

1 **A 1-km resolution soil organic carbon dataset for frozen**
2 **ground in the Third Pole**

3
4 Dong Wang^{1,2}, Tonghua Wu^{1,3*}, Lin Zhao^{1,4}, Cuicui Mu⁵, Ren Li¹, Xianhua Wei^{1,2,6},
5 Guojie Hu¹, Defu Zou¹, Xiaofan Zhu¹, Jie Chen¹, Junmin Hao⁷, Jie Ni^{1,2}, Xiangfei Li^{1,2},
6 Wensi Ma^{1,2}, Amin Wen^{1,2}, Chengpeng Shang^{1,2}, Yune La^{1,2}, Xin Ma^{1,2}, Xiaodong Wu¹

7
8 ¹ Cryosphere Research Station on the Qinghai-Tibetan Plateau, State Key Laboratory of
9 Cryospheric Science, Northwest Institute of Eco-Environment and Resource, Chinese
10 Academy of Sciences, Lanzhou, Gansu 730000, China

11 ² University of Chinese Academy Sciences, Beijing, 100049, China.

12 ³ Southern Marine Science and Engineering Guangdong Laboratory, Guangzhou 511458,
13 China.

14 ⁴ School of Geographical Sciences, Nanjing University of Information Science &
15 Technology, Nanjing 210000, China

16 ⁵ Key Laboratory of Western China's Environmental Systems (Ministry of Education),
17 College of Earth and Environmental Sciences, Lanzhou University, Lanzhou, 730000,
18 China.

19 ⁶ College of geography and environmental science, Northwest Normal University,
20 Lanzhou 730070, China.

21 ⁷ School of civil engineering, Lanzhou University of Technology, Lanzhou, 730050,
22 China.

23 *Correspondence: Tonghua Wu (thuawu@lzb.ac.cn)

24 **Abstract:** Soil organic carbon (SOC) is very important in the vulnerable ecological
25 environment of the Third Pole; however, data regarding the spatial distribution of
26 SOC are still scarce and uncertain. Based on multiple environmental variables and
27 soil profile data from 458 pits (depth of 0–1 m) and 114 cores (depth of 0–3 m), this
28 study uses a machine-learning approach to evaluate the SOC storage and spatial
29 distribution at a depth interval of 0–3 m in the frozen ground area of the Third Pole
30 region. Our results showed that SOC stocks (SOCS) exhibited a decreasing spatial
31 pattern from the southeast towards the northwest. The estimated SOC storage in the
32 upper 3 m of the soil profile was 46.18 Pg for an area of 3.27×10^6 km², which
33 included 21.69 Pg and 24.49 Pg for areas of permafrost and seasonally frozen ground,
34 respectively. Our results provide information on the storage and patterns of SOCS at a
35 1–km resolution for areas of frozen ground in the Third Pole region, thus providing a
36 scientific basis for future studies pertaining to Earth system models. The dataset is
37 open-access and available at <https://doi.org/10.5281/zenodo.4293454> (Wang et al.,
38 2020).

39 **1 Introduction**

40 Soil is an important part of the global terrestrial ecosystem and represents the
41 largest terrestrial organic carbon pool with the longest turnover time (Amundson,
42 2001). This is especially true in areas of frozen ground, including permafrost and
43 seasonally frozen ground. In cold environments, soil accumulates substantial organic
44 carbon due to slow decomposition rates and repeated freeze–thaw cycles (Fan et al.,
45 2012; Li et al., 2020). It has been reported that more than half of the world’s soil
46 organic carbon (SOC) is stored in permafrost regions (Hugelius et al., 2014; Ping et
47 al., 2015). Even slight changes in the decomposition of the SOC pool in permafrost
48 regions might lead to significant changes in the atmospheric CO₂ concentration,
49 which plays an important role in regulating and stabilizing the carbon balance of
50 global ecosystems (Schuur et al., 2015). Therefore, it is of great significance to
51 accurately estimate the storage and spatial distribution of SOC in regions of frozen
52 ground in order to study the carbon cycle of this ecosystem as well as global change.

53 As the “roof of the world”, the Third Pole is the area of frozen ground at the highest
54 average altitude in the middle and low latitudes of the Northern Hemisphere. The
55 Third Pole is also one of the most sensitive areas with respect to global climate
56 change, and has a warming rate that is approximately twice the global average
57 (Stocker et al., 2013). In the past few decades, permafrost in the Third Pole region has
58 experienced obvious degradation (Mu et al., 2020; Ran et al., 2017; Turetsky et al.,
59 2019; Wu et al., 2012). Permafrost degradation will not only cause serious geological
60 disasters and affect engineering construction in cold areas, but will also accelerate the
61 decomposition of the huge SOC pool stored in permafrost (Cheng et al., 2007; Cheng
62 et al., 2019; Ding et al., 2021). Moreover, it will emit a large amount of greenhouse
63 gases into the atmosphere, thus increasing the rate of climate change in the future
64 (Schuur et al., 2015). Therefore, accurate estimates of the SOC storage and spatial
65 distribution in the areas of frozen ground in the Third Pole region have become
66 important for Earth system modeling. Such estimates are widely used to study the
67 carbon cycle of this ecosystem and global change (Koven et al., 2011; Lombardozzi et
68 al., 2016; McGuire et al., 2018).

69 Early studies were mostly based on data from China’s national soil survey, and
70 were combined with regional vegetation/soil maps to estimate the SOC pool for a
71 certain vegetation type or relatively small area (Wang et al., 2002; Zeng et al., 2004).
72 Up until 2008, the Chinese part of the Qinghai-Tibet Plateau (QTP) was taken as an
73 independent geographical unit to estimate the SOC pool in the upper 100 cm of the
74 soil profile (Tian et al., 2008; Wu et al., 2008). However, these studies did not
75 distinguish between regions of permafrost and seasonally frozen ground. In recent
76 years, based on soil profile data and vegetation/soil maps, some studies have
77 estimated the SOC pool in the QTP permafrost region (Mu et al., 2015; Zhao et al.,
78 2018; Jiang et al., 2019). The aforementioned studies improved our understanding of
79 SOC storage in the Third Pole region, but estimation results of 0-3m SOC pool have
80 large uncertainties, ranging from 17.1 Pg to 40.9 Pg. In addition, the large-scale maps
81 of vegetation and soil types used in these studies were associated with large
82 uncertainties because they were created years ago and have a low spatial resolution,

83 thus leading to potentially large errors in the estimated total SOC pools (Mishra et al.,
84 2013; Mu et al., 2020). Recently, considerable progress has been made in digital soil
85 mapping methods. Spatial interpolation, linear regression, and machine learning have
86 been widely used to simulate the spatial distribution of SOC in the permafrost region
87 of the QTP (Ding et al., 2016; Ding et al., 2019; Wang et al., 2020; Yang et al., 2008).
88 These studies have provided new spatial data and improved the prediction accuracy of
89 SOC compared with earlier studies. However, few studies to date have systematically
90 assessed SOC pools across areas of seasonally frozen ground in the Third Pole region,
91 which limits many investigations requiring SOC data for these areas.

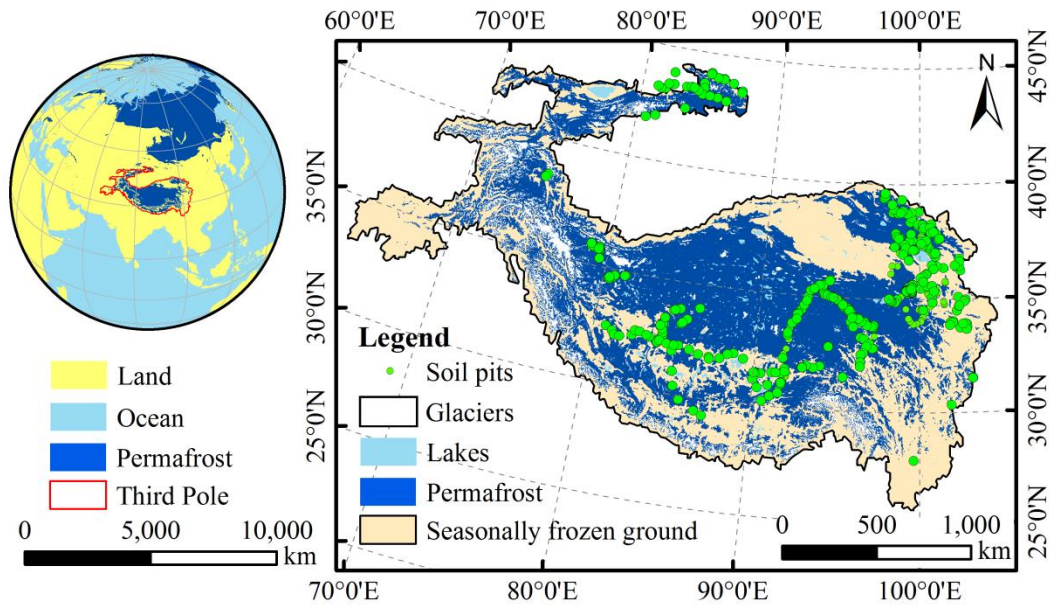
92 To evaluate the size and high-resolution spatial patterns of SOC stocks in the Third
93 Pole region, we carried out a large-scale field-sampling plan that covered
94 representative permafrost zones over the region's bioclimatic gradient, including a
95 large unpopulated area with harsh natural conditions. A total of 200 soil pits were
96 excavated, most of which were deeper than 2 m. In addition, we collected field-
97 measured SOCS data for the Third Pole region from relevant literature published
98 between 2000 and 2016 (Ding et al., 2016; Song et al., 2016; Xu et al., 2019; Yang et
99 al., 2008). By combining high-resolution remotely sensed data and interpolated
100 meteorological datasets, we simulated the spatial distribution of SOCS in the Third
101 Pole region by three machine learning methods and calculated the SOC storage of
102 specific soil intervals (0–30 cm, 0–50 cm, 0–100 cm, 0–200 cm, and 0–300 cm). The
103 results provide basic data for Earth system modeling, and reference methods for
104 studying the spatial distribution of soil elements under complex terrain.

105 **2 Materials and Methods**

106 **2.1 Study area**

107 The Third Pole is the highest plateau in the world, and is located on the QTP and its
108 surrounding mountains, which include Pamir and Hindu Kush mountain ranges in the
109 west, the Hengduan Mountains in the east, the Kunlun and Qilian mountains in the
110 north, and the Himalayas in the south (Yao et al., 2012). In addition, the Third Pole is
111 the largest high-altitude permafrost zone in the Northern Hemisphere, with a total
112 permafrost area of approximately 1.72×10^6 km², thus representing ~8% of

113 permafrost regions in the Northern Hemisphere (Obu et al., 2019). The area of
 114 seasonally frozen ground covers an area of approximately $1.55 \times 10^6 \text{ km}^2$, which is
 115 mainly located in the eastern and southern parts of the Third Pole as well as at lower
 116 elevations of basins (Fig.1). The Third Pole is mainly covered by five ecosystems:
 117 forests, shrubs, grasslands, croplands, and deserts (Hao et al., 2017).



118
 119 **Figure 1.** Distribution of soil pits in the Third Pole region (the frozen ground map is derived from
 120 Obu et al., 2019).

121 2.2 Data Processing

122 2.2.1 Soil organic carbon data

123 The collected SOC data used in this study included field investigated data and
 124 available published data for total 371 soil sample (458 samples for the 0–100 cm soil
 125 layer, and 113 samples for the 0–300 cm soil layer).

126 (1) Field measured data: a total of 200 soil pits were excavated between 2009 and
 127 2011; 72 soil pits were excavated manually in 2009, and 128 soil pits were excavated
 128 with hydraulic excavators in 2010 and 2011. Most of the pits were deeper than 2m,
 129 unless rock layers were detected. For each soil profile, we collected soil samples at
 130 depth intervals of 0–10 cm, 10–20 cm, 20–30 cm, 30–50 cm, 50–100, and 100–200
 131 cm (Fig. 2).

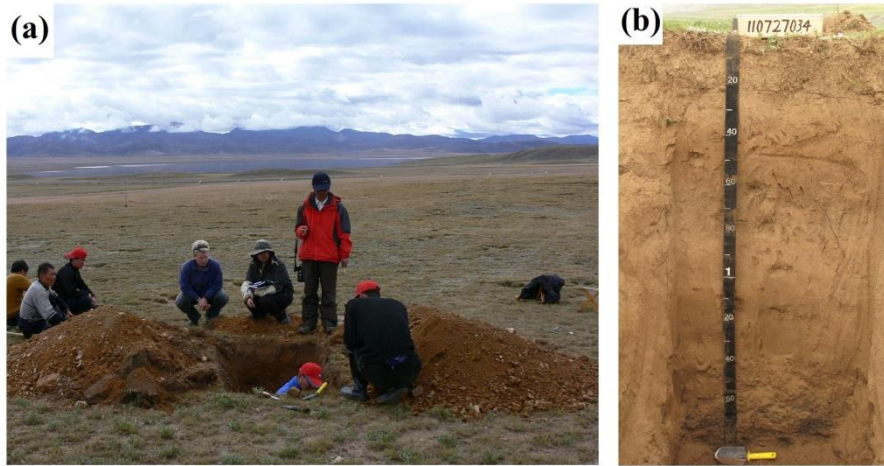


Figure 2. Field work photographs showing (a) soil sample collection, and (b) a soil profile.

The bulk density samples were obtained for each layer using a standard soil sampler (5 cm diameter and 5-cm-high stainless-steel cutting ring), and bulk density was calculated as the ratio of the oven-dry soil mass to the container volume. Soil samples for carbon analysis were air-dried, handpicked to remove plant detritus, and then sieved through a 2mm mesh to calculate the volume percentage of the gravel. The SOC content was determined using the Walkley-Black method after soil samples were pretreated by air drying, grinding, and screening. The analyses were carried out in triplicate using subsamples, and the mean of three values was used as the SOC content. The SOCS was calculated using Eq. (1):

$$SOCS = \sum_{i=1}^n T_i \times BD_i \times SOC_i \times \frac{(1 - C_i)}{10} \quad (1)$$

where T_i , BD_i , SOC_i , and C_i are soil thickness (cm), dried bulk density ($\text{g}\cdot\text{cm}^{-3}$), SOC content (%) and > 2mm rock fragment content (%) at layer i .

(2) Available published data: we compiled all available information from the studies on SOC stocks in the Third Pole regions published after 2000. The following 3 criteria are used to screen the data of SOC stocks from the published literature: (1) The SOC data must be field investigated data; (2) Eliminate sample data with missing geographic location information and sampling time; (3) SOC measuring methods were similar as our experimental procedure. Finally, the 4 papers selected encompassed the main ecosystems in Third Pole, namely forest, grassland, desert, cropland, and shrub ecosystems. Specifically, data pertaining to a soil depth interval of 0–30 cm ($n = 135$)

154 was retrieved from Yang et al. (2010) for the SOC database; data pertaining to a depth
 155 interval of 0–100 cm (n = 93) was obtained from Xu et al. (2019), data pertaining to a
 156 depth interval of 0–100 cm (n = 30) retrieved from Song et al. (2016). Moreover,
 157 additional data for 0–3 m and 0–2 m depth intervals (n = 113) were retrieved from
 158 Ding et al. (2016).

159 **Table 1** Summary of soil organic carbon datasets used in this study

Number of samples	Depth interval	Period	Method	Source
135	0–100 cm	2001–2005	Walkley-Black method	Yang et al., 2010
30	Genetic horizon	2012–2013	Walkley-Black method	Song et al., 2016
93	0–100 cm	2004–2014	Walkley-Black method	Xu et al., 2019
113	0–200 cm and 0–300 cm	2013–2014	Walkley-Black method	Ding et al., 2016
200	0–200 cm	2009–2013	Walkley-Black method	Field–investigated

160 Combined with the available published data and field investigated data (Table 1),
 161 the 458 soil pits (depth of 0–1 m) and 114 soil cores (depth of 0–3 m) can represent
 162 the ecosystem types and characters in large areas of the Third pole (Table 2).

163 **Table 2** Number of soil sample points of different ecosystems in the Third pole region

Ecosystem types	Forest	Shrub	Grassland	Desert	Cropland
Number	10	22	371	49	6

164 2.2.2 Environmental Covariates

165 The environmental covariates used in this study included a digital elevation model
 166 (DEM), remotely sensed data, and spatial interpolation data (Table S1).

167 A DEM at a spatial resolution of 1–km was downloaded from the International
 168 Scientific Data Service Platform (<http://datamirror.csdb.cn>). Using the DEM data and
 169 SAGA GIS software, we calculated 14 terrain attributes: elevation (H), slope (S),
 170 aspect (A), plan curvature (PlanC), profile curvature (ProC), topographic wetness
 171 index (TWI), total catchment area (TCA), relative slope position (RSP), slope length
 172 and steepness factor (LS), convergence index (CI), channel network base level (CNB),
 173 channel network distance (CND), valley depth (VD), and closed depressions (CD).

174 Mean annual air temperature (MAT) and mean annual precipitation (MAP) data
175 were downloaded from WorldClim version 2.1 (<https://www.worldclim.org>). These
176 datasets were generated by organizing, calculating, and spatially interpolating
177 observed data from global meteorological stations for the period 1970–2000.

178 Normalized difference vegetation index (NDVI) data were obtained from the
179 United States Geological Survey (USGS) (<http://modis.gsfc.nasa.gov/>). The datasets
180 underwent atmospheric, radiometric, and geometric correction, with a spatial
181 resolution of 1–km for every 1–month interval over the period 2000–2015. The NDVI
182 product was calculated using the maximum value composite (MVC) method, which
183 can minimize the effects of aerosols and clouds (Stow et al., 2004).

184 The net primary productivity (NPP) and leaf area index (LAI) data were obtained
185 from the Global Land Surface Satellite (GLASS, V3.1), which is estimated from the
186 MODIS reflectance data using the general regression neural network (GRNN) method
187 (Liang et al., 2013). Data were at a 1–km resolution for 8–day periods between 2000
188 and 2015, and were downloaded from the National Earth System Science Data Center
189 of the National Science & Technology Infrastructure of China
190 (<http://www.geodata.cn>).

191 The soil texture data, including Sand, Silt, and Clay contents, were obtained from
192 the “SoilGrids250m database” (<http://www.isric.org>). The original 250 m spatial
193 resolution data were resampled to a 1–km resolution based on nearest neighbor
194 interpolation using ArcGIS 10.2 software (ESRI, Redlands, CA, USA).

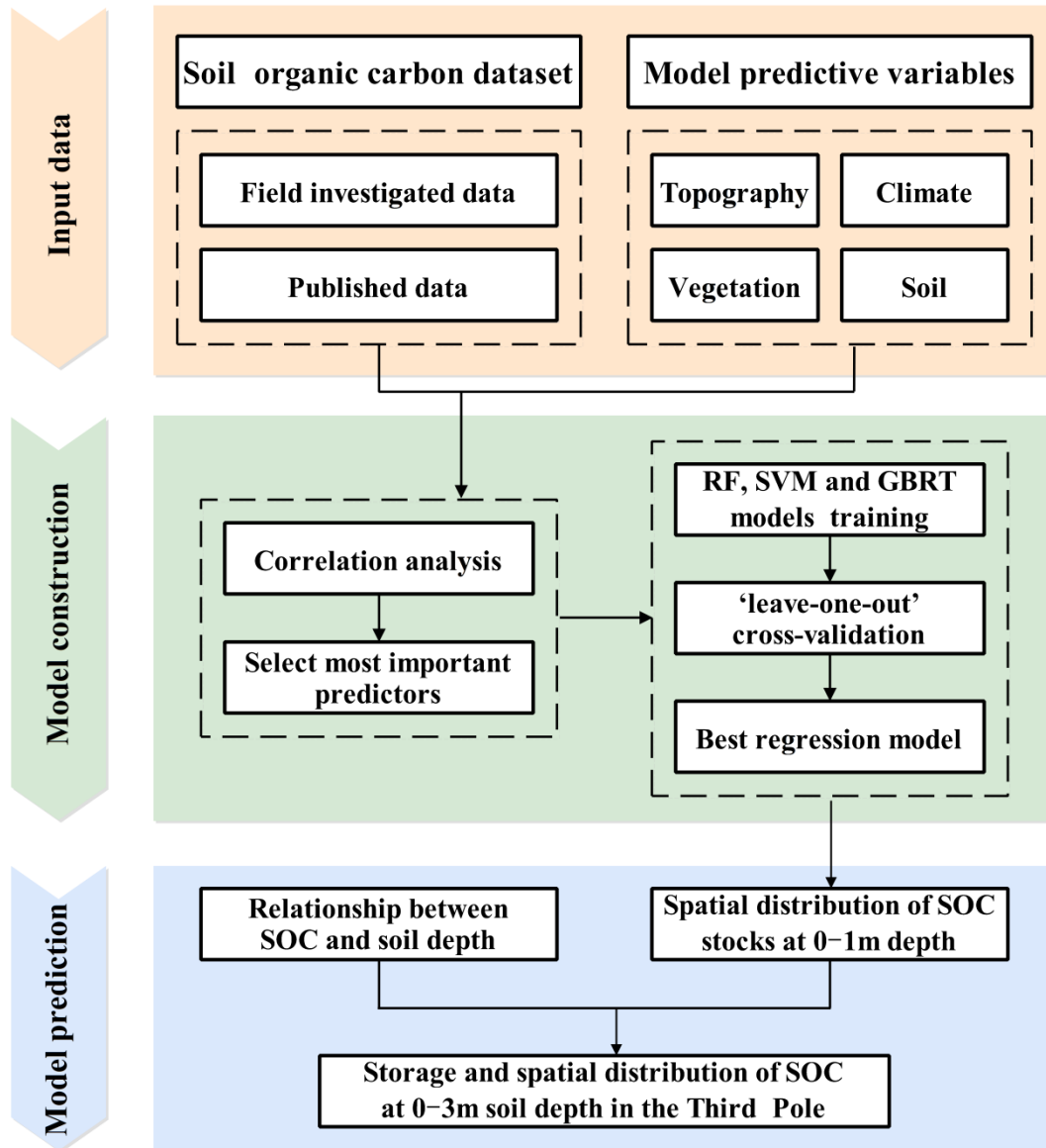
195 The land cover data used in this study were collected from the Land Cover Type
196 Climate Modeling Grid (CMG) product (MCD12C1) from 2010
197 (<https://lpdaac.usgs.gov>). The classification schemes in this study were based on the
198 global vegetation classification scheme of the International Geosphere Biosphere
199 Programme (IGBP). We reclassified the land cover types into five major categories:
200 forest, shrub, grassland, cropland, and desert.

201 **2.3 Model predictions**

202 **2.3.1. Geographical modelling and selection of the predictors**

203 In this study, three machine learning methods (random forest (RF), gradient

204 boosted regression tree (GBRT), and support vector machine (SVM)) were
 205 constructed and validated using the SOCS in the upper 30 cm of soil profiles along
 206 with associated variables (Fig.3).



207
 208 **Figure 3.** Workflow diagram for predicting SOCS in this study. RF: random forest; SVM: support
 209 vector machine; GBRT: gradient boosted regression tree.

210 With respect to the machine learning methods used, RF is used for classification,
 211 regression, and other tasks. It is operated by constructing a large number of decision
 212 trees during training, and outputs the class as the classification or regression patterns
 213 of single trees (Tin Kam, 1998). The GBRT method is an iterative fitting algorithm
 214 composed of multiple regression trees, and combines regression trees with a boosting
 215 technique to improve predictive accuracy (Elith et al., 2008). The SVM regression

216 method uses kernel functions to construct an optimal hyperplane, which has a minimal
 217 total deviation (Drake and Guisan, 2006). Combined with the remotely sensed data
 218 and spatial interpolation data, RF, GBRT, and SVM regression were conducted to
 219 predict the SOCS in the Third Pole region. The ‘randomForest’, ‘gbm’, and ‘e1071’
 220 packages in R were used to perform RF, GBRT, and SVM analyses.

221 The 15 input variables (H, S, TWI, TCA, RSP, CNB, CND, VD, NDVI, NPP, LAI,
 222 MAP, MAT, Sand, and Silt) for the three regression models were selected because
 223 they can reflect the effects of topography, climate, vegetation, and soil properties on
 224 regional SOCS. Moreover, these variables were significantly associated with the
 225 SOCS at a depth interval of 0–30 cm ($P < 0.01$, Table S2), whereas other
 226 environmental factors were eliminated due to their low correlation coefficients.

227 2.3.2 Estimation method of SOCS in deep soils

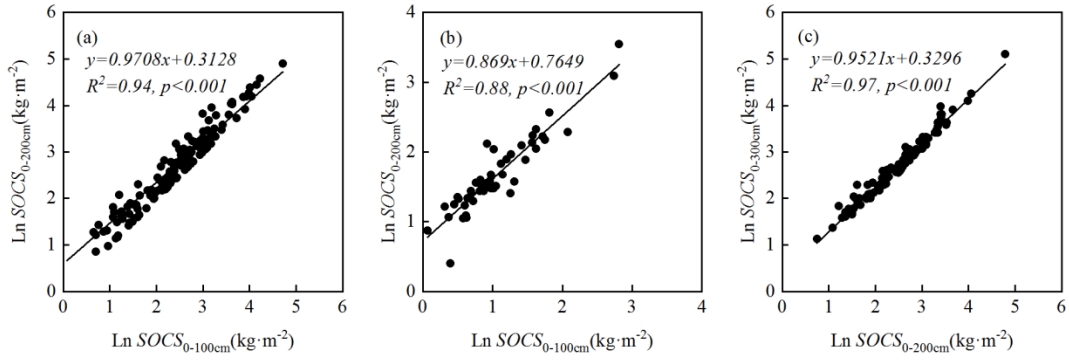
228 To generate the spatial distributions of SOCS in deep layers (below a depth of 100
 229 cm), we established nonlinear extrapolation models (Fig. 4.a–b; Eqs. (2)–(4)) between
 230 the SOCS in the upper 100 cm interval and the SOCS in the upper 200 cm interval
 231 using the data from the 200 soil pits in grassland ($n = 151$) and desert ecosystems ($n =$
 232 49, Fig. S1). A third extrapolation model between the SOCS in the upper 200 cm
 233 interval and the SOCS in the upper 300 cm interval in grassland ecosystems was
 234 established using the data from 114 sites reported by Ding et al. (2016) (Fig 4.c; Eq.
 235 (4)).

$$236 \quad \ln SOCS_{G(0-200\text{cm})} = 0.9708 \times \ln SOCS_{G(0-100\text{cm})} + 0.3128 \quad (2)$$

$$237 \quad \ln SOCS_{D(0-200\text{cm})} = 0.8690 \times \ln SOCS_{D(0-100\text{cm})} + 0.7649 \quad (3)$$

$$238 \quad \ln SOCS_{G(0-300\text{cm})} = 0.9521 \times \ln SOCS_{G(0-200\text{cm})} + 0.3296 \quad (4)$$

239 where $\ln SOCS_{G(0-100\text{cm})}$, $\ln SOCS_{G(0-200\text{cm})}$ and $\ln SOCS_{G(0-300\text{cm})}$ are the natural
 240 logarithms of the SOC stocks ($\text{kg}\cdot\text{m}^{-2}$) in grassland ecosystems at the depth intervals
 241 of 0–100 cm, 0–200 cm, and 0–300 cm, respectively; likewise, $\ln SOCS_{D(0-100\text{cm})}$ and
 242 $\ln SOCS_{D(0-200\text{cm})}$ are the natural logarithms of the SOC stocks ($\text{kg}\cdot\text{m}^{-2}$) in desert
 243 ecosystems at the depth intervals of 0–100 cm and 0–200 cm, respectively.



244

245 **Figure 4.** Extrapolation function of the SOCS between soil depth intervals of (a) 0–100 cm and 0–
 246 200 cm in grassland ecosystems, (b) 0–100 cm and 0–200 cm in desert ecosystems, and (c) 0–200
 247 cm and 0–300 cm in grassland ecosystems

248 It is impossible to build extrapolation models directly to estimate deep SOC storage
 249 in forest, shrub, and cropland ecosystems, which lack deep soil pits below 100 cm.
 250 Therefore, according to the vertical distribution of the SOCS associated with different
 251 land cover types worldwide from Jobbagy and Jackson (2000), the extrapolation
 252 models shown in Eqs. (5)–(6) were established indirectly to estimate deep SOC
 253 storage (below a depth of 100 cm) in areas of these land cover types (Fig. S1).
 254 Correspondingly, Eq. (7) was established to estimate the deep SOC storage (below a
 255 depth of 200 cm) in desert ecosystems due to a lack of deep soil pits below 200 cm.

256
$$SOCS_{0-200cm} = (1 + \beta_{100-200cm}) \times SOCS_{0-100cm} \quad (5)$$

257
$$SOCS_{0-300cm} = (1 + \beta_{100-200cm} + \beta_{200-300cm}) \times SOCS_{0-100cm} \quad (6)$$

258
$$SOCS_{0-300cm} = SOCS_{0-200cm} + \beta_{200-300cm} \times SOCS_{0-100cm} \quad (7)$$

259 where $\beta_{100-200cm}$ and $\beta_{200-300cm}$ are proportion of $SOCS_{100-200cm}$ and $SOCS_{200-300cm}$ in
 260 $SOCS_{0-100cm}$, respectively.

261 The calculation of the SOC storage (Pg) for a region generally uses Eq. (8):

262
$$SOC_{storage} = \sum_{i=1}^n SOCS_i \times A \times 10^{-12} \quad (8)$$

263 where $SOCS_i$ is the SOCS ($kg \cdot m^{-2}$) at site i and A is the area (m^2) of each grid unit.

264 2.3.3 Model validation

265 To test the predictive effects of the three machine learning methods, “leave-one-
 266 out” cross-validation was conducted. We used the R^2 value, the mean error (ME, Eq.

267 (9)), and the root mean square error (*RMSE*, Eq. (10)) to evaluate the performance of
268 the prediction models.

$$269 \quad ME = \frac{1}{n} \sum_{i=1}^n [D(x_i) - D^*(x_i)] \quad (9)$$

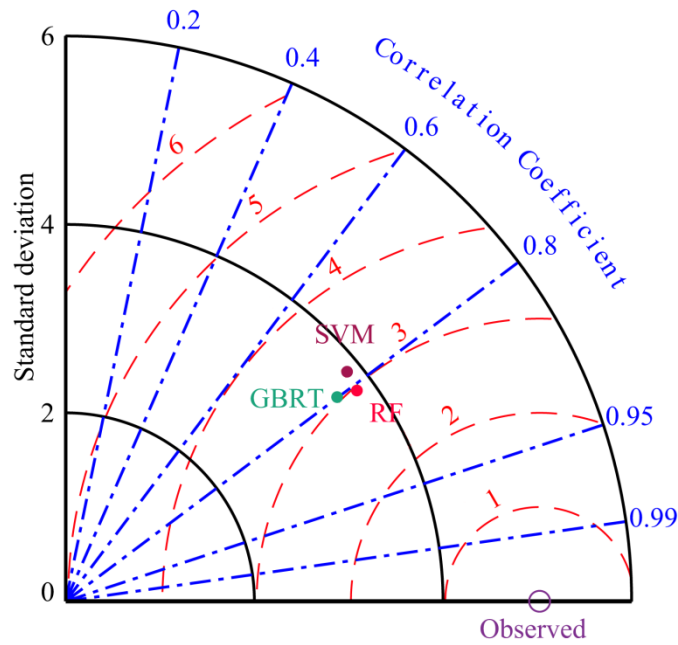
$$270 \quad RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n [D(x_i) - D^*(x_i)]^2} \quad (10)$$

271 where $D(x_i)$ is the measured SOCS, $D^*(x_i)$ is the predicted SOCS, and n is the number
272 of validation sites.

273 **3 Results**

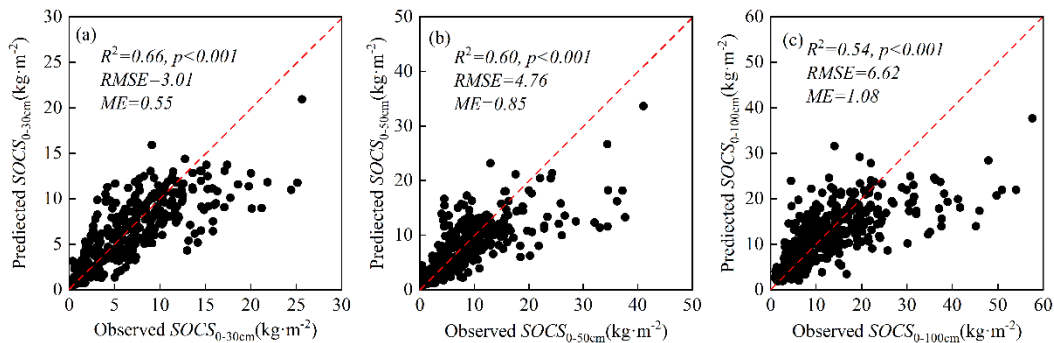
274 **3.1 Performance of machine learning methods**

275 The results of the “leave-one-out” cross-validation showed that the RF model
276 exhibited a Pearson’s correlation coefficient of 0.81, which was higher than that of the
277 GBRT model (0.79) and SVM model (0.77). In addition, the *RMSE* of the RF model
278 ($3.01 \text{ kg}\cdot\text{m}^{-2}$) was lower than that of the GBRT model ($3.11 \text{ kg}\cdot\text{m}^{-2}$) and SVM model
279 ($3.21 \text{ kg}\cdot\text{m}^{-2}$) for the upper 30 cm of the soil profile (Fig. 5). These results suggest
280 that the RF model provides a better tool for predicting the spatial distribution of
281 SOCS in the Third Pole region. Moreover, in order to further discuss the simulation
282 accuracy of the RF model in this study, “leave-one-out” cross-validations were
283 conducted for depth intervals of 0–50 cm and 0–100 cm. The results revealed high R^2
284 as well as low *RMSE* and *ME* values (Fig. 6).



285
286
287
288
289
290

Figure 5. A Taylor diagram used to evaluate the model performance of random forest (RF), support vector machine (SVM), and gradient boosting regression tree (GBRT) models, which were used to predict the SOCS in the upper 30 cm of soil profiles across the Third Pole. The contour centered on the observed indicates the root-mean-square error (RMSE, $\text{kg}\cdot\text{m}^{-2}$) between the predicted value and observed value.



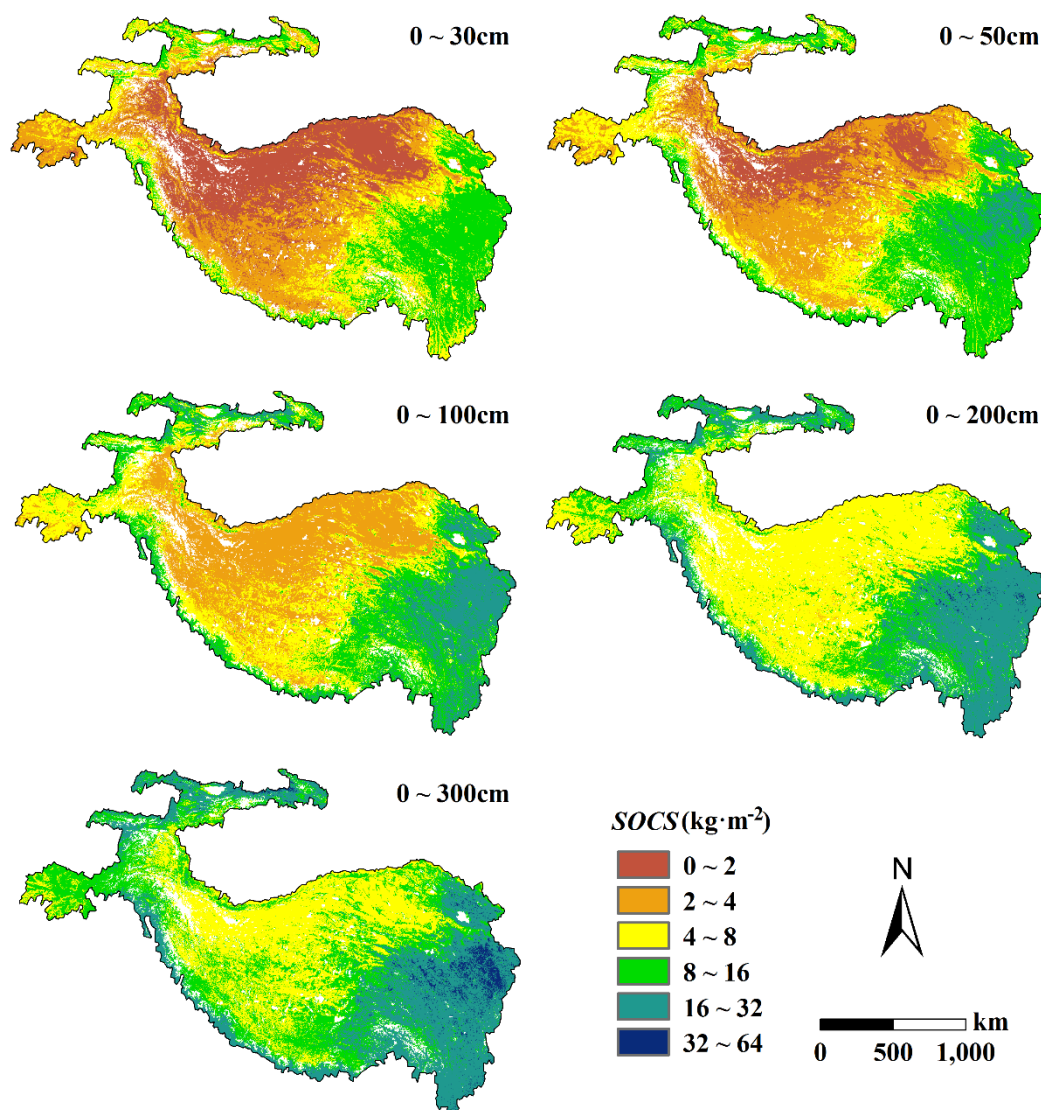
291
292
293
294

Figure 6. “Leave-one-out” cross-validation for the RF model used to predict the SOCS at (a) 0–30 cm, (b) 0–50 cm, and (c) 0–100 cm depth intervals.

295 3.2 Storage and spatial distribution of soil organic carbon

296 Figure 7 shows a large spatial variability of the SOCS across the Third Pole region,
297 whereby an overall decreasing trend can be observed from the southeast towards the
298 northwest. The wetland area in the eastern region of the Third Pole (Ruergai) had the
299 highest predicted SOCS for a depth interval of 0–300 cm ($> 32 \text{ kg}\cdot\text{m}^{-2}$), whereas the
300 northern region (Qiangtang Plateau and Qaidam Basin) had the lowest SOCS (< 8

301 $\text{kg}\cdot\text{m}^{-2}$). The estimated mean SOCS for the entire Third Pole region at depth intervals
 302 of 0–30 cm, 0–50 cm, 1–100 cm, 0–200 cm, and 0–300 cm was $4.84 \text{ kg}\cdot\text{m}^{-2}$, 6.45
 303 $\text{kg}\cdot\text{m}^{-2}$, $8.51 \text{ kg}\cdot\text{m}^{-2}$, $11.57 \text{ kg}\cdot\text{m}^{-2}$, and $14.17 \text{ kg}\cdot\text{m}^{-2}$, respectively. Correspondingly,
 304 the total estimated SOC storage was 15.79 Pg, 21.04 Pg, 27.75 Pg, 37.71 Pg, and
 305 46.18 Pg at 0–30 cm, 0–50 cm, 0–100 cm, 0–200 cm, and 0–300 cm, respectively
 306 (Table 3). In addition, the SOCS decreased with increasing soil depth across the Third
 307 Pole region, with 34.26% of the total SOC storage for a depth interval of 0–300 cm
 308 being contained in the uppermost 30 cm, and only 17.89% in the 200–300 cm depth
 309 interval.



310

311 **Figure 7.** Spatial distribution of SOCS at different depth intervals over the Third Pole.

312 Compared with the area of seasonally frozen ground, the mean SOCS and total

313 SOC storage in the permafrost region were lower in each soil layer. The estimated
 314 amount of SOC stored at a depth interval of 0–300 cm in the permafrost and seasonal
 315 frozen ground zone were 21.69 Pg and 24.49 Pg, respectively, which accounted for
 316 46.97% and 53.03% of the total SOC pools, respectively.

317 **Table 3** Summary of the estimated mean SOC stocks and storages in permafrost and seasonally
 318 frozen ground of the Third Pole

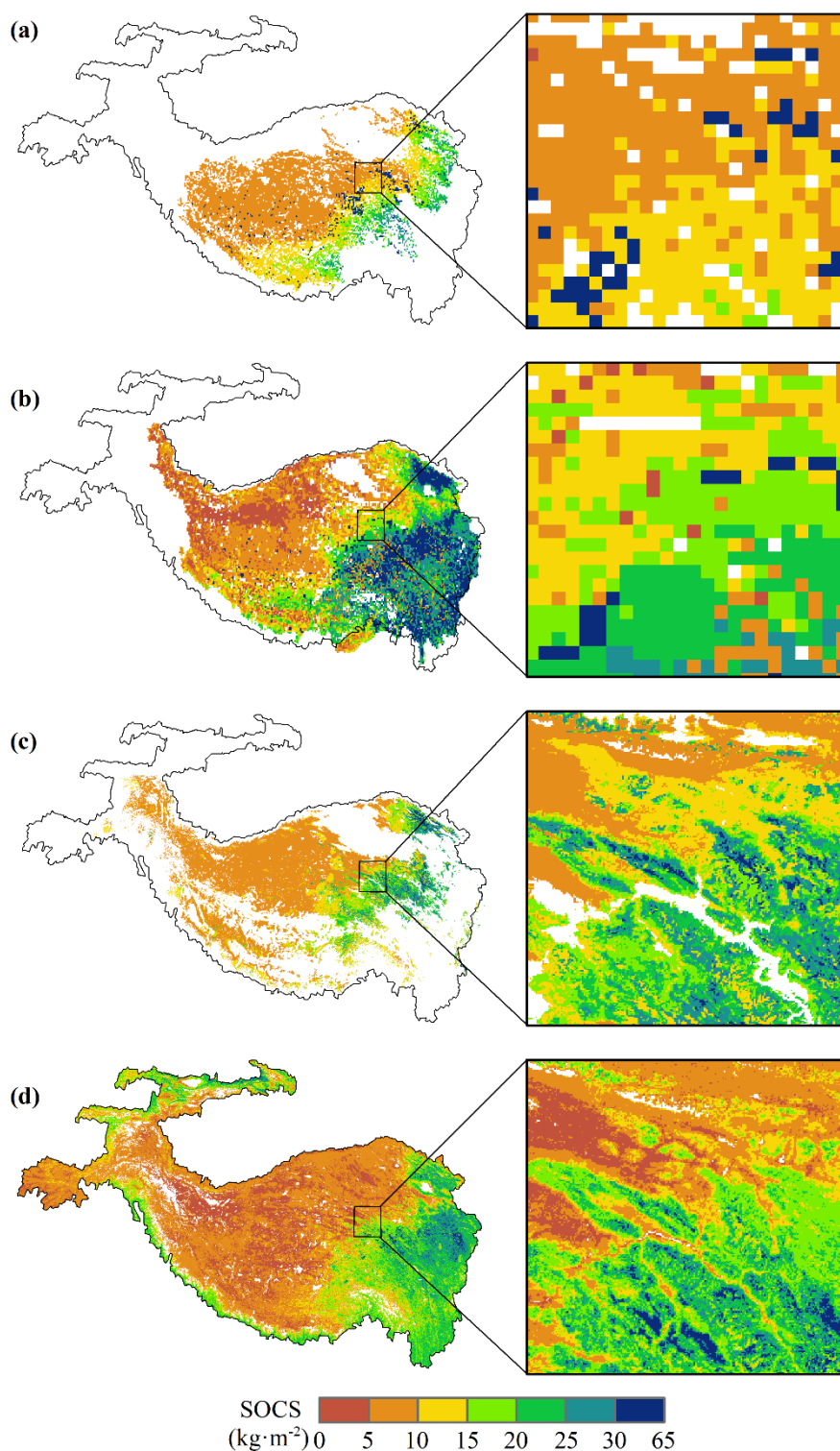
Depth (cm)	SOC stock (kg·m ⁻²)			SOC storage (Pg)		
	Permafrost	Seasonally frozen ground	Third Pole	Permafrost	Seasonally frozen ground	Third Pole
0–30	4.13	5.56	4.84	7.61	8.63	15.79
0–50	5.72	7.16	6.45	10.53	11.12	21.04
0–100	7.28	9.70	8.51	13.41	15.06	27.75
0–200	10.25	12.88	11.57	18.88	19.99	37.71
0–300	12.52	15.40	14.17	21.69	24.49	46.18

319

320 **4 Discussion**

321 In this study, we provided the new version of 1–km resolution maps of SOCS
 322 across the Third Pole at 0–300cm depth intervals, and largely makes up for the
 323 deficiencies of previous studies (Ding et al., 2016; Ding et al., 2019; Wang et al.,
 324 2020). On the one hand, our predictions have higher resolution than those studies.
 325 Take an example and focus on a 4.5×10^4 km² local area situated in the Budongquan
 326 area of Qinghai province, China (Fig. 8). It can be seen from the excerpts of the map
 327 that our prediction is much more detailed than previous studies. Thus, our predictions
 328 better represented spatial variation of the SOCS across the Third pole region,
 329 especially for those regions with large heterogeneity. On the other hand, these reports
 330 most focused on the permafrost regions rather than the whole Third Pole (Ding et al.,
 331 2016; Wang et al., 2020). To date, few studies have investigated the SOC storage and
 332 spatial patterns in areas of seasonally frozen ground in the Third Pole region. In this
 333 study, we created high spatial resolution data of SOCS distribution in the whole Third

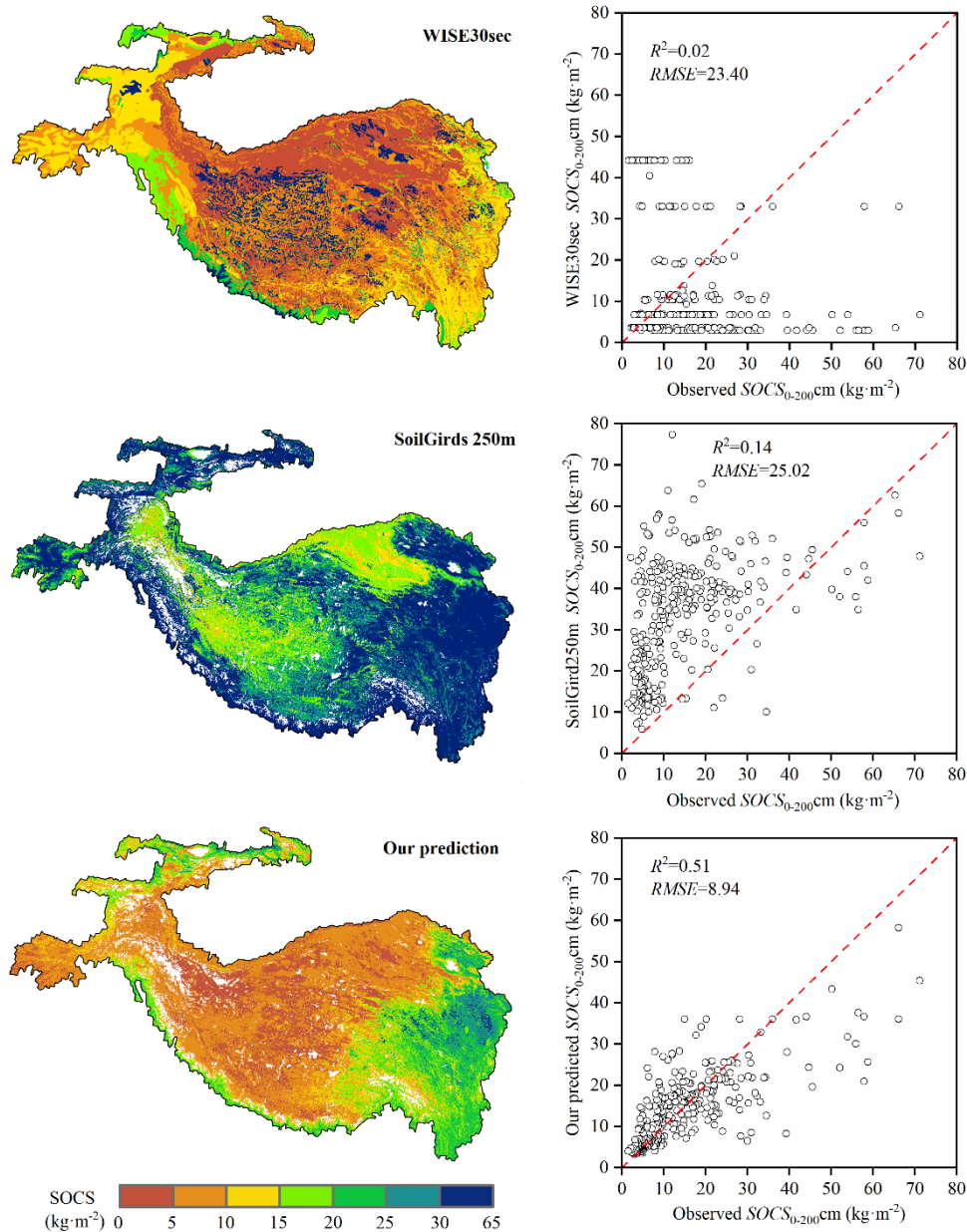
334 Pole by compiling all the field data and using machine learning methods, thus
335 providing more accurate data than previous studies.



336

337 **Figure 8.** Comparison of spatial details of the predictions with the previous studies: SOCS at 0–
338 300 cm depth in the map excerpt of Budongquan area of Qinghai province, China. (a) Ding et al.,
339 2016; (b) Ding et al., 2019; (c) Wang et al., 2020; (d) This study.

340 In addition, our predictions were much more accurate than the existing global SOC
341 datasets. Figure 9 shows accuracy assessments of our predictions, the SoilGrids250m
342 from Hengl et al., (2017) and the WISE30sec SOCS data from Batjes., (2016) at 0–
343 2m depth intervals based on the 213 SOC stocks data from Ding et al., (2016) and
344 field investigations. We found that our prediction had a higher R^2 value and lower
345 *RMSE* value than SoilGrids250m and WISE30sec. The lowest accuracy was found for
346 the WISE30sec maps, showing the advantage of digital soil mapping based on
347 machine learning over conventional mapping method based on the vegetation/soil
348 units (Liu et al., 2020). The remarkably lower accuracy of SoilGrids250m than our
349 predictions mainly because of serious over-estimation of bulk density, and neglected
350 the influence of coarse gravel content (Hengl et al., 2017). Soil profile data used in
351 SoilGrids250m at the Third Pole region are mainly from second China's national soil
352 survey, which lacked accurate information on coarse gravel content and bulk density
353 (Shi et al., 2016). In addition, almost all of these soil profiles are within 1–m depth,
354 which could be a great instability in calculating the deeper SOC by SoilGrids250m.
355 Moreover, the global model building could be less accurate than the regional model
356 building when focusing on a regional extent (Vitharana et al., 2019; Liu et al., 2020).
357 Consequently, our predictions were much more accurate than the existing maps of
358 SOCS.



359

360 **Figure 9.** Comparison of the SOCS prediction with the WISE30sec from Batjes., (2016) and the
 361 SoilGrids250m from Hengl et al., (2017) at 0–200 cm depth intervals based on the 213 SOCS data
 362 from Ding et al., (2016) and field investigations.

363 Our study provides new and more accurate data on SOC storage and spatial
 364 patterns for a depth interval of 0–3 m at a 1–km resolution over the Third Pole region,
 365 thus providing basic data for future studies pertaining to Earth system modeling. We
 366 note that a lack of deep soil pits in forest, shrub, and cropland ecosystems (Fig. S2)
 367 means some uncertainties in the estimation of deep SOC pools remain; however, the
 368 collective area of these ecosystems accounts for < 6% of the total area of the Third

369 Pole region and may have a relatively small influence on total SOC pools (Fig. S1).
370 Regardless, there is a need for large-scale soil surveys that include these areas in order
371 to obtain more accurate information on the SOC storage and distribution in the Third
372 Pole region. Furthermore, regional SOC pools are affected by many other factors,
373 such as soil moisture (Wu et al., 2016) and grazing activities (Zhou et al., 2017),
374 which were not considered in our study due to lack of high-resolution data with a high
375 accuracy. Future work should consider the influence of these factors on SOC at a
376 regional scale to obtain more accurate datasets.

377 **5. Data availability**

378 The datasets of SOC stocks distribution in GeoTiff format are available at
379 <https://doi.org/10.5281/zenodo.4293454> (Wang et al., 2020). The file name is "TP-
380 SOC-d.tif", where d represents soil depth, for example, "TP-SOC-30.tif" represents
381 the spatial distribution of SOC stocks in the Third Pole regions of the upper 30 cm
382 depth interval.

383 **6. Conclusions**

384 This study simulated the spatial pattern of the SOCS over the Third Pole region,
385 and systematically estimated the SOC storage (46.18 Pg) at a depth interval of 0–3 m
386 for the first time. Our results demonstrated that combining multi-environmental
387 factors with machine learning techniques (RF, SVM, and GBRT) can offer an
388 effective and powerful modeling approach for mapping the spatial patterns of SOC.
389 Furthermore, this study provided datasets of SOCS and SOC storage for permafrost
390 and seasonally frozen ground at different soil depths (0–30 cm, 0–50 cm, 0–100 cm,
391 0–200 cm, and 0–300 cm) across the Third Pole region. These datasets can be used to
392 modify existing Earth system models and improve prediction accuracy, and also serve
393 as a reference for policymakers to formulate more effective carbon budget
394 management strategies.

395 **Author contributions**

396 The study was completed with cooperation between all authors. Tonghua Wu and
397 Xiaodong Wu conceived the idea of mapping the spatial distribution of the SOC

398 across the Third Pole regions. Dong Wang conducted the data analyses and wrote the
399 paper. All authors discussed the simulation results and helped revise the paper.

400 **Competing interests**

401 The authors declare that they have no conflict of interest.

402 **Acknowledgements**

403 This work was financially supported by the State Key Laboratory of Cryospheric
404 Science (SKLCS–ZZ–2020), the National Natural Science Foundations of China
405 (41690142, 41721091, 41771076, 41961144021, 41671070), and the CAS "Light of
406 West China" Program.

407 **References**

- 408 Amundson, R.: The Carbon Budget in Soils, *Annual Review of Earth & Planetary Sciences*, 29,
409 535–562, <https://doi.org/10.1146/annurev.earth.29.1.535>, 2001.
- 410 Batjes, N.H.: Harmonized soil property values for broad-scale modelling (WISE30sec) with
411 estimates of global soil carbon stocks. *Geoderma* 269, 61–68,
412 <https://doi.org/10.1016/j.geoderma.2016.01.034>, 2016.
- 413 Cheng, G., Wu, T.: Responses of permafrost to climate change and their environmental
414 significance, Qinghai-Tibet Plateau, *Journal of Geophysical Research Earth Surface*, 112,
415 F02S03, <https://doi.org/10.1029/2006JF000631>, 2007.
- 416 Cheng, G., Zhao L., Li R., Wu, X., Sheng., Y, Hu G., Zou D, Jin, H, Li, X., and Wu., Q.:
417 Characteristic, changes and impacts of permafrost on Qinghai-Tibet Plateau (in Chinese),
418 *Chin Sci Bull*, 64: 2783–2795, <https://doi.org/10.1360/TB-2019-0191>, 2019.
- 419 Ding, J., Li, F., Yang, G., Chen, L., Zhang, B., Liu, L., Fang, K., Qin, S., Chen, Y., Peng, Y., Ji,
420 C., He, H., Smith, P., and Yang, Y.: The permafrost carbon inventory on the Tibetan Plateau:
421 a new evaluation using deep sediment cores, *Global Change Biology*, 22, 2688–2701,
422 <https://doi.org/10.1111/gcb.13257>, 2016.
- 423 Ding, J., Wang, T., Piao, S., Smith, P., and Zhao, L.: The paleoclimatic footprint in the soil
424 carbon stock of the Tibetan permafrost region, *Nature Communications*, 10, 1–9,
425 <https://doi.org/10.1038/s41467-019-12214-5>, 2019.
- 426 Ding, Y., Mu, C., Wu, T., Hu, G., Zou, D., Wang, D., Li, W., and Wu, X.: Increasing
427 cryospheric hazards in a warming climate, *Earth-Science Reviews*, 213,
428 <https://doi.org/10.1016/j.earscirev.2020.103500>, 2021.
- 429 Drake, J. M. and Guisan, R. A.: Modelling Ecological Niches with Support Vector Machines,
430 *Journal of Applied Ecology*, 43, 424–432,
431 <https://doi.org/10.1111/j.1365-2664.2006.01141.x>, 2006.
- 432 Elith, J., Leathwick, J. R., and Hastie, T.: A working guide to boosted regression trees, *Journal*
433 *of Animal Ecology*, 77, 802–813, <https://doi.org/10.1111/j.1365-2656.2008.01390.x>, 2008.
- 434 Fan, J., Cao, Y., Yan, Y., Lu, X., Wang, X., Fan, J., Cao, Y., Yan, Y., Lu, X., and Wang, X.:
435 Freezing-thawing cycles effect on the water soluble organic carbon, nitrogen and microbial
436 biomass of alpine grassland soil in Northern Tibet, *African Journal of Microbiology*

437 Research, 6, 562–567, <https://doi.org/10.5897/AJMR11.1218>, 2012.

438 Hao, Y., Luo, X., Zhong, B., and Yang, A.: Methods of the National Vegetation Classification
439 based on Vegetation Partition, Remote Sensing Technology and Application, 32, 315–323,
440 <https://doi.org/10.2991/mmme-16.2016.60>, 2017.

441 Hengl T, Mendes de Jesus J, Heuvelink GBM, Ruiperez Gonzalez M, Kilibarda M, Blagotić
442 A, et al.: SoilGrids250m: Global gridded soil information based on machine learning. PLoS
443 ONE 12(2): e0169748. <https://doi.org/10.1371/journal.pone.0169748>, 2017.

444 Hugelius, G., Strauss, J., Zubrzycki, S., Harden, J. W., Schuur, E. A. G., Ping, C. L.,
445 Schirmer, L., Grosse, G., Michaelson, G. J., Koven, C. D., O'Donnell, J. A., Elberling,
446 B., Mishra, U., Camill, P., Yu, Z., Palmtag, J., and Kuhry, P.: Estimated stocks of
447 circumpolar permafrost carbon with quantified uncertainty ranges and identified data gaps,
448 Biogeosciences, 11, 6573–6593, <https://doi.org/10.5194/bg-11-6573-2014>, 2014.

449 Jiang, L., Chen, H., Zhu, Q., Yang, Y., Li, M., Peng, C., Zhu, D., and He, Y.: Assessment of
450 frozen ground organic carbon pool on the Qinghai-Tibet Plateau, Journal of Soils and
451 Sediments, 19, 128–139, <https://doi.org/10.1007/s11368-018-2006-3>, 2019.

452 Jobbagy, E. G. and Jackson, R. B.: The vertical distribution of soil organic carbon and its
453 relation to climate and vegetation, Ecological Applications, 10, 423–436,
454 <https://doi.org/10.2307/2641104>, 2000.

455 Koven, C. D., Ringer, B., Friedlingstein, P., Ciais, P., Cadule, P., Khvorostyanov, D.,
456 Krinner, G., and Tarnocai, C.: Permafrost carbon-climate feedbacks accelerate global
457 warming, Proceedings of the National Academy of Sciences, 2011.
458 <https://doi.org/10.1073/pnas.1103910108>, 2011.

459 Li, F., Zang, S., Liu, Y., Li, L., and Ni, H.: Effect of Freezing–Thawing Cycle on Soil Active
460 Organic Carbon Fractions and Enzyme Activities in the Wetland of Sanjiang Plain,
461 Northeast China, Wetlands, 40, 167–177, <https://doi.org/10.1007/s13157-019-01164-9>,
462 2020.

463 Liang, S., Zhao, X., Liu, S., Yuan, W., Cheng, X., Xiao, Z., Zhang, X., Liu, Q., Cheng, J.,
464 Tang, H., Qu, Y., Bo, Y., Qu, Y., Ren, H., Yu, K., and Townshend, J.: A long-term Global
465 Land Surface Satellite (GLASS) dataset for environmental studies, International Journal of
466 Digital Earth, 6, 5–33, <https://doi.org/10.1080/17538947.2013.805262>, 2013.

467 Hengl T, Mendes de Jesus J, Heuvelink GBM, Ruiperez Gonzalez M, Kilibarda M, Blagotić
468 A, et al.: SoilGrids250m: Global gridded soil information based on machine learning. PLoS
469 ONE 12(2): e0169748. <https://doi.org/10.1371/journal.pone.0169748>, 2017.

470 Lombardozzi, D. L., Bonan, G. B., Smith, N. G., Dukes, J. S., and Fisher, R. A.: Temperature
471 acclimation of photosynthesis and respiration: A key uncertainty in the carbon cycle–
472 climate feedback, *Geophysical Research Letters*, 42, 8624–8631,
473 <https://doi.org/10.1002/2015GL065934>, 2016.

474 McGuire, A. D., Lawrence, D. M., Koven, C., Clein, J. S., Burke, E., Chen, G., Jafarov, E.,
475 Macdougall, A. H., Marchenko, S., Nicolsky, D., Peng, S., Rinke, A., Ciais, P., Gouttevin, I.,
476 Hayes, D. J., Ji, D., Krinner, G., Moore, J. C., Romanovsky, V., Schädel, C., Schaefer, K.,
477 Schuur, E. A. G., and Zhuang, Q.: Dependence of the evolution of carbon dynamics in the
478 northern permafrost region on the trajectory of climate change, *Proceedings of the National
479 Academy of Sciences*, 115, 3882–3887, <https://doi.org/10.1073/pnas.1719903115>, 2018.

480 Mishra, U., Jastrow, J. D., Matamala, R., Hugelius, G., Koven, C. D., Harden, J. W., Ping, C.
481 L., Michaelson, G. J., Fan, Z., and Miller, R. M.: Empirical estimates to reduce modeling
482 uncertainties of soil organic carbon in permafrost regions: a review of recent progress and
483 remaining challenges, *Environmental Research Letters*, 8, 1402–1416,
484 <https://doi.org/10.1088/1748-9326/8/3/035020>, 2013.

485 Mu, C. C., Abbott, B. W., Norris, A. J., Mu, M., Fan, C. Y., Chen, X., Jia, L., Yang, R. M.,
486 Zhang, T. J., Wang, K., Peng, X. Q., Wu, Q. B., Guggenberger, G., and Wu, X. D.: The
487 status and stability of permafrost carbon on the Tibetan Plateau, *Earth-Science Reviews*,
488 211, 21, <https://doi.org/10.1016/j.earscirev.2020.103433>, 2020.

489 Mu, C., Shang, J., Zhang, T., Fan, C., Wang, S., Peng, X., Zhong, W., Zhang, F., Mu, M., and
490 Jia, L.: Acceleration of thaw slump during 1997–2017 in the Qilian Mountains of the
491 northern Qinghai-Tibetan plateau, *Landslides*, 17, 1051–1062,
492 <https://doi.org/10.1007/s10346-020-01344-3>, 2020.

493 Mu, C., Zhang, T., Wu, Q., Peng, X., Cao, B., Zhang, X., Cao, B., and Cheng, G.: Editorial:
494 Organic carbon pools in permafrost regions on the Qinghai–Xizang (Tibetan) Plateau, 9,
495 479–486, <https://doi.org/10.5194/tc-9-479-2015>, 2015.

496 Obu, J., Westermann, S., Bartsch, A., Berdnikov, N., Christiansen, H. H., Dashtseren, A.,

497 Delaloye, R., Elberling, B., Etzelmüller, B., Kholodov, A., Khomutov, A., Kääh, A.,
498 Leibman, M. O., Lewkowicz, A. G., Panda, S. K., Romanovsky, V., Way, R. G.,
499 Westergaard-Nielsen, A., Wu, T., Yamkhin, J., and Zou, D.: Northern Hemisphere
500 permafrost map based on TTOP modelling for 2000–2016 at 1 km² scale, *Earth-Science*
501 *Reviews*, 193, 299–316, <https://doi.org/10.1016/j.earscirev.2019.04.023>, 2019.

502 Ping, C. L., Jastrow, J. D., Jorgenson, M. T., Michaelson, G. J., and Shur, Y. L.: Permafrost
503 soils and carbon cycling, *Soil*, 1, 147–171, <https://doi.org/10.5194/soil-1-147-2015>, 2015.

504 Ran, Y., Li, X., and Cheng, G.: Climate warming has led to the degradation of permafrost
505 stability in the past half century over the Qinghai-Tibet Plateau. Copernicus GmbH,
506 <https://doi.org/10.5194/tc-2017-120>, 2017.

507 Schuur, E. A. G., McGuire, A. D., Schädel, C., Grosse, G., Harden, J. W., Hayes, D. J.,
508 Hugelius, G., Koven, C. D., Kuhry, P., Lawrence, D. M., Natali, S. M., Olefeldt, D.,
509 Romanovsky, V. E., Schaefer, K., Turetsky, M. R., Treat, C. C., and Vonk, J. E.: Climate
510 change and the permafrost carbon feedback, *Nature*, 520, 171–179,
511 <https://doi.org/10.1038/nature14338>, 2015.

512 Shi Jianping, Song Ge.: Soil Type Database of China: A nationwide soil dataset based on the
513 Second National Soil Survey (in Chinese). *China Scientific Data*, (2):1–12,
514 <http://dx.doi.org/10.11922/sciencedb.180.88>, 2016.

515 Song, X. D., Brus, D. J., Liu, F., Li, D.-C., Zhao, Y. G., Yang, J. L., and Zhang, G. L.:
516 Mapping soil organic carbon content by geographically weighted regression: A case study
517 in the Heihe River Basin, China, *Geoderma*, 261, 11–22,
518 <https://doi.org/10.1016/j.geoderma.2015.06.024>, 2016.

519 Stocker, T. F., Qin, D., Plattner, G. K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia,
520 Y., Bex, B., and Midgley, B. M.: IPCC, 2013: Climate Change 2013: The Physical Science
521 Basis. Contribution of Working Group I to the Fifth Assessment Report of the
522 Intergovernmental Panel on Climate Change, *Computational Geometry*, 18, 95–123, 2013.

523 Stow, D. A., Hope, A., McGuire, D., Verbyla, D., Gamon, J., Huemmrich, F., Houston, S.,
524 Racine, C., Sturm, M., Tape, K., Hinzman, L., Yoshikawa, K., Tweedie, C., Noyle, B.,
525 Silapaswan, C., Douglas, D., Griffith, B., Jia, G., Epstein, H., Walker, D., Daeschner, S.,
526 Petersen, A., Zhou, L., and Myneni, R.: Remote sensing of vegetation and land-cover

527 change in Arctic Tundra Ecosystems, *Remote Sensing of Environment*, 89, 281–308,
528 <https://doi.org/10.1016/j.rse.2003.10.018>, 2004.

529 Tian, Y., Ouyang, H., Xu, X., Song, M., and Zhou, C.: Distribution characteristics of soil
530 organic carbon storage and density on the Qinghai-Tibet Plateau, *Acta Pedologica Sinica*,
531 45, 933–942, 2008.

532 Tin Kam, H.: Random subspace method for constructing decision forests, *IEEE Transactions*
533 *on Pattern Analysis and Machine Intelligence*, 20, 832–844,
534 <https://doi.org/10.1109/34.709601>, 1998.

535 Turetsky, M. R., Abbott, B. W., Jones, M. C., Walter Anthony, K., Olefeldt, D., Schuur, E. A.
536 G., Koven, C., McGuire, A. D., Grosse, G., Kuhry, P., Hugelius, G., Lawrence, D. M.,
537 Gibson, C., and Sannel, A. B. K.: Permafrost collapse is accelerating carbon release, *Nature*,
538 569, 32–34, <https://doi.org/10.1038/d41586-019-01313-4>, 2019.

539 Vitharana, U., Mishra, U., and Mapa, R. B.: National soil organic carbon estimates can
540 improve global estimates, *Geoderma*, 337, 55–64,
541 <https://doi.org/10.1016/j.geoderma.2018.09.005>, 2019.

542 Wang, G., Qian, J., Cheng, G., and Lai, Y.: Soil organic carbon pool of grassland soils on the
543 Qinghai-Tibetan Plateau and its global implication, *Science of the Total Environment*, 291,
544 207–217, [https://doi.org/10.1016/S0048-9697\(01\)01100-7](https://doi.org/10.1016/S0048-9697(01)01100-7), 2002.

545 Wang, T. H., Yang, D. W., Yang, Y. T., Piao, S. L., Li, X., Cheng, G. D., and Fu, B. J.:
546 Permafrost thawing puts the frozen carbon at risk over the Tibetan Plateau, *Science*
547 *Advances*, 6, <https://doi.org/10.1126/sciadv.aaz3513>, 2020.

548 Wu, Q., Zhang, T., and Liu, Y.: Thermal state of the active layer and permafrost along the
549 Qinghai-Xizang (Tibet) Railway from 2006 to 2010, *The Cryosphere*, 6, 607–612,
550 <https://doi.org/10.5194/tc-6-607-2012>, 2012.

551 Wu, X., Zhao, L., Fang, H., Zhao, Y., Smoak, J. M., Pang, Q., and Ding, Y.: Environmental
552 controls on soil organic carbon and nitrogen stocks in the high-altitude arid western
553 Qinghai-Tibetan Plateau permafrost region, *Journal of Geophysical Research*
554 *Biogeosciences*, 121, 176–187, <https://doi.org/10.1002/2015JG003138>, 2016.

555 Wu, Y., Liu, G., Fu, B., and Guo, Y.: Study on the vertical distribution of soil organic carbon
556 density in the Tibetan Plateau, *Acta Scientiae Circumstantiae*, 28, 362–367,

557 <https://doi.org/10.3724/SP.J.1148.2008.00259>, 2008.

558 Xu, L., Yu, G., and He, N.: Increased soil organic carbon storage in Chinese terrestrial
559 ecosystems from the 1980s to the 2010s, *Journal of Geographical Sciences*, 29, 49–66,
560 <https://doi.org/10.1007/s11442-019-1583-4>, 2019.

561 Yang, Y., Fang, J., Ma, W., Smith, P., Mohammat, A., Wang, S., and Wang, W.: Soil carbon
562 stock and its changes in northern China's grasslands from 1980s to 2000s, *Global Change*
563 *Biology*, 16, 3036–3047, <https://doi.org/10.1111/j.1365-2486.2009.02123.x>, 2010.

564 Yang, Y., Fang, J., Tang, Y., Ji, C., Zheng, C., He, J., and Zhu, B.: Storage, patterns and
565 controls of soil organic carbon in the Tibetan grasslands, *Global Change Biology*, 14,
566 1592–1599, <https://doi.org/10.1111/j.1365-2486.2008.01591.x>, 2008.

567 Yao, T., Thompson, L. G., Mosbrugger, V., Zhang, F., Ma, Y., Luo, T., Xu, B., Yang, X.,
568 Joswiak, D. R., Wang, W., Joswiak, M. E., Devkota, L. P., Tayal, S., Jilani, R., and Fayziev,
569 R.: Third Pole Environment (TPE), *Environmental Development*, 3, 52–64,
570 <https://doi.org/10.1016/j.envdev.2012.04.002>, 2012.

571 Zeng, Y., Feng, Z., Cao, G., and Xu, L.: The Soil Organic Carbon Storage and Its Spatial
572 Distribution of Alpine Grassland in the Source Region of the Yellow River, *Acta*
573 *Geographica Sinica*, 59, 497–504, <https://doi.org/10.1007/BF02873091>, 2004.

574 Zhao, L., Wu, X., Wang, Z., Sheng, Y., Fang, H., Zhao, Y., Hu, G., Li, W., Pang, Q., Shi, J.,
575 Mo, B., Wang, Q., Ruan, X., Li, X., and Ding, Y.: Soil organic carbon and total nitrogen
576 pools in permafrost zones of the Qinghai-Tibetan Plateau, *Scientific Reports*, 8,
577 <https://doi.org/10.1038/s41598-018-22024-2>, 2018.

578 Zhou, G., Zhou, X., He, Y., Shao, J., Hu, Z., Liu, R., Zhou, H., and Hosseinibai, S.: Grazing
579 intensity significantly affects belowground carbon and nitrogen cycling in grassland
580 ecosystems: a meta-analysis, *Global Change Biology*, 23, <https://doi.org/1167-1179,>
581 10.1111/gcb.13431, 2017.

582