late 1970s and slowed down after the late 1990s (Zhu et al., 2016). Variability in warming rates may also influence SOC responses by affecting temperature sensitivity of factors related to carbon input and output, such as vegetation activities (Lambers, 2015) and soil moisture (Naumann et al., 2018). Understanding long-term SOC dynamics at different depths and their relationships with the changing warming rate and other environmental factors at large-scale will contribute to improving Earth system modelling for predicting long-term carbon cycle feedbacks to climate change and optimizing carbon management strategies.

Manipulative experiments have been commonly carried out to observe soil carbon change under warming. The generally reported positive carbon-climate feedback in surface soil carbon (Crowther et al., 2016) and the more obvious efflux in whole-profile caused by simulated warming has raised concerns about SOC loss under global warming (Hicks Pries et al., 2017; Zosso et al., 2023). However, most current warming experiments maintain a fixed warming magnitude, such as a constant 2 °C or 4 °C rise throughout the experimental period. This design overlooks the dynamic nature of real-world temperature changes, leaving uncertainty about how carbon loss might respond when temperature is at a high level after a period of temperature increase but warming decelerates. In addition, carbon changes in ecosystems are influenced by multiple factors under real environmental conditions (such as net primary productivity (NPP) and soil water content) (Ding et al., 2022). But most manipulative experiments explore the effects of one factor in isolation from others (Knorr et al., 2024), and are limited to short-term duration, rarely exceeding two to three decades (Melillo et al., 2017).

Repeated sampling has been applied in some regions to assess real-world SOC changes at sites or over regions (Senthilkumar et al., 2009; Zhu et al., 2020). While site-based SOC and other environmental data are repeatedly collected by ecological stations offering precious insights into environment changes, it is insufficient to reflect SOC dynamics over a large area because ecological stations representing different background environmental conditions are still spatially sparse. Some large-scale repeated sampling programs are being conducted, but sampling frequency is always limited due to the high cost of soil sampling and measurement. For example, the Forest Inventory and Analysis program (https://research.fs.usda.gov/programs/nfi) collects surface soil data in forest plots across the United States every 5–10 years in the recent two decades (Hogan et al., 2024), and the Land Use/Land Cover Area Frame Survey (LUCAS) program conducted surface soil surveys across EU member states in 2009, 2015 and 2018, with 5,722 sample points revisited twice (De Rosa et al., 2024). However, the frequency and span of existing sampling programs are insufficient to support a comprehensive understanding of the long-term SOC dynamics. Moreover, these datasets mainly focus on surface soil, not whole-profile depth. Given that no long-term yearly repeated sampling over large spatial scale has been carried out yet, reconstructing SOC dynamics based on existing database of whole-profile soil measurements can serve as an alternative way to fill the data gap.

The contiguous United States (CONUS) has experienced notable temperature trajectory since the 1970s: temperature increases since the 1970s and a slowing-down in warming from the late 1990s to the mid-2010s (US EPA, 2016). This two-phase temperature change provides an ideal natural laboratory to study how SOC stock responds to changing warming rates, as well as other factors. We hypothesize that continental-scale SOC stocks may exhibit different stages of responses to two phases of temperature change, and these responses in human-dominated ecosystem may differ from natural ecosystem, as well as between topsoil and subsoil. According to these hypotheses, we utilized quality-assessed database of whole-profile SOC measurements labeled with sampling time spanning over half a century, and reconstructed SOC dynamics of cropland and forest from 1970 to 2014 in the CONUS using moving subset window analysis. To identify key drivers of SOC temporal dynamics, we then analyzed the dominant environmental dynamic factors of temporal SOC changes in both topsoil (0–30 cm) and subsoil (30–100 cm) under the natural conditions (forest ecosystems) and managed conditions (cropland ecosystems). Specifically, we evaluated dynamic drivers representing climate (temperature/precipitation), soil (soil temperature and water content), vegetation (NPP) and anthropogenic factors (Nitrogen deposition and fertilization). Finally, we predicted the spatial pattern of SOC stock change at 1-meter depth using a machine-learning-based model. Our analysis aims to answer the following two questions: 1) How has SOC stock changed in the CONUS since the 1970s, and how has it responded to changing warming rates? 2) What are the differences of SOC dynamics and main driving factors between topsoil and subsoil in forest and agricultural ecosystems from 1970 to 2014?

2. Material and methods

2.1. Soil organic carbon data from 1970 to 2014

2.1.1. Soil profiles collection and harmonization

We collected the soil organic carbon sample data in the CONUS from two open-access soil profile datasets, WoSIS (World Soil Information Service) snapshot 2019 (Batjes et al., 2020) and International Soil Carbon Network version 3 Database (ISCN3) (Luke et al., 2022). The WoSIS (https://www.isric.org/) collates the largest quality-assessed and standardized database of explicit soil profile observations worldwide. The ISCN is an international scientific community devoted to the advancement of soil carbon research. We selected high-quality profiles of the CONUS according to the following four criteria, 1) high accuracy of geographical coordinates, 2) explicit sampling year, 3) the depth of profiles larger than 1 meter, and 4) in ecosystems without land use transformations for at least twenty years before the sampling date. Specifically, the position error for location is under 1 arc-second (~30 m) in WoSIS and 0.0001 arc-degree (~11 m) in ISCN3. In addition, to minimize noises from land use change on SOC change, we only remained profiles with unchanged land use type over the 20 years before sampling (Qin et al., 2016).

2.1.2. SOC stock calculation

We focused on the mineral soil organic carbon stock, excluding the litter layers and organic layers of each profile, because of the inconsistent soil sampling rules regarding organic layer in sampling history of the U.S. For soil data of WoSIS, we extracted the observed soil organic carbon content (SOC_c [g kg^{-1}]), bulk density (BD [g cm^{-3}]) and coarse fragments (CRF [%]) of each profile and harmonized to two standard depths (0–30 cm and 30–100 cm) by using numerical integration based

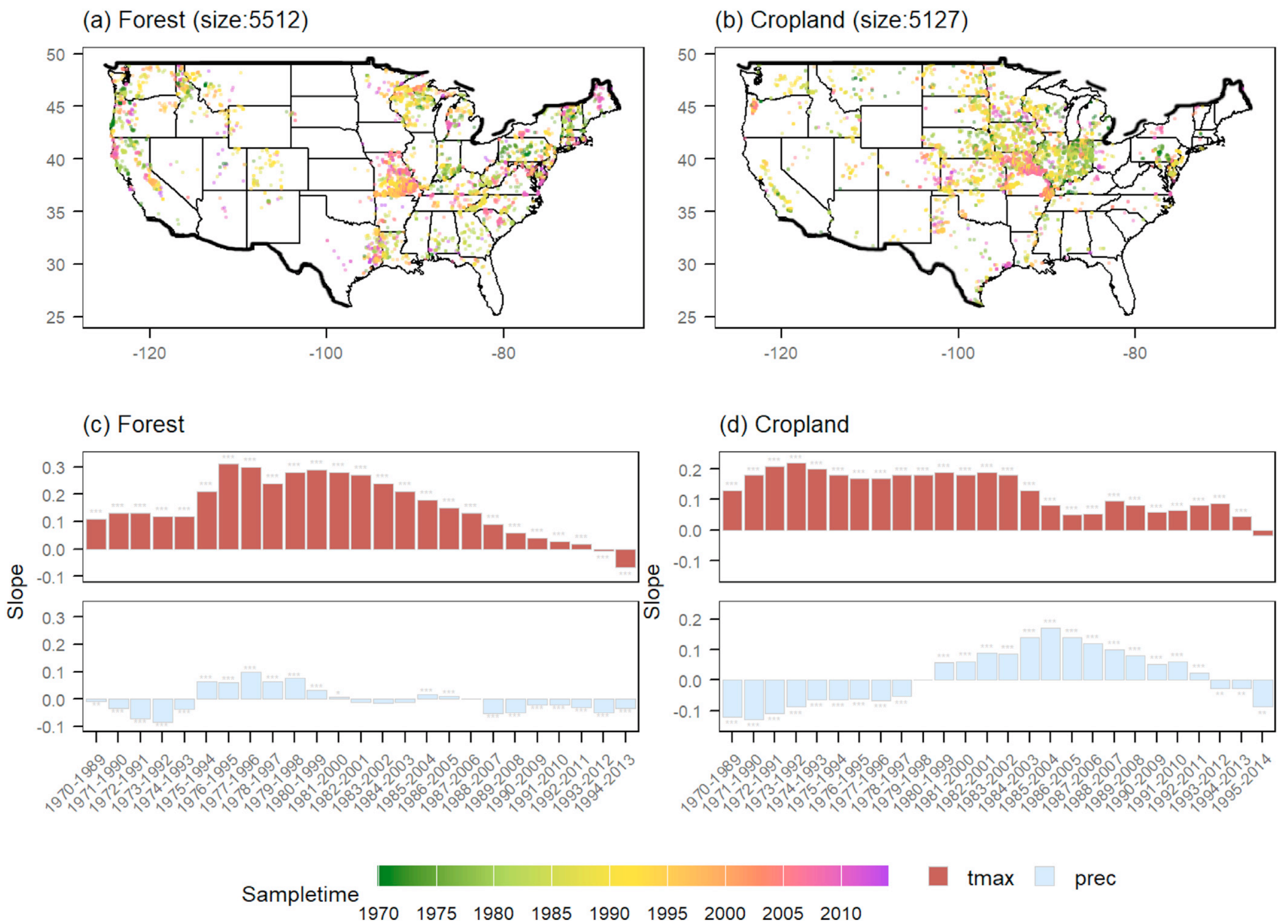

Fig. 1. Distribution of collected soil profiles and corresponding climate changes. The spatial distribution of soil profiles in forest (a) and cropland (b). Slopes of annual mean maximum temperature (tmax, °C yr $^{-1}$) (c) and annual total precipitation (prec, 100 mm yr $^{-1}$) (d) were generated using tmax and prec at locations of all the soil profiles based on a moving subset analysis.

on a rectangle rule (Hengl et al., 2017), following Eq. (1):

$$\frac{1}{b-a}\int_{a}^{b} f(x)\mathrm{d}x \approx \frac{1}{b-a}\sum_{i=0}^{n-1} f\left(x_i\right)\cdot \Delta x_i \tag{1}$$

where a is the left point of the target depth range (i.e., 0 or 30) and b is the right point (i.e., 30 or 100), n is the number of depths used, $f(x_i)$ is a constant of target soil property at depth $(x_i,\ x_{i+1})$ and Δx_i is the width of each depth i. If the right point of depth i is larger than b, the Δx_i is equal to b-x_i .

After scaling the above properties, the soil organic carbon stock (SOC_s [Mg C ha^{-1}]) was calculated according to the following Eq. (2):

$$\mathrm{SOCs} = \mathrm{SOCc} \cdot \mathrm{BD} \cdot (1-\mathrm{CRF}) \cdot \mathrm{Depth} \cdot 0.1 \tag{2}$$

Among these soil profiles, only half have measurements for both BD and CRF. We followed the approach of Wang et al. (2022) by using a machine learning-based pedo-transfer function to perform imputation for missing data. Specifically, we developed random forest models based on all measurements of the respective property (e.g., BD) using other observed soil properties including SOC content, clay, sand, and silt from the WoSIS as the data input. The accuracy of models is shown in Table S1 in the Supplementary materials. We also compared our results of BD with three traditional pedo-transfer functions reviewed by Abdelbaki (2018).

The ISCN3, released in December 2015, provides observed soil profiles containing SOC stock, BD and SOC content measurements. We harmonized the SOC stock with our stock calculation equations (details in Supplementary materials). After harmonization, the histograms of SOC stock in topsoil and subsoil from two databases before 2000s show consistency with many of profiles sharing the same locations, indicating minimal impacts of data sources on SOC dynamics (Fig. S1 in the Supplementary materials). Duplicates in ISCN3 matching WoSIS coordinates were excluded. In the end, we derived a total of 10,639 observations (8,485 from WoSIS and 2,154 from ISCN3) of topsoil (0–30 cm) organic carbon stock and subsoil (30–100 cm) organic carbon stock in forest and cropland in the CONUS spanning 1970 to 2014 (Fig. 1a and b). And the temperature trends represented by all soil profiles of our dataset accurately reflect the documented shift in warming rates in the CONUS (Fig. 1c, d).

2.2. *Historic land use*

To distinguish the soil profiles in areas with unchanged land use, we downloaded the Historic Land Dynamics Assessment+ (HILDA+) from Winkler et al. (2020). The HILDA+ reconstruction was derived from multiple openly available global, continental, regional, and national LUC datasets, including remote sensing data, reconstructions, and statistics. This dataset provides a long-term global annual land use record from 1899 to 2019 at a 1 km spatial resolution, covering six categories: urban areas, cropland, pasture/rangeland, forest, unmanaged grass/shrubland, and sparse/no vegetation areas.

2.3. Climate, topography, soil, vegetation and anthropogenic variables

To examine the relationships between SOC and environmental variables, we collected high-resolution variables representing climate, topography, soil, vegetation and anthropogenic factors from published studies and open databases. Values from all gridded environmental layers were extracted for each independent sample point based on its location, sampling year, and sampling depth where appropriate. Monthly data were integrated into annual data. More details can be seen in Table S2 in the Supplementary materials.

2.3.1. Climate

The dynamic mean maximum/minimum temperature and total precipitation at a 60 arc-second resolution (approximately 2 km) were from MacDonald et al (2020). We download climate background condition indices, including high-resolution (~1 km) bioclimatic variable BIO1 (annual mean temperature) and BIO12 (annual precipitation) from WorldClim (https://worldclim.org/) and aridity index from Zomer et al. (2022).

2.3.2. Topography

Topography directly influences soil carbon accumulation and redistribution, and indirectly influences micro-climates that support species diversity and resilience to climate change. We derived elevation and slope from the USGS 3DEP on the GEE (google earth engine) platform. We also downloaded topographic diversity (td), physiographic diversity (pd), continuous Heat-Insolation Load Index (chili) on GEE provided by Theobald et al. (2015).

2.3.3. Soil

Soil water and temperature reflect the status within soil and directly influence the microbial activities. We collected the dynamic water content and temperature of topsoil (0–28 cm) and subsoil (28–100 cm) at 0.1° by 0.1° resolution from the dataset of ERA5-Land on GEE platform (Copernicus Climate Change Service, 2019). Additionally, soil background condition indices were downloaded or derived, including lithology (soil parent material) from Theobald et al. (2015), clay and available water content (awc) from gNATSGO (Soil Survey Staff, 2023).

2.3.4. Vegetation

Vegetation biomass determines the amount of litter (leaves, branches, etc.) and root input to the soil, which are important sources of SOC (Sun et al., 2021). NPP can represent the net accumulation of vegetation biomass, but the longest NPP observations can only date back to the 1980s. We downloaded the dynamic NPP data from Liang et al. (2021). Ecoregions represent unique assemblies of biodiversity, encompassing all taxa essential for maintaining ecological processes. The RESOLVE Ecoregions dataset was downloaded from GEE (Dinerstein et al., 2017).

2.3.5. Nitrogen

Nitrogen is a key nutrient for plant growth and soil organisms, thus influencing SOC dynamics (Bala et al., 2013). Human-driven changes in nitrogen inputs to soils have evolved over time. We collected two long-term nitrogen addition indicators: annual atmosphere nitrogen wet deposition from the National Trends Network (https://nadp.slh.wisc.edu/maps-data/), and annual grid-based surface and deep total nitrogen fertilizer application amounts from Adalibieke et al. (2023).

2.4. Geographic environmental representativeness of the collected samples

To examine the representativeness of the collected soil samples, we adopted the Mahalanobis distance (Mahalanobis, 1936) to assess how well a grid location fits within the multi-dimensional environmental space of the SOC profiles in each ecosystem for each five-year period. This multi-dimensional environmental space is defined by five basic geographic environmental variables: elevation, slope, annual mean maximum/minimum temperature and total precipitation ignoring the fluctuations within the five-year period. The distance of a certain grid location higher than a specified threshold indicates that the environmental condition at that location is reasonably incapable of being represented by the multi-dimensional environmental space. We set the threshold as $\chi^2 = 0.975$ in our study, following Patoine et al. (2022). The result of this part is shown in Fig. S2 in the Supplementary materials.

2.5. Moving subset window analysis

To generate robust and reliable estimates of temporal trends of SOC stock on a continental scale since the 1970s, we conducted a one-dimensional moving subset window analysis to reduce noise in the temporal examination of SOC stock. The sliding window (moving subset) algorithm is an effective data processing technique for handling time-series data (Jin et al., 2018). It reduces the instability of estimates caused by data fluctuations or noise, particularly in cases of small sample sizes or data with temporal correlations. This method has been employed in long-term environmental change studies, such as examining changes in the atmospheric carbon dioxide fertilization effect (Obermeier et al., 2017), global temporal changes in soil respiration rates (Lei et al., 2021) and soil microbial carbon and nitrogen (Shi et al., 2024).

In particular, all SOC stock data in each ecosystem were arranged in ascending order of the sample years. Then, they were iteratively divided into subsets using a 20-year moving window as the minimum detectability threshold for changes (Smith et al., 2020). Consequently, the first subset includes the first 20 years of SOC data, with subsequent subsets formed by removing the earliest year and adding the next new year. Finally, linear regression between SOC stock and year was performed for each subset, with the slope and *P*-value indicating the rate of SOC stock changes and its significance, respectively. To ensure that the trends of linear regression were not affected by anomalous data, we built linear regressions using the Theil-Sen estimator with the R package '*mblm*'. This is a median-based linear model, which is a robust measure of central tendency that is less affected by extreme values (Birkes and Dodge, 1993).

2.6. Examination of temporal relations between SOC stock and environmental variables

To explore these confounding relationships temporally, we propose a hybrid analytical framework that incorporates moving subset windows analysis with statistical methods. First, to depict 45-year temporal variability of dynamic environmental factors as well as SOC, average values (e.g., median) over time were derived by conducting moving subset window analysis using a 20-year time window. We then also conducted partial correlation analysis between these temporal average values of SOC and environment factors using the '*ppcor*' package in R, which allowed us to account for interdependencies. To examine responses of SOC dynamics to the warming rates, both linear and quadratic regressions were performed referencing the methodology of Sáez-Sandino et al. (2023). Specifically, we built optimal regressions (linear or quadratic) between rates of SOC change and temperature change from 1970 to 2014 at two depths across two ecosystems. The change rates (e.g., slope) of SOC stock and temperature on the continental scale over time were derived by conducting moving subset window analysis using the 20-year time window from 1970 to 2014.

2.7. Spatial pattern of SOC stock change trends

By adopting a spatio-temporal digital soil mapping (ST-DSM) approach (Heuvelink et al., 2021), we generated SOC stock data at five-year intervals from 1970 to 2014. The data resolution matched that of climate data (~2 km). ST-DSM establishes relationships between SOC and relevant dynamics and static environmental factors (such as temperature and elevation) for all available factors. Using these relationships, the model then estimates the spatial distribution of SOC for each specific time by applying the corresponding environmental conditions. The environmental factors details can be seen in Table S2. We ensured good spatial representativeness of the geographic environment at five-year intervals (Fig. S2 and Fig. S3a in the Supplementary materials). Therefore, mean values of dynamic environmental covariates for each interval were adopted as environmental predictors. For NPP and nitrogen wet deposition dataset which is not available in 1970s, the value of the earliest year was set as replacement. Recursive Feature Elimination was applied to identify the optimal combination of covariates (Nussbaum et al., 2018).

Given the differing mechanisms driving SOC changes across depths and ecosystems, we developed separate Quantile ERandom Forest (QRF) models for two layers respectively in forest and cropland to predict SOC stock at five-year intervals using '*caret*' package in R. The model accuracy was validated using ten-fold cross-validation (Fig. S4 in the Supplementary materials). Lastly, SOC stock map for each five-year interval (e.g., 1970–1974, etc.) was predicted. The SOC change trend over a given time period (e.g., 1970–2014) was calculated using linear regression for each pixel, with the SOC stock value as the dependent variable and the corresponding year (taken as the first year of every five-year interval) as the independent variable (Shen et al., 2023).

3. Results

3.1. Halts of topsoil and subsoil SOC stock losses since the 1990s

The temporal trend of SOC stock from 1970 to 2014 shows that both forest and cropland soils exhibited two stages of changes, experiencing losses during rapid warming since 1970 (Fig. 2a and b), while the SOC stock losses halted or even shifted to increases as warming slowed down since the late 1990s. This shows a good association between SOC and temperature change (Fig. 2c and d). These results are robust against potential spatial data imbalances, as evidenced by the good spatial representativeness of samples, i.e., the average spatial representativeness of the soil profiles up to 82 % for forest and to 86 % for cropland (Fig. S3a). Besides, the boxplot of SOC stock at five-year intervals (Fig. S3a) also shows a similar changing trend with Fig. 2.

Topsoil and subsoil in forest exhibit a similar 'loss-gain' two-stage pattern. In cropland, only subsoil loss turned to a carbon gain stage, while topsoil turned to a steady state started from the window of 1986–2005. Interestingly, in contrast to forest, the magnitude of SOC change in the subsoil of cropland is more pronounced than those in the topsoil. And cropland subsoil retains a more significant amount of SOC stock compared with forest subsoil (Fig. S3b). These results emphasize the distinct SOC dynamics in surface and deeper layers in different ecosystems.

3.2. Relationships between SOC with temperature and other factors over time

The partial correlation analysis shows that the significant factor associated with SOC stocks depends on soil depths (topsoil vs. subsoil) of both ecosystems (Fig. 3). In forest, temperature (Tmax) (partial *r*, −0.69) and NPP (partial *r,* 0.69) were the main factors associated with topsoil SOC stock significantly. Additionally, a positive relationship was observed between Tmax and NPP (partial *r,* 0.47). This suggests that SOC losses may be caused by even faster increasing respiration (carbon output) since warming enhanced carbon input through promoting NPP in forest topsoil. For cropland topsoil, temperature is also negatively related to SOC changes with the strongest partial correlation (partial *r,* −0.56), followed by surface nitrogen fertilizer application amount (Nf_s) (partial *r,* 0.49) and total nitrogen wet deposition (TNWD) (partial *r,* −0.48). These findings indicate consistent key negative associations between temperature and topsoil SOC stock over time across both ecosystems. Meanwhile, nitrogen deposition also showed a negative association with SOC stock in cropland topsoil, while nitrogen fertilization showed a positive association.

In subsoil, forest SOC change showed the strongest negative correlation with soil water content (SoilW) (partial *r,* −0.62), followed by total nitrogen wet deposition (partial *r,* −0.46). These relationships may indicate that higher soil water content and nitrogen deposition amount tend to co-occur with reduced SOC stocks in forest subsoil, while the opposite conditions may be beneficial for SOC accumulation. We also found a significant positive relationship between soil water content and NPP, but an insignificant positive relation between NPP and SOC might imply a weak positive role of soil water content on subsoil SOC accumulation through promoting NPP. For cropland subsoil, SOC change exhibited associations with a broader set of factors than forest. The strongest negative correlation was observed with the soil water content (partial *r,* −0.85), followed by temperature, TNWD, deep nitrogen fertilizer application amount (Nf_d), and NPP, with partial correlation coefficients of −0.64, −0.64, 0.56, and 0.54, respectively. Similar to forest subsoil, these quantified correlations suggest that increases in soil water content and TNWD were associated with SOC decreases in cropland subsoil, while increased nitrogen fertilization amount at deep placement and vegetation productivity were correlated with SOC accumulation. Unlike the weak correlation in forest subsoil, significant and stronger correlations were observed between temperature and SOC stock in cropland subsoil, indicating that higher temperatures also might contribute to subsoil SOC decreases in cropland.

3.3. Relationships between SOC change and temperature change rate

Linear negative relations were identified between the change rate of annual mean maximum temperature and SOC stock in both depths in forest and cropland are found to be significant ($P < 0.001$) (Fig. 4). These regressions resulted from change rates of profiles reveal a threshold effect of warming rate on SOC loss, namely, carbon gains convert to losses (from positive to negative) once the rate of temperature increase surpasses a certain threshold (the *x*-intercept where the regression line crosses SOC change rate becomes 0). Additionally, we observed that in forest, the thresholds of warming rate were similar for topsoil and subsoil, while in cropland topsoil, the threshold was lower than subsoil. These results indicate that faster warming can lead to faster SOC losses in the whole-profile of two ecosystems, but high temperature alone does not necessarily result in SOC depletion when the warming rate slowdowns. This is also supported by the weakened negative relationship between temperature and SOC stock at the highest temperature level in the 2010s (Fig. S6 in the Supplementary materials).

3.4. Spatial patterns of SOC stock changes

From 1970 to 2014, the spatial pattern of SOC stock changes in the top 1 meter demonstrated shifts in both forest and cropland across two stages, with most areas showing opposite trends between the first (Fig. 5a and d) and second stages (Fig. 5b and e). During Stage I, forests in the northeastern high-latitude regions and along the East Coast experienced substantial SOC losses exceeding 0.2 Mg ha^{-1} yr^{-1}, while large parts of western forests, such as the Pacific Northwest and northern Rocky Mountains, exhibited SOC gains of similar magnitude. However, in Stage II, characterized by decelerated warming, the direction of carbon change reversed in nearly all forest areas. Overall, we found that approximately 54 % of the stable forest showed SOC stocks gains over the 45-year period (Fig. 5c). SOC stocks in stable forests within the top 1-meter depth across the CONUS increased by 1.41 % (from 19.05 Pg to 19.32 Pg) (Table S4 in the Supplementary materials). Additionally, SOC

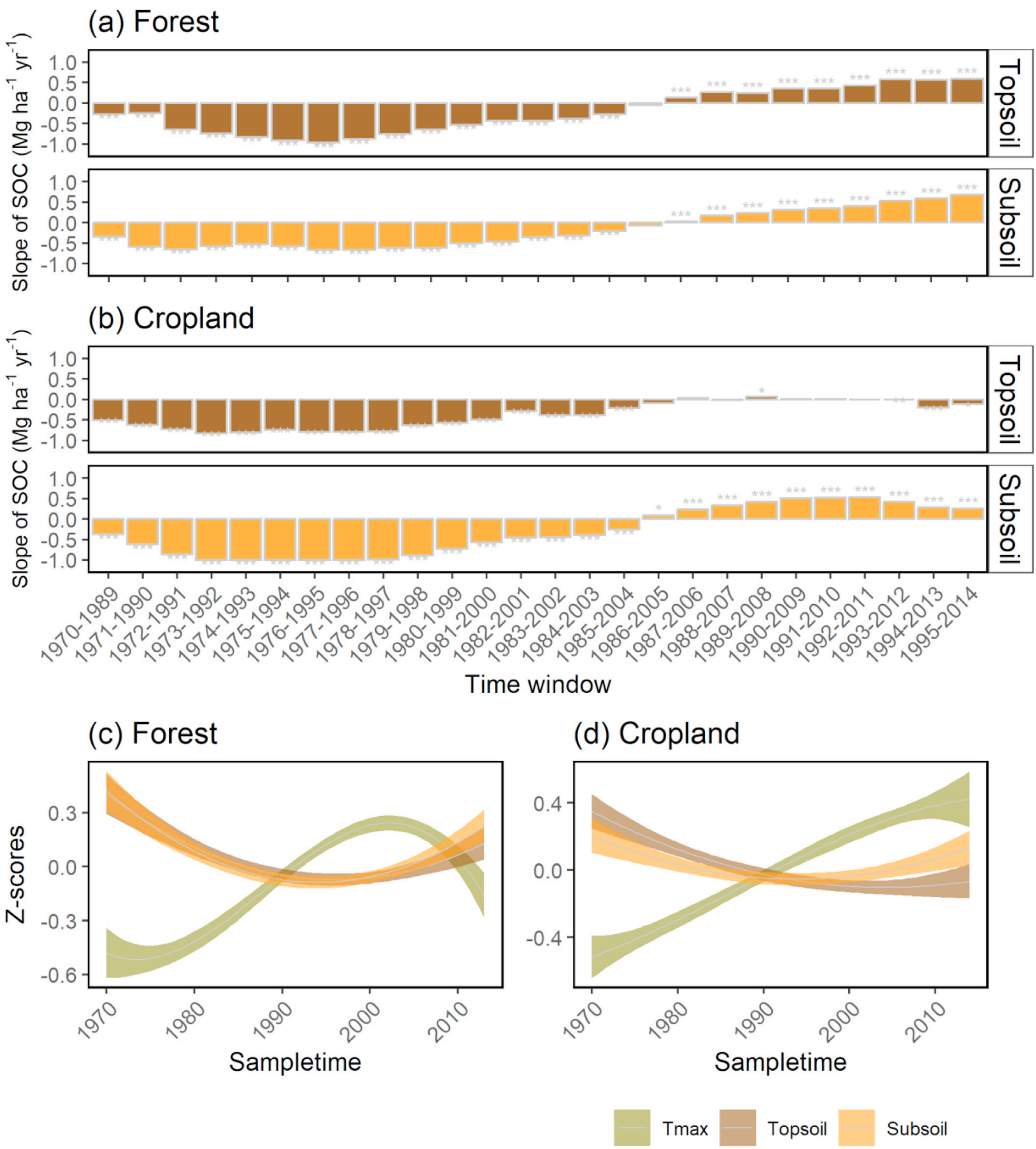

Fig. 2. The trends of topsoil and subsoil SOC stock changes. SOC stock trends were calculated based on a moving subset window approach in cropland (a) and forest (b). The bar indicates the slope of SOC stock change in each two decades. Stars above the bars indicate the significance of slopes: $^{***}P < 0.001$, $^{**}P < 0.01$, $^{*}P < 0.05$. To compare trends of temperature and SOC in forest (c) and cropland (d), we standardized each factor using the *Z*-scores method, then fit the curves using polynomial regression. To keep the consistency, the polynomial degree was set to be 3 for temperature, and 2 for SOC based on a sensitive experiment as shown in Fig. S5 in the Supplementary materials.

gains were more frequently observed in forest located in relatively arid and higher-altitude regions with higher topographic and physiographic diversity (Fig. 6).

During Stage I, large areas of cropland experienced severe carbon losses. However, the core region of the Corn Belt, along with croplands in Kansas and Oklahoma, showed obvious SOC gains during this stage. In Stage II, regions that had previously experienced severe SOC losses showed recoveries. However, a larger proportion of stable cropland areas (45.1 %) compared to forest showed SOC losses over the 45-year period (Fig. 5f). Overall, SOC stocks in stable cropland within the top

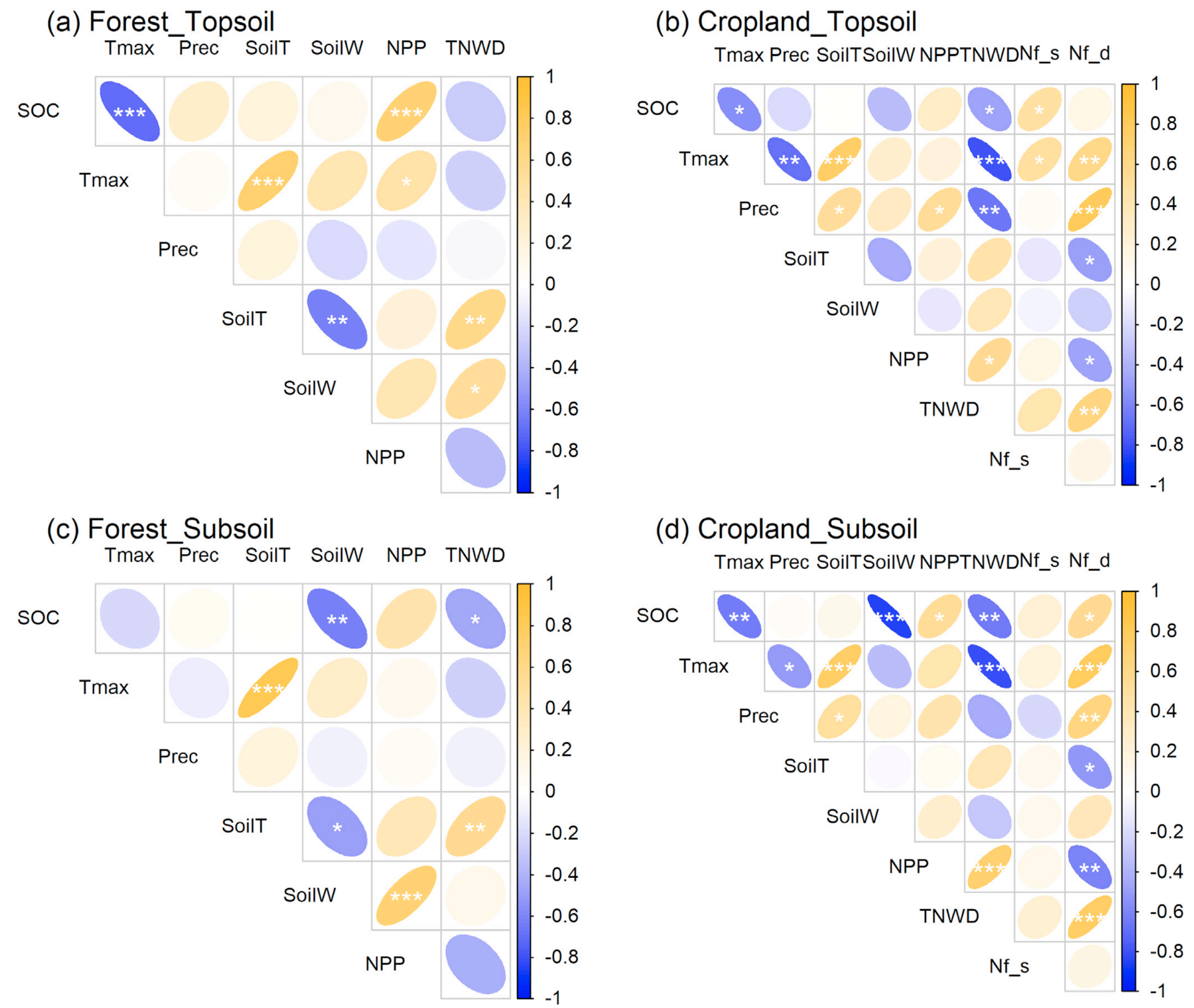

Fig. 3. Temporal relationships among environmental factors. Partial correlation coefficients (partial *r*) among averages of all variables in each twenty-years-window in forest topsoil (a), cropland topsoil (b), forest subsoil (c) and cropland subsoil (d). The orientation and color of ellipses indicate the sign of correlation, with color intensity representing the strength. Significance levels: $^{***}P < 0.001$, $^{**}P < 0.01$, $^{*}P < 0.05$. Abbreviations are as follows: SOC, soil organic carbon stock; Tmax, annual mean maximum temperature; Prec, annual total precipitation; SoilT, soil temperature; SoilW, soil water content; NPP, net primary production; TNWD, total nitrogen wet deposition; Nf_s, surface total nitrogen fertilizer application amount; Nf_d, deep total nitrogen fertilizer application amount.

1-meter depth across the CONUS increased by 1.14 % (from 13.1 Pg to 13.25 Pg). Unlike forest, the environmental characteristics of regions with SOC gains and losses in croplands were not very different except for the topographic diversity (Fig. 6).

4. Discussion

4.1. Two-stage of SOC change

From 1970 to 2014, analysis of SOC dynamics across the CONUS revealed a two-stage pattern in both forests and croplands, evident at continental and regional scales. Inconsistencies found in previous studies (Table S5 in the Supplementary materials) imply that examining only segments of one period could lead to misunderstandings about the SOC changes and their relationship with temperature changes.

Our findings suggest that the halts of SOC losses in the CONUS coincide temporally with the deceleration of warming, supporting our hypothesis that SOC responses vary depending on temperature change rates. And our regression analysis between SOC change and temperature change rates identified a threshold effect of warming rates on SOC changes. This threshold phenomenon suggests that lower warming rates may promote SOC accumulation instead of losses. This continental-scale finding is consistent with the Tibetan alpine grassland case study showing differential effects at +2 °C versus +4–6 °C increasing level of temperature (Liang et al., 2024). A global study reported a plateau in soil respiration rates during 2000–2016 compared with a rapid rise during 1987–2000, which may help explain our results on a large spatial scale. Similarly, another global study reported a two-stage change in topsoil (0–30 cm) microbial carbon, with stabilization during 1988–2014 followed by a decline after 2015 when warming accelerated again (Shi et al., 2024).

Our study further demonstrated that similar threshold-driven dynamics of warming rates occur in deeper soil layers (30–100 cm). Notably, we found that forest exhibited a more pronounced recovery than cropland in both topsoil and subsoil. Additionally, during the warming hiatus, we found that the observed halts of SOC stock losses (especially

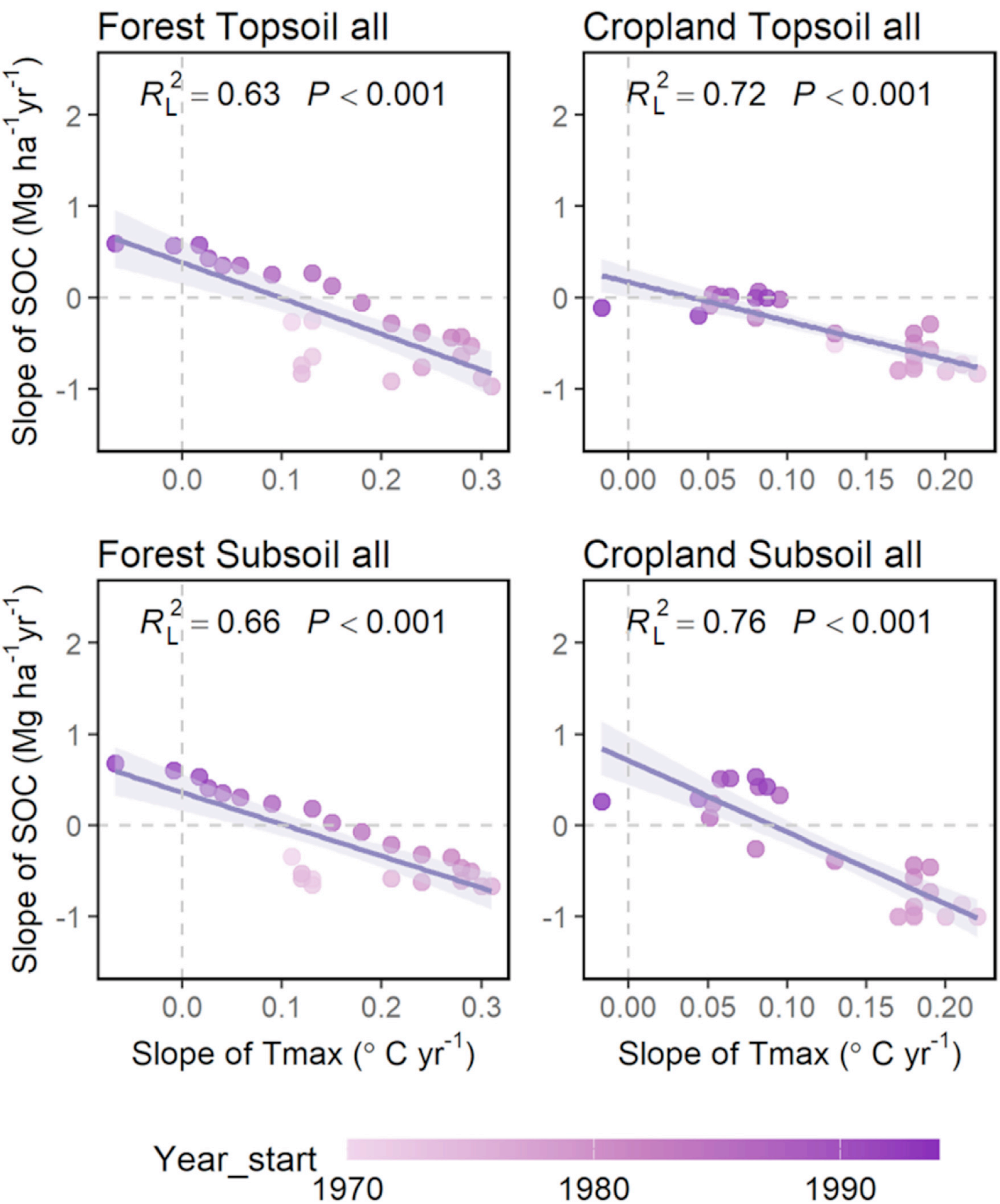

Fig. 4. Regressions between change rate of SOC stock and warming. The dots represent the slope of SOC stock in each twenty-year-wide moving window from 1955 to 2014. The lines represent the fitted linear regressions (L) selected between the linear regression or quadratic regression. Statistical supports for these regressions are provided in Table S3 in the Supplementary materials.

in the subsoil of both ecosystems) may be in part caused by changes in other environmental factors, such as the possible slowed SOC decomposition due to the reduced soil water content (Fig. 1c and d) under droughts (Peterson et al., 2013), increased NPP in forest (Fig. S7 in the Supplementary materials) and nitrogen fertilization in cropland (Fig. S8 in the Supplementary materials). These findings underscore the need for more studies on the role of varying warming rates in long-term SOC changes and considering influences from other factors, which will enhance our ability to model the nonlinear characteristics of SOC fluctuations.

The regional pattern demonstrated that under conditions of rapid warming, a higher proportion of forest areas experienced SOC gains, particularly in western and southern regions characterized by relative low aridity, higher elevations and complex topography (Fig. S9a in the Supplementary materials). Due to that these areas support higher biodiversity, which can enhance carbon sequestration (Spohn et al., 2023). However, in Stage II, these regions showed SOC losses with less differences of geographic characteristics (Fig. S10b), suggesting that the negative impacts of sustained high temperatures outweighed the benefits of the deceleration in warming in western and southern regions. Conversely, most croplands experienced SOC losses during Stage I, but a greater proportion displayed SOC gains in Stage II (Fig. S10 in the Supplementary materials). These recoveries can be attributed to both the slowing pace of warming and improved agricultural management prac-

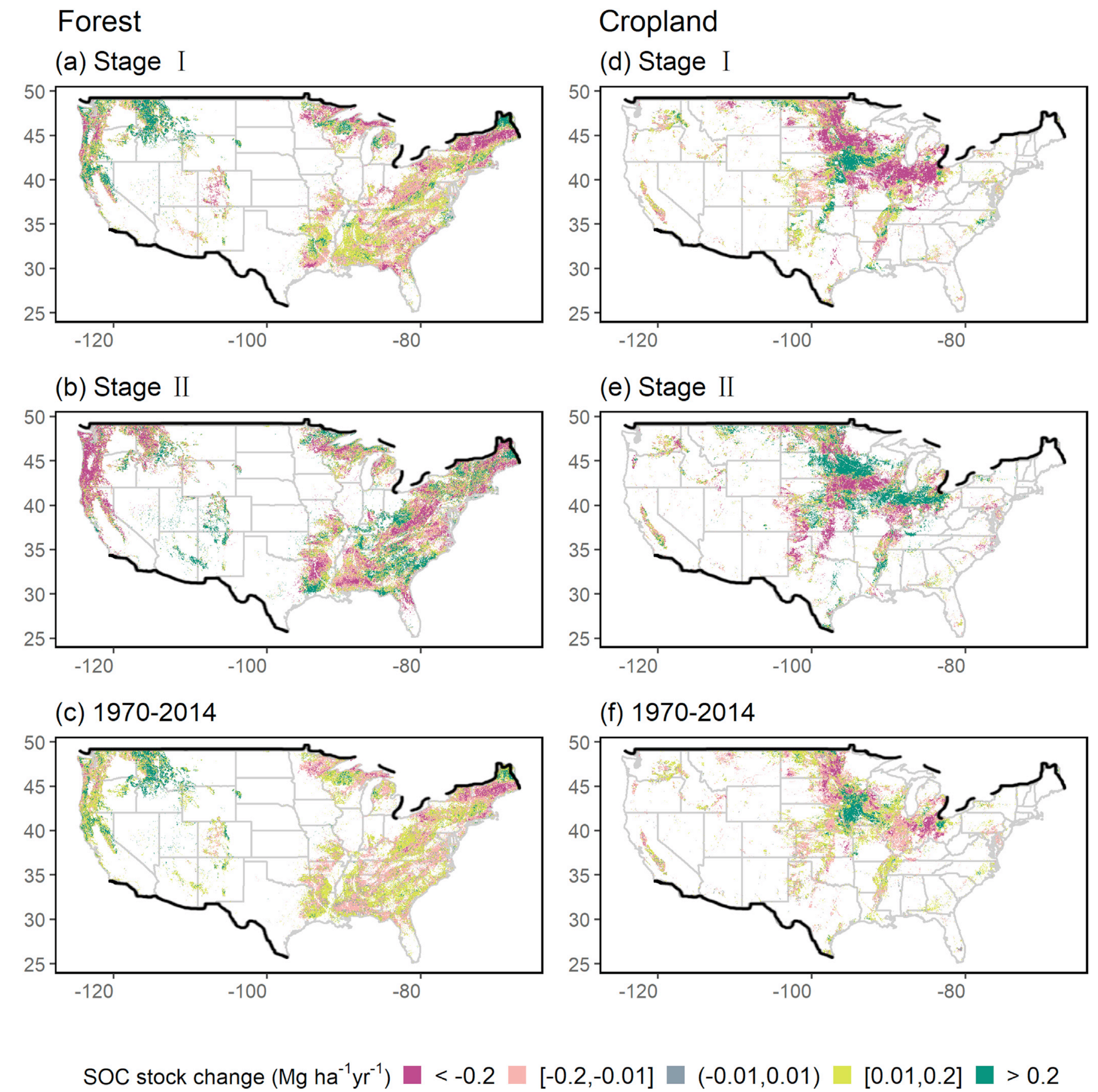

Fig. 5. Spatial pattern of SOC stock change in the top 1 m of the CONUS. The SOC change was the slope of linear regression, with the SOC stock value as the dependent variable and the corresponding year as the independent variable. Stage I includes the data from 1970 to 1974 to 1995–1999, and Stage II includes the data from 1995 to 1999 to 2010–2014.

tices, such as optimized fertilization and crop residue retention (Fig. S11 in the Supplementary materials).

4.2. Depth- and ecosystem-dependent SOC changes

Our findings indicate that prominent SOC changes occur not only in the topsoil, but also in the subsoil, although subsoil SOC stocks have traditionally been considered relatively stable, largely due to enhanced chemical and physical protection mechanisms at deeper layers (Luo et al., 2019). In forest, both topsoil and subsoil displayed consistent change patterns, but subsoil exhibited greater resistance to carbon loss, as it experienced smaller losses during periods of depletion and accumulated more carbon than the topsoil during recovery stages. In contrast, the cropland SOC in subsoil was even more responsive than in topsoil during the two phases of temperature change. The more carbon loss of subsoil than topsoil during the first phase with high warming rate is consistent with the finding in China cropland (Zhou et al., 2025), indicating that changes in subsoil are just as obvious as those in topsoil under rapid warming. During the warming hiatus phase, subsoil SOC stocks increased in both ecosystems, suggesting that subsoil may contribute to carbon sequestration under temperature fluctuations. Possible explanations for the carbon sequestration potential in subsoil include reduced direct warming effects and a stronger dependence on soil moisture relative to topsoil based on our results. These insights un-

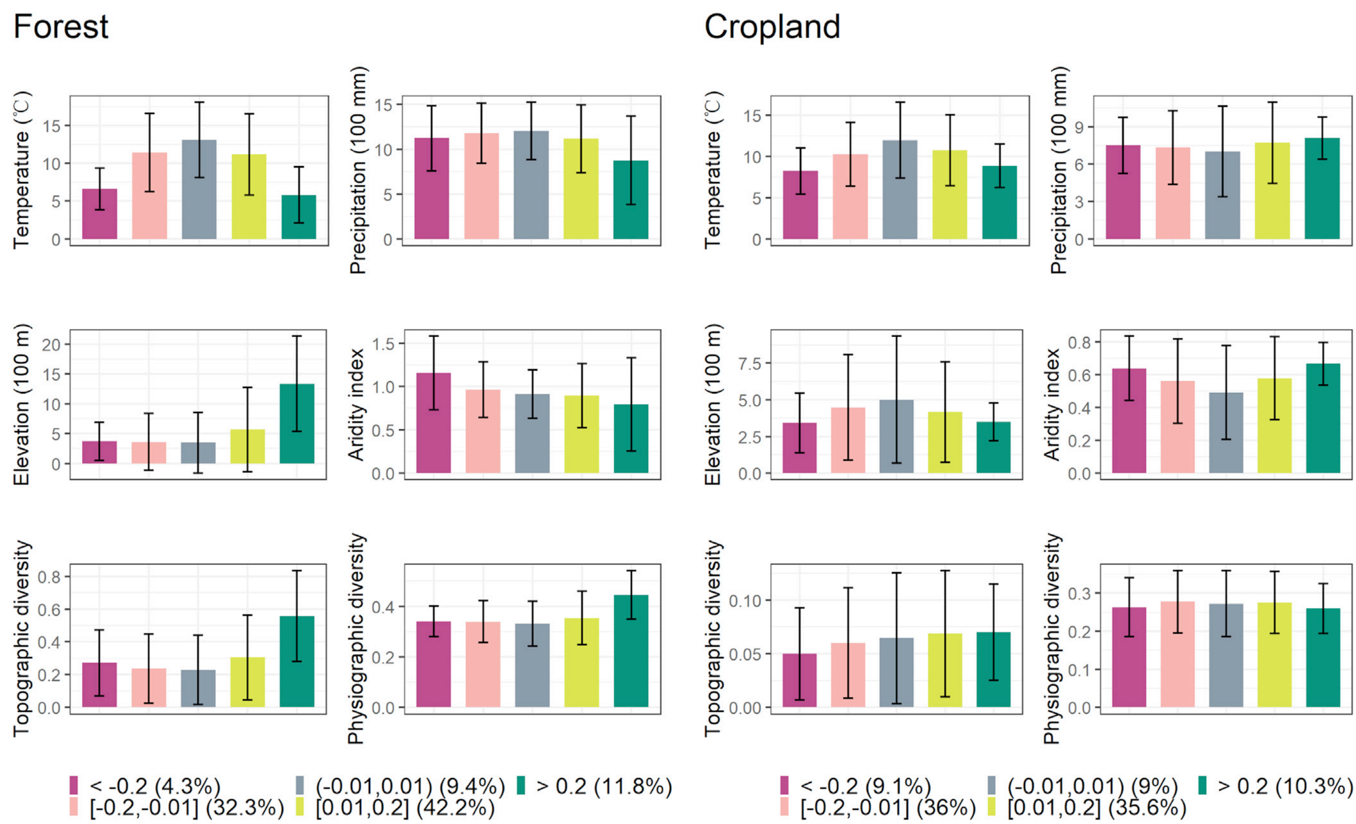

Fig. 6. Background environment of SOC stock change types from 1970 to 2014. The percentages in parentheses represent the proportion of each type's area relative to the total area. The classification of types is based on the magnitude of slope, as detailed in Fig. 5. The error bars represent the mean ± standard deviation (SD).

derscore the instability of SOC stock both in topsoil and subsoil under climate warming and suggest the sensitivity of subsoil and topsoil to environmental changes varies across different ecosystems.

4.3. Distinct dominated factors influencing topsoil and subsoil SOC dynamics

Our findings reveal that temperature was the most influential factor potentially driving topsoil SOC changes, which is consistent with expectations from warming experiments. Our results further highlight distinct influence of other factors in each ecosystem. In forest ecosystems, the positive role of increased NPP on topsoil SOC cannot be overlooked. Similar trade-off between SOC and plant-derived C were found in the forest ecosystem by a meta-analysis of warming experiments (Lu et al., 2013). But our results indicate the rise in soil respiration could ultimately lead to overall net SOC losses in forest topsoil of the CONUS under rapid warming from 1970s to 1990s. Meanwhile, our results support the view that nitrogen influences cannot be ignored in cropland topsoil carbon dynamics (Beillouin et al., 2023). Previous studies found that nitrogen addition can enhance plant growth and thus organic carbon input, but excessive nitrogen can also lead to increased organic matter decomposition and potential SOC loss (Bala et al., 2013). In our study, despite both being nitrogen addition, nitrogen fertilization may have a positive effect on SOC with a positive partial correlation, whereas nitrogen deposition has a negative correlation in the topsoil of cropland. This divergence may be due to differences in nitrogen sources under varying human management context (Bala et al., 2013; Deng et al., 2020). While nitrogen fertilization is primarily aimed to increase crop yields (thereby enhancing plant carbon inputs), modern agricultural practices that combine fertilization with organic amendments and residues management (Fig. S12) may further benefit soil health and carbon accumulation (Lu et al., 2011; Bai et al., 2023), especially as the United States has actively promoted organic fertilizers since the 1980s (Harwood, 1993). This potential positive effects of nitrogen fertilization was consistent with a global meta-analysis (Ling et al., 2025). In contrast, the nitrogen deposition, as an inorganic nitrogen source without complementary management, may primarily accelerate carbon decomposition (Song et al., 2020; Püspök et al., 2023) or changing the stability of SOC (Bala et al., 2013; Tang et al., 2023) on a long-term scale.

For subsoil SOC dynamics, soil water content emerges as a crucial negative factor in both forest and cropland. Yet, the relative importance of soil moisture among SOC drivers is not well studied and the responses of SOC to moisture are less uniformly described than temperature in some models (Pallandt et al., 2022). Given the lower carbon density and higher proportion of mineral-associated organic carbon (MAOC) in subsoil compared to topsoil, the importance of soil moisture in subsoil is likely because water availability typically limits microbial and enzymatic activities more strongly than temperature (Guo et al., 2024). The elevated moisture may override this limitation by undermining physical protection of subsoil SOC (Cates et al., 2022; Hao et al., 2025), thereby enhancing SOC decomposition. This result aligns with evidence that excessive saturation can disrupt carbon stabilization where mineral surfaces dominate stabilization (Huang and Hall, 2017). Apart from soil moisture, atmospheric nitrogen deposition also has significant negative impacts on subsoil carbon in both forest and cropland. This result agrees with the long-term negative effects of nitrogen deposition on subsoil (Hu et al., 2024), suggesting a long-term monitoring of the effect of atmospheric nitrogen deposition on subsoil carbon dynamics is needed. Additionally, subsoil SOC stock in cropland is also significantly positively influenced by deep nitrogen fertilization and NPP. The stronger positive effects of NPP on subsoil SOC, compared to topsoil, highlights different mechanisms of subsoil SOC accumulation in cropland. These insights underscore the variation of carbon change mechanisms across different soil depths and ecosystems and the need for targeted management strategies to enhance carbon storage.

Some studies have utilized spatial temperature or precipitation gradients to elucidate carbon-climate relationships, while our data shows that the temporal patterns of these relationships (Fig. 3) are significantly more pronounced compared to those derived from spatial patterns (Fig. S12). This highlights the importance of examining temporal relationships among environmental factors to gain a more accurate understanding of their impacts on SOC changes.

4.4. Limitations and outlook

It is important to note the limitations of this study. First, similar to any observational analysis, there may be underlying bias caused by the spatial and temporal inconsistency of soil profile data. Our 10,639 soil profiles have generally good spatial representativeness, especially for the cropland, as can be seen from Fig. S2. The relatively low representativeness for Florida and forest in areas of the Rocky Mountain suggests the necessity for more observations to investigate these regions. Second, our study area (25°N to 49°N) mainly experiences a temperate climate, so the findings may not represent other climate conditions, such as tropical and arctic climates. Third, our analysis of environmental drivers of SOC changes faces inherent limitations due to data constraints. While the moving window approach successfully captured continental-scale temporal correlations between SOC dynamics and environmental factors, its limitations in sample size—combined with the lack of long-term resampled SOC observations under real environmental conditions—constrain our ability to reliably investigate more complex interactive effects or conduct detailed analyses across environmental gradients (e.g., variations in initial clay content or climate type among samples can influence the SOC changes). We stress that the partial correlations identified in this study reflect statistical associations rather than demonstrated causal relationships, therefore, these continental-scale correlations warrant targeted investigation into the specific mechanisms, such as the subsoil SOC responses to dynamic soil moisture. In addition, some important dynamic factors (e.g., atmospheric CO_2 concentration, microbial traits, harvesting and fires in forest) are not considered due to lack of long-term high-resolution data and the resolution of available data, such as the spatial resolution of soil water content is also relatively low. With improvement of the spatial and temporal resolution of related data, future studies incorporating experimental manipulations, long-term monitoring, and causal inference approaches will be essential to validate and mechanistically explain these large-scale SOC changes.

Our study shows a halt of SOC stock loss in forest and cropland in the CONUS since the 1990s following the warming-induced loss since the 1970s. However a noticeable accelerated increase in temperature in the U.S. since 2015 (Modak and Mauritsen, 2021) might contribute to renewed SOC losses in forest and cropland. More available data after 2014 can extend and verify our findings. Accordingly, in forest, as vegetation growth is increasingly vulnerable as the global CO_2 fertilization effect declines (Wang et al., 2020), it is necessary to assess how current shifts in vegetation growth impact SOC storage in forest presently and in future. This is particularly critical for forests at higher elevations. As for cropland, by tailoring fertilizer strategies to topsoil and subsoil, we can potentially enhance soil carbon sequestration in a more sustainable manner. Importantly, threshold effects of warming rates on SOC change are noticeable but the specific threshold values identified in this study (e.g., the about 0.1 $^{\circ}C\ yr^{-1}$ warming rate threshold for SOC loss in forest topsoil) should be interpreted with caution. The environmental change represented by our profiles may amplify the observed effects, potentially influencing these quantitative estimates. Hence, our findings highlight the critical need for future mechanistic experiments on SOC dynamics to consider the effects of warming rates across the entire soil profile and to validate the observed threshold effects. These results further emphasize that Earth system models should adopt ecosystem-dependent and depth-dependent parameters to better capture the complex, nonlinear responses of SOC to climate change. Our findings not only provide a deeper observational understanding of a whole-profile SOC dynamics on a continental scale, but also offer practical insights for addressing the sustainable development challenges posed by global climate change.

5. Conclusions

This study, as one long-term (1970–2014) and large-scale analysis of SOC change based on field measurements, provides a comprehensive understanding of the soil organic carbon (SOC) in forest and cropland across the CONUS. By leveraging whole-profile SOC measurements and integrating temporal analysis with statistical methods and machine-learning, our data indicates a robust ecosystem-dependent two-stage change of SOC stock, characterized by continental-scale halts in SOC loss following warming deceleration since the late 1990s. Overall, SOC stocks increased by 1.41 % (from 19.05 Pg to 19.32 Pg) in forest and 1.14 % (from 13.1 Pg to 13.25 Pg) in cropland within the top 1-meter across the CONUS. Our results revealed that the two-stage patterns across both topsoil and subsoil might be closely related to the warming rates change, with a threshold effect of warming rates on SOC loss. Partial correlation analyses highlight that the temperature is likely the primary factor influencing topsoil SOC stock, showing the strongest significant negative partial correlations in both forest and cropland. Meanwhile, soil water content emerged as the dominant factor correlated with subsoil SOC changes, exhibiting significant negative correlations in cropland and forest. Furthermore, various other environmental factors across different soil depths and ecosystems suggest the need for targeted management strategies to enhance carbon storage, such as the possible positive effects from increasing NPP on forest topsoil and nitrogen fertilization on two layers of cropland. These findings emphasize the necessity of capturing responses of whole-profile SOC dynamics to varying warming rates and combined effects from different environment drivers, which supports the modeling of long-term carbon fluxes and formulation of ecosystem and depth-dependent strategies to achieve carbon neutrality for sustainable development in the context of global climate change.

Declaration of competing interestss

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Feixue Shen: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lin Yang:** Writing – review & editing, Resources, Project administration, Funding acquisition, Conceptualization. **Lei Zhang:** Writing – review & editing, Validation, Methodology, Formal analysis. **A-Xing Zhu:** Writing – review & editing, Visualization, Investigation. **Xiang Li:** Writing – review & editing, Validation. **Chenconghai Yang:** Validation, Data curation. **Chenghu Zhou:** Project administration, Funding acquisition. **Yiqi Luo:** Writing – review & editing, Formal analysis. **Shilong Piao:** Writing – review & editing, Resources.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.geosus.2025.100359.

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