



A physically consistent soil thickness map of the Qinghai-Tibet Plateau derived from coupled erosion mechanisms

Lihua Chen^{1,2†}, Xingyu Ding^{3†}, Shuping Zhao^{1,2*}, Fujun Niu¹, Keting Feng⁴, Zhuotong Nan^{1,2,5*}

¹School of Environment and Geographic Sciences, Shanghai Normal University, Shanghai, 200234, China

5 ²Key Laboratory of Ministry of Education on Virtual Geographic Environment, Nanjing Normal University, Nanjing 210023, China

³Hangzhou No.14 High School Qingshanhu, Hangzhou 311300, China

⁴Institute of Earth Environment, Chinese Academy of Sciences, Xi'an 710061, China

10 ⁵Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing 210023, China

† Authors contribute equally to this work

* Correspondence to: Shuping Zhao (shuping@njnu.edu.cn) and Zhuotong Nan (nanzt@njnu.edu.cn)

Abstract. Accurate, spatially explicit data on soil thickness is a critical missing link for Earth system modeling on the Qinghai-Tibet Plateau (QTP), where complex terrain and a lack of subsurface observations limit the performance of traditional empirical mapping approaches. This study presents a new high-resolution (1 km) soil thickness dataset for the QTP, specifically defined as the solum thickness extending from the surface to the C horizon interface. To overcome the inherent biases of sparse observation networks in high-altitude regions, we developed a revised mass balance model that ensures physical consistency across the plateau's diverse landscapes. Unlike existing products derived from statistical extrapolation or machine learning, our dataset is grounded in the mechanistic coupling of climate-driven weathering with a multi-processes erosion framework that partitions sediment transport into wind, hydraulic, and gravitational components. The resulting dataset reveals that solum thickness on the QTP ranges from 0.39 m to 2.04 m, with a spatially averaged mean of 0.89 m, exhibiting a pronounced decreasing gradient from the warm, humid southeast to the cold, arid northwest. Validation against 552 soil profile observations demonstrates that this physically-based approach achieves a Root Mean Square Error of 0.34 m and a Mean Relative Error of 0.78, outperforming existing national-scale soil maps (e.g., the Shangguan and Liu maps) by approximately 10–17%. Crucially, the model effectively reproduces realistic geomorphological patterns, such as the sharp differentiation between depositional basins and erosional ridges, which purely data-driven models often fail to capture in undersampled high-altitude regions. This dataset provides essential model parameter for hydrological,



ecological, and cryosphere models, facilitating more reliable assessments of the “Third Pole” under a changing climate. The dataset is available at figshare via <https://doi.org/10.6084/m9.figshare.30925358>.

30 **Keywords:** soil thickness; mass balance model; process-based modeling; Qinghai–Tibet Plateau

1 Introduction

As the central medium for material and energy exchange within terrestrial ecosystems, soil acts as a fundamental regulator of surface hydrological processes (Zhang et al., 2024a; Fu et al., 2011) and global biogeochemical cycles (Smith et al., 2015). Soil thickness, specifically defined in this study as the solum thickness (the vertical distance from the ground surface to the C horizon or parent material interface) (Xiao et al., 2023), governs hydraulic storage capacity, nutrient availability, and rooting depth (Berhe et al., 2018). While total regolith depth (depth to bedrock) includes the underlying saprolite, the solum represents the zone of active pedogenesis and high-frequency land-atmosphere interaction (Liu et al., 2013), making its accurate spatial characterization essential for terrestrial and Earth system models.

The Qinghai-Tibet Plateau (QTP) is a globally significant, ecologically sensitive region that is highly vulnerable to climate change (Zhang et al., 2022; Piao et al., 2019). The plateau's unique environment drives distinct soil formation mechanisms, including cryogenic constraints on organic matter decomposition (Chen et al., 2019), intense physical disintegration via frost action (Hall et al., 2002), and high rates of mass transfer from glacial and fluvial incision (Montgomery, 2002; Korup and Montgomery, 2008). These processes create pronounced spatial heterogeneity in soil development and preservation across the plateau. Consequently, a physically consistent soil thickness map is a fundamental prerequisite for modeling the region's hydrological regime (Fu et al., 2011), quantifying carbon stocks (Ke et al., 2025), and assessing the stability of its fragile alpine ecosystems (Berhe et al., 2018).

Despite this need, existing soil thickness datasets for the QTP, such as the China Dataset of Soil Properties for Land Surface Modelling, version 1 (hereafter Shangguan map) (Shangguan et al., 2013) and the Chinese High-Resolution National Soil Information Grid Basic Attribute Dataset (hereafter Liu map) (Liu et al., 2021), are primarily produced using empirical and machine learning models. These methods are fundamentally constrained by their reliance on extensive, representative field measurements (Gupta et al., 2024; Rosin et al., 2025). The extreme altitude and logistical challenges of the QTP result in a sparse and unevenly distributed network of soil profiles, which are largely clustered in accessible, flat areas while hillslopes remain significantly undersampled. In such data-scarce and topographically complex environments, empirical models often suffer from poor generalization and fail to reproduce realistic geomorphic gradients.

55 To address this critical data gap, process-based models offer a robust alternative by mechanistically linking soil thickness to the physical interplay between weathering and surface erosion. By grounding simulation in geomorphic mass balance



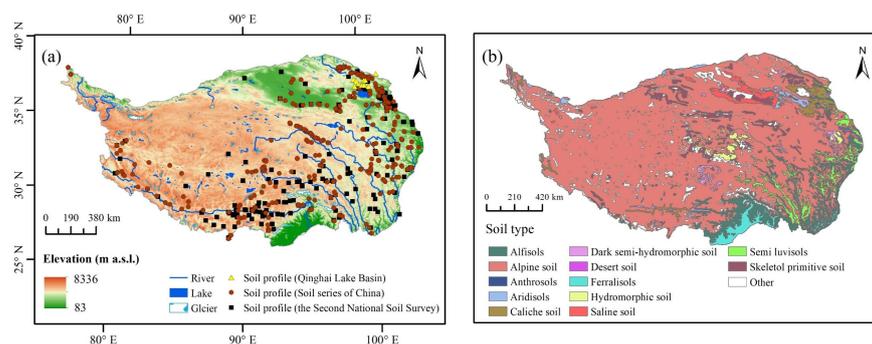
principles (Dietrich et al., 1995), this approach reduces the structural dependence on dense field measurements and is especially well-suited for estimating soil thickness on complex terrain where observations are absent.

In this study, we present a revised mass balance model to simulate solum thickness across the QTP at a 1 km resolution. We enhance the traditional modeling framework by explicitly partitioning total erosion into wind, hydraulic, and gravitational components, which account for the plateau's multi-process erosional environment, and introducing adjustable weighting coefficients to handle regional environmental heterogeneity. We then validate the resulting high-resolution dataset against field observations and compare it with existing national products. This work delivers a foundational, physically-consistent dataset essential for reducing uncertainty in regional hydrological and ecological simulations.

2 Materials and Methods

2.1 Study Area

The QTP, extending across 26°00'–39°47'N and 73°19'–104°47'E, represents the world's largest and highest physiographic unit, covering an area of approximately 2.5 million km² with an average elevation exceeding 4000 m a.s.l. (Fig. 1a). The region is characterized by a pronounced continental climate marked by significant spatial gradients; mean annual air temperature (MAT) decreases from approximately 10°C in the humid southeast to -8°C in the arid northwest (Yu et al., 2024). Mean annual precipitation (MAP) follows a similar trend, declining from over 1000 mm to less than 100 mm (Yang et al., 2010). Alpine grassland is the dominant land cover type (Wang et al., 2022), reflecting these severe climatic constraints. Permafrost is widespread, underlying approximately 67% of the plateau's total area and acting as a primary regulator of cryogenic soil processes (Cao et al., 2023). Soils on the QTP are typically pedogenically young and fragile, shaped by the combined effects of intense glacial erosion, pervasive freeze-thaw cycles, and wind erosion (Wei et al., 2025; Montgomery, 2002; Li et al., 2012). These active geomorphic processes drive rapid surface renewal, resulting in a complex soil-forming environment where diverse soil types exhibit high spatial heterogeneity (Fig. 1b).





80 **Fig. 1 Overview of the study area. (a) Topography of the Qinghai-Tibet Plateau (QTP) showing the spatial distribution of the 552 soil profiles used for model calibration and validation. (b) Distribution of major genetic soil types across the QTP.**

2.2 Data Acquisition and Preprocessing

Multiple datasets were compiled to drive the revised mass balance model, calibrate its parameters, and validate the outputs. A total of 552 soil profile observations were compiled across the QTP to serve as the ground truth for model calibration and performance assessment (Fig. 1a). These profiles were integrated from several primary sources, including the Second
85 National Soil Survey (Pan and Shi, 2015), the Chinese Soil Series Chronicle (Central and Western Volumes) (Zhao and Li, 2020; Li et al., 2020; Yuan, 2020; Huang and Lu, 2020; Wu et al., 2020; Yang and Zhang, 2020), and a study of parent material age in the Qinghai Lake Basin (Zhang et al., 2024b). It is a critical methodological distinction that these observations represent the vertical distance from the ground surface to the base of the pedogenic horizons, effectively measuring solum depth. Because excavations in these national surveys typically terminated at the C horizon interface rather
90 than the lithic contact (Shangguan et al., 2013), these data provide a consistent reference for the solum thickness (h_s) simulated in this study.

Climate forcing was derived from high-resolution datasets for the period 2000-2015 to represent the modern steady-state climate. MAT data were sourced from the Dataset of 0.01° Surface Air Temperature over Tibetan Plateau (1979-2018) (Ding et al., 2022), while MAP data were extracted from the 1 km Monthly Precipitation Dataset for China (1901-2024) (Peng,
95 2025). Vegetation conditions, which regulates surface erosion, was parameterized using a 1km MODIS(MOD13A2)-derived Normalized Difference Vegetation Index (NDVI) product (2001-2020) (Zhu, 2022) over the 2000-2015 interval. Topographic attributes, including slope, aspect, and curvature, were extracted from the 30 m NASADEM digital elevation model and subsequently resampled to a 1 km spatial grid using bilinear interpolation. Land use data for 2015 in 300 m resolution (Xu, 2019) and soil parent material from the 1:2.5 million scale Quaternary Geological Map of the QTP (Li, 2020)
100 were similarly standardized to 1 km resolution grid.

The model's erosion framework is driven by spatially explicit estimates of hydraulic and aeolian mass transfer. The hydraulic erosion rate (E_{water}) was adopted from a 1 km resolution dataset (2002-2016) (Teng et al., 2018) generated using the Revised Universal Soil Loss Equation (RUSLE), while the wind erosion rate (E_{wind}) was sourced from a 1 km resolution map (1980-2015) (Teng et al., 2021) created via the Revised Wind Erosion Equation (RWEQ) model. To ensure physical
105 realism, we integrated the global depth-to-bedrock (DTB) dataset developed by Shangguan et al. (2017) as a critical structural constraint. This dataset, generated at a 250 m resolution using an ensemble of machine learning algorithms, defines the total available weathered mantle.



To evaluate the performance of our model, two existing national-scale datasets were utilized for comparison. The first dataset, the Shangguan map (Shangguan et al., 2013), was developed at a spatial resolution of 30 arc-seconds (~1km) using a polygon linkage method that integrated 8,979 soil profiles from the Second National Soil Survey (1979–1985) with the 1:1 million Soil Map of China. Notably, the Shangguan map explicitly delineates non-soil map units (e.g., glaciers, rock debris, and water bodies), which appear as void spaces (null values) in the dataset. The second dataset, the Liu map (Liu et al., 2021), is a high-resolution (90 m) gridded dataset generated through a predictive mapping paradigm using a quantile regression forest algorithm. The model was trained on approximately 5000 representative soil profiles from the more recent National Soil Series Survey (2009–2019). While both datasets utilize extensive national survey data, their performance on the QTP is potentially limited by the lower density of profiles in high-altitude regions compared to eastern China. The observational dataset compiled for our study integrates the primary data sources used in both the Shangguan map (Second National Soil Survey) and the Liu map (National Soil Series Survey), supplemented by additional regional survey data to maximize representativeness.

Finally, to ensure the physical realism of the simulation, non-soil map units were excluded by masking glaciers and water bodies using the Second Chinese Glacier Inventory (Guo et al., 2015b) and the China Lake Dataset (1960s–2020) (Zhang et al., 2019), with the aquatic mask specifically based on the 2020 lake distribution.

2.3 The Revised Mass Balance Model

To simulate the spatial heterogeneity of soil thickness across the QTP, we revised the classical mass balance framework to account for the region's specific geomorphic processes. Unlike traditional landscape evolution models that treat the subsurface as a single homogeneous layer, our framework employs a coupled two-interface system. This system distinguishes between the solum (h_s ; m), defined as the genetically developed A and B horizons, and the underlying saprolite or C horizon (h_c ; m). This distinction is critical for the QTP, where the physical and chemical coupling between surface erosion and the deep weathering front is mediated by the thickness of the solum.

2.3.1 Governing Mass Balance Equations

The temporal evolution for the solum and saprolite thicknesses is governed by the conservation of mass. The change in thickness over time (t) for each layer is defined by the balance between material production from the underlying interface and material loss at the upper interface:

$$\frac{\partial h_s}{\partial t} = \frac{\rho_c}{\rho_s} P_{c \rightarrow s} - E, \quad (1)$$



$$135 \quad \frac{\partial h_c}{\partial t} = \frac{\rho_r}{\rho_c} P_{r \rightarrow c} - \frac{\rho_c}{\rho_s} P_{c \rightarrow s}, \quad (2)$$

where $P_{c \rightarrow s}$ represents the production of solum from the C horizon ($\text{m} \cdot \text{a}^{-1}$), $P_{r \rightarrow c}$ is the production of the C horizon from the unweathered bedrock ($\text{m} \cdot \text{a}^{-1}$), and E represents the total physical erosion rate at the surface ($\text{m} \cdot \text{a}^{-1}$). The bulk density terms for rock (ρ_r ; $\text{kg} \cdot \text{m}^{-3}$), saprolite (ρ_c ; $\text{kg} \cdot \text{m}^{-3}$), and solum (ρ_s ; $\text{kg} \cdot \text{m}^{-3}$) are integrated to account for the volumetric expansion occurring during pedogenesis. Given the cold, arid environment of the QTP, chemical weathering terms are
 140 omitted as physical processes and cryoturbation are the dominant mass-loss drivers.

2.3.2 Climate Control on Pedogenesis

The production of solum from the C horizon ($P_{c \rightarrow s}$) is modelled as an exponential decay function of the solum thickness (Pelletier and Rasmussen, 2009a), representing the insulating effect of the soil mantle on the weathering front. However, to account for the extreme climatic gradients of the QTP, we strictly define the potential production rate as a thermodynamic
 145 function rather than a static constant. The production function is formulated as:

$$P_{c \rightarrow s} = \Phi(T, P) P_{s0} e^{\frac{-h_s}{h_0}}, \quad (3)$$

where h_0 is the characteristic soil depth (m) and P_{s0} is the potential production rate at the interface ($\text{m} \cdot \text{a}^{-1}$). In this context, P_{s0} represents the maximum rate at which the C horizon is converted to solum when $h_s = 0$. The term $\Phi(T, P)$ represents the climate-dependency of the process, specifically integrating the effects of air temperature (T ; $^{\circ}\text{C}$) and precipitation (P ;
 150 mm). $\Phi(T, P) P_{s0}$ represents the maximum rate of solum formation under specific climatic conditions. We quantify this potential weathering rate using the Effective Energy and Mass Transfer (EEMT) model (Rasmussen et al., 2005; Rasmussen and Tabor, 2007; Pelletier et al., 2013), which calculates the energy available for mineral transformation based on local thermodynamics:

$$\Phi(T, P) P_{s0} = a e^{b \cdot EEMT}, \quad (4)$$

155 where a (lithology adjustment coefficient, $\text{m} \cdot \text{a}^{-1}$) and b (climate response coefficient, $\text{m}^2 \cdot \text{a} \cdot \text{kJ}^{-1}$) are lithological dependent coefficients. $EEMT$ ($\text{kJ} \cdot \text{m}^{-2} \cdot \text{a}^{-1}$) is calculated from MAT ($^{\circ}\text{C}$) and MAP (mm) (Rasmussen and Tabor, 2007):

$$EEMT = 347134 \exp \left\{ -\frac{1}{2} \left[\left(\frac{MAT-21.5}{-10.1} \right)^2 + \left(\frac{MAP-4412}{1704} \right)^2 \right] \right\}, \quad (5)$$

This formulation ensures that the model dynamically adjusts the weathering potential based on the varying thermal and moisture regimes across the plateau's vast area.



160 2.3.3 Multi-Process Erosion Framework

Standard mass balance models typically approximate erosion solely as a diffusive process driven by gravity. However, the QTP is characterized by a multi-process erosional environment where wind and water play dominant roles in different regions (Wei et al., 2025). Other potential factors (such as freeze-thaw erosion and human activities) were not modeled as separate erosion categories. The process of freeze-thaw erosion involves two phases (Guo et al., 2015a): a weathering phase where frost action generates loose particles, and a transport phase where these particles are moved by other forces. For the purposes of this model, which focuses on sediment transport mechanisms, freeze-thaw processes are treated as a weathering agent rather than a distinct erosion category. The detrital particles it produces are then accounted for in the simulations of fluvial, aeolian, and gravitational transport. Meanwhile, given the QTP's vast area and sparse population, the impact of direct human activities on regional-scale erosion patterns is considered minimal (Sun et al., 2020) and was therefore excluded from the model.

To reflect the environmental heterogeneity of the region, we expanded the erosion term (E) into Eq. 1 into a weighted sum of three distinct components:

$$E = \alpha \frac{E_{water}}{10\rho_s} + \beta \frac{E_{wind}}{10\rho_s} + \gamma E_{gravity}, \quad (6)$$

where E_{water} and E_{wind} ($t \cdot ha^{-1} \cdot a^{-1}$) are input erosion rates derived from the RUSLE method (Renard et al., 1994) and the RWEQ model (Fryrear et al., 2000), respectively. For the QTP, the two erosion inputs for the QTP were sourced from regional datasets (Teng et al., 2018; Teng et al., 2021). Gravitational erosion ($E_{gravity}$; $m \cdot a^{-1}$) representing downslope movement such as soil creep or freeze-thaw action, is modeled as a linear function of topographic curvature (Roering, 2008):

$$E_{gravity} = D\nabla^2 z, \quad (7)$$

where D is the soil diffusion coefficient ($m^2 \cdot a^{-1}$) and $\nabla^2 z$ is the topographic curvature over the elevation grid z .

The term $10\rho_s$ converts mass-based erosion rates into linear lowering rates ($m \cdot a^{-1}$). The dimensionless weighting coefficients (α, β, γ) are introduced to account for the spatial heterogeneity of process dominance. These coefficients allow the model to be calibrated such that wind erosion determines thickness in the arid interior, while hydraulic erosion dominates in the humid monsoon zones.

2.3.4 Steady-State Solution and Boundary Conditions

To solve for the solum thickness (h_s), we assume a geomorphic steady state where the production of soil is balanced by surface erosion over long timescales ($\partial h/\partial t=0$) (Phillips, 2010). While instantaneous fluxes may fluctuate (Gabet and Mudd, 2009), the steady-state framework remains a robust and widely applied approach for simulating large-scale spatial patterns



over geomorphic timescales (Phillips, 2010). Substituting Eq. 3 and Eq. 6 into Eq. 1 and rearranging the terms yields the equilibrium condition:

$$190 \quad \frac{\rho_c}{\rho_s} (\Phi(T, P) P_{s0} e^{-h_s^*/h_0}) = \alpha \frac{E_{water}}{10\rho_s} + \beta \frac{E_{wind}}{10\rho_s} + \gamma E_{gravity}, \quad (8)$$

Solving this equity for the steady-state thickness (h_s^*), we obtain the final equation used for mapping:

$$h_s^* = -h_0 \ln \left[\frac{\rho_s (\alpha E_{water} + \beta E_{wind} + \gamma E_{gravity})}{\rho_c \Phi(T, P) P_{s0}} \right], \quad (9)$$

Within this derivation, the ratio of saprolite to solum bulk density (ρ_c/ρ_s) is assumed to be a constant value of 1.35, a standard parameter adopted from established geomorphological modeling studies (Pelletier and Rasmussen, 2009b) to represent volumetric expansion during pedogenesis. Equation (9) allows us to resolve the solum thickness. However, the second governing equation (Eq. 2) describing the saprolite evolution cannot be similarly solved due to a lack of constraints on the bedrock-to-saprolite production rate ($P_{r \rightarrow c}$). To resolve this, we utilize the spatially explicit DTB dataset from Shanguan et al. (2017) as a physical boundary condition. Since DTB represents the total regolith depth ($DTB = h_s + h_c$), the saprolite thickness is constrained by the relationship $h_c^* = DTB - h_s^*$. This ensures that the simulated solum thickness (h_s^*) is always physically bounded by the total available regolith, effectively closing the system of equations.

2.4 Environmental Clustering for Parameterization

The application of the mass balance model (Eq. 9) requires the specification of distinct kinetic and transport coefficients that govern soil evolution. Given the vast area and extreme environmental gradients of the QTP, assuming a single set of global parameters would oversimplify regional geomorphic distinctiveness and introduce systematic bias. To address this, we implemented a zonally adaptive parameterization strategy that partitions the plateau into homogeneous environmental clusters, allowing the model to explicitly account for the spatial non-stationarity of weathering and erosion processes. The process involved two main steps.

We first evaluated the predictive importance of 16 potential covariates derived from topographic, climatic, and ecological datasets (Table 1) (Yamashita et al., 2024; Wang et al., 2021). A Random Forest algorithm was employed to rank the predictive importance of these variables for soil thickness using the Mean Decrease Accuracy (MDA) metric. Variables with non-positive MDA values were deemed as non-contributory and were excluded to reduce noise.

Second, based on the remaining key predictors, we partitioned the study area into eight environmentally distinct clusters using the k -prototypes (Huang, 1998) unsupervised clustering algorithm ($k=8$). This algorithm was specifically selected for its ability to handle mixed data types, effectively integrating both continuous variables and categorical variables. Consistent with the data processing in Section 2.2, non-soil areas (glaciers and water bodies) were excluded from the clustering process.



This resulting zoning system provided the framework for calibrating the revised mass balance model independently for each cluster, thereby better capturing the region's complex environmental gradients.

Table 1 The initial pool of environmental variables.

Category	Environmental Variable	Abbreviation
Terrain Attributes	Elevation	Ele
	Slope	Slo
	Aspect	Asp
	Slope Length (Hickey et al., 1994)	SIL
	Slope Position	SIP
	General Curvature	GeC
	Plane Curvature	PIC
	Profile Curvature	PrC
Ecological Indicators	Terrain Ruggedness Index (Moreno et al., 2003)	TRI
	Normalized Difference Vegetation Index	NDVI
Hydrological Indicators	Topographic Wetness Index	TWI
Source Indicators	Parent Material of Soil Formation	PMSF
Climatic Factors	Mean Annual Precipitation	MAP
	Mean Annual Temperature	MAT
Land Cover	Land Use Type	LUT
Erosion Potential	Sediment Transport Index	STI

220 2.5 Model Calibration and Performance Assessment

Obtaining direct field measurement for the model parameters (Table 2) required by the mass balance model is practically infeasible across the vast and extreme environment of the QTP. We therefore implemented a parameter optimization approach using inverse modeling against the available soil profile datasets. The model parameters (Table 2) were calibrated independently for each of the eight environmental clusters using the Shuffled Complex Evolution (SCE-UA) algorithm (Duan et al., 1993). This method was selected for its robust performance in calibrating physical land surface models (Guo et al., 2013; Vrugt et al., 2003) as its complex shuffling mechanism is highly effective at avoiding convergence on local



minima. To prevent equifinality and ensure physical realism, the parameters were constrained within physically permissible ranges derived from literature (Table 2).

230 **Table 2 Parameters of the revised mass balance model.**

Parameter	Description	Value Range	Unit
h_0	Characteristic soil depth	0-0.5	m
ρ_s	Soil bulk density	2400-2900	$\text{kg} \cdot \text{m}^{-3}$
a	Lithology adjustment coefficient	0.5-100	$\text{m} \cdot \text{a}^{-1}$
b	Climate response coefficient	0-0.1	$\text{m}^2 \cdot \text{a} \cdot \text{kJ}^{-1}$
α	Hydraulic erosion weight	0-1	-
β	Aeolian erosion weight	0-1	-
γ	Gravitational erosion weight	0-1	-
D	Soil diffusion coefficient	0.00001-0.01	$\text{m}^2 \cdot \text{a}^{-1}$

To rigorously evaluate the reliability of the simulated solum thickness, we implemented a two-tiered assessment strategy comprising internal cross-validation and external benchmarking against existing national datasets. Given the practical difficulty of collecting independent validation samples in the extreme environment of the QTP, we employed a k -fold cross-validation scheme (with $k = 4$) to maximize the utility of the 552 available soil profiles. Within each environmental cluster, the observational data were randomly partitioned into four equal subsets. The model was then iteratively trained using three of the subsets, with the remaining subset reserved for validation. This process was repeated four times to ensure every subset served as a validation set exactly once.

The accuracy of the soil thickness simulation was quantitatively characterized using three statistical metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Relative Error (MRE). These metrics characterize the deviation between simulated values ($\hat{m}(x_i)$) against measured values ($m(x_i)$):

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{m}(x_i) - m(x_i))^2}, \quad (10)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |\hat{m}(x_i) - m(x_i)|, \quad (11)$$

$$\text{MRE} = \frac{1}{n} \sum_{i=1}^n \frac{|\hat{m}(x_i) - m(x_i)|}{m(x_i)}, \quad (12)$$



245 Beyond internal consistency, we conducted a comparative performance analysis against two state-of-the-art regional
products: the Shangguan map and the Liu map. Error metrics for all three datasets were calculated against the compiled 552
soil profiles. It is important to acknowledge that these observations represent a common ground truth rather than a strictly
independent external validation set, as the underlying surveys (Second National Soil Survey and National Soil Series Survey)
served as primary data sources for the reference maps as well. However, this approach provides a rigorous benchmark of
250 how well the process-based framework reproduces geomorphic reality compared to traditional polygon-linkage and
machine-learning paradigms using the best available data for the region.

3 Results

3.1 Environmental Clusters and Model Calibration

The Random Forest-based importance analysis revealed significant disparities in the predictive power of the 16 potential
255 environmental variables. As illustrated in Fig. 2a, Elevation and NDVI emerged as the dominant factors controlling the
spatial heterogeneity of the QTP environment. This reflects the fundamental thermodynamic constraints on pedogenesis
across the QTP: elevation governs the thermal energy available for chemical weathering, while precipitation and vegetation
regulate both the moisture necessary for mineral transformation and the surface stability against erosion. Conversely, local
morphometric variables such as general curvature (GeC), the Sediment Transport Index (STI), land use type (LUT), the
260 Terrain Ruggedness Index (TRI) and the Topographic Wetness Index (TWI) exhibited non-positive MDA values, indicating
negligible contribution to the environmental zoning. Consequently, these five variables were excluded, retaining 11 key
environmental variables for clustering process.

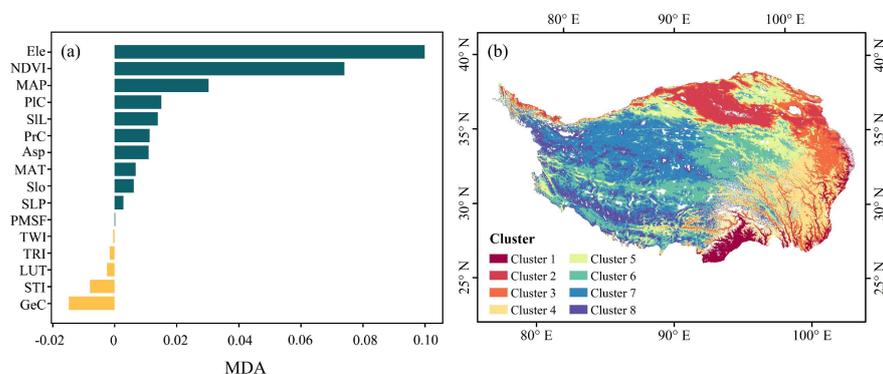
Based on these variables, the QTP was partitioned into eight spatially distinct clusters (Fig. 2b). These clusters exhibit high
homogeneity but significant inter-cluster heterogeneity, effectively capturing the plateau's diverse environmental regimes
265 (Table 3). Cluster 1, located in the southeastern and eastern margins, represents the zone with the most favorable moisture
and thermal regimes; it features the lowest mean elevation (2,136 m a.s.l.) and the highest precipitation (832.41 mm) and air
temperature (MAT: 13.09 °C), supporting the densest vegetation on the plateau (mean NDVI: 0.86) and rapid soil
development. In sharp contrast, Cluster 2 is concentrated in the Qaidam Basin (northeastern QTP) and represents the
plateau's arid interior, characterized by flat terrain, minimal precipitation (~ 222 mm), and desert vegetation. Clusters 3 and
270 4 serve as transitional zones in the eastern and southeastern QTP; they exhibit similar temperature and precipitation patterns
and vegetation conditions to one another but differentiated by elevation (3597 m and 4354 m, respectively). The remaining
groups, Clusters 5 through 8, constitute the high-altitude cold zones. Clusters 5 and 6 dominate the northeastern and northern



QTP, including the Three Rivers Source Region, and are defined by high elevations (>4200 m a.s.l.) and reduced climatic variability. Cluster 7 covers the central and western interior, the core permafrost zone, exhibiting low temperatures (MAT: 275 -3.32 °C) and sparse vegetation. Finally, Cluster 8 occupies the most extreme high-elevation zone, such as the northern Himalayas where soil formation is kinetically limited by low temperatures and sparse biomass production.

The calibrated model parameters (Table 4) provide physical insights into these zonal differences. The lithology adjustment coefficient (a), which scales the maximum potential weathering rate, reveals a fundamental divergence between the plateau's interior core and its margins. In the central permafrost and high-mountain zones (Clusters 7 and 8), a values are extremely 280 low ($<1 \text{ m} \cdot \text{a}^{-1}$), reflecting severe lithological constraints that inhibit soil production regardless of climatic inputs. In contrast, the surrounding regions (Clusters 1-4, 6) exhibit high potential weathering rates ($a > 80 \text{ m} \cdot \text{a}^{-1}$). This suggests that in these active soil-forming zones, the model relies on high base production rates to sustain the observed soil thickness against environmental erosion.

The erosion weighting coefficients (α , β , γ) highlight spatial disparities in sediment transport. In the arid interior (Cluster 7), 285 coefficients are near unity (≈ 0.99), indicating that empirical erosion estimates closely match the low weathering rates. Conversely, in the humid southeast (Cluster 1) and the source regions (Cluster 6), the hydraulic erosion weights are notably low ($\alpha < 0.06$), suggesting that vegetation cover significantly dampens actual sediment export relative to the potential erosion energy predicted by RUSLE. It is worth noting that the model achieves its lowest RMSE (0.29 m) in the interior permafrost zone (Cluster 7). While this likely reflects the region's lower environmental heterogeneity compared to the rugged southeast, 290 the limited sample size ($n=15$) in this cluster warrants a cautious interpretation of this high statistical accuracy.



295 **Fig. 2 Environmental variable importance and environmental zoning of the QTP. (a) Importance ranking of the initial environmental variables based on the Random Forest algorithm. Higher Mean Decrease Accuracy (MDA) values indicate greater predictive importance. (b) Spatial distribution of the eight environmental clusters derived from the k -prototype clustering algorithm.**



Table 3 Summary of the representative environmental characteristics for the eight clusters. MAT, MAP: mean annual air temperature and mean annual precipitation (2000-2015), respectively.

	Elevation (m a.s.l.)	MAT (°C)	MAP (mm)	NDVI
Cluster 1	2136	13.09	832.41	0.86
Cluster 2	2938	4.58	222.49	0.21
Cluster 3	3597	3.05	610.26	0.64
Cluster 4	4354	2.23	809.56	0.66
Cluster 5	4230	-1.15	399.75	0.32
Cluster 6	4697	-1.27	449.22	0.34
Cluster 7	5036	-3.32	412.39	0.20
Cluster 8	5419	-4.01	505.06	0.16

Table 4 Calibrated parameters of the revised mass balance model for the eight environmental clusters. *n*: the number of soil profile observations used for calibration in each cluster; RMSE: root mean square error resulting from the simulation. The RMSE for Cluster 8 was not calculated due to insufficient sample size required for valid cross-validation.

	h_0	ρ_s	a	b	α	β	γ	D	RMSE	<i>n</i>
Cluster 1	0.038	2764.99	86.03	0.00039	0.0012	0.00075	0.18	0.0016	0.38	35
Cluster 2	0.048	2895.88	98.34	1.42e-06	0.0024	0.0021	0.014	0.00041	0.34	131
Cluster 3	0.043	2855.11	99.7	4.02e-05	0.0014	0.0069	0.017	0.00011	0.38	136
Cluster 4	0.026	2895.74	99.69	0.0012	0.00043	0.0072	0.0035	6.23e-05	0.40	51
Cluster 5	0.056	2895.67	6.89	4.13e-05	0.15	0.0092	0.94	0.0096	0.34	71
Cluster 6	0.042	2899.59	99.18	3.84e-05	0.053	0.0012	0.052	6.95e-05	0.30	79
Cluster 7	0.10	2401.88	0.58	0.00014	0.99	0.96	0.99	0.0093	0.29	15
Cluster 8	0.084	2400.32	0.63	0.00069	0.99	0.0004	0.0056	0.00065	-	4

3.2 Spatial Distributions of Simulated Soil Thickness

The simulation results from the revised mass balance model indicate that soil thickness across the QTP ranges from 0.39 to 2.04 m, with a spatially averaged mean of 0.89 m. Spatially, soil thickness generally decreases from the southeast to the northwest (Fig. 3). Regions with the greatest soil thickness are primarily concentrated in the southeastern and eastern



margins of the plateau, particularly within the Yellow River Basin, where the average thickness reaches 1.16 m. This area corresponds mainly to Cluster 1, which features the most favorable moisture and thermal regimes on the plateau, fostering dense vegetation cover ($NDVI > 0.6$) and rapid soil development. Crucially, the high-resolution simulation resolves distinct geomorphic signatures that are often obscured in coarser empirical maps. The eastern drainage systems (Yangtze, Mekong, and Salween basins) display distinct dendritic patterns of soil thickness (Fig. 3). Thicker colluvial deposits (indicated by yellow to orange bands in Fig. 3) extend along the river valleys, contrasting sharply with the thinner soils on the adjacent bedrock-dominated mountain ridges. This ridge-valley differentiation physically validates the model's gravitational erosion module, which correctly simulates the transport of material from steep slopes to valley floors.

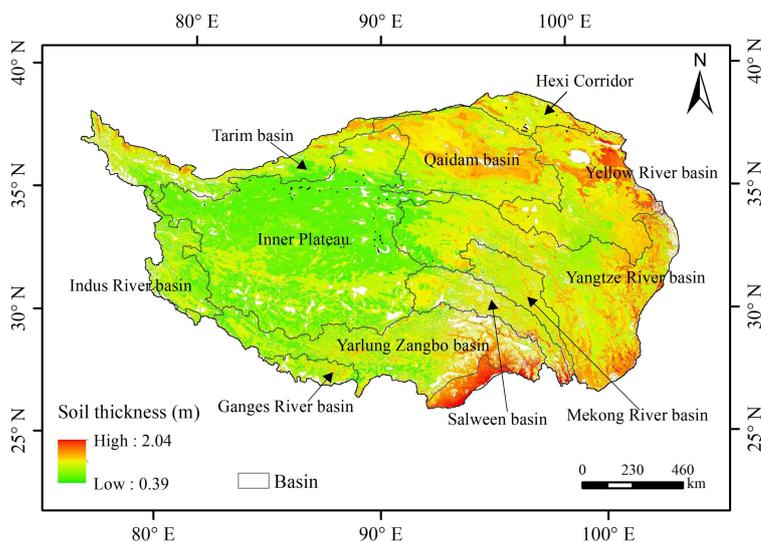
310

A similar depositional signature is evident in the Qaidam Basin (Cluster 2), which appears as a coherent "island" of moderately thick soil amidst the rugged terrain of the surrounding Qilian and Altun Mountains. This reflects the basin's nature as a stable depositional zone. Similarly, in the south, a continuous linear band of high soil thickness marks the Yarlung Zangbo River (Brahmaputra) valley. This depositional corridor stands in stark contrast to the immediate adjacent high-altitude zones, the Himalayas to the south and the Gangdise Mountains to the north, which exhibit some of the lowest thickness values on the plateau due to intense glacial and periglacial erosion.

315

Conversely, the vast interior of the plateau (Clusters 7 and 8) is dominated by uniformly low solum (< 0.60 m). This broad expanse reflects the core permafrost zone, where extreme cold and aridity kinetically inhibit pedogenesis, and the lack of vegetation leaves the surface vulnerable to deflation by strong westerly winds.

320



325 **Fig. 3** Spatial distribution of simulated soil thickness on the QTP. The delineated areas for the Mekong, Salween, and Yarlung Zangbo (Brahmaputra) rivers represent the catchment sections located within China. White patches indicate non-soil areas (glaciers and water bodies) where soil thickness was not simulated.



3.3 Dominant Environmental Controls on Soil Thickness

Correlation analysis between simulated solum thickness and key environmental variables (Fig. 4) confirms that pedogenesis on the QTP is fundamentally regulated by available energy and mass transfer. Pearson correlation analysis identifies MAT ($r = 0.66$) and elevation ($r = -0.66$) as the primary inverse drivers of the regional thickness gradient. This strong coupling validates the thermodynamic basis of our model: lower-elevation regions provide the necessary thermal energy to accelerate chemical weathering kinetics ($P_{c \rightarrow s}$), whereas the extreme cold of the high-altitude interior kinetically inhibits mineral transformation, resulting in a thin, skeletal regolith.

Vegetation, represented by NDVI ($r = 0.45$), acts as a critical secondary control by modulating surface stability. The positive correlation reflects a biophysical feedback loop where favorable hydrothermal regimes support denser biomass, which in turn increases root cohesion and surface roughness, effectively decoupling the solum from erosive shear stresses. Conversely, the lack of correlation with local morphometric variables like general curvature ($r = -0.01$) at the plateau scale suggests that while topography drives local catenary differentiation, the regional mean state of the soil is overridden by broad climatic forcing.



Fig. 4 Pearson correlation matrix between simulated soil thickness (h) and environmental variables. Red represents positive correlations and blue represents negative correlations. Asterisks denote statistically significant correlations ($p < 0.05$). Refer to Table 1 for the full definitions of the variable abbreviations.



345 However, at the hillslope scale, topography re-emerges as the dominant control on spatial redistribution. This is clearly
illustrated by the transect analysis across the Hengduan Mountains (Fig. 5), a region of extreme relief and vertical zonation.
Here, soil thickness varies systematically with terrain features: steep ridges act as sediment sources where erosion outpaces
production, preventing accumulation, whereas gentler slopes and valley floors function as sediment sinks. Consequently, a
distinct inverse relationship is observed (Fig. 5c), where soil thickness peaks in the warm, vegetated valley bottoms and
350 diminishes rapidly towards the cold, barren ridges. This distinct ridge-to-valley sorting confirms that the inclusion of the
diffusive transport term in our mass balance framework correctly reproduces the physical laws of hillslope geomorphology.

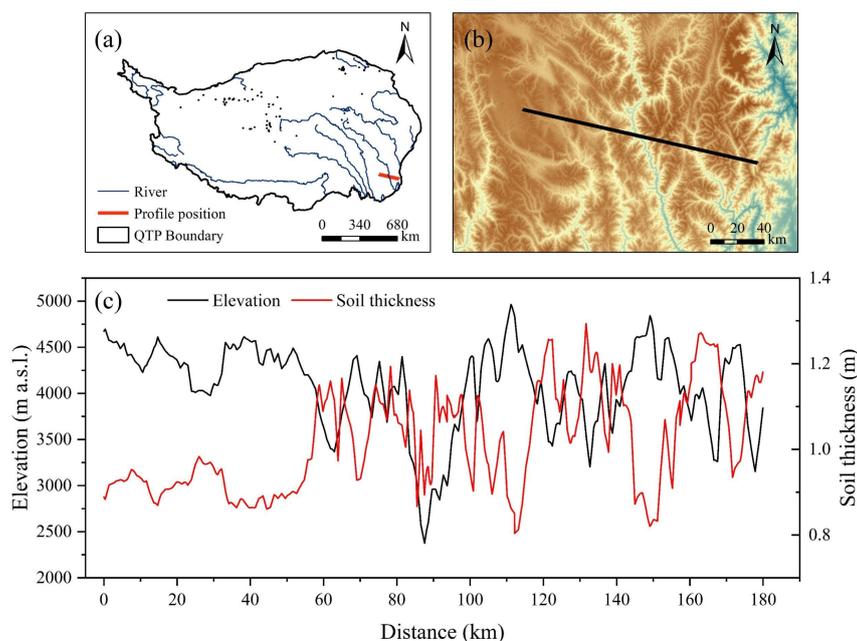


Fig. 5 Topographic controls on soil thickness along a transect in the Hengduan Mountains. (a) Location of the study transect on
the southeastern QTP. (b) Local topography of the transect area. (c) Cross-sectional profile illustrating the inverse relationship
355 between elevation (black line) and simulated soil thickness (red line), where thickness peaks in valley floors and minimizes on ridge
crests.

3.4 Accuracy Assessment and Comparative Analysis

3.4.1 Validation against Field Observations

The model performance was evaluated using a 4-fold cross-validation approach based on 552 available soil profile
360 observations. The results indicate an overall RMSE of 0.34 m for the entire QTP. At the cluster level, RMSE values range
from 0.29 m to 0.40 m (Table 4). Cluster 7 (interior permafrost zone) exhibited the lowest RMSE (0.29 m). While this



suggests high accuracy, it likely reflects the relatively low environmental heterogeneity of the central plateau combined with a limited sample size ($n=15$), which warrants a cautious interpretation. Conversely, slight increases in RMSE were observed in the transitional zones (Clusters 1, 3, and 4) where complex topography and active monsoon climates introduce greater variability in the soil thickness. Overall, the consistency of RMSE values across diverse environmental zones suggests that the calibrated mass balance model effectively generalizes the relationship between soil formation processes and the chosen environmental covariates.

3.4.2 Comparison with Existing Soil Thickness Datasets

We compared our simulated results against two widely used regional datasets (the Shangguan map and the Liu map) (Table 5). In terms of magnitude, our model estimates a mean of 0.89 m (range: 0.39-2.04 m) across the QTP, which is notably higher than both the Shangguan map (mean: 0.65 m) and the Liu map (mean: 0.66 m).

To quantitatively assess accuracy, we calculated error metrics for all three datasets against the 552 compiled soil profile observations (Table 5). Despite the fact that these observations were used to calibrate our model and partially overlap with the source data used to generate the reference maps, the revised mass balance model yielded the lowest RMSE (0.34 m) and MRE (0.78), outperforming both the Shangguan map (RMSE = 0.45 m, MRE = 0.98) and the Liu map (RMSE = 0.42 m, MRE = 0.91). While our model exhibited a slightly higher MAE (0.13 m) compared to the Shangguan map (0.06 m), this is likely attributable to our model's ability to capture the full range of soil thickness, from negligible depths on ridges to thick deposits in the valleys (Fig. 3 and Fig. 5). The reference maps, by contrast, tend to predict spatially smoothed values, which artificially minimizes absolute error but fails to represent the landscape's physical extremes (Fig. 6a and b). This results in a wider error distribution (higher MAE) but a better overall structural fit to the landscape (lower RMSE) for our model.

Table 5 Statistical comparison of soil thickness and error metrics between this study and existing datasets. Min, Max and Mean refer to the soil thickness values (m) across the QTP. Error metrics (RMSE, MAE, MRE) were calculated against the 552 soil profiles.

	Min (m)	Max (m)	Mean (m)	RMSE (m)	MAE (m)	MRE
This study	0.39	2.04	0.89	0.34	0.13	0.78
Shangguan map	0.12	1.60	0.65	0.45	0.06	0.98
Liu map	0	2.35	0.66	0.42	0.11	0.91



385 Spatially, the difference maps (Fig. 6b and d) reveal where our process-based approach diverges from the previous maps. The grey masked regions indicate areas of strong agreement where the difference between our simulation and the reference datasets is within $\pm 5\%$. Comparison with the Shuangguan map (Fig. 6b) reveals substantial negative differences in the Qaidam Basin and the inner QTP, indicating that the Shuangguan map predicts significantly thicker soils in these arid, erosional landscapes than our model. This aligns with our earlier finding that the Shuangguan map tends to overestimate soil depth on steep slopes and ridges. Conversely, distinct positive differences are concentrated in the deep valleys of the southeastern Hengduan mountains, suggesting our model correctly identifies thicker colluvial deposits where the Shuangguan map likely underestimates accumulation. The difference map for the Liu dataset (Fig. 6d) displays a higher degree of spatial fragmentation, reflecting the stochastic nature of the machine learning extrapolation used in the Liu map. Similar to the Shuangguan comparison, negative differences are prevalent in the inner QTP, suggesting the Liu map also overestimates thickness immature soil region. In contrast, our model predicts higher thickness in the active depositional valleys of the Yarlung Zangbo and eastern river basins and lower thickness in the zone of inhibited pedogenesis in the interior of the QTP.

390
395

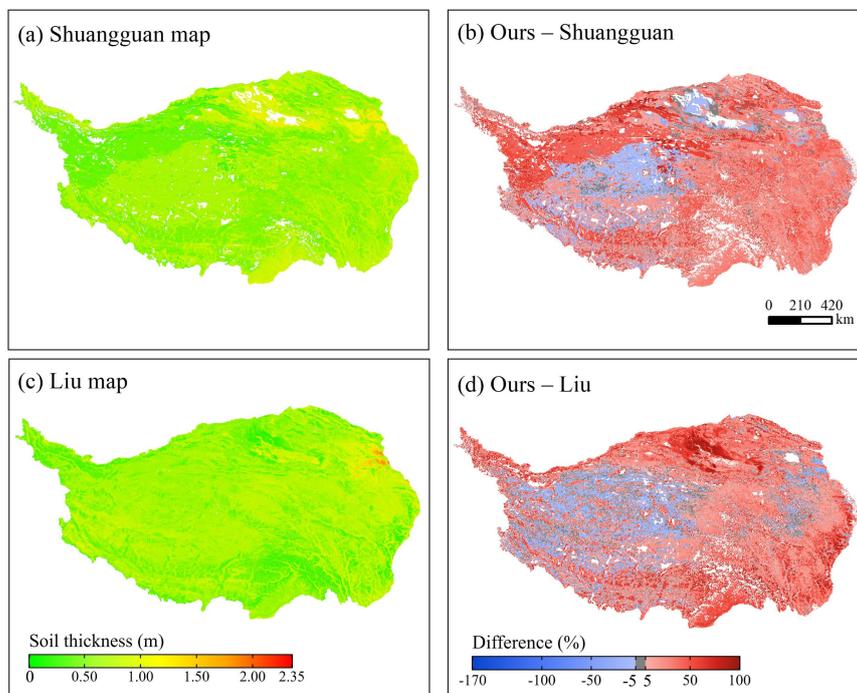


Fig. 6 Comparison of soil thickness datasets across the QTP. Spatial distribution of soil thickness derived from (a) the Shuangguan map and (c) the Liu map. Relative percentage difference between the simulated results of this study and (b) the Shuangguan map and (d) the Liu map. Positive values indicate that our model predicts thicker soils than the reference datasets, while negative

400

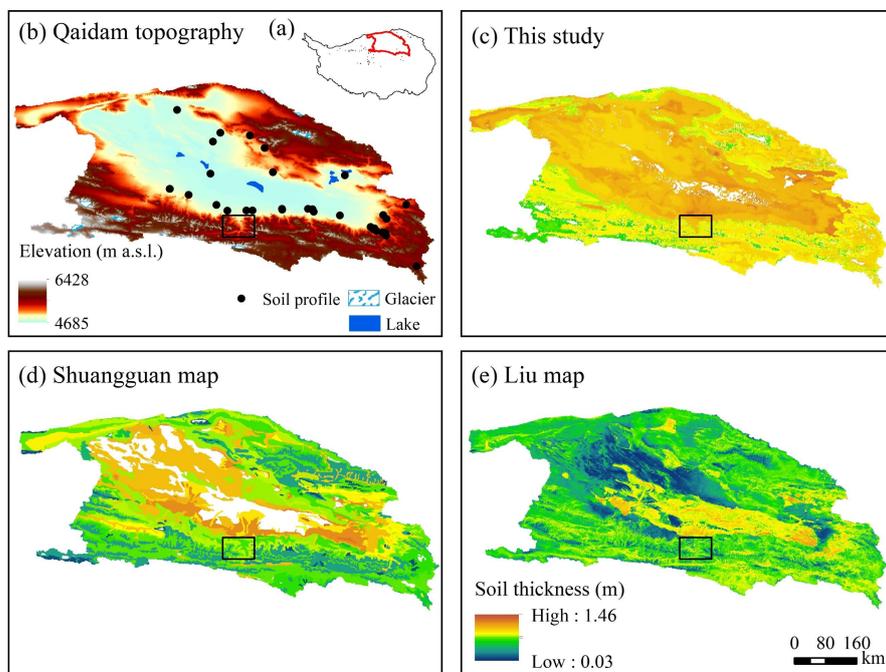


values indicate thinner soils. White patches represent null values (no data). In the Shangguan map, these correspond to defined non-soil units, while in our study, these correspond to masked glaciers and lakes.

3.4.3 Performance in Representative Zones

Although the difference maps (Fig. 6) reveal substantial discrepancies between the datasets, numerical differences alone do not determine which map better represents the actual soil thickness. We conducted a detailed examination of two representative regions, the Qaidam Basin and the Qiangtang Plateau, where the divergence between our model and the reference datasets is pronounced. In the absence of dense independent validation data in these remote areas, we evaluated the results based on physical plausibility, specifically assessing whether the simulated spatial patterns align with the expected geomorphological processes of erosion and deposition.

The Qaidam Basin (Fig. 7), located in the northeastern QTP, serves as a critical test case for depositional environments. Physically, this region is a stable, flat basin surrounded by high mountain ranges, where long-term sedimentation should result in a relatively continuous and uniform soil layer. Our model simulates a continuous layer of moderately thick soil (mean: 0.99 m) across the basin floor, with a low standard deviation (0.13 m) that is geomorphologically consistent with the basin's depositional nature. In contrast, the Liu map (Fig. 7e) displays anomalous patches of extreme high and low values (standard deviation: 0.24 m), resulting in a fragmented spatial pattern that contradicts the expected uniformity of a lacustrine basin floor. Similarly, the Shangguan map (Fig. 7d), while spatially continuous, predicts extremely thick soils (up to 1.36 m) extending onto the erosional ridges of the surrounding mountains, suggesting an overestimation of thickness in steep terrain. Our results most accurately resolve the sharp physical boundary between the depositional basin (thick soils) and the erosional mountain ridges (thin soils). A compelling example of this precision is visible in the southern mountain rim (boxed in Fig. 7), where a distinct topographic gap breaks the continuity of the ridge. Our model (Fig. 7c) perfectly captures this geomorphological feature, showing a corresponding break in soil thickness that mirrors the terrain. In contrast, the Shangguan map (Fig. 7d) and Liu map (Fig. 7e) smooths over this gap with a continuous block of thick soil, failing to reflect the topographic interruption.



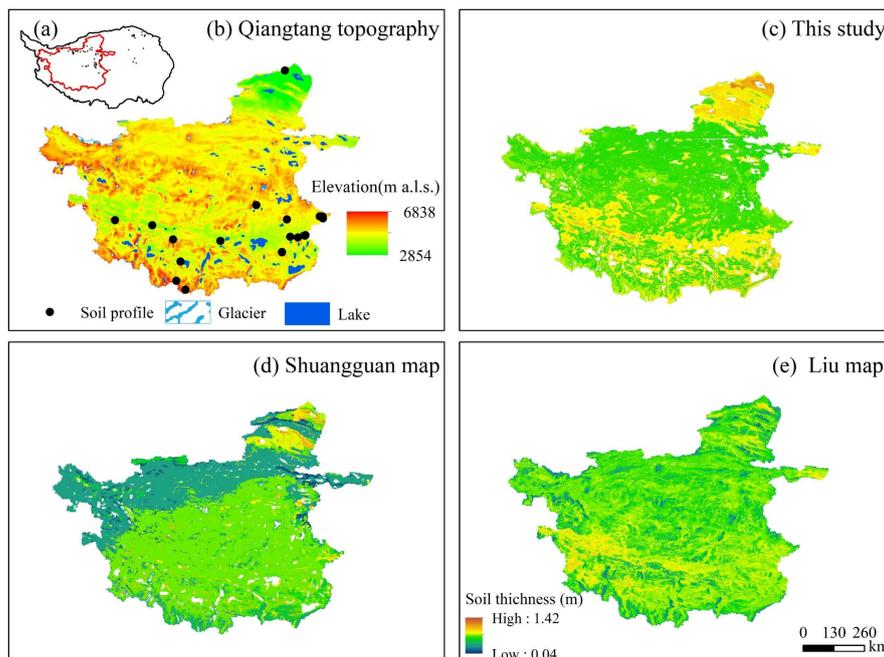
425 **Fig. 7 Comparison of soil thickness datasets in the Qaidam Basin. (b) Topography of the basin with an inset (a) showing its location on the QTP. Spatial distribution of soil thickness simulated by (c) this study, (d) the Shangguan map, and (e) the Liu map. The black box highlights the topographic gap in the southern mountain rim discussed in the text. White patches represent no data.**

The Qiangtang Plateau (Fig. 8) represents the harsh, high-altitude permafrost core of the QTP. This region is characterized by an average elevation of 4,964 m and extremely sparse vegetation (mean NDVI: 0.18). In this environment, soil formation
430 is physically controlled by the coupled effects of low temperature, sparse vegetation and topography. Statistically, the three datasets yield relatively comparable ranges, though our model predicts slightly thicker soils overall. Our simulation estimates a mean soil thickness of 0.74 m (range: 0.41–1.42 m), compared to a mean of 0.58 m (range: 0.12–1.22 m) for the Shangguan map and 0.67 m (range: 0.04–1.16 m) for the Liu map.

Despite these moderate numerical differences, the spatial distributions exhibit notable divergences. Our revised mass balance
435 model captures a clear topographic dependency: soil thickness decreases systematically from the lower-elevation northeast to the high-altitude southwest (Fig. 8a and b). This gradient mirrors the spatial patterns of NDVI and elevation, with the lowest thickness values correctly located in the central high-altitude permafrost areas where weathering is kinetically limited. Conversely, the reference datasets exhibit patterns that are difficult to explain physically. The Shangguan map (Fig. 8d) displays a distinct layered artifact, while the Liu map (Fig. 8e) shows a spatially uniform distribution that correlates poorly
440 with the local topography. By effectively reproducing the elevation-dependent thinning of soils, our model demonstrates a



superior capacity to represent soil thickness in extreme environments where empirical and machine learning models often fail due to the scarcity of training data (Jordan and Mitchell, 2015; Li and Heap, 2011).



445 **Fig. 8** Comparison of soil thickness datasets in the Qiangtang Plateau. (b) Topography of the region with an inset (a) showing its location on the QTP. Spatial distribution of soil thickness simulated by (c) this study, (d) the Shuangguan map, and (e) the Liu map. White patches represent no data.

4 Discussion

4.1 Advantages of Process-Based Modeling in Data-Scarce Regions

The accuracy of spatially explicit soil models on the QTP has long been constrained by the scarcity and bias of observational data. As evidenced by the distribution of the 552 soil profiles used in this study (Fig. 1a), sampling is predominantly clustered in accessible, lower-elevation regions, while high-altitude zones, which are characterized by cryogenic conditions, low atmospheric pressure, and rugged terrain, remain significantly undersampled. This spatial imbalance poses a fundamental challenge for empirical and machine learning approaches (e.g., the Shuangguan and Liu maps), which operate on the assumption that the training data statistically represent the entire domain. When trained on biased datasets where hillslopes are underrepresented, these models tend to overfit the characteristics of flat terrain, leading to poor generalization in complex topography. This explains the artifacts observed in the reference datasets, such as the noisy fragmentation in the Qaidam Basin (Fig. 7e) or the artificial layered patterns in the Qiangtang Plateau (Fig. 8d).

450

455



Despite utilizing the same biased observational dataset for calibration, the revised mass balance model offers a distinct advantage that stems from its reliance on physical mechanisms of pedogenesis rather than statistical correlation. By grounding the simulation in the mass balance equations (Eqs. 1, 2), the model reduces dependence on dense field observations and the structural constraint implies that soil thickness is mathematically forced to respond to topographic curvature and slope dependent erosion, regardless of the training data distribution. Specifically, even if the model parameters are calibrated using data primarily from flat areas, the inclusion of the gravitational erosion term ensures that the model systematically removes soil from convex ridges and accumulates it in concave valleys. The physics of the model effectively fills in the gaps where data is missing, applying universal geomorphic laws to predict thinning on hillslopes that were never sampled. This explains why our model successfully resolved the geomorphological boundaries in the Qaidam Basin and the elevation-dependent gradients in the Qiangtang Plateau (Fig. 8c), whereas purely data-driven models failed to capture these structural landscape features.

4.2 Uncertainty Analysis

While the mass balance framework ensures physical consistency, the accuracy of the simulation remains partially contingent on the quality of the environmental forcing data. A primary source of uncertainty lies in the spatially explicit erosion rates (E_{water} and E_{wind}), which were derived from the empirical RUSLE and RWEQ models, respectively. Originally developed for low-altitude temperate zones, these empirical models may have limited adaptability to the cryogenic environment of the QTP, where freeze-thaw cycles and distinct surface roughness characteristics significantly alter sediment transport dynamics. Despite these inherent limitations, these datasets currently represent the best available spatially explicit estimates of erosion for the region. Previous validations have demonstrated their reliability, with reported coefficients of determination of 0.93 for wind erosion and 0.81 for hydraulic erosion against ^{137}Cs measurements (Teng et al., 2018; Teng et al., 2021). Moreover, our model structure mitigates these input uncertainties through the cluster-based calibration of erosion weighting coefficients (α , β , γ). By treating the erosion terms as adjustable components weighted by coefficients, the inverse modeling process effectively functions as a physically constrained bias correction. For example, if the standard RUSLE model overestimates hydraulic erosivity in a densely vegetated alpine meadow, the optimization algorithm will retrieve a low α value (e.g., $\alpha < 0.06$ in Cluster 6) to dampen the input flux, ensuring it balances with the thermodynamically limited soil production rate. Consequently, the model relies on the spatial pattern of the erosion inputs to identify relative hotspots of mass removal, while the magnitude is rigorously scaled to match the local solum thickness observed in the calibration profiles. This capability allows the model to produce reliable thickness estimates even in the presence of systematic uncertainties in the raw erosion forcing.



4.3 Limitations and Future Directions

While the revised mass balance framework offers a significant advance in physical consistency, its application relies on two fundamental assumptions that warrant critical discussion: the validity of the steady-state approximation and the structural accuracy of the lower boundary constraint.

490 First, our solution for solum thickness (Eq. 9) assumes a geomorphic dynamic equilibrium ($\frac{\partial h}{\partial t} = 0$) (Dietrich et al., 1995), implying that soil production at the weathering front is balanced by surface erosion flux. On the tectonically active QTP (Ding et al., 2019; Pan et al., 2022), this assumption is an idealization. Its soil systems are subject to continuous adjustment driven by intense uplift (Zhao et al., 2023; Wei et al., 2025), climatic oscillations, and frequent freeze-thaw cycles (Li et al., 495 2012). Furthermore, localized non-linear processes, such as landslides, debris flows, and retrogressive thaw slumps caused by permafrost degradation (Luo et al., 2022), can cause rapid changes in soil thickness that linear diffusion models fail to capture (Dixon et al., 2009; Dietrich et al., 1995; Roering et al., 1999).

However, modeling non-steady-state soil evolution at a continental scale requires detailed chronosequence data and historical erosion records that simply do not exist for the QTP. In the absence of such data, the steady-state assumption 500 remains the most robust framework for capturing broad-scale spatial patterns. We addressed the potential bias of this assumption by introducing the adjustable weighting coefficients, which essentially act as a proxy for the deviation from equilibrium, allowing the model to balance production and erosion mathematically even in transient landscapes.

Second, the partitioning of the regolith into solum and saprolite ($h_c = DTB - h_s$) is structurally constrained by the global depth-to-bedrock product of Shangguan et al. (2017). While this dataset provides the best available estimate of total 505 weathered thickness, it is inherently limited by the scarcity of deep borehole data in the plateau's interior. Any systematic underestimation in the global DTB product would effectively compress our calculated saprolite thickness, particularly in deep depositional basins. However, it is crucial to note that the solum thickness is derived independently through the erosion-production balance (Eq. 9) and is not mathematically dependent on the DTB constraint. Even if uncertainties exist in the deeper regolith interface, the accuracy of solum depth reported here remains relatively robust. Future research should aim 510 to couple this mass balance framework with landscape evolution models and time-dependent permafrost simulations to explicitly resolve the transient response of soil thickness to climate change and tectonic uplift. This would allow for the simulation of soil response to future climate change scenarios, such as the potential deepening of the active layer due to permafrost degradation.



5 Conclusions

515 This study developed a revised mass balance model to simulate the spatial heterogeneity of soil thickness across the QTP. By explicitly incorporating wind and hydraulic erosion processes into the traditional gravity-dominated framework and employing a cluster-based parameterization strategy, we successfully generated a 1 km resolution soil thickness (solum depth) dataset that balances physical realism with statistical accuracy. The key findings are summarized as follows:

(1) The simulated solum thickness on the QTP ranges from 0.39 m to 2.04 m, with a spatially averaged mean of 0.89 m. The 520 distribution exhibits a clear southeast-to-northwest decreasing gradient, aligning with the plateau's climatic and biological transitions from warm, humid, vegetated margins to the cold, arid, barren interior.

(2) Validated against 552 soil profile observations, the revised model achieved an RMSE of 0.34 m and a MRE of 0.78. Comparative analysis demonstrates that this process-based approach outperforms existing national-scale datasets, reducing the RMSE by approximately 17% compared to the Shangguan map (0.45 m) and 10% compared to the Liu map (0.42 m).

525 (3) A critical advantage of this model is its ability to reproduce physical landscape features in regions where observational data is sparse. Unlike empirical and machine learning models which produced fragmented artifacts in the Qaidam Basin or artificial layering in the Qiangtang Plateau, our model accurately resolved the sharp boundaries between depositional basins and erosional ridges. This confirms that grounding simulations in mass balance principles significantly reduces uncertainty in extreme, undersampled environments.

530 6 Appendix A: Sources of Model Input

The specific sources and access links for these input variables to the revised mass balance model are listed below:

Meteorological Forcing. The mean annual air temperature (1979–2018) and precipitation (1901–2024) data were sourced from the National Tibetan Plateau Data Center. These datasets are available at <https://doi.org/10.11888/Meteoro.tpd.270339> (Ding et al., 2022) and <http://doi.org/10.12041/geodata.192891852410344.ver1.db> (Peng, 2025), respectively.

535 **Erosion Forcing.** The hydraulic erosion data generated via the RULSE (Teng et al., 2018) and the wind erosion via RWEQ (Teng et al., 2021) are available upon request to the respective authors of those studies.

Vegetation and Land Use. Vegetation conditions were parameterized using the MODIS-derived NDVI product (2001–2020), accessible at <https://doi.org/10.11888/Geogra.tpd.270050> (Zhu, 2022). Land use data for the year 2015 was obtained from <https://doi.org/10.11888/Geogra.tpd.270198> (Xu, 2019).

540 **Geological and Topographic Drivers.** Soil parent material information was extracted from the Dataset of Soil Parent Material of China, available at <http://doi.org/10.12072/ncdc.westdc.db3894.2023> (Li, 2020). Topographic attributes were



derived from the NASADEM dataset, which is available through the National Aeronautics and Space Administration's Earthdata platform.

Hydrological Masks. To mask non-soil areas, glacier extents were derived from the Second Chinese Glacier Inventory at
545 <https://doi.org/10.3972/glacier.001.2013.db> (Guo et al., 2015b), and water bodies were identified using the China Lake
Dataset at <https://doi.org/10.11888/Hydro.tpd.270302> (Zhang et al., 2019).

Data Availability

The resulting high-resolution (1 km) soil thickness dataset for the Qinghai-Tibet Plateau generated in this study, alongside
supplementary datasets necessary for reproducing the analysis is freely available at figshare (Chen et al., 2025) via
550 <https://doi.org/10.6084/m9.figshare.30925358>. The soil profile observations used for model calibration and validation were
obtained from the National Earth System Science Data Center (<https://doi.org/10.11666/00003.ver1.db>) (Pan and Shi, 2015),
the Chinese Soil Series Chronicle (Zhao and Li, 2020; Li et al., 2020; Yuan, 2020; Huang and Lu, 2020; Wu et al., 2020;
Yang and Zhang, 2020) and regional studies (Zhang et al., 2024b). The existing national-scale soil thickness datasets used
for comparative analysis are available from their respective publications (Shangguan et al., 2013; Liu et al., 2021). All other
555 environmental covariates and input datasets used to drive the mass balance model are detailed in Appendix A.

Author Contributions

Conceptualization, Z.N. and S.Z.; Methodology, Z.N. and X.D.; Formal Analysis, L.C., X.D. and K.F.; Writing—original
draft, L.C., Z.N., X.D., and S.Z.; Writing—review and editing, Z.N., L.C., S.Z., F.N. and X.D.; Supervision, S.Z. and Z.N.;
Funding acquisition, S.Z., and Z.N.

560 Competing Interests

The authors declare that they have no conflict of interest.

Acknowledgments

The authors are grateful to Jinyan Zhao from Beijing Normal University and Zhou Shi from Zhejiang University for
providing the wind and hydraulic erosion datasets, respectively.



565 **Financial support**

This research was funded by the Grants of National Natural Science Foundation of China (42571149, 42171125).

References

- Berhe, A. A., Barnes, R. T., Six, J., and Marin-Spiotta, E.: Role of Soil Erosion in Biogeochemical Cycling of Essential Elements: Carbon, Nitrogen, and Phosphorus, *Annual Review of Earth and Planetary Sciences*, 46, 521-548, <https://doi.org/10.1146/annurev-earth-082517-010018>, 2018.
- 570 Cao, Z., Nan, Z., Hu, J., Chen, Y., and Zhang, Y.: A new 2010 permafrost distribution map over the Qinghai-Tibet Plateau based on subregion survey maps: A benchmark for regional permafrost modeling, *Earth System Science Data*, 15, 3905-3930, <https://doi.org/10.5194/essd-15-3905-2023>, 2023.
- Chen, L., Ding, X., Zhao, S., and Nan, Z.: Dataset associated with the paper “A physically consistent soil thickness map of the Qinghai-Tibet Plateau derived from coupled erosion mechanisms, figshare [dataset], <https://doi.org/10.6084/m9.figshare.30925358>, 2025.
- 575 the Qinghai-Tibet Plateau derived from coupled erosion mechanisms, figshare [dataset], <https://doi.org/10.6084/m9.figshare.30925358>, 2025.
- Chen, L., Liu, L., Qin, S., Yang, G., Fang, K., Zhu, B., Kuzyakov, Y., Chen, P., Xu, Y., and Yang, Y.: Regulation of priming effect by soil organic matter stability over a broad geographic scale, *Nature Communications*, 10, <https://doi.org/10.1038/s41467-019-13119-z>, 2019.
- 580 Dietrich, W. E., Reiss, R., Hsu, M. L., and Montgomery, D. R.: A process-based model for colluvial soil depth and shallow landsliding using digital elevation data, *Hydrological Processes*, 9, 383-400, <https://doi.org/10.1002/hyp.3360090311>, 1995.
- Ding, J., Wang, T., Piao, S., Smith, P., Zhang, G., Yan, Z., Ren, S., Liu, D., Wang, S., Chen, S., Dai, F., He, J., Li, Y., Liu, Y., Mao, J., Arain, A., Tian, H., Shi, X., Yang, Y., Zeng, N., and Zhao, L.: The paleoclimatic footprint in the soil carbon stock of the Tibetan permafrost region, *Nature Communications*, 10, 4195, <https://doi.org/10.1038/s41467-019-12214-5>, 2019.
- 585 2019.
- Ding, L., Zhou, J., Wang, W., and Ma, J.: Dataset of 0.01° Surface Air Temperature over Tibetan Plateau (1979-2018), National Tibetan Plateau Data Center [dataset], <https://doi.org/10.11888/Meteoro.tpdc.270339>, 2022.
- Dixon, J. L., Heimsath, A. M., Kaste, J., and Amundson, R.: Climate-driven processes of hillslope weathering, *Geology*, 37, 975-978, <https://doi.org/10.1130/G30045A.1>, 2009.
- 590 Duan, Q. Y., Gupta, V. K., and Sorooshian, S.: Shuffled complex evolution approach for effective and efficient global minimization, *Journal of Optimization Theory and Applications*, 76, 501-521, <https://doi.org/10.1007/BF00939380>, 1993.



- Fryrear, D. W., Bilbro, J. D., Saleh, A., Schomberg, H., Stout, J. E., and Zobeck, T. M.: RWEQ: Improved wind erosion technology, *Journal of Soil and Water Conservation*, 55, 183-189, <https://doi.org/10.1080/00224561.2000.12436392>, 2000.
- Fu, Z. Y., Li, Z. X., Cai, C. F., Shi, Z. H., Xu, Q. X., and Wang, X. Y.: Soil thickness effect on hydrological and erosion characteristics under sloping lands: A hypopedological perspective, *Geoderma*, 167-68, 41-53, <https://doi.org/10.1016/j.geoderma.2011.08.013>, 2011.
- Gabet, E. J. and Mudd, S. M.: A theoretical model coupling chemical weathering rates with denudation rates, *Geology*, 37, 151-154, <https://doi.org/10.1130/G25270A.1>, 2009.
- Guo, B., Zhou, Y., Zhu, J., Liu, W., Wang, F., Wang, L., and Jiang, L.: An estimation method of soil freeze-thaw erosion in the Qinghai-Tibet Plateau, *Natural Hazards*, 78, 1843-1857, <https://doi.org/10.1007/s11069-015-1808-5>, 2015a.
- Guo, J., Zhou, J., Zou, Q., Liu, Y., and Song, L.: A Novel Multi-Objective Shuffled Complex Differential Evolution Algorithm with Application to Hydrological Model Parameter Optimization, *Water Resources Management*, 27, 2923-2946, <https://doi.org/10.1007/s11269-013-0324-1>, 2013.
- Guo, W., Liu, S., Xu, J., Wu, L., Shangguan, D., Yao, X., Wei, J., Bao, W., Yu, P., and Liu, Q.: The second Chinese glacier inventory: data, methods and results, *Journal of Glaciology*, 61, 357-372, <https://doi.org/10.3189/2015JoG14J209>, 2015b.
- Gupta, K., Satyam, N., and Segoni, S.: A comparative study of empirical and machine learning approaches for soil thickness mapping in the Joshimath region (India), *Catena*, 241, 108024, <https://doi.org/10.1016/j.catena.2024.108024>, 2024.
- Hall, K., Thorn, C. E., Matsuoka, N., and Prick, A.: Weathering in cold regions: Some thoughts and perspective, *Progress in Physical Geography*, 26, 577-603, <https://doi.org/10.1191/0309133302pp353ra>, 2002.
- Hickey, R., Smith, A., and Jankowski, P.: Slope length calculations from a DEM within ARC/INFO grid, *Computers, Environment and Urban Systems*, 18, 365-380, [https://doi.org/10.1016/0198-9715\(94\)90017-5](https://doi.org/10.1016/0198-9715(94)90017-5), 1994.
- Huang, B. and Lu, S.: *Soil Series of China-Yunnan*, Science Press: Beijing, China, 2020.
- Huang, Z.: Extensions to the k-means algorithm for clustering large data sets with categorical values, *Data Mining and Knowledge Discovery*, 2, 283-304, <https://doi.org/10.1023/A:1009769707641>, 1998.
- Jordan, M. I. and Mitchell, T. M.: Machine learning: Trends, perspectives, and prospects, *Science*, 349, 255-260, <https://doi.org/10.1126/science.aaa8415>, 2015.
- Ke, L., Lei, N., Zhang, S., Yin, C., Lu, Y., Wang, L., Tan, Q., Zhao, Y., and Wang, Q.: Estimation of blue carbon stock in the Liaohe Estuary wetland based on soil thickness and multi-scenario modeling, *Ecological Indicators*, 171, 113201, <https://doi.org/10.1016/j.ecolind.2025.113201>, 2025.
- Korup, O. and Montgomery, D. R.: Tibetan plateau river incision inhibited by glacial stabilization of the Tsangpo gorge, *Nature*, 455, 786-789, <https://doi.org/10.1038/nature07322>, 2008.



- Li, D., Zhao, X., and Zhang, G.: Soil Series of China-Qinghai, Science Press: Beijing, China, 2020.
- Li, J. and Heap, A. D.: A review of comparative studies of spatial interpolation methods in environmental sciences: Performance and impact factors, *Ecological Informatics*, 6, 228-241, <https://doi.org/10.1016/j.ecoinf.2010.12.003>, 2011.
- 625 Li, X.: Comprehensive data set of Cryosphere in the Qinghai Tibet Plateau, National Cryosphere Desert Data Center [dataset], <http://doi.org/10.12072/ncdc.westdc.db3894.2023>, 2020.
- Li, X., Jin, R., Pan, X. D., Zhang, T. J., and Guo, J. W.: Changes in the near-surface soil freeze-thaw cycle on the Qinghai-Tibetan Plateau, *International Journal of Applied Earth Observation and Geoinformation*, 17, 33-42, <https://doi.org/10.1016/j.jag.2011.12.002>, 2012.
- 630 Liu, F., Wu, H., Zhao, Y., Li, D., Yang, J., Song, X., Shi, Z., Zhu, A., and Zhang, G.: Mapping high resolution national soil information grids of China, *Science Bulletin*, 67, 328-340, <https://doi.org/10.1016/j.scib.2021.10.013>, 2021.
- Liu, J., Chen, X., Lin, H., Liu, H., and Song, H.: A simple geomorphic-based analytical model for predicting the spatial distribution of soil thickness in headwater hillslopes and catchments, *Water Resources Research*, 49, 7733-7746, <https://doi.org/10.1002/2013WR013834>, 2013.
- 635 Luo, J., Niu, F., Lin, Z., Liu, M., Yin, G., and Gao, Z.: Inventory and Frequency of Retrogressive Thaw Slumps in Permafrost Region of the Qinghai-Tibet Plateau, *Geophysical Research Letters*, 49, <https://doi.org/10.1029/2022GL099829>, 2022.
- Montgomery, D. R.: Valley formation by fluvial and glacial erosion, *Geology*, 30, 1047-1050, [https://doi.org/10.1130/0091-7613\(2002\)030<1047:Vfbfag>2.0.Co;2](https://doi.org/10.1130/0091-7613(2002)030<1047:Vfbfag>2.0.Co;2), 2002.
- 640 Moreno, M., Levachkine, S., Torres, M., and Quintero, R.: Geomorphometric Analysis of Raster Image Data to detect Terrain Ruggedness and Drainage Density, *Progress in Pattern Recognition, Speech and Image Analysis*. pp. 643-650., https://doi.org/10.1007/978-3-540-24586-5_79, 2003.
- Pan, G., Wang, L., Yin, F., Geng, Q., Li, G., and Zhu, D.: Researches on geological-tectonic evolution of Tibetan Plateau: A review, recent advances, and directions in the future, *Sedimentary Geology and Tethyan Geology*, 42, 151-175, <https://doi.org/10.19826/j.cnki.1009-3850.2022.05004>, 2022.
- 645 Pan, X. and Shi, J.: National Second Soil Census Typical Soil Profile Database (1980-1996), National Earth System Science Data Center [dataset], <https://doi.org/10.11666/00003.ver1.db>, 2015.
- Pelletier, J. D. and Rasmussen, C.: Geomorphically based predictive mapping of soil thickness in upland watersheds, *Water Resources Research*, 45, <https://doi.org/10.1029/2008WR007319>, 2009a.
- 650 Pelletier, J. D. and Rasmussen, C.: Quantifying the climatic and tectonic controls on hillslope steepness and erosion rate, *Lithosphere*, 1, 73-80, <https://doi.org/10.1130/L3.1>, 2009b.



- Pelletier, J. D., Barron-Gafford, G. A., Breshears, D. D., Brooks, P. D., Chorover, J., Durcik, M., Harman, C. J., Huxman, T. E., Lohse, K. A., Lybrand, R., Meixner, T., McIntosh, J. C., Papuga, S. A., Rasmussen, C., Schaap, M., Swetnam, T. L., and Troch, P. A.: Coevolution of nonlinear trends in vegetation, soils, and topography with elevation and slope aspect: A case study in the sky islands of southern Arizona, *Journal of Geophysical Research: Earth Surface*, 118, 741-758, <https://doi.org/10.1002/jgrf.20046>, 2013.
- Peng, S.: 1-km monthly precipitation dataset for China (1901-2024), National Tibetan Plateau Data Center [dataset], <https://doi.org/10.5281/zenodo.3114194>, 2025.
- Phillips, J. D.: The convenient fiction of steady-state soil thickness, *Geoderma*, 156, 389-398, <https://doi.org/10.1016/j.geoderma.2010.03.008>, 2010.
- Piao, S., Zhang, X., Wang, T., Liang, E., Wang, S., Zhu, J., and Niu, B.: Responses and feedback of the Tibetan Plateau's alpine ecosystem to climate change, *Chinese Science Bulletin*, 64, 2842-2855, <https://doi.org/10.1360/TB-2019-0074>, 2019.
- Rasmussen, C. and Tabor, N. J.: Applying a quantitative pedogenic energy model across a range of environmental gradients, *Soil Science Society of America Journal*, 71, 1719-1729, <https://doi.org/10.2136/sssaj2007.0051>, 2007.
- Rasmussen, C., Southard, R. J., and Horwath, W. R.: Modeling energy inputs to predict pedogenic environments using regional environmental databases, *Soil Science Society of America Journal*, 69, 1266-1274, <https://doi.org/10.2136/sssaj2003.0283>, 2005.
- Renard, K. G., Foster, G. R., Yoder, D. C., and McCool, D. K.: RUSLE revisited: Status, questions, answers, and the future, *Journal of Soil and Water Conservation*, 49, 213-220, <https://doi.org/10.1080/00224561.1994.12456855>, 1994.
- Roering, J. J.: How well can hillslope evolution models “explain” topography? Simulating soil transport and production with high-resolution topographic data, *Geological Society of America Bulletin*, 120, 1248-1262, <https://doi.org/10.1130/B26283.1>, 2008.
- Roering, J. J., Kirchner, J. W., and Dietrich, W. E.: Evidence for nonlinear, diffusive sediment transport on hillslopes and implications for landscape morphology, *Water Resources Research*, 35, 853-870, <https://doi.org/10.1029/1998WR900090>, 1999.
- Rosin, N. A., Mello, D. C. d., Bonfatti, B. R., Hartemink, A. E., Ferreira, T. O., Silvero, N. E. Q., Poppiel, R. R., Mendes, W. d. S., Veloso, G. V., Francelino, M. R., Alves, M. R., Falcioni, R., and Demattê, J. A. M.: Mapping soil thickness using a mechanistic model and machine learning approaches, *Catena*, 249, 108621, <https://doi.org/10.1016/j.catena.2024.108621>, 2025.
- Shangguan, W., Hengl, T., Mendes de Jesus, J., Yuan, H., and Dai, Y.: Mapping the global depth to bedrock for land surface modeling, *Journal of Advances in Modeling Earth Systems*, 9, 65-88, <https://doi.org/10.1002/2016ms000686>, 2017.



- Shangguan, W., Dai, Y. J., Liu, B. Y., Zhu, A. X., Duan, Q. Y., Wu, L. Z., Ji, D. Y., Ye, A. Z., Yuan, H., Zhang, Q., Chen, D. D., Chen, M., Chu, J. T., Dou, Y. J., Guo, J. X., Li, H. Q., Li, J. J., Liang, L., Liang, X., Liu, H. P., Liu, S. Y., Miao, C. Y., and Zhang, Y. Z.: A China data set of soil properties for land surface modeling, *Journal of Advances in Modeling Earth Systems*, 5, 212-224, <https://doi.org/10.1002/jame.20026>, 2013.
- Smith, P., Cotrufo, M. F., Rumpel, C., Paustian, K., Kuikman, P. J., Elliott, J. A., McDowell, R., Griffiths, R. I., Asakawa, S., Bustamante, M., House, J. I., Sobocká, J., Harper, R., Pan, G., West, P. C., Gerber, J. S., Clark, J. M., Adhya, T., Scholes, R. J., and Scholes, M. C.: Biogeochemical cycles and biodiversity as key drivers of ecosystem services provided by soils, *Soil*, 1, 665-685, <https://doi.org/10.5194/soil-1-665-2015>, 2015.
- Sun, Y., Liu, S., Shi, F., An, Y., Li, M., and Liu, Y.: Spatio-temporal variations and coupling of human activity intensity and ecosystem services based on the four-quadrant model on the Qinghai-Tibet Plateau, *Science of the Total Environment*, 743, <https://doi.org/10.1016/j.scitotenv.2020.140721>, 2020.
- Teng, H., Liang, Z., Chen, S., Liu, Y., Viscarra Rossel, R. A., Chappell, A., Yu, W., and Shi, Z.: Current and future assessments of soil erosion by water on the Tibetan Plateau based on RUSLE and CMIP5 climate models, *Science of The Total Environment*, 635, 673-686, <https://doi.org/10.1016/j.scitotenv.2018.04.146>, 2018.
- Teng, Y. M., Zhan, J. Y., Liu, W., Sun, Y. X., Agyemang, F. B., Liang, L., and Li, Z. H.: Spatiotemporal dynamics and drivers of wind erosion on the Qinghai-Tibet Plateau, China, *Ecological Indicators*, 123, <https://doi.org/10.1016/j.ecolind.2021.107340>, 2021.
- Vrugt, J. A., Gupta, H. V., Bouten, W., and Sorooshian, S.: A Shuffled Complex Evolution Metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters, *Water Resources Research*, 39, <https://doi.org/10.1029/2002wr001642>, 2003.
- Wang, W., Zhao, Y., Zhang, T., Wang, R., Wei, Z., Sun, Q., and Wu, J.: Regional soil thickness mapping based on stratified sampling of optimally selected covariates, *Geoderma*, 400, <https://doi.org/10.1016/j.geoderma.2021.115092>, 2021.
- Wang, Y., Lv, W., Xue, K., Wang, S., Zhang, L., Hu, R., Zeng, H., Xu, X., Li, Y., Jiang, L., Hao, Y., Du, J., Sun, J., Dorji, T., Piao, S., Wang, C., Luo, C., Zhang, Z., Chang, X., Zhang, M., Hu, Y., Wu, T., Wang, J., Li, B., Liu, P., Zhou, Y., Wang, A., Dong, S., Zhang, X., Gao, Q., Zhou, H., Shen, M., Wilkes, A., Miede, G., Zhao, X., and Niu, H.: Grassland changes and adaptive management on the Qinghai-Tibetan Plateau, *Nature Reviews Earth and Environment*, 3, 668-683, <https://doi.org/10.1038/s43017-022-00330-8>, 2022.
- Wei, P., Du, J., Bahadur, A., Zhang, H., Wang, S., Wu, T., and Chen, S.: Soil erosion and risk assessment on the Qinghai-Tibetan Plateau, *Communications Earth & Environment*, 6, 365, <https://doi.org/10.1038/s43247-025-02355-5>, 2025.
- Wu, K., Wu, H., and Ju, B.: *Soil Series of China-Xijiang*, Science Press: Beijing, China2020.



- Xiao, T., Segoni, S., Liang, X., Yin, K., and Casagli, N.: Generating soil thickness maps by means of geomorphological-empirical approach and random forest algorithm in Wanzhou County, Three Gorges Reservoir, *Geoscience Frontiers*, 14, <https://doi.org/10.1016/j.gsf.2022.101514>, 2023.
- 715 Xu, E.: Land use of the Tibet Plateau in 2015 (Version 1.0), National Tibetan Plateau Data Center [dataset], <https://doi.org/10.11888/Geogra.tpdc.270198>, 2019.
- Yamashita, N., Ohnuki, Y., Iwahashi, J., and Imaya, A.: National-scale mapping of soil-thickness probability in hilly and mountainous areas of Japan using legacy and modern soil survey, *Geoderma*, 446, <https://doi.org/10.1016/j.geoderma.2024.116896>, 2024.
- 720 Yang, J. and Zhang, G.: *Soil Series of China-Gansu*, Science Press: Beijing, China, 2020.
- Yang, Y., Fang, J., Fay, P. A., Bell, J. E., and Ji, C.: Rain use efficiency across a precipitation gradient on the Tibetan Plateau, *Geophysical Research Letters*, 37, <https://doi.org/10.1029/2010GL043920>, 2010.
- Yu, Y., You, Q., Zhang, Y., Jin, Z., Kang, S., and Zhai, P.: Integrated warm-wet trends over the Tibetan Plateau in recent decades, *Journal of Hydrology*, 639, <https://doi.org/10.1016/j.jhydrol.2024.131599>, 2024.
- 725 Yuan, D.: *Soil Series of China-Sichuan*, Science Press: Beijing, China, 2020.
- Zhang, G., Yao, T., Chen, W., Zheng, G., Shum, C., Yang, K., Piao, S., Sheng, Y., Yi, S., and Li, J.: Regional differences of lake evolution across China during 1960s–2015 and its natural and anthropogenic causes, *Remote Sensing of Environment*, 221, 386–404, <https://doi.org/10.1016/j.rse.2018.11.038>, 2019.
- Zhang, J., Wang, S., Fu, Z. Y., Wang, F., Wang, K. L., and Chen, H. S.: Soil thickness influences the control effect of micro-topography on subsurface runoff generation in the karst hillslope critical zone, *Catena*, 239, <https://doi.org/10.1016/j.catena.2024.107957>, 2024a.
- 730 Zhang, Q., Yuan, R., Singh, V. P., Xu, C. Y., Fan, K., Shen, Z., Wang, G., and Zhao, J.: Dynamic vulnerability of ecological systems to climate changes across the Qinghai-Tibet Plateau, China, *Ecological Indicators*, 134, <https://doi.org/10.1016/j.ecolind.2021.108483>, 2022.
- 735 Zhang, S., E, C., Ji, X., Li, P., Peng, Q., Zhang, Z., and Zhang, Q.: Soil Genesis of Alluvial Parent Material in the Qinghai Lake Basin (NE Qinghai–Tibet Plateau) Revealed Using Optically Stimulated Luminescence Dating, *Atmosphere*, 15, 1066, <https://doi.org/10.3390/atmos15091066>, 2024b.
- Zhao, W., Cheng, Y., Jian, J., Jiao, J., Cheng, C., Li, J., and Chen, T.: Water erosion changes on the Qinghai-Tibet Plateau and its response to climate variability and human activities during 1982–2015, *Catena*, 229, 107207, <https://doi.org/10.1016/j.catena.2023.107207>, 2023.
- 740 Zhao, Y. and Li, D.: *Soil Series of China-Xizang*, Science Press: Beijing, China, 2020.

<https://doi.org/10.5194/essd-2025-809>
Preprint. Discussion started: 12 March 2026
© Author(s) 2026. CC BY 4.0 License.



Zhu, J.: Dataset of Normalized Difference Vegetation Index over Tibetan Plateau From 2001 to 2020, National Tibetan Plateau Data Center [dataset], <https://doi.org/10.5067/MODIS/MOD13A2.006>, 2022.