Catena 252 (2025) 108777

Contents lists available at ScienceDirect

Catena

journal homepage: www.elsevier.com/locate/catena

Silent soils have been awakened by climate change

Dongliang Han [a,b], Jianping Huang [a,b,*], Xiaoyue Liu [a,c], Li Fu [a,b], Lei Ding [a,d], Guolong Zhang [a,b], Changyu Li [a,b], Fan Yang [a,b], Jinsen Shi [a,b], Beidou Zhang [a,b]

[a] *Collaborative Innovation Center for Western Ecological Safety Lanzhou University Lanzhou China*
[b] *College of Atmospheric Sciences Lanzhou University Lanzhou China*
[c] *Saw Swee Hock School of Public Health National University of Singapore Singapore*
[d] *Institute of Disaster Prevention Sanhe City Hebei Province China*

ARTICLE INFO

Keywords:
Oxygen footprint barrier effect
Anthropocene
Method of optimal soil quality index
Tibetan Plateau
Detection

ABSTRACT

We propose a theory of atmospheric oxygen footprint barrier effect. This effect is specifically characterized as the influence exerted by the atmospheric oxygen content upon climate forcing. Under low oxygen content and low-density atmosphere, shortwave scattering from oxygen molecules is less frequent, resulting in a substantial increase in surface shortwave temperature forcing. Whether the significant changes in the oxygen footprint indicate the accelerated change in soil quality over the Tibetan Plateau is largely unknown. Here, we combine six soil quality index methods with more than forty environmental factors, including climatic, plant, soil and microbial properties, to explore the determinants of soil quality along a 2200 km grassland transect over the Tibetan Plateau. We find that there is a significant reduction in the oxygen footprint during the period from 2006 to 2099, and this finding is based on the projection of the ensemble mean of Fifth Coupled Model Intercomparison Project (CMIP5) models, under representative concentration pathways (RCPs) RCP4.5 and RCP8.5, respectively. The standardized total effects of climatic, plant, soil and microbial property on the soil quality was −0.48, 0.87, 0.96, and 0.11, respectively. The surface temperature acts as a major climatic factor that regulates soil quality changes through modifying biological (effect-size: 0.20) and physiochemical (effect-size: 0.91) pathways. Consequently, in the context of soil quality change, biological mechanisms are the main drivers and physiochemical mechanisms are the results. On these grounds, we develop a novel conceptual framework to identify the crucial role of soil quality in arid-cold ecosystems under climate change.

1. Introduction

Oxygen footprint (Of) is defined as the ratio of oxygen consumption (Oc) to oxygen production (Op) (Han et al., 2021). Under the high (RCP8.5) emission scenarios, Han et al. (2021) found significant linear regression ($P < 0.01$) positive relationships between Of and air temperature, potential evapotranspiration, precipitation, and dryland areas, respectively. When Op is unsustainable (for example, water limitation to plant growth) combined with Oc (for example, extensive fossil-fuel combustions), this scenario will accelerate land ecosystem imbalance (Han et al., 2022). Soil degradation (Table 1) caused by land ecosystem imbalance may lead to the loss of soil organic carbon, affecting the photosynthesis rate of vegetation capable of absorbing CO_2 and emitting O_2. This alters atmospheric Of and creates positive feedback that expedites global warming. As a result, global land surface temperatures increase as O_2 content decrease, which may enhance the warming forcing of CO_2, and ultimately restrain soil ecosystem growth (Poulsen et al., 2015; Huang et al., 2020).

Soil is a complex system (Ladyman et al., 2013; Weil and Brady, 2017), not only because soil is the intersection of the atmosphere, the hydrosphere and the biosphere (Lehmann et al., 2020), but also because soil is relevant to biological, physical and chemical processes that are critical to plant growth. Soil is also key to sustainability, as it supports vital ecosystem services and human well-being (Bünemann et al., 2018). Plant growth needs nutrients, primarily soil nitrogen, to meet the stoichiometric requirements for plant productivity linked to carbon fixation (Wieder et al., 2015). Thus, this multifunctionality of soils at many scales and locations is also addressed when soil quality is described as

* Corresponding author.
E-mail addresses: handl@lzu.edu.cn (D. Han), hjp@lzu.edu.cn (J. Huang), liuxiaoyue14@lzu.edu.cn (X. Liu), ful2021@lzu.edu.cn (L. Fu), dingl13@lzu.edu.cn (L. Ding), zhangguolong@lzu.edu.cn (G. Zhang), lichy2013@lzu.edu.cn (C. Li), yangfan309@yeah.net (F. Yang), shijs@lzu.edu.cn (J. Shi), zbd@lzu.edu.cn (B. Zhang).

https://doi.org/10.1016/j.catena.2025.108777
Received 18 November 2024; Received in revised form 24 December 2024; Accepted 24 January 2025

Table 1
The relationship between major soil parameters and soil quality.

Main parameters	Description
Soil texture and aggregate	• Soil texture, which refers to the ratio and combination of particles of diverse sizes in the soil like sand, silt and clay, has a significant relationship with soil aggregates. For instance, soils with a higher clay content are inclined to form more stable aggregates as clay particles have a stronger adsorption capacity and can bond smaller particles together. • Aggregates are capable of adsorbing and conserving nutrients such as nitrogen. They behave like a "nutrient reservoir", gradually discharging nutrients when plants require them. Microorganisms are vigorous in the micro-environment within the aggregates and are implicated in the material transformation and nutrient cycling processes in the soil. • Larger and stable aggregates can oppose erosion by rain and runoff, diminishing the risk of soil loss. During drought periods, they provide necessary moisture for plants. Thus, soil aggregate helps with the even distribution of water and avoids local waterlogging or excessive drought (Bünemann et al., 2018; Cen et al., 2024).
Soil organic carbon	• Firstly, soil organic carbon (act as a cementing agent) contributes to the formation of stable soil aggregates, which enhance soil porosity and improve water and air movement within the soil profile. • Secondly, it also promotes microbial activity, because soil microorganisms depend on soil organic carbon as an energy source, and their activities contribute to nutrient cycling and decomposition processes that are crucial for soil quality. • Thirdly, soil organic carbon helps to buffer against changes in soil pH, maintaining a more stable and suitable soil environment for plant growth and microbial processes (Chen et al., 2022; Zhang et al., 2024).
Soil bulk density	• Reflecting soil compactness. A higher soil bulk density typically implies that the soil is more compact. Compact soil constrains the growth and elongation of roots, influencing the uptake of water and nutrients by plants. • Assessing soil aeration and water permeability. Soil with a lower bulk density has larger porosity and better aeration and water permeability, facilitating the exchange of oxygen and the infiltration of water in the soil (Martín et al., 2017; Panagos et al., 2024).
Soil total nitrogen	• Supplying nitrogen for plant growth. Nitrogen is a crucial element of vital organic substances in plants, such as chlorophyll, nucleic acids, and proteins. The total nitrogen in soil offers a source of nitrogen for plants, facilitating their growth, reproduction and development. • Affecting soil fertility. The amount of total nitrogen in soil is one of the significant indicators for assessing soil fertility. A greater nitrogen content typically implies a more robust nitrogen supply capacity of the soil, which is conducive to sustaining soil fertility (Chen et al., 2024; Misbah et al., 2024).
Soil acid-base scale	• An appropriate pH contributes to the formation and stability of soil colloids, thereby facilitating a good soil structure. In acidic soils, magnesium and calcium may be lacking, while alkaline soils can restrict the availability of boron and copper. Therefore, understanding and managing soil pH is crucial for maintaining soil quality (Wang et al., 2024).

the capacity of soil to sustain above- and below-ground biomass, to enhance air and water quality, and to promote animal and human health (Karlen et al., 1997). On this basis, researchers should consider soil quality as a major driver that contributes to the global biodiversity targets and the sustainable development goals (Lehmann et al., 2020), not just as a property to be measured (Andrews et al., 2002; Vasu et al., 2016; Yu et al., 2023).

Soil quality assessment is to understand the state of the soil and develop measures for protection and rational utilization. However, due to climate change, soil quality assessment in natural/semi-natural ecosystems is often affected (Qiao et al., 2022). Consequently, climate change, which regulates soil physical, chemical and biological properties that are crucial for the change of soil quality. We believe that incorporating the soil quality (include site-specificity) into Earth System Models allows for better predictions of land–atmosphere feedback. Thus, changes in soil quality must consider climatic drivers (Karlen et al., 2003). Although surface heat links air temperature and soil moisture and is one of the dominant drivers of the soil quality changes, the role of surface heat as soil moisture dynamics in land–atmosphere interactions has not been extensively studied (García-García et al., 2023), due to the tight coupling between surface heat and air temperature at climate temporal scales (García-García et al., 2023). However, the relationship between surface heat and air temperature is largely affected by changes in soil water content, aerodynamic conductance land cover and associated changes in soil properties (García-García et al., 2023). Though trends differ among meteorological stations, higher warming rates of soil than that of air have been observed in Europe (García-García et al., 2023), Germany (Dorau et al., 2022), and China (Zhang et al., 2016).

During the last few decades, the evaluation of soil quality by microbial (microorganisms' composition, activity and biomass), physical (bulk density, porosity and texture) and chemical (soil carbon, nitrogen, pH) properties has been studied intensively (Vasu et al., 2016; Yu et al., 2023), however, our understanding of the major soil quality drivers across a wide range of geographic scale is still inadequate, as current research is dominated by site-level studies (Yu et al., 2018; 2018b; 2023). In addition, it is a grand challenge to investigate the crucial role of warming (for example, the greenhouse effect caused by fossil fuel combustion) in determining soil quality changes (Huang et al., 2016; 2018; 2020). Moreover, soil quality in turn may also mediate the climate through the vegetation photosynthesis associated with atmospheric oxygen fluctuations (Han et al., 2022). It is important to note that atmospheric oxygen fluctuations are characterized by oxygen production and consumption processes (Huang et al., 2018). The oxygen production process is associated with the cooling effect, but the oxygen consumption process is linked to the warming effect (see 'Plain Language Summary' and Methods in Section 2.2). Hence, it is urgent to conduct a comprehensive study of soil quality at broad geographic scales to systematically analyze these potential mechanisms and environmental factors.

In this work, we focus on understanding the characteristics, drivers, and transitions of soil quality across 2200 km alpine grasslands on the Tibetan Plateau. For this purpose, we collected microbial data (for example, total phospholipid fatty acids, 6.83 ~ 82.37 nmol g^{-1}), soil data (for example, soil organic carbon, 1.1 ~ 118 g kg^{-1}), plant data (for example, net primary productivity, 38 ~ 488 g m^{-2} yr^{-1}) and climatic data (for example, surface temperature, -3.40 ~ 4.86 °C) from a total of 30 sites. Our results demonstrate that the barrier effect of atmospheric oxygen footprint has an impact on the changes of soil quality. The objectives of this study were to (1) propose a novel perspective regarding the "oxygen footprint barrier effect" to serve as an indicator for the assessment of climate change; (2) investigate the influences of climate change on soil quality in arid-cold grasslands.

2. Materials and methods

2.1. Study area

The Tibetan Plateau (70-105°E, 25-40°N) is the highest and largest plateau in the world, with broad elevational and environmental gradients and minimal human disturbance (Yang et al., 2008). The Tibetan Plateau has an annual mean rainfall of less than 450 mm and covers approximately 60 % of alpine grasslands, which are mainly composed of alpine meadow and alpine steppe (Jiao et al., 2021). It has the largest high-altitude mountain permafrost in the world, covering an area of 1.06×10^6 km^2 and accounting for about 74 % of soil carbon (Wu et al., 2021). Meanwhile, permafrost on the Tibetan Plateau is undergoing a

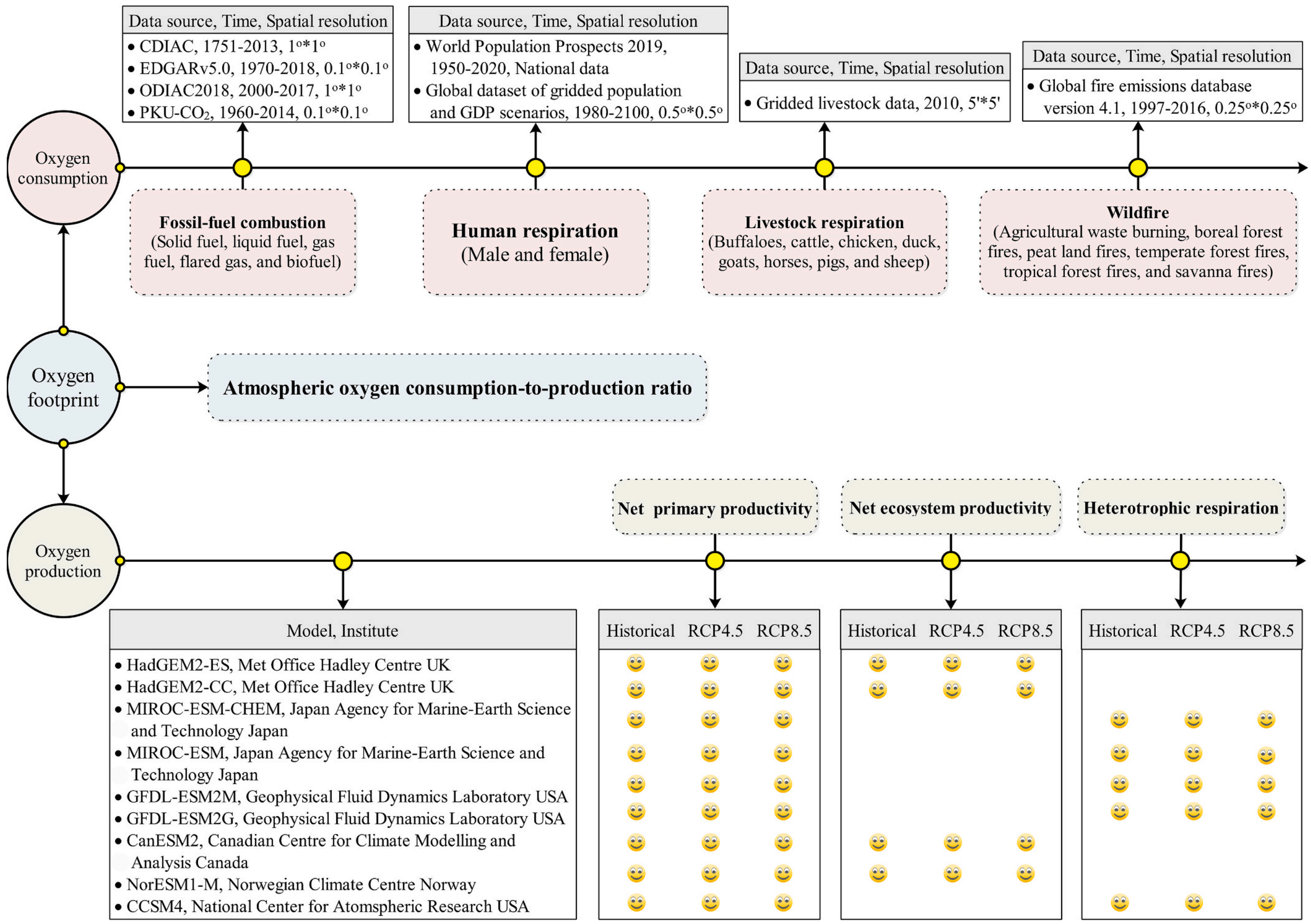


Fig. 1. Illustration of the oxygen footprint methodology and procedural steps of this study. CDIAC, Carbon Dioxide Information Analysis Center; EDGAR, Emissions Database for Global Atmospheric Research; ODIAC, Open-sourceData Inventory for Anthropogenic CO2; PKU-CO2, Peking University-CO2. “Smiling face” implies that the variables are generated as outputs in the modelsunder diverse scenarios. See details in Liu et al., 2020 and Huang et al., 2018.

temperature rise at a rate about twice the global average. The thickness of the active layer and the average annual soil temperature have increased markedly since the mid-1950 s, causing a reduction in alpine permafrost of ~ 23.8 % (Wu et al., 2021). Thus, this area serves as an ideal location to explore key drivers of soil quality on a broad geographic scale. Notably, the climate on the plateau is dry and cold, with a northwest (~84 mm yr^{-1}) to southeast (~593 mm yr^{-1}) precipitation gradient, and the average annual air temperature in this region ranges from −4.9 to 6.9 °C (Ding et al., 2016). The alpine grassland is one of the most fragile and sensitive ecosystems to anthropogenic climate warming, and it has shifted from alpine steppe in the northwest to alpine meadow in the southeast (Yang et al., 2009). Of the two main grassland covers, the alpine steppe is dominated by *Carex moorcroftii* and *Stipa purpurea*, while the alpine meadow is dominated by *K. tibetica*, *K. humilis* and *Kobresia pygmaea* (Chen et al., 2019). The soil orders in this area include Chernozem, Kastanozem, Calcisol, and Cambisol according to the World Reference Base for Soil Resources (Shi et al., 2004).

2.2. The CMIP5 models simulation

Based on the terrestrial net ecosystem productivity (NEP), net primary productivity (NPP) and soil heterotrophic respiration (Rh), atmospheric oxygen production (Op) is derived from the mean of nine CMIP5 models results (Fig. 1). Since the CMIP5 historical results end in 2005, we extend them to approximately 2100 by combining them with the corresponding RCP8.5 and RCP4.5 scenarios (Han et al., 2022). NPP and Rh data are obtained from GFED4 at a spatial resolution of 0.25°.

We calculate the Op based on the following linear regression (Huang et al., 2018):

$$Op = \{(NPP - Rh) = NEP\} \times 2.667 \quad (1)$$

here, oxygen molar mass is 32 g per mole, carbon molar mass is 12 g per mole, and the ratio is 2.667. The Op content (1 Gt = 10^{15} g) is calculated based on the area-weighted sum of Op flux (kg m^{-2}; 1 kg = 10^3 g). Further details of these methods of Op can be found in Huang et al. (2018).

Meanwhile, atmospheric oxygen consumption (Oc) is mainly driven by fossil fuel combustion (FFC), livestock respiration (LR), human respiration (HR), and wildfires (WF) as follows (Liu et al., 2020):

$$Oc = FFC + LR + HR + WF \quad (2)$$

Data on fossil fuel combustion are obtained from the PKU-CO_2 and the Emissions Database for Global Atmospheric Research (EDGARv5.0). Livestock respiration (sheep, pigs, horses, ducks, buffalo, chickens, cattle and goats) is calculated according to gridded data of livestock population (GLW 3), and human respiration is derived from daily total energy expenditure and population density, which further depended on the sex ratio and age structure of each grid cell. Wildfires data are obtained from the global fire emissions database version 4 (GFED v4) at a spatial resolution of 0.25° (Fig. 1). Further details of these methods of Oc can be found in Wei et al. (2021) and Liu et al. (2020).

On these grounds, oxygen footprint (Of) based on the ratio between Oc and Op is calculated as follows (Han et al., 2021):

$$\mathrm{Of} = \frac{\mathrm{Oc}}{\mathrm{Op}} \tag{3}$$

In this study, oxygen footprint, a key driver of the anthropogenic climate changes, is characterized by the annual changes of atmospheric oxygen consumption and oxygen production from 1900 to 2099, respectively.

2.3. Climatic data

We collected climatic properties data consistent with the location of plant, soil and microbial properties that occurred in 2013–2014. The GLDAS, that is, global land data assimilation system, uses ground- and satellite-based observational data products to generate land surface state and flux fields by combining land surface modeling and data assimilation (Rodell et al., 2004). All the variables used were obtained from the dataset of Land Information System GLDAS 2.1 land surface model (Noah version 3.3) monthly mean output at https://ldas.gsfc.nasa.gov/data. All the GLDAS database were used at a spatial resolution of $1.0^{\circ} \times 1.0^{\circ}$. The input longwave and shortwave data were derived from the Air Force Weather Agency (AFWA) radiation data. We analyzed the annual mean values of the data and used them as the land surface and meteorological indicators. Further details of the methods for climatic data can be found in (Han et al., 2022).

2.4. Plant-soil-microbial data

We collected data from 30 sites data, including 18 steppe sites and 12 meadow sites (Supplementary Table S1 and Table S2), that were from field sampling during the 2013 and 2014 growing seasons from early July to early September (Chen et al., 2019). At each site, field sampling was random established five (each 1 m × 1 m) quadrats at four corners and one center of a 10 m × 10 m plot. For each quadrat, the mean coverage of each species was then determined by clipping the above-ground biomass at ground level to the above-ground net primary productivity (ANPP) (Chen et al., 2019). Soil samples at a depth of 10 cm were collected from three sampling quadrats along a diagonal direction in the plot. The soil bulk density samples were collected with 100 cm^3 containers and oven-dried at approximately 105 °C to obtain their masses, and the soil acid-base scale was measured by a pH electrode in a 2.5:1 water:soil suspension (PB-10, Sartorius, Germany) (Chen et al., 2019). Phospholipid fatty acids (PLFA) were extracted from fresh soil following the protocol provided by Bossio, D. A and Scow, K. M (Bosso and Scow, 1998), which were used to appraise the abundance of fungi and bacteria, as well as the change of fungi/bacteria ratio. The activities of the C-acquiring enzyme, N-acquiring enzyme, and P-acquiring enzyme were analyzed by constructing calibration curves for each sample through a fluorometry technique (Chen et al., 2019). Except for total carbon (TC) (soil organic carbon plus soil inorganic carbon) (Yu et al., 2014) and total carbon:total nitrogen ratio (CN) (ratio of total carbon to total nitrogen) (Batjes, 1996), methodological details of the remaining plant, soil, and microbial datasets are available from previous studies (Chen et al., 2019). See Fig. 3 for environmental factors abbreviations.

2.5. Biotic and abiotic analysis

Given plant, soil and microbial properties as well as climatic properties are the key parameters of the changes in soil quality, to facilitate our interpretation, this study classified all ecosystem factors into four properties to explore their critical roles in regulating soil quality: plant properties (CS, CF, CG, CIA, EVI, RB, ANPP and NPP), soil properties (BD, Sand, Silt, Clay, pH, CN, TN, TC, SIC and SOC), microbial properties (lnCP, lnNP, lnCN, Penzy, Nenzy, Cenzy, FB, BPLFA, FPLFA and TPLFA), and climatic properties (WS, TF, SUSH, SULH, ST, SH, RZSM, PRES, PRE, PET, DHFS, DEBS, AT and ALB). Fig. 3 shows the indicators of four groups, that is, microbial, soil, plant and climatic properties, as well as their extended names, acronyms, and significant changes under different land covers.

2.6. Developing the soil quality index

Although many conceptual frameworks have been proposed to assess the changes of soil quality, there are no universal standardized techniques to evaluate soil quality over broad environmental gradients (Bünemann et al., 2018). Soil quality index (SQI) is an efficient tool or method for evaluating soil quality, featured with ease of use, flexibility in quantification, and close relevance to soil management practices. SQI refers to a measurement or calculation that evaluates and quantifies the overall condition of soil (Andrews et al., 2002). It takes various factors related to the soil into consideration, such as physical properties like texture and structure, chemical properties like pH and soil organic carbon, and biological properties like the phospholipid fatty acids and enzyme activity (Bünemann et al., 2018). As a result, SQI has been successfully used to evaluate soil quality at many sites and scales (Liu et al., 2018).

Three dataset methods were used to identify appropriate soil indicators: (i) the total dataset method, (ii) the minimum dataset method, and (iii) the revised minimum dataset method (Yu et al., 2018). Firstly, independent-samples *t* test was performed on twenty soil indicators (soil and microbial properties) to assess the effect of different land covers on these indicators. Only the soil indicators confirming significant ($P < 0.05$) differences were chosen as members of total dataset method. Secondly, a principal component analysis (PCA) was performed on the total dataset method to identify these potential indicators, following the traditional procedure for minimum dataset method. The traditional procedure for a minimum dataset typically involves several sequential steps: (a), for each soil factor, only attributes with high loading were retained for the minimum dataset; (b), when more than one attribute was kept under a single soil factor, multivariate correlation coefficients were employed to determine if the variables could be regarded as redundant and then removed from the minimum dataset; (c), well-correlated variables were regarded as redundant and only one was taken into account for the minimum dataset (Andrews et al., 2002; Raiesi, 2017). Thirdly, the PCA was also performed separately on the two-soil microbial and soil physiochemical indicators, to identify these potential soil factors that expressed the revised minimum dataset (Yu et al., 2018).

Soil indicators can be divided into two soil functional groups in light of the sensitivity of soil productivity. The ‘more is better’ scoring curve was characterized by an increase in these soil indicators as soil quality increases. In turn, the ‘less is better’ scoring curve was applied as an indicator of soil quality, with a high level considered unfavorable. The following linear scoring curves are used as ‘more is better’ (Equation (4) or ‘less is better’ (Equation (5) functions:

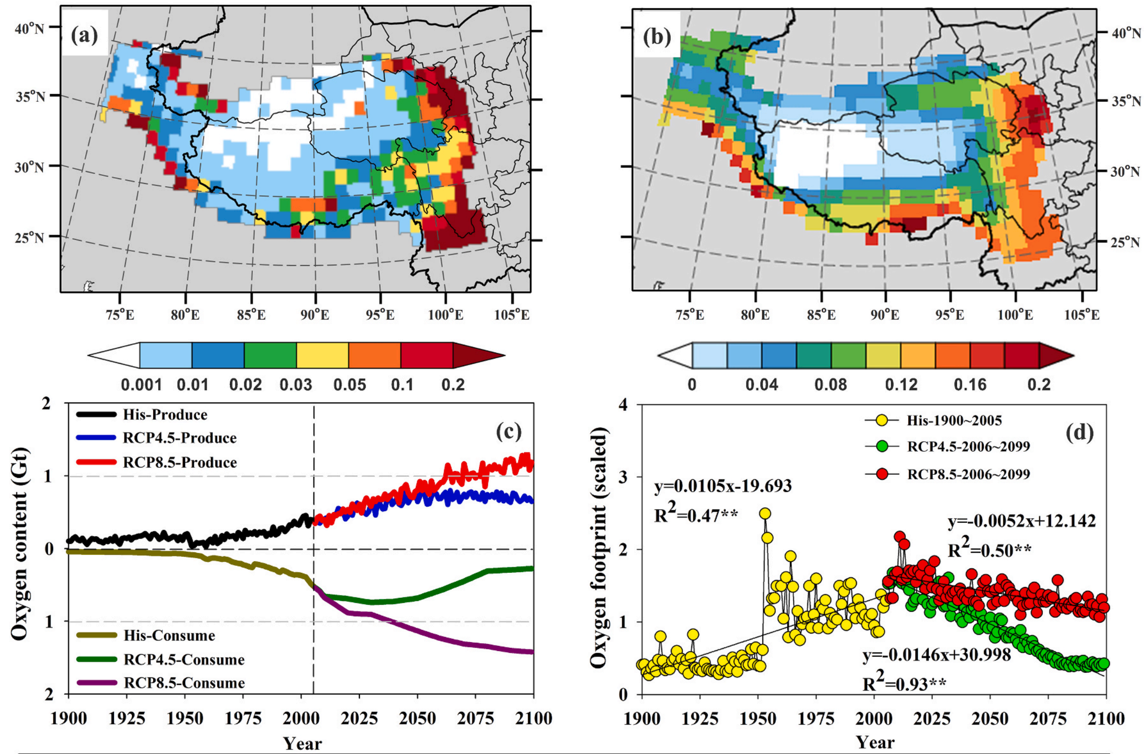
$$LS = \frac{N}{N_{max}} \tag{4}$$

$$LS = \frac{N_{min}}{N} \tag{5}$$

here, LS is the linear score of these soil indicators. N, N_{max} and N_{min} are the measured, maximum, and minimum values of each soil indicator observed in this work. For nonlinear scoring, the sigmoidal curve (Equation (6) is used as follows:

$$NLS = \frac{1}{1 + \left(\frac{N}{N_m}\right)^b} \tag{6}$$

here, NLS is the nonlinear score of these soil indicators. N is the measured value of soil indicator, N_m is the average value of soil indicator, and b is the slope, which is set to be −2.5 in the ‘more is better’



(e) Study area	Of / Oc:Op ratio	Data source	Signal	Time scale	*N*	Reference
Global land and ocean	↑	Obs/Mod	+	1900-2100	200	Huang et al. (2018)
Global land	↑	Obs/Mod	+	2000-2018	18	Liu et al. (2020)
Global dryland	↑	Obs/Mod/Rev	+	1948-2099	151	Han et al. (2020)
Global arid and humid regions	↑	Obs/Mod	+	1948-2100	152	Huang et al. (2020)
Global cities	↑	Obs	+	2001-2015	14	Wei et al. (2021)
Yellow River Basin	↑	Obs	+	2000-2014	14	Zhang et al. (2023)
Tibetan Plateau	↓	Obs/Mod	-	1900-2099	199	This study

Fig. 2. Comparing the variations in oxygen footprint across the Tibetan Plateau withthose observed in other regions. The main distribution of oxygen consumption, that is, fossil-fuel combustion (see other components in Supplementary FigureS1) from 2000 to 2013 on average (kg m-2), is shown in panel (a). The averagehistorical (1975–2005) oxygen production (kg m-2) is presented in panel (b). The atmospheric oxygen content, oxygen footprint fluctuation, andcomparative analysis with previous studies are respectively shown in the Fig. (c), (d), and (e). The changes of oxygen footprint (Of), associated with redarrow or green arrow, indicate an increase or a decrease. The symbols "+" (positive) or "-" (negative) represent the relationships of oxygen footprint (riseor fall) and climate effects (warm or cool). N, number of data points; Oc, oxygen consumption; Op, oxygen production; Obs, observed; Mod, model (s); Rev, review; RCP4.5/8.5, representative concentration pathway 4.5/8.5. **P < 0.01.

curve and 2.5 in the 'less is better' curve (Supplementary Table S3).

For the indicator selection methods of minimum dataset and total dataset, the weights values are identified by the ratio of their communality to the sum of the communalities of all variables in the minimum dataset and total dataset (Yu et al., 2018). Meanwhile, soil microbial and physiochemical groups are subjectively given equal weighting (0.50) to emphasize the same importance of the two groups of soil processes in their contribution to soil ecosystems (Nakajima et al., 2015). After weighting and scoring the soil indicators, SQI is calculated using the weighted additive (Equation (7) methods as follows:

$$SQI = \sum_{i=1}^{n} Wi \times Si \tag{7}$$

hcere, SQI is the soil quality index, Wi is the weighting value of indicators, Si is the indicator score (nonlinear or linear), and n is the number of indicators in the minimum dataset, revised minimum dataset, or total dataset. Further details of these methods for soil quality assessment can be found in Yu et al. (2018). Overall, higher SQI values mean better soil processes and functions, reflecting the positive influence of land covers on soil ecosystems (Raiesi, 2017).

2.7. Major physico-chemical protection parameters for soil quality

The main parameters used for evaluating soil quality:

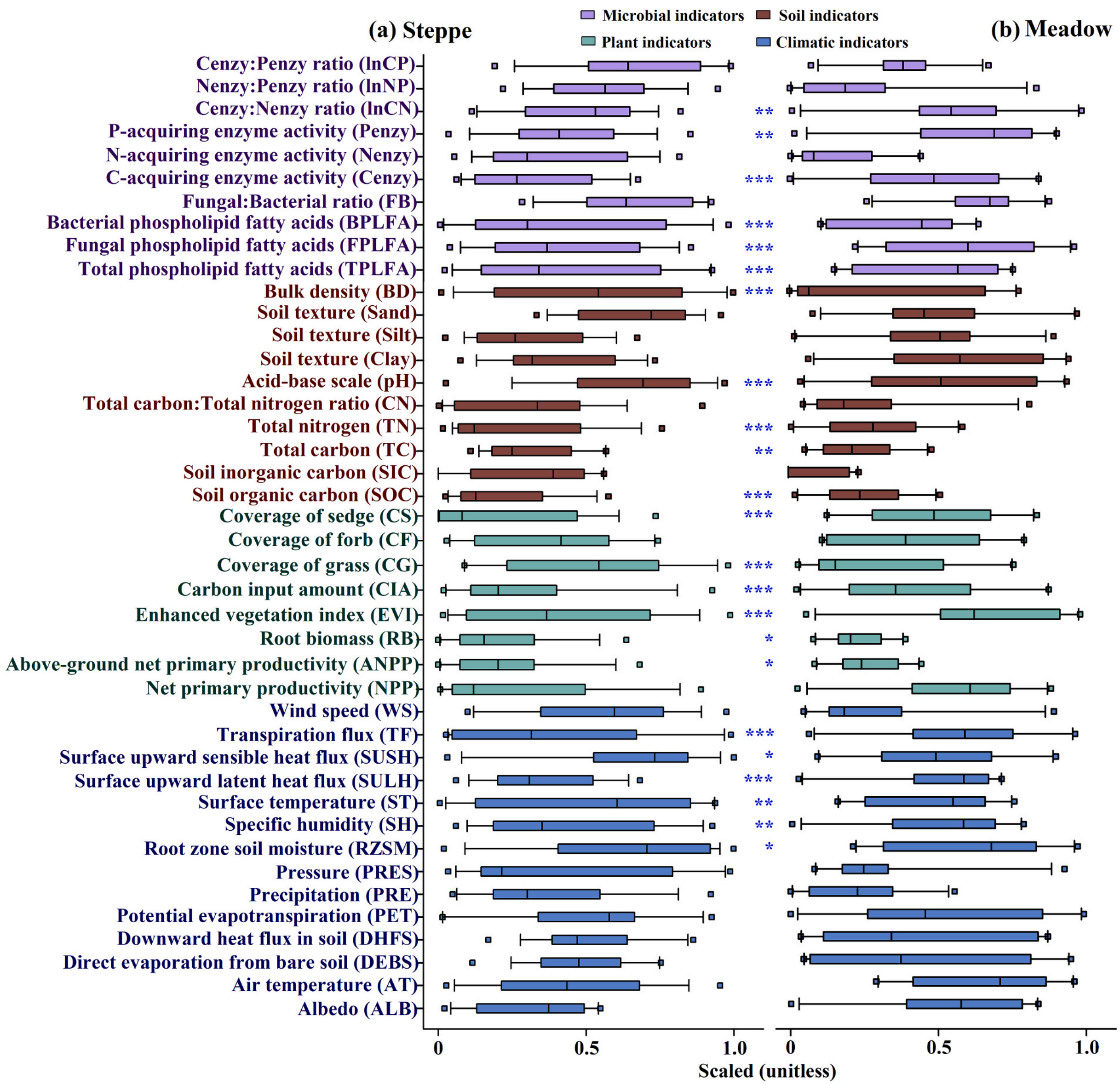


Fig. 3. Comparison of environmental indicators and changes between steppe andmeadow. Independent-samples *t* test show that comparison of microbial (purple), soil (brown), plant (green), and climatic (blue) factors between steppe (a, n = 18) and meadow (b, n = 12). The x-axis shows the min–max normalized. The y-axis shows the factors, including description and abbreviation. *0.05 < P < 0.1; **P < 0.05; ***P < 0.01.

2.8. Statistical analysis

Before doing all the statistical analysis in this work, all data were performed for 'min-max' normalized, that is, {actual value (x_i)-minimum (x)} / {maximum (x)-minimum (x)}. Independent-samples *t* test, Pearson correlation, and Simple regression analysis were used to reveal the relationships among environmental factors, land covers and years, as well as to test the influences of land covers on microbial, soil, plant and climatic indicators. Given the strong interconnections and correlations among various indicators, Pearson correlation matrix (Fig. 5b, Supplementary Fig. S2 and Fig. S4) was analyzed using the R package vegan v.3.6.1 (R Development Core Team, 2016). Residual charting work along with statistical analyses (include PCA, Supplementary Fig. S3) were performed using Edraw Mind Map 7.9, SigmaPlot 10.0, and SPSS statistics 17.0.

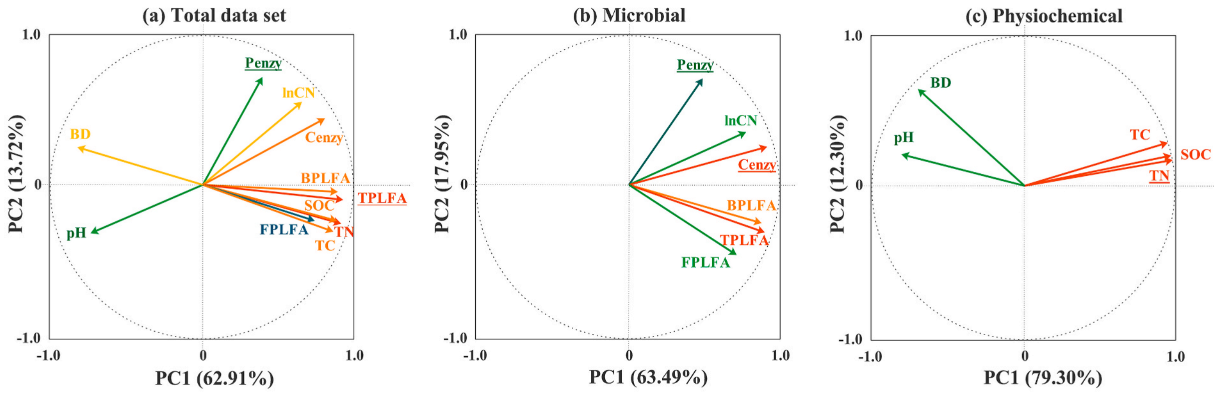
Before performing the structural equation modeling (SEM), we first standardized each indicator using the 'min-max' normalized methods. Then, establish a prior SEM according to our prior knowledge of the total, direct and indirect effects (Li et al., 2020) of microbial, plant, soil and climatic properties on soil quality, respectively. Lastly, we selected a final SEM according to an overall goodness-of-fit (Eldridge et al., 2018), including the normed fit index (NFI), goodness of fit index (GFI), comparative fit index (CFI), root mean square residual (RMR), and chi-square(χ^2) / degree of freedom (df). The standardized total effect is equal to the sum of the direct effect plus the indirect effect (Li et al., 2020). The structural equation modeling analyses were conducted using the AMOS 17.0 (Amos Development Corporation, Chicago, IL, USA).

3. Results

3.1. Oxygen footprint

3.1.1. Atmospheric oxygen

Atmospheric oxygen is mostly consumed by fossil fuel combustion (Fig. 2a), livestock respiration, human respiration and wildfires (Supplementary Fig. S1a–c), and it is mainly produced via vegetation photosynthesis (Fig. 2b), resulting in a northwest to southeast atmospheric oxygen gradient (Fig. 2a–b). We explored the temporal trends of



(d) Soil quality index	Description
SQI-LT or SQI-NLT	0.086*BD+0.103*SOC+0.093*TC+0.108*TN+0.078*pH+0.103*TPLFA+0.071*FPLFA+0.095*BPLFA+0.100 *Cenzy+0.073*Penzy+0.090*lnCN
SQI-LM or SQI-NLM	0.58*TPLFA+0.42*Penzy
SQI-LRM or SQI-NLRM	0.50*TN+0.29*Cenzy+0.21*Penzy

Fig. 4. The soil quality index and its dataset method. Results from principalcomponent analysis for the total dataset (a) and the two soil processes (b microbial and c physiochemical). The description of soil quality index (SQI) in panel (d). The color character and underline are selected as the minimum dataset and the revised minimum dataset. Six SQIs, including the linear scoring-total dataset (SQI-LT); the nonlinear scoring-total dataset (SQI-NLT); the linear scoring-minimum dataset (SQI-LM); the nonlinear scoring-minimum dataset (SQI-NLM); the linear scoring-revised minimum dataset (SQI-LRM); and the nonlinear scoring-revised minimum dataset (SQI-NLRM). See Fig. 3 for abbreviations.

multiyear averaged Oc and Op contents over the Tibetan Plateau from 1900 to 2005, and our results indicated that the contents of Oc ($y = 0.0036x-6.9147$, $R^2 = 0.82$) and Op ($y = 0.002x-3.7241$, $R^2 = 0.49$) increased significantly (all $P < 0.01$) with increasing time scales, and Oc increased faster than Op. Then, we forecast the temporal changes of Oc and Op contents from 2006 to 2099 under moderate (RCP4.5) and high (RCP8.5) emission scenarios. The results of Oc and Op for both scenarios show a significant increasing trend by ~ 2100, with Op increasing faster than Oc (Fig. 2c).

3.1.2. Changes of oxygen footprint

The ensemble means of multiple CMIP5 models suggest that the oxygen footprint (atmospheric oxygen consumption-to-oxygen production ratio) increased significantly ($P < 0.01$) under historical period ($y = 0.0105x-19.693$, $R^2 = 0.47$) from 1900 to 2005. This might be primarily attributed to ongoing urbanization, fast economic development and rapid population growth (Du et al., 2004). In contrast, the oxygen footprint will accelerate decline (all $P < 0.01$) over the Tibetan Plateau under the moderate (RCP4.5: $y = -0.0146x + 30.998$, $R^2 = 0.93$) and high (RCP8.5: $y = -0.0052x + 12.142$, $R^2 = 0.50$) emission scenarios from 2006 to 2099 (Fig. 2d). These changes in different emission scenarios may lead to a lower oxygen footprint under RCP4.5 than under RCP8.5. This is partly due to climate warming associated with CO_2 fertilization effects on plant photosynthetic capacity, that is, carbon fixation capacity, within a proper range (Piao et al., 2020). There was a significant difference in oxygen footprint fluctuations between the Tibetan Plateau (decrease significantly) and other regions, like urban areas (increase significantly) (Fig. 2e). This is mainly owing to the rapid global warming, which leads to an earlier vegetation growing season and enhanced vegetation photosynthetic rate in most alpine areas of the Tibetan Plateau, and a relatively low intensity of anthropogenic disturbances (Yang et al., 2008). As a result, the oxygen production is much greater than the oxygen consumption in this study.

3.2. Characteristics of soil quality

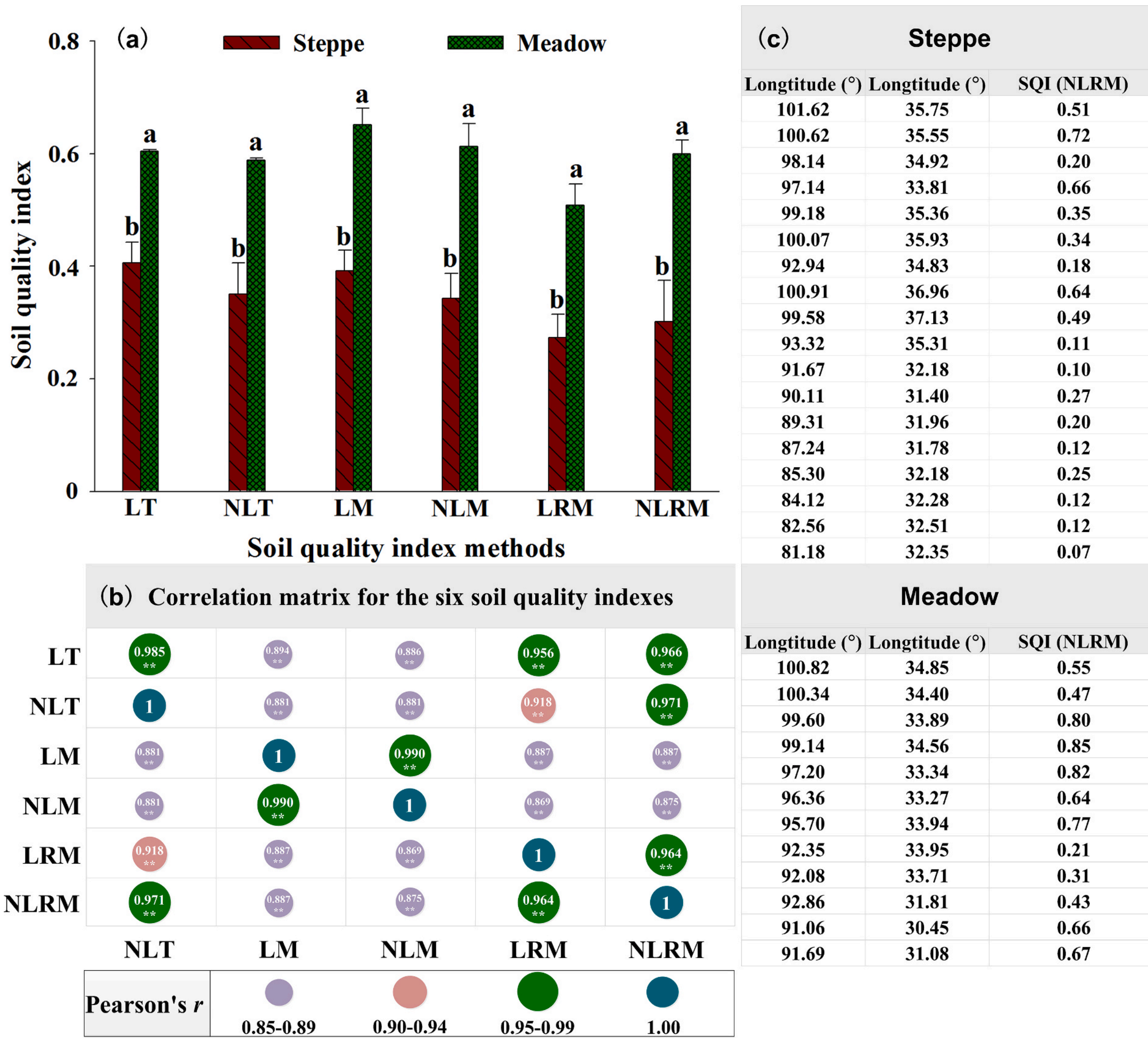
3.2.1. Land covers

Results of all six methods (Figs. 4 and 5) show that soil quality index (SQI) values differ greatly under the two main land covers, in the order of meadow (SQI, mean 0.60 level) > steppe (SQI, mean 0.40 level). It indicates that high soil quality is closely associated with high nutrient content and microbial biomass along with low soil bulk density and soil acid-base scale, using both linear and nonlinear scoring models for the total dataset (BD, SOC, TC, TN, pH, TPLFA, FPLFA, BPLFA, Cenzy, Penzy and lnCN), the minimum dataset (TPLFA and Penzy), and the revised minimum dataset (TN, Cenzy and Penzy) (Figs. 4 and 5). See Fig. 3 for environmental factors abbreviations.

3.2.2. Spatial patterns

Similarly, SQI varied markedly across 30 sampling sites. All soil quality index analyses show that soil quality increases from the northwestern area to the southeastern part, corresponding well to the atmospheric oxygen distributions across the plateau. Additionally, the low soil quality in northwestern region is closely linked to the decrease of vegetation biomass input and the increase of surface heat disturbance. Based on nonlinear scoring-revised minimum dataset method, SQI for northwestern regions ranges from 0.07 (81.18°E, 32.35°N) to 0.72 (100.62°E, 35.55°N), while that for southeastern regions varies from 0.21 (92.35°E, 33.95°N) to 0.85 (99.14°E, 34.56°N). Compared to the southeastern region, the mean SQI value in the northwestern region is reduced by ~ 50 % (Fig. 5).

In general, the *Pearson* correlation matrix results of the six soil quality indices are significantly (all $P < 0.01$) positively correlated with each other; hereinto, the nonlinear scoring-revised minimum dataset method is considered to be the most useful and sensitive metric for soil quality assessment, because it incorporates data dimension reduction and has higher correlation coefficients with other methods (Fig. 4d and



Steppe		
Longtitude (°)	Longtitude (°)	SQI (NLRM)
101.62	35.75	0.51
100.62	35.55	0.72
98.14	34.92	0.20
97.14	33.81	0.66
99.18	35.36	0.35
100.07	35.93	0.34
92.94	34.83	0.18
100.91	36.96	0.64
99.58	37.13	0.49
93.32	35.31	0.11
91.67	32.18	0.10
90.11	31.40	0.27
89.31	31.96	0.20
87.24	31.78	0.12
85.30	32.18	0.25
84.12	32.28	0.12
82.56	32.51	0.12
81.18	32.35	0.07

Meadow		
Longtitude (°)	Longtitude (°)	SQI (NLRM)
100.82	34.85	0.55
100.34	34.40	0.47
99.60	33.89	0.80
99.14	34.56	0.85
97.20	33.34	0.82
96.36	33.27	0.64
95.70	33.94	0.77
92.35	33.95	0.21
92.08	33.71	0.31
92.86	31.81	0.43
91.06	30.45	0.66
91.69	31.08	0.67

Fig. 5. Changes and relationships of the six soil quality indexes. Values of soil quality indexes between steppe and meadow (a). Independent samples *t* test with different lowercase letters within land cover types are significant different at P < 0.01. The bars show standard errors. Pearson correlation matrix of six soil quality indexes in panel (b). Spatial patterns from soil quality index based on nonlinear scoring-revised minimum dataset method (c). LT, linear scoring-total dataset; NLT, nonlinear scoring-total dataset; LM, linear scoring-minimum dataset; NLM, nonlinear scoring-minimum dataset; LRM, linearscoring-revised minimum dataset; NLRM, nonlinear scoring-revised minimum dataset. Soil quality index, SQI. **Significant correlation between the soil quality indexes at the 0.01 level.

Fig. 5b).

3.3. Drivers of soil quality

3.3.1. Oxygen footprint barrier effect

Our results reveal that there are significant differences in transpiration flux, sensible heat flux, latent heat flux, surface temperature, specific humidity, and root zone soil moisture (Fig. 3) from the northwestern area to the southeastern part of the plateau. These differences correspond closely to the distributions of the atmospheric oxygen footprint (Fig. 2). According to Poulsen et al. (2015), in an atmosphere with low oxygen content and reduced density, shortwave scattering of O_2 molecules occurs less frequently, resulting in a notable enhancement of surface shortwave forcing. This surface shortwave forcing contributes to an increase in sensible heat flux by feeding back surface heat to the atmosphere, intensifying greenhouse forcing, elevating land surface temperature, and ultimately restricting soil quality growth (Huang et al., 2016). We define this phenomenon as the oxygen footprint barrier effect, which is extremely helpful in understanding the driving mechanism of climate change on soil quality assessment.

3.3.2. Environmental factors

On the Tibetan Plateau, incorporating more than 40 environmental factors, including climatic, plant, soil and microbial properties into a structural equation modelling reveals a strong negative relationship between the climatic factors and soil quality, while plant, soil and microbial factors had a significant positive effect on soil quality (Fig. 6a). The standardized total effect of climatic, plant, soil and microbial on soil quality was −0.48, 0.87, 0.96 and 0.11, respectively (Fig. 6b). In terms of biological mechanism, the structural equation model shows that plant productivity has a positive effect on soil quality, mainly through increasing above- and below-ground biomass along with microbial biomass (standardized total effect = 0.20). In terms of physiochemical mechanism, the structural equation model indicates that the SOC and physico-chemical protective associations appear to have the greatest effect (standardized total effect = 0.91) in predicting soil quality than biological mechanism (Fig. 6).

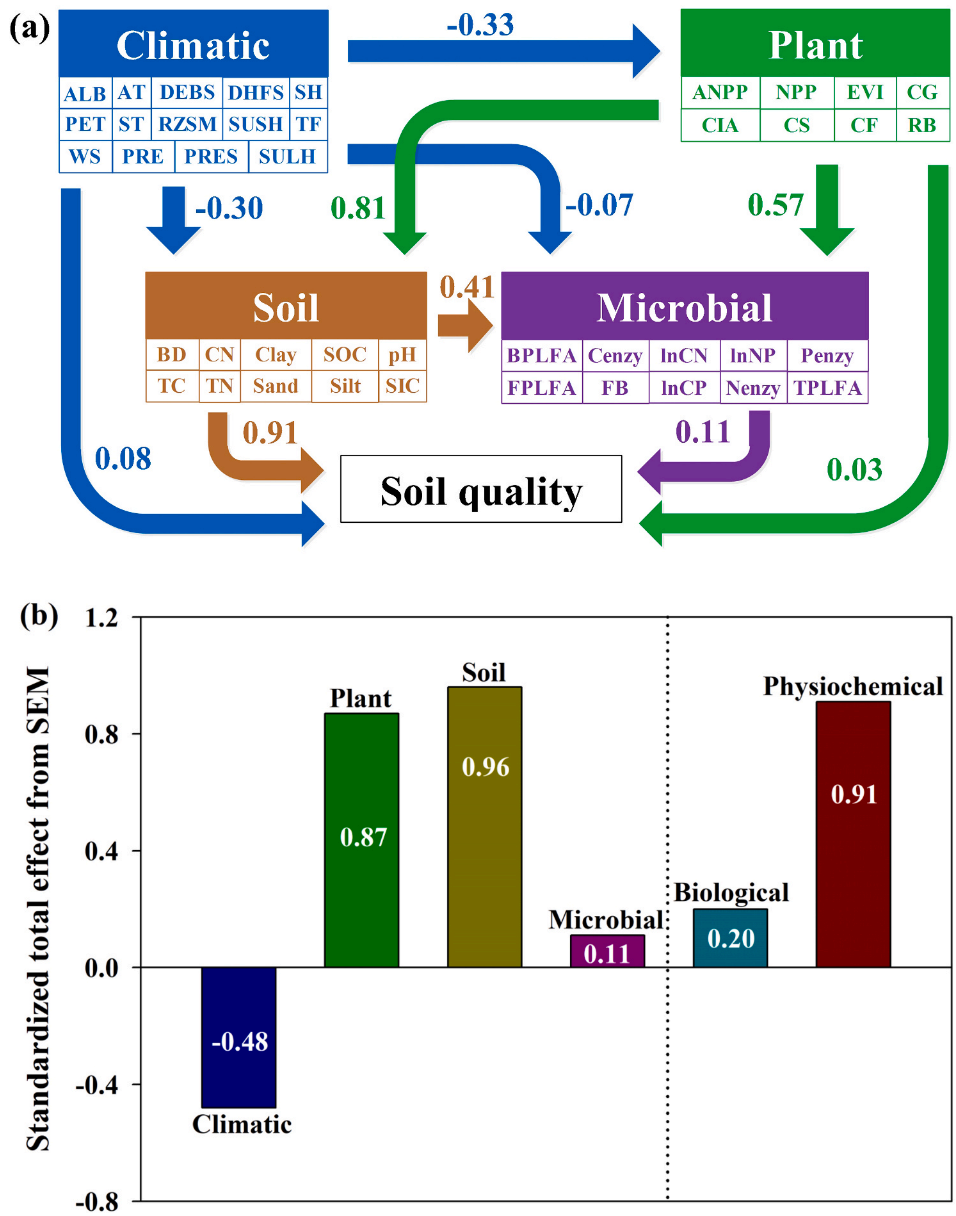


Fig. 6. The effects of the combined group properties on the soil quality from the structural equation modelling (SEM) analysis. SEM analysis was conducted to identify the direct and indirect effect (a), the standardized total effect (direct plus indirect effects, b) explained by these groups of biotic and abiotic factors. Multiple-layer rectangles represent the indicators for climatic (blue), plant (green), soil (brown) and microbial (purple) properties, respectively. The arrows show the hypothesized direction of causation, and the numbers adjacent to the arrows are the standardized path coefficients. The results of the optimal model fitting: chi-square ($\chi 2$)/degree of freedom (df) < 0.001, root mean square residual (RMR) < 0.005, comparative fit index (CFI) > 0.950, goodness of fit index (GFI) > 0.980, and normed fit index (NFI) $= 1.000$. See Fig. 3 for abbreviations.

4. Discussion

In the Anthropocene, many studies have shown that human activities have induced an irreversible decline of the content of atmospheric oxygen (Huang et al., 2018; Wei et al., 2021). Oxygen decline may have amplified carbon dioxide-driven climate change (Poulsen et al., 2015), thereby affecting soil structures and functions. As a result, disturbing the balance of atmospheric oxygen will accelerate soil degradation at the global scales (Han et al., 2021). In this work, we primarily focus on the study of the oxygen footprint barrier effect determine the consequences of alterations in soil quality. Based on the changes of oxygen footprint, the identification of such phase transitions in climate and soil is crucial for the maintenance of terrestrial ecosystem sustainability.

4.1. *Long-term climate forcing due to oxygen footprint*

Our study demonstrates that an increasing trend in atmospheric O_2 over the Tibetan Plateau can be well represented by the oxygen footprint from 2006 to 2099 (Fig. 2). In fact, O_2 concentrations is regarded as a crucial factor in climate change forcing, owing to its effect on atmospheric quantity and density, and thus on the optical depth of the atmosphere (Poulsen et al., 2015). Shortwave scattering of air molecules is more common at high partial pressure oxygen and increased atmospheric mass, which leads to a significant reduction of the land surface shortwave forcing (Poulsen et al., 2015). Therefore, regional and global surface temperature decrease with raising oxygen content, and it may lessen atmospheric warming forcing, ultimately promoting ecosystem growth. Clearly, the RCP4.5 scenario for each year, indicates that the moderate global warming scenario plays a relatively more critical role in the oxygen footprint decline (Fig. 2), and it mainly because of anthropogenic greenhouse warming (for example, CO_2 fertilization) effects on leaf-level carboxylation rate, net primary productivity, and vegetation photosynthetic capacity within a proper range (Piao et al., 2020).

In relatively warm and wet conditions, net radiation is predominantly emitted from soil in the form of latent heat flux (latent heat flux is the transfer of heat energy associated with phase changes, such as evaporation and condensation), cooling soil temperature and limiting sensible heat (sensible heat flux is the transfer of heat energy due to temperature differences) (García-García et al., 2023). The emission of latent heat from the soil enhances the atmospheric water vapor content, resulting in stronger precipitation rates, which are closely related to the increase in soil water content (García-García et al., 2023). On the contrary, net radiation is primarily used to enhance soil temperature in relatively warm and dry conditions, owing to soil water content limitations (García-García et al., 2023). If air temperature is lower than soil temperature, heat flux is released from soil to the atmosphere as sensible heat flux, since the latent heat flux is constrained by the soil moisture deficits; however, if soil temperature is warmer than subsoil temperature, the heat can also be diffused through the soil, dissipating the heat by conduction and increasing the heat flux from the ground (Huang et al., 2016; García-García et al., 2023). Thus, surface heat is an important factor in soil water and temperature feedback, which may regulate biological and physiochemical processes (Figs. 6 and 7).

4.2. Soil quality changes

The inconsistent response of the twenty selected soil quality assessment indicators in response to different land covers suggests that the impacts of different land covers on these indicators are complex and related to different soil functions and processes. Vegetation biomass increases soil organic carbon (SOC) content, enhances soil aggregate stability, and creates better habitats for soil microbiomes (Hebb et al., 2017). Our research shows that aboveground net primary productivity (ANPP), enhanced vegetation index (EVI), root biomass (RB), and carbon input amount (CIA) under meadow treatment are significantly higher than that under the steppe treatment (Fig. 3). Meanwhile, a significantly higher SOC content under meadow than steppe can enhance the volume of porosity, and thus decrease the soil acid-base scale (pH) and bulk density (BD) based on the reports of Nath et al. (2017) and Yu et al. (2018). Total nitrogen (TN) content reflects soil nutrient availability and can be affected by global warming (Han et al., 2022). The higher soil nutrient associated with SOC content under meadow compared to steppe leads to the higher soil quality (Figs. 4 and 5). Similar, to our results, Yang et al. (2009) in Tibetan grasslands and Chen et al. (2019) over a broad geographic scale also find that the conversion of steppe to meadow could result in the increase of soil ‘fertility’ or ‘health’.

Developing SQI using minimum dataset method is widely accepted due to the availability of sufficient information for soil quality assessment and the low price and time cost of measuring effective indicators. Selecting the appropriate soil indicators for a minimum dataset can be achieved by the PCA, but it may return unsatisfactory results as it lacks indicators that represent biological and physiochemical properties (Pulido et al., 2017). Thus, a modified method of soil indicator selection is used in this study. Our research shows that the nonlinear scoring-revised minimum dataset method (SQI-NLRM) is superior to other scoring methods to score the selecting soil indicators, because it has a better discriminative power than other scoring methods under the land cover, and it can provide insight into the function of each soil indicator in the system. These results are in line with the finding of Yu et al. (2018). The SQI-NLRM developed in this work provides a sensitive and efficient method for quantitative evaluation of soil quality.

4.3. The three phases of soil quality change

First, soil quality changes associated with increased in atmospheric oxygen begin with a ‘climate change phase’ characterized by the oxygen footprint barrier effect. This barrier effect is employed to describe long-term climate forcing by atmospheric O_2 content. In an atmosphere with high oxygen content, collisions between photons and oxygen molecules are more frequent, thereby enhancing scattering and reducing surface temperature (Poulsen et al., 2015). Our results show that, under the emission scenarios of RCP4.5 ($R^2 = 0.93$) and RCP8.5 ($R^2 = 0.50$), the ratio of oxygen consumption to production on the Tibetan Plateau will see an accelerated decline (all $P < 0.01$) from 2006 to 2099, respectively (Fig. 2d). Surface temperatures decrease with increasing atmospheric oxygen content, which may alleviate CO_2-warming forcing, and ultimately altered the effects of climate change on soil quality. For example, soil quality index values are significantly different between the two land uses, with alpine grassland having larger values than temperate grassland (Yu et al., 2018 and 2018b). This suggests that ‘high’ temperature has led to undesirable soil degradation (Huang et al., 2016).

Second, as atmospheric oxygen continues to increase, we find a ‘heat drive phase’ characterized by changes in sensible heat and latent heat fluxes under the surface temperature transitions. The effect of O_2 variability associated with ‘vegetation greening’ (it is defined as statistically significant enhance in seasonal or annual vegetation greenness at a location resulting (Piao et al., 2020)) on surface heat in many cases can be viewed as the energy imbalance between sensible heat and latent heat (Methods; Piao et al., 2020; Ding et al., 2022), which is estimated globally to be $+ 0.1$ W/m^{-2}($-$|-) from sensible heat warming and -0.9 W/m^{-2}($-$|-) from latent heat cooling from 1982 to 2011 (Zeng et al., 2017; Piao et al., 2020). We find that the standardized total effects of heat condition, plant property, soil fertility and microbial biomass on the soil quality was -0.48, 0.87, 0.96 and 0.11 over the Tibetan Plateau, respectively (Fig. 6b). Therefore, surface energy imbalance may support a highly variable response of the soil quality to recent anthropogenic climate warming. For example, high surface heat can lead to increased evaporation of soil moisture, resulting in drier soil conditions (see discussion in Section 4.1). This can affect the availability of water for plants and microorganisms, potentially reducing plant growth and microbial activity (Jansson & Hofmockel, 2020).

Finally, we detect an ‘physiochemical protection phase’ featured with variations of physiochemical factors. Our study suggests that the physiochemical pathway accounts for the best effect on soil quality explanation than biological pathway over the broad and highly variable gradients of the environment (Fig. 6). (i), biological mechanisms are sensitive indicators of land cover changes and are commonly used to assess the soil quality changes in land degradation. The soil quality in this steppe is relatively lower than that in meadow, and there are less accumulations of live, litter, and roots, leading to a lower soil organic matter associated with microorganism-enzyme activity, ultimately contributing to the limiting factors for soil cementing agents (for example, SOC adsorption ratio and hyphal entanglement) (Figs. 3-6). (ii), soil structure changes greatly under global climate warming, owing to changes in permafrost thaw (accelerated decrease in aggregate size) and snow-ice melting (increased runoff erosion) may continue over this survey region under warming (Shen et al., 2015). Physiochemical mechanisms may contribute to a larger effect size, that is, ‘protective carrier’, on soil quality changes (Rillig et al., 2002). As a result, the biological mechanisms are major drivers in the context of soil quality change, and physiochemical mechanisms are results, which reflect the starting point and ultimate purpose of soil processes, respectively. On these grounds, we conclude that physiochemical mechanisms play a more crucial role in determining soil quality than biological mechanisms in this work.

Clearly, geoscientists can use this “atmospheric oxygen footprint barrier effect” to look into and figure out how stable the terrestrial ecosystem is, especially when it comes to soil getting worse and how it

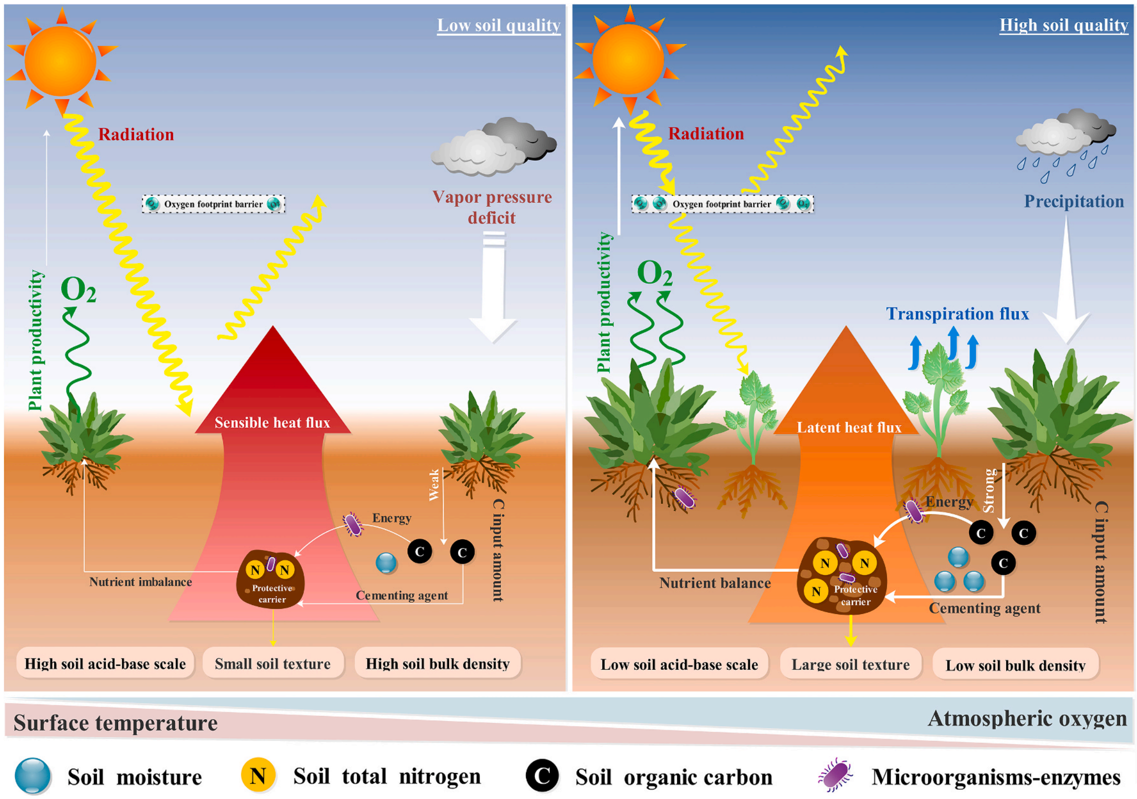


Fig. 7. A fresh conceptual framework for recognizing the influence of climate change on soil quality over the arid-cold regions. Notably, the mechanism framework primarily focuses on independent-samples *t* test and principal component analysis, as well as the most important direct, indirect and total effects derived from the structural equation modelling and path analysis.

copes. This is because soil quality exhibits an extremely high degree of sensitive to climate conditions which are correlated with the drivers of oxygen consumption and production. In addition, according to human-induced O_2 consumption and natural O_2 production drivers, the oxygen footprint barrier effect can effectively reflect the local warm/cool conditions (Fig. 7). Thereby, it can serve as a measure of soil quality changes and assumes a vital function in the assessment and projection of terrestrial ecosystem stability.

5. Conclusions

Different from previous studies, for the first time we propose three phases of soil quality change characterized by consecutive change trends in oxygen footprints. The three phases, namely ‘climate change phase’, ‘heat drive phase’ and ‘physiochemical protection phase’, play a crucial role in understanding the development of soil quality in arid-cold regions. Under equilibrium conditions, a well-defined framework for atmospheric oxygen footprint barrier effect is provided by our study (Fig. 7). It can inspire researchers to develop a new generation of multiscale models to explore soil quality responses to climate change. Also, the framework presented here can be utilized to identify the effect of oxygen footprint on soil quality, thereby indicating the consequences of continuously evolving terrestrial ecosystem, especially in fragile and sensitive regions.

The attenuation of the oxygen footprint barrier effect is a commonality witnessed, accelerating and happening globally due to urbanization, fast economic development and rapid population growth. When the oxygen footprint barrier effect is weak, the frequency of short wave scattering by air molecules is reduced, resulting in a considerable elevation of land surface shortwave forcing. As a result, an increase in global land surface temperatures is observed with the attenuation of the oxygen footprint barrier effect. Such a phenomenon may have intensified the greenhouse warming forcing and eventually inhibited the growth of soil quality. Although our work demonstrates the essential role of atmospheric oxygen footprint barrier effect in assessing the soil quality over a wide range of geographic scale, there are still several limitations that need to be addressed in future studies. A key challenge is to validate Earth System Models based on atmospheric oxygen cycles with systematic measurements to enable accurate prediction of land–atmosphere feedbacks in a changing environment. Hence, expansion of the existing network of atmospheric oxygen measurements is a top priority.

CRediT authorship contribution statement

Dongliang Han: Writing – original draft, Investigation, Formal analysis. **Jianping Huang:** Writing – review & editing, Investigation, Formal analysis. **Xiaoyue Liu:** Data curation. **Li Fu:** Data curation. **Lei Ding:** Data curation. **Guolong Zhang:** Investigation. **Changyu Li:** Investigation. **Fan Yang:** Investigation. **Jinsen Shi:** Formal analysis. **Beidou Zhang:** Formal analysis.

Declaration of competing interest

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.

Acknowledgments

This work was jointly supported by the National Natural Science Foundation of China (41991231, 42041004, and 42105116), the Second Tibetan Plateau Scientific Expedition and Research Program (STEP) (Grant 2019QZKK0602), the Fundamental Research Funds for the

Central Universities (lzujbky-2024-07, lzujbky-2024-jdzx07 and lzujbky-2022-kb09), and the Lanzhou Special Fund for Talent Program.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.catena.2025.108777.

Data Availability Statement.

The authors declare that the data supporting the results and findings of this study are available within the paper.

References

Andrews, S., Karlen, D., Mitchell, J., 2002. A comparison of soil quality indexing methods for vegetable production systems in northern California. Agr Ecosyst Environ 90, 25–45. https://doi.org/10.1016/S0167-8809(01)00174-8.

Batjes, N., 1996. Total carbon and nitrogen in the soils of the world. Eur. J. Soil Sci. 47, 151–163. https://doi.org/10.1111/j.1365-2389.1996.tb01386.x.

Bosso, D., Scow, K., 1998. Impacts of carbon and flooding on soil microbial communities: phospholipid fatty acid profiles and substrate utilization patterns. Microb. Ecol. 35, 265–278. https://doi.org/10.1007/s002489900082.

Bünemann, E., Bongiorno, G., Bai, Z., Creamer, R., Deyn, G., Goede, R., Fleskens, L., Geissen, V., Kuyper, T., Mäder, P., Pulleman, M., Sukkel, W., Groenigen, J., Brussaard, L., 2018. Soil quality-A critical review. Soil Biology Biochemistry 120, 105–125. https://doi.org/10.1016/j.soilbio.2018.01.030.

Chen, L., Liu, L., Qin, S., Yang, G., Fang, K., Zhu, B., Kuzyakov, Y., Chen, P., Xu, Y., Yang, Y., 2019. Regulation of priming effect by soil organic matter stability over a broad geographic scale. Nat. Commun. 10, 5112. https://doi.org/10.1038/s41467-019-13119-z.

Ding, J., Li, F., Yang, G., Chen, L., Zhang, B., Liu, L., Fang, K., Qin, S., Chen, Y., Peng, Y., Ji, C., He, H., Smith, P., Yang, Y., 2016. The permafrost carbon inventory on the Tibetan Plateau: a new evaluation using deep sediment cores. Glob. Chang. Biol. 22, 2688–2701. https://doi.org/10.1111/gcb.13257.

Ding, L., Huang, J., Li, C., Han, D., Liu, X., Li, H., Bai, Y., Huang, J., 2022. Variations in terrestrial oxygen sources under climate change. Sci. China Earth Sci. 65, 1810–1823. https://doi.org/10.1007/s11430-021-9956-5.

Dorau, K., Bamminger, C., Koch, D., Mansfeldt, T., 2022. Evidences of soil warming from long-term trends (1951-2018) in North Rhine-Westphalia. Germany. Climatic Change 170, 9. https://doi.org/10.1007/s10584-021-03293-9.

Du, M., Kawashima, S., Yonemura, S., Zhang, X., Chen, S., 2004. Mutual influence between human activities and climate change in the Tibetan Plateau during recent years. Global Planet. Change 41, 241–249. https://doi.org/10.1016/j.gloplacha.2004.01.010.

Eldridge, D., Maestre, F., Koen, T., Delgado-Baquerizo, M., 2018. Australian dryland soils are acidic and nutrient-depleted, and have unique microbial communities compared with other drylands. J. Biogeogr. 45, 2803–2814. https://doi.org/10.1111/jbi.13456.

García-García, A., Cuesta-Valero, F., Miralles, D., Mahecha, M., Quaas, J., Reichstein, M., Zscheischler, J., Peng, J., 2023. Soil heat extremes can outpace air temperature extremes. Nat. Clim. Chang. 13, 1237–1241. https://doi.org/10.1038/s41558-023-01812-3.

Han, D., Huang, J., Ding, L., Liu, X., Li, C., Yang, F., 2021. Oxygen footprint: an indicator of the anthropogenic ecosystem changes. Catena 206, 105501. https://doi.org/10.1016/j.catena.2021.105501.

Han, D., Huang, J., Ding, L., Zhang, G., Liu, X., Li, C., Yang, F., 2022. Breaking the ecosystem balance over the Tibetan Plateau. Earth's. Future 10, e2022EF002890. https://doi.org/10.1029/2022EF002890.

Hebb, C., Schoderbek, D., Hernandez-Ramirez, G., Hewins, D., Carlyle, C., Bork, E., 2017. Soil physical quality varied among contrasting land uses in Northern Prairie regions. Agr Ecosyst Environ 240, 14–23. https://doi.org/10.1016/j.agee.2017.02.008.

Huang, J., Yu, H., Guan, X., Wang, G., Guo, R., 2016. Accelerated dryland expansion under climate change. Nat. Clim. Chang. 6, 166–172. https://doi.org/10.1038/nclimate2837.

Huang, J., Huang, J., Liu, X., Li, C., Ding, L., Yu, H., 2018. The global oxygen budget and its future projection. Science Bulletin 63, 1180–1186. https://doi.org/10.1016/j.scib.2018.07.023.

Huang, J., Yu, H., Han, D., Zhang, G., Wei, Y., Huang, J., An, L., Liu, X., Ren, Y., 2020. Declines in global ecological security under climate change. Ecol. Ind. 117, 106651. https://doi.org/10.1016/j.ecolind.2020.106651.

Jansson, J., Hofmockel, K., 2020. Soil microbiomes and climate change. Nat. Rev. Microbiol. 18, 35–46. https://doi.org/10.1038/s41579-019-0265-7.

Jiao, K., Gao, J., Liu, Z., 2021. Precipitation drives the NDVI distribution on the Tibetan Plateau while high warming rates may intensify its ecological droughts. Remote Sens. (Basel) 13, 1305. https://doi.org/10.3390/rs13071305.

Karlen, D., Mausbach, M., Doran, J., Cline, R., Harris, R., Schuman, G., 1997. Soil quality: a concept, definition, and framework for evaluation. Soil Sci. Soc. Am. J. 61, 4–10. https://doi.org/10.2136/sssaj1997.03615995006100010001x.

Karlen, D., Ditzler, C., Andrews, S., 2003. Soil quality: why and how? Geoderma 114, 145–156. https://doi.org/10.1016/S0016-7061(03)00039-9.

Ladyman, J., Lambert, J., Wiesner, K., 2013. What is a complex system? Eur. J. Philos. Sci. 3, 33–67. https://doi.org/10.1007/s13194-012-0056-8.

Lehmann, J., Bossio, D., Kögel-Knabner, I., Rillig, M., 2020. The concept and future prospects of soil health. Nat. Rev. Earth Environ. 1, 544–553. https://doi.org/10.1038/s43017-020-0080-8.

Li, J., Pei, J., Pendall, E., Fang, C., Nie, M., 2020. Spatial heterogeneity of temperature sensitivity of soil respiration: A global analysis of field observations. Soil Biol. Biochem. 141, 107675. https://doi.org/10.1016/j.soilbio.2019.107675.

Liu, J., Wu, L., Chen, D., Yu, Z., Wei, C., 2018. Development of a soil quality index for Camellia oleifera forestland yield under three different parent materials in southern China. Soil Tillage Research 176, 45–50. https://doi.org/10.1016/j.still.2017.09.013.

Liu, X., Huang, J., Huang, J., Li, C., Ding, L., Meng, W., 2020. Estimation of gridded atmospheric oxygen consumption from 1975 to 2018. J. Meteorolog. Res. 34, 646–658. https://doi.org/10.1007/s13351-020-9133-7.

Nakajima, T., Lai, R., Jiang, S., 2015. Soil quality index of a Crosby silt loam in central Ohio. Soil Tillage Research 146, 323–328. https://doi.org/10.1016/j.still.2014.10.001.

Piao, S., Wang, X., Park, T., Chen, C., Lian, X., He, Y., Bjerke, J., Chen, A., Ciais, P., Tømmervik, H., Nemani, R., Myneni, R., 2020. Characteristics, drivers and feedbacks of global greening. Nat. Rev. Earth Environ. 1, 14–27. https://doi.org/10.1038/s43017-019-0001-x.

Poulsen, C., Tabor, C., White, J., 2015. Long-term climate forcing by atmospheric oxygen concentrations. Science 348, 12381241. https://doi.org/10.1126/science.1260670.

Pulido, M., Schnabel, S., Contador, J., Lozano-Parra, J., Gomez-Gutierrez, A., 2017. Selecting indicators for assessing soil quality and degradation in rangelands of Extremadura (SW Spain). Ecol. Ind. 74, 49–61. https://doi.org/10.1016/j.ecolind.2016.11.016.

Qiao, L., Wang, X., Smith, P., Fan, J., Lu, Y., Emmett, B., Li, R., Dorling, S., Chen, H., Liu, S., Benton, T., Wang, Y., Ma, Y., Jiang, R., Zhang, F., Piao, S., Müller, C., Yang, H., Hao, Y., Li, W., Fan, M., 2022. Soil quality both increases crop production and improves resilience to climate change. Nat. Clim. Chang. 12, 574–580. https://doi.org/10.1038/s41558-022-01376-8.

Raiesi, F., 2017. A minimum data set and soil quality index to quantify the effect of land use conversion on soil quality and degradation in native rangelands of upland arid and semiarid regions. Ecol. Ind. 75, 307–320. https://doi.org/10.1016/j.ecolind.2016.12.049.

Rillig, M., Wright, S., Rebecca Shaw, M., Field, C., 2002. Artificial climate warming positively affects arbuscular mycorrhizae but decreases soil aggregate water stability in an annual grassland. Oikos 97, 52–58. https://doi.org/10.1034/j.1600-0706.2002.970105.x.

Rodell, M., Houser, P., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C., Arsenault, K., Cosgrove, B., Radakovich, J., Bosilovich, M., Entin, J., Walker, J., Lohmann, D., Toll, D., 2004. The global land data assimilation system. Bull. Am. Meteorol. Soc. 85, 381–394. https://doi.org/10.1175/BAMS-85-3-381.

Shen, M., Piao, S., Jeong, S., Zhou, L., Zeng, Z., Ciais, P., Chen, D., Huang, M., Jin, C., Li, L., Li, Y., Myneni, R., Yang, K., Zhang, G., Zhang, Y., Yao, T., 2015. Evaporative cooling over the Tibetan Plateau induced by vegetation growth. Proc. Natl. Acad. Sci. USA 112, 9299–9304. https://doi.org/10.1073/pnas.1504418112.

Shi, X., Yu, D., Warner, E., Pan, X., Petersen, G., Gong, Z., Weindorf, D., 2004. Soil database of 1:1,000,000 digital soil survey and reference system of the Chinese genetic soil classification system. Soil Survery Horizons 45, 129–136. https://doi.org/10.2136/sh2004.4.0129.

Vasu, D., Singh, S., Ray, S., Duraisami, V., Tiwary, P., Chandran, P., Nimkar, A., Anantwar, S., 2016. Soil quality index (SQI) as a tool to evaluate crop productivity in semi-arid Deccan plateau, India. Geoderma 282, 70–79. https://doi.org/10.1016/j.geoderma.2016.07.010.

Wei, Y., Wu, J., Huang, J., Liu, X., Han, D., An, L., Yu, H., Huang, J., 2021. Declining oxygen level as an emerging concern to global cities. Environmental Science Technology 55, 7808–7817. https://doi.org/10.1021/acs.est.1c00553.

Weil, R., Brady, N., 2017. The nature and properties of soils, 15th edition. Person Education Inc, New Jersey.

Wieder, W., Cleveland, C., Smith, W., Todd-Brown, K., 2015. Future productivity and carbon storage limited by terrestrial nutrient availability. Nat. Geosci. 8, 441–444. https://doi.org/10.1038/NGEO2413.

Wu, M., Chen, S., Chen, J., Xue, K., Chen, S., Wang, X., et al., 2021. Reduced microbial stability in the active layer is associated with carbon loss under alpine permafrost degradation. PNAS 118, e2025321118. https://doi.org/10.1073/pnas.2025321118.

Yang, Y., Fang, J., Tang, Y., Ji, C., Zheng, C., He, J., Zhu, B., 2008. Storage, patterns and controls of soil organic carbon in the Tibetan grasslands. Glob. Chang. Biol. 14, 1592–1599. https://doi.org/10.1111/j.1365-2486.2008.01591.x.

Yang, Y., Fang, J., Pan, Y., Ji, C., 2009. Aboveground biomass in Tibetan grasslands. J. Arid Environ. 73, 91–95. https://doi.org/10.1016/j.jaridenv.2008.09.027.

Yu, P., Li, Q., Jia, H., Li, G., Zheng, W., Shen, X., Diabate, B., Zhou, D., 2014. Effect of cultivation on dynamics of organic and inorganic carbon stocks in Songnen Plain. Agron. J. 106, 1574–1582. https://doi.org/10.2134/agronj14.0113.

Yu, P., Han, D., Liu, S., Wen, X., Huang, Y., Jia, H., 2018. Soil quality assessment under different land uses in an alpine grassland. Catena 171, 280–287. https://doi.org/10.1016/j.catena.2018.07.021.

Yu, P., Liu, J., Tang, H., Sun, X., Liu, S., Tang, X., Ding, Z., Ma, M., Ci, E., 2023. Establishing a soil quality index to evaluate soil quality after afforestation in a karst region of Southwest China. Catena 230, 107237. https://doi.org/10.1016/j.catena.2023.107237.

Zeng, Z., Piao, S., Li, L., Zhou, L., Ciais, P., Wang, T., Li, Y., Lian, X., Wood, E., Friedlingstein, P., Mao, J., Estes, L., Myneni, R., Peng, S., Shi, X., Seneviratne, S., Wang, Y., 2017. Climate mitigation from vegetation biophysical feedbacks during the past three decades. Nat. Clim. Chang. 7, 432–436. https://doi.org/10.1038/nclimate3299.

Zhang, H., Wang, E., Zhou, D., Luo, Z., Zhang, Z., 2016. Rising soil temperature in China and its potential ecological impact. Sci. Rep. 6, 35530. https://doi.org/10.1038/srep35530.