

1 **A dataset of 10-year regional-scale soil moisture and soil temperature** 2 **measurements at multiple depths on the Tibetan Plateau**

3 Pei Zhang^{1,2}, Donghai Zheng², Rogier van der Velde¹, Jun Wen³, Yaoming Ma², Yijian Zeng¹, Xin
4 Wang⁴, Zuoliang Wang⁴, Jiali Chen^{2,5}, and Zhongbo Su¹

5 ¹Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, Enschede, 7514AE, the Netherlands

6 ²State Key Laboratory of Tibetan Plateau Earth System, Environment and Resources, Institute of Tibetan Plateau Research,
7 Chinese Academy of Sciences, Beijing, 100101, China

8 ³College of Atmospheric Sciences, Chengdu University of Information Technology, Chengdu, 610225, China

9 ⁴Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences, Lanzhou, 730000, China

10 ⁵College of Earth and Environmental Sciences, Lanzhou University, Lanzhou, 730000, China

11

12 *Correspondence:* Donghai Zheng (zhengd@itpcas.ac.cn) and Zhongbo Su (z.su@utwente.nl)

13

14 **Abstract.** Soil moisture and soil temperature (SMST) are important state variables for quantifying exchange of heat and water
15 between land and atmosphere. Yet, long-term regional-scale in-situ SMST measurements are scarce on the Tibetan Plateau
16 (TP), even fewer are available for multiple soil depths. “Tibet-Obs” is such a long-term regional-scale SMST observatory in
17 the TP established 10 years ago that includes three SMST monitoring networks, i.e., Maqu, Naqu, and Ngari (including Ali
18 and Shiquanhe), located in the cold humid area covered by [grassland](#), the cold semiarid area dominated by tundra, and the cold
19 arid area dominated by desert, respectively. This paper presents a long-term (~10 years) SMST profile dataset collected from
20 the Tibet-Obs, which includes the original in-situ measurements at a 15-min interval collected between 2008 and 2019 from
21 all the three networks and the spatially upscaled data (SM_{ups} and ST_{ups}) for the Maqu and Shiquanhe networks. The quality of
22 the upscaled data is proved to be good with errors that are generally better than the measured accuracy of adopted SMST
23 sensors. Long term analysis of the upscaled SMST profile data shows that the amplitudes of SMST variations decrease with
24 increasing soil depth, and the deeper soil layers present later onset of freezing and earlier start of thawing and thus shorter
25 freeze-thaw duration in both Maqu and Shiquanhe networks. In addition, there are notably differences noted between the
26 relationships of SM_{ups} and ST_{ups} under freezing conditions for the Maqu and Shiquanhe networks. No significant trend can be
27 found for the SM_{ups} profile in the warm season (from May to October) for both networks that is consistent with the tendency
28 of precipitation. Similar finding is also found for the ST_{ups} profile and air temperature in the Shiquanhe network during the
29 warm season. For the cold season (from November to April), a drying trend is noted for the SM_{ups} above 20 cm in the Maqu
30 network, while no significant trend is found for those in the Shiquanhe network. Comparisons between the long-term upscaled
31 data and five reanalysis datasets, [namely ERA5, MERRA2, GLDAS-2.1 CLSM, Noah, and VIC](#), indicate that none of current
32 model-based products can reproduce the seasonal variations and inter-annual trend changes of measured SMST profile
33 dynamics in both networks. All the products underestimate the ST_{ups} at every depth, leading to earlier onset of freezing and
34 later onset of thawing, which essentially demonstrates the current model are not able to adequately simulate winter conditions

35 on the TP. In short, the presented dataset would be valuable for evaluation and improvement of long-term satellite- and model-
36 based SMST products on the TP, enhancing the understanding of TP hydrometeorological processes and their response to
37 climate change. The dataset is available in the 4TU.ResearchData repository at <https://doi.org/10.4121/20141567.v1> (Zhang
38 et al., 2022).

39 **1 Introduction**

40 Soil moisture and soil temperature (SMST) are important state variables for quantifying water, energy, and carbon exchange
41 processes in the soil-vegetation-atmosphere system (Zheng et al., 2018; van der Velde et al., 2009). Quantifying the seasonal
42 dynamics and trend changes of the SMST is important to understand the response of hydrological cycle and vegetation
43 dynamics to climate change. Over the past decades, many efforts have been dedicated to obtain worldwide reliable SMST data
44 through in-situ measurements, remote sensing, and model simulations (Dorigo et al., 2011; Entekhabi et al., 2010; Rodell et
45 al., 2004). Thereinto, in-situ measurements are essential for the creation of ground reference for the validation of remote
46 sensing and model-based products (Colliander et al., 2017; Chen et al., 2017; Zeng et al., 2015), as well as improving model
47 parametrizations (Zheng et al., 2017, 2015a, b) and remote sensing retrieval algorithms (Zheng et al., 2019, 2018). Since the
48 SMST measurements at a single site cannot well represent the value of a satellite pixel or model grid due to spatial variability,
49 several regional-scale monitoring networks were established to collect SMST measurements at regional-scale, some of which
50 are contributing to the International Soil Moisture Network (ISMN) (Dorigo et al., 2011, 2021).

51 Known as the third pole, exchange of water and energy between land and atmosphere on the Tibetan Plateau (TP) plays a
52 crucial role in regulating climate processes in the Northern Hemisphere and the evolution of the Asian monsoon (Wu et al.,
53 1998; Yao et al., 2012). Soil freeze-thaw (F/T) cycle is a typical process on the TP, which has a significant impact on the
54 energy exchange between land and atmosphere as well as water cycle (Zheng et al., 2017, 2018a). Knowledge on SMST
55 seasonal variations, trend changes and the F/T states on the TP can, therefore, contribute to a better understanding of the Asian
56 monsoon circulation and cryosphere changes. However, SMST monitoring networks are scarce on the TP compared to its vast
57 territory, and even fewer exist with a long time series measurements and/or with measurements at multiple soil depths. To our
58 knowledge, there are only two operational SMST observatories that provide long-term measurements at multiple soil depths
59 on the TP, i.e., Tibet-Obs (Tibetan Plateau observatory of plateau scale SMST) (Su et al., 2011; Zhang et al., 2021) and CTP-
60 SMTMN (Soil Moisture and Temperature Monitoring Network on the central TP) (Yang et al., 2013).

61 The Tibet-Obs is the first operational SMST observatory on the TP that started to provide SMST measurements in 2008, which
62 was designed to provide a representative coverage of distinct climate regimes and land surface conditions across the TP (Su et
63 al., 2011). The Tibet-Obs comprises three in-situ monitoring networks, i.e., Maqu, Naqu, and Ngari (including Ali and
64 Shiquanhe) (Fig. 1), *which are respectively located in the cold humid area with cold dry winter and rainy summer covered by
65 grassland, the cold semiarid area dominated by tundra, and the cold arid area dominated by desert* (Su et al., 2011; Beck et al.,
66 2018; Zhang et al., 2021). In the Tibet-Obs, SMST sensors were installed at multiple depths, which facilitate the

67 calibration/validation of satellite-based retrieval algorithms and products, as well as the model-based SMST products. Table 1
68 summarizes the main applications of the Tibet-Obs SMST data with focus on simultaneous usage of SM and ST measurements
69 or usage of SM/ST measurements at multiple depths for the product validations. A summary related to the usage of only surface
70 SM data is included in Zhang et al. (2021). Based on Table 1 and the summary made in Zhang et al. (2021), it may be concluded
71 that the Tibet-Obs data were mainly applied to evaluate surface SM products, whereas a few studies simultaneously evaluated
72 SM and ST products, and even less focused on the investigation of profile dynamics using measurements at multiple depths.
73 In addition, most of previous studies focused on a certain short-term period (e.g., several years) while the Tibet-Obs holds
74 SMST data for more than 10 years (Zhang et al., 2021), and most of current satellite- and model-based products also provide
75 long-term (e.g., ≥ 10 years) SMST data. Moreover, previous assessments were mainly concentrated on estimating error metrics
76 between SMST products and measurements, while how well these SMST products can capture the long-term trend and
77 variations of in-situ SMST dynamics is still unknown. Therefore, development of a long-term dataset of SMST measurements
78 at multiple depths based on the Tibet-Obs is essential to comprehensively assess and improve the reliability of current SMST
79 products regarding to seasonal variations and trend changes, enhancing their applications to improve our understanding on
80 changes of hydrological and cryosphere processes on the TP.

81 In this paper, we present a long-term (~10 years) SMST profile dataset collected from the Tibet-Obs, which expands the surface
82 SM dataset introduced by Zhang et al. (2021) to include both SM and ST measurements collected at multiple depths. As such,
83 analysis of freezing and thawing characteristics become possible. The analysis of seasonal dynamics and trend changes as well
84 as validation of model-based products are also extended to multiple depths for an approximately 10-year period. In addition,
85 more model-based products are evaluated in this paper. In the Tibet-Obs, Decagon (now: METER Group) EC-TM/5TM probes
86 and EM50 data loggers were deployed for each site at multiple depths (e.g., 5, 10, 20, 40, 60 or 80 cm below the surface) to
87 record SMST profile measurements with a 15-minute interval. The presented SMST profile dataset includes in-situ
88 measurements collected between May 2008 and August 2019 for all three networks of the Tibet-Obs, and spatially upscaled
89 data for the Maqu and Shiquanhe networks.

90 The objective of this paper is two folds: 1) to describe the long-term in-situ SMST profile dataset including its generation and
91 validation, and 2) to demonstrate its uniqueness for evaluating model-based SMST profile products for a long-term period
92 (~10 years). The paper is organized as follows: Section 2 describes the in-situ SMST measurements collected from the Tibet-
93 Obs, as well as other data used in this research including meteorological data and model-based products. Section 3 presents
94 the spatial upscaling method, data pre-processing steps, statistical performance metrics, and Mann-Kendall trend test methods.
95 The preliminary analysis and applications of the SMST profile dataset are presented in Section 4. The information of data
96 availability is shown in Section 5. Finally, the conclusions are drawn in Section 6.

97 **2 Data**

98 **2.1 Tibet-Obs network and in-situ SMST profile measurements**

99 **2.1.1 Network design and instrumentation**

100 The Tibet-Obs was originally established in 2008 and includes three regional-scale SMST monitoring networks (Fig. 1): the
101 Maqu network at the eastern TP located in cold humid climate area, the Naqu network in the central TP located in cold semiarid
102 climate area, and the Ngari network (including Ali and Shiquanhe) in the western TP located in cold arid climate area (see
103 Table 2). Each network includes various numbers of in-situ SMST monitoring sites, and each monitoring site is configured
104 with one Decagon EM50 data logger and several Decagon SMST probes (i.e., EC-TM and 5TM) to record SMST profile
105 dynamics every 15-minute. The SMST probes were installed with the pins inserted in horizontal direction at multiple depths
106 up to 80 cm (see Fig. 1f). The measured range of the ST sensor is from -40 to 60 °C at 0.1 °C resolution with ± 1 °C accuracy.
107 The SM sensor measures liquid water content at a $0.0008 \text{ m}^3 \text{ m}^{-3}$ resolution with $\pm 0.03 \text{ m}^3 \text{ m}^{-3}$ accuracy. The accuracy of the
108 SM sensor was further improved via a soil-specific calibration, leading to a root mean square difference (RMSD) of about 0.02
109 $\text{m}^3 \text{ m}^{-3}$ (Dente et al., 2012). Nominally instruments maintenance, battery replacement, and data collection took place every
110 year. Several initially established SMST monitoring sites were damaged by local people or animals, and there are more than
111 15 sites newly installed between 2014 and 2016 (see Figs. A1-A3). Therefore, there are only few monitoring sites that could
112 provide long-term continuous SMST data records throughout the period from 2008 to 2019. Brief descriptions of SMST profile
113 data records at each monitoring network are further provided in the following subsections, and additional information about
114 the Tibet-Obs can be found in Zhang et al. (2021) and Su et al. (2011).

115 **2.1.2 Maqu network**

116 The Maqu network is located in the headwaters of the Yellow River (33.60°-34.20°N, 101.70°-102.70°E) with a land cover
117 dominated by [grassland](#). It covers a large river valley and its surroundings have elevations varying from 3400 to 3800 m above
118 sea level (a.s.l). Its annual mean air temperature is about 1.2 °C and precipitation is around 600 mm per year. The Maqu
119 network includes 26 SMST monitoring sites and covers an area of approximately 40 km by 80 km (Fig. 1b). There are 13 sites
120 collecting SMST measurements at depths of 5, 10, 20, 40 and 80 cm, 4 sites with measurements at 5, 10, 20, and 40 cm, one
121 site with measurements at 5, 10, and 20 cm, and 8 sites with measurements at 5 and 10 cm. The corresponding data length for
122 every depth of each site is presented in Fig. A1 for every year from May 2008 to May 2019. Eight initially established
123 monitoring sites were damaged before 2015, and 6 new sites were installed between 2014 and 2016. Fig. 2a shows further the
124 number of available monitoring sites for collecting SMST measurements at different depths in the Maqu network for every
125 month between 2008 and 2019. The number of available monitoring sites providing SMST measurements of 5 cm is up to 19
126 in 2009, which however, decreased as time progressed. The number of sites providing SMST measurements of 10 cm is
127 comparable to that of 5 cm, but the SMST measurements at 20, 40, and 80 cm depths are considerably less. It can be found
128 that the period between May 2010 and May 2011 contains the largest number of available monitoring sites. Among all the

129 sites, the CST05 and NST01 sites provide with 11 years of data the longest records of SMST measurements for depths of 5,
130 10, 20, 40, and 80 cm from 2008 to 2019 (see Fig. A1).

131 **2.1.3 Ngari network**

132 The Ngari network is located in the Ngari prefecture and includes the Shiquanhe and Ali networks. The land cover of the
133 network is dominated by desert system at elevations varying from 4200 to 4700 m a.s.l. Its annual mean air temperature is
134 about 7.0 °C and precipitation is less than 100 mm per year. The Shiquanhe network situated in vicinity of the Shiquanhe
135 county (32.36°-32.76°N, 79.75°-80.25°E), which includes 20 monitoring sites and covers an area of approximately 30 km by
136 40 km (Fig. 1d). There are 9 sites collecting the SMST measurements at depths of 5, 10, 20, 40, and 60 cm, 9 sites with
137 measurements at 5, 10, 20, and 40 cm, and 2 sites with measurements at 5, 10, and 20 cm. The corresponding data length for
138 every depth of each site is presented in Fig. A2 for every year from August 2010 to August 2019. Six initially established
139 monitoring sites were damaged before 2016, and 5 new sites were installed in 2016. Fig. 2b shows further the number of
140 available monitoring sites for collecting SMST measurements at different depths in the Shiquanhe network every month
141 between 2010 and 2019. The number of available monitoring sites providing SMST measurements of 5 cm is up to 14 in 2010,
142 which then decreased as time progressed until 2016 when new additional sites were installed, making the total up to 13 sites
143 in 2017. The number of sites providing SMST measurements of 10, 20, and 40 cm are comparable to that of 5 cm, which is,
144 however, significantly less for the SMST measurements at 60 cm. It can be also found that the period between August 2017
145 and August 2018 contains the largest number of available monitoring sites. Among all the sites, the SQ03 and SQ14 sites
146 provide with 10 years of data the longest records of SMST measurements for depths of 5, 10, 20, and 40 cm from 2010 to 2019
147 (see Fig. A2). The Ali network is located near the Ngari station for the Desert Environment Observation and Research of the
148 Chinese Academy of Science (NASDE/CAS) (33.30°-33.50°N, 79.60°-79.80°E). It consists of 4 monitoring sites (Fig. 1c) that
149 all collect the SMST measurements at depths of 5, 10, 20, 40, and 60 cm. The corresponding data length for every depth and
150 each site are presented in Fig. A2 for every year from August 2010 to August 2019 as well. Fig. 2c shows further the number
151 of available monitoring sites for collecting SMST measurements at different depths in the Ali network every month between
152 2010 and 2018. It can be found that the number of available monitoring sites providing SMST measurements for every depth
153 is generally less than 4 and the valid data records are not continuous, and thus the Ali network will not be used for further
154 analysis in this study.

155 **2.1.4 Naqu network**

156 The Naqu network is located in the Naqu River basin (31.20°-31.40°N, 91.75°-92.15°E) with a land cover dominated by
157 tundra. It covers a flat terrain with rolling hills at 4500 m a.s.l. on average. It exhibits the dry winter and rainy summer receiving
158 about 400 mm precipitation per year. The Naqu network includes 11 SMST monitoring sites (Fig. 1e) that all collect the SMST
159 measurements at around 5, 10, 20, 40, and 60 cm depths. The corresponding data length for every depth of each site is presented
160 in Fig. A3 for every year from June 2010 to August 2019. Three initially established monitoring sites were damaged before

161 2016, and 4 new sites were installed in 2016. Fig. 2d shows further the number of available monitoring sites for collecting
162 SMST measurements at different depths in the Naqu network every month between 2010 and 2019. The number of available
163 monitoring sites providing SMST measurements for every depth is generally less than 4 before 2016, which increased
164 significantly after 2016 but with continuous valid data of less than 2 years. Therefore, the SMST data in the Naqu network will
165 also not be used for further analysis in this study.

166 **2.2 Meteorological data**

167 Precipitation and air temperature used in this study for the Maqu and Shiquanhe networks are obtained from the meteorological
168 dataset provided by the China Meteorological Administration (<http://data.cma.cn/en/?r=data/detail&dataCode=A.0012.0001>,
169 last access: 9th September 2022). The dataset includes air pressure, air temperature, evaporation, precipitation, relative
170 humidity, sunshine duration, and wind speed, which were collected by the automatic weather stations. The daily precipitation
171 and air temperature collected at the Maqu (34.00°N, 102.08°E) and Shiquanhe (32.50°N, 80.08°E) weather stations are used
172 for comparison with the time series of SMST profile data, and the corresponding monthly values are used for trend analysis.
173 The daily precipitation is the cumulative value for the period between 20h of the previous day and 20h of the current day in
174 Beijing time, while the daily air temperature is the mean value. The monthly precipitation is calculated by summing the daily
175 precipitation, while the monthly mean air temperature is the average of daily air temperature within each month.

176 **2.3 Model-based SMST products**

177 Basic information of selected model-based SMST products is given in Table 3, and brief descriptions of each product are
178 provided in the following subsections. [The reason to select these products is due to the fact that they are more widely adopted
179 and extensively assessed.](#)

180 **2.3.1 ERA5**

181 The ERA5 is a reanalysis product obtained through the assimilation of as many observations as possible in the upper air and
182 near surface. The SMST data are available from 1979 till present, with a grid spacing of 0.25°*0.25° and a temporal resolution
183 of hourly. The SMST data of the top three model layers are used in this study, which represent the soil depths of 0-7, 7-28,
184 and 28-100 cm, respectively. The ERA5 product is available in the Climate Change Service (CSC) Climate Data Store (CDS)
185 at <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form> (last access: 27th June 2022).
186 More information about the ERA5 product can be found in Hersbach et al. (2020).

187 **2.3.2 GLDAS-2.1 CLSM**

188 The GLDAS-2.1 CLSM product (Global Land Data Assimilation System Version 2 Catchment Land Surface Model) is based
189 on simulations by the Catchment-F2.5 land surface model (LSM) performed with the Land Information System (LIS) Version
190 7. The SMST data are available from 2000 till present, with a grid resolution of 1.0°*1.0° and at a time interval of 3-hour. The

191 ST data for the depths of 0-10, 10-29, and 29-68 cm are selected in this study, and the surface SM (0-2 cm) and rootzone SM
192 (0-100 cm) data are also used. The GLDAS-2.1 CLSM product is available in the Goddard Earth Science Data and Information
193 Services Center (GES DISC) at https://disc.gsfc.nasa.gov/datasets/GLDAS_CLSM10_3H_2.1/summary (last access: 27th June
194 2022). More information about the GLDAS product can be found in Rodell et al. (2004).

195 **2.3.3 GLDAS-2.1 Noah**

196 The GLDAS-2.1 Noah product is based on the Noah LSM version 3.6 simulations performed with the LIS Version 7. The
197 SMST data are available from 2000 to present, with a grid resolution of 0.25°*0.25° and with a 3-hour interval. The SMST
198 data for the depths of 0-10, 10-40, and 40-100 cm are used in this study. The GLDAS-2.1 Noah product is available in the
199 GES DISC at https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_3H_2.1/summary (last access: 27th June 2022).

200 **2.3.4 GLDAS-2.1 VIC**

201 The GLDAS-2.1 VIC (Variable Infiltration Capacity) product is based on the VIC 4.1.2 LSM simulations performed with the
202 LIS Version 7. The coverage period, grid spacing and time interval of the SMST data are the same as the GLDAS-2.1 CLSM
203 product. The SMST data of the first and second model layers are selected in this study. The surface layer has a 30 cm depth,
204 whereas the depth of second layer varies with region that is about 30-130 cm for our study areas as can be found at
205 <https://ldas.gsfc.nasa.gov/gldas/specifications> (last access: 27th June 2022). The GLDAS-2.1 VIC product is available in the
206 GES DISC at https://disc.gsfc.nasa.gov/datasets/GLDAS_VIC10_3H_2.1/summary (last access: 27th June 2022).

207 **2.3.5 MERRA2**

208 The MERRA2 (Modern-Era Retrospective analysis for Research and Applications version 2) is the latest version of global
209 atmospheric reanalysis product, which uses the Goddard Earth Observing System Model (GEOS) version 5.12.4. The SMST
210 data are available from 1980 to present, with a grid size of 0.5°*0.625° and hourly interval. The ST data of the top three model
211 layers as well as SM data of surface (0-5 cm) and rootzone (0-100 cm) are selected in this study. The layer thicknesses of
212 model layers for the ST data also varies with region, which are 0-10, 10-30, and 30-70 cm for our study areas as can be found
213 at https://disc.gsfc.nasa.gov/datasets/M2C0NXLND_5.12.4/summary (last access: 27th Feb 2022). The MERRA2 product is
214 available in the GES DISC at https://disc.gsfc.nasa.gov/datasets/M2T1NXLND_5.12.4/summary (last access: 27th June 2022).
215 More information about the MERRA2 product can be found in Gelaro et al. (2017).

216 3 Methods

217 3.1 Production and uncertainty analysis of upscaled SMST profile dataset

218 Spatial upscaling is used to create regional-scale SMST data from in-situ measurements collected at individual location that
219 matched with the spatial domain of satellite-based and model-based products. Zhang et al. (2021) demonstrated the better
220 performance of the arithmetic averaging approach in upscaling the surface SM of the Tibet-Obs network in comparison to the
221 voronoi diagrams, time stability, and apparent thermal inertia methods that are widely adopted in existing literatures (Qin et
222 al., 2015; Colliander et al., 2017). Therefore, the arithmetic averaging approach is also adopted in this study to obtain the
223 regional-scale SMST profile data for Maqu and Shiquanhe. The arithmetic averaging method assigns equal weights to each
224 SMST monitoring site of the network, which can be formulated as:

$$225 X_t^{ups} = \frac{1}{M} \sum_{i=1}^M X_{t,i}^{obs} \quad (1)$$

226 where t represents the time in days, i represents the i^{th} SMST monitoring site, M represents the total number of monitoring
227 sites, X_t^{ups} stands for the upscaled SMST, and $X_{t,i}^{obs}$ is the SMST measurements for the i^{th} site.

228 Considering that the number of available SMST monitoring sites in the Tibet-Obs network generally changes with time (see
229 Fig. 2), Zhang et al. (2021) suggested to use only the sites that provide the longest continuous measurements to obtain the
230 long-term upscaled dataset. They also showed that the upscaled surface SM with input of all active monitoring sites regardless
231 of the continuity tends to produce an inconsistent trend. Therefore, we use the sites of Maqu and Shiquanhe networks that have
232 the longest records of SMST profile data from 2009 to 2019 to produce the long-term upscaled dataset. Specifically,
233 measurements collected from the CST05 and NST01 sites in the Maqu network are selected to produce the long-term regional-
234 scale SMST dataset for depths of 5, 20, 40, and 80 cm for the period between May 2009 and May 2019. The measurements at
235 the 10 cm are not used for the upscaling because the sensor at the 10 cm of CST05 site was changed one time in the mid of
236 May 2011 which leads to a discontinuity in the collected time series. As in Zhang et al. (2021), the measurements collected in
237 the year with the largest number of available monitoring sites, i.e., May 2010 and May 2011 for the Maqu network (see Fig.
238 2), are used to preliminarily quantify the uncertainty of upscaled SMST profile data, whereby the average of the measurements
239 at all the available sites are treated as ground reference for the Maqu network. Similarly, measurements collected from the
240 SQ03 and SQ14 sites in the Shiquanhe network are selected to produce the long-term regional-scale SMST dataset for depths
241 of 5, 10, 20, and 40 cm for the period between August 2010 and August 2019 since both sites only provide SMST profile
242 measurements up to 40 cm. The average of measurements collected at the period between August 2017 and August 2018 that
243 has the largest number of available sites are used to quantify the uncertainty of upscaled SMST data in the Shiquanhe network.

244 3.2 Pre-processing of model-based products

245 We select five widely-used model-based products (see Section 2.3) which contain both SM and ST profile simulations. To
246 make an objective evaluation of these products using the Tibet-Obs in-situ SMST data, some essential pre-processing steps

247 are undertaken regarding to three aspects: unify time interval and units of SMST simulations, determine number of model
248 grids that cover the in-situ network, and match the model layers to the depths of in-situ measurements.

249 The units of SM data from the GLDAS-2.1 CLSM, Noah, and VIC products is converted from “kg m⁻²” to “m³ m⁻³” following
250 Eq. (2), and the units for the ERA5 and MERRA2 SM data is already with “m³ m⁻³”.

$$251 \text{ SM} = \text{SWC}/(L * \rho_{H_2O}) \quad (2)$$

252 where *SWC* represents the soil water content (kg m⁻²), *L* (m) represents the layer thickness, ρ_{H_2O} represents the soil water
253 density (kg m⁻³). The units of ST data from all the model-based products is converted from “K” to “C”. The hourly or 3-hour
254 SMST data from all the products are averaged to daily values. We define the period between 1st May and 31st October as the
255 warm season, and the period between 1st November of the previous year and 30th April of the following year as the cold season.
256 The ERA5, GLDAS-2.1 CLSM and VIC SM data in the cold seasons are excluded for the analysis in this study since their
257 values represent the total soil water content including both liquid water and ice content, while the in-situ SM data only provide
258 measurements of liquid water content.

259 All the model grids falling into the scope of in-situ network are extracted from each product. Afterwards, the native grids of
260 each product are downscaled to 0.25°*0.25° sub-grid cells using a bilinear interpolation. Subsequently, the SMST data in all
261 the sub-grid cells falling into the scope of in-situ network are averaged to match the upscaled in-situ SMST data that represent
262 the regional-scale mean values of in-situ network (see Fig. B1).

263 To match the depths of in-situ SMST measurements, we compared the linear interpolation method and the depth-weighted
264 interpolation method that are widely used to resample the SMST data across the vertical soil profile in the previous studies
265 (Gao et al., 2017), and the results were found to be comparable to each other (Fig not shown). To make full use of the valid
266 in-situ measurements, the linear interpolation method was thus adopted in this study. We assume that the SMST values of each
267 model layer are representative for the mid-point of this layer. For example, the SMST for the layer of 10-40 cm in the GLDAS-
268 2.1 Noah product are representative for the depth of 25 cm. The detailed calculation processes are presented in the Appendix
269 B.

270 3.3 Statistical indicator

271 Four statistical indicators are used in this study for the evaluation of upscaled in-situ SMST data as well as the model-based
272 products, including Bias, root-mean-square-difference (RMSD), unbiased RMSD, and Pearson correlation coefficient (R).
273 They can be formulated as:

$$274 \text{ Bias} = \frac{\sum_{t=1}^n (X_t^{est} - X_t^{obs})}{N} \quad (3)$$

$$275 \text{ RMSD} = \sqrt{\frac{\sum_{t=1}^n (X_t^{obs} - X_t^{est})^2}{N}} \quad (4)$$

$$276 \text{ ubRMSD} = \sqrt{\text{RMSD}^2 - \text{Bias}^2} \quad (5)$$

$$R = \frac{\sum_{t=1}^n (X_t^{obs} - \overline{X^{obs}})(X_t^{est} - \overline{X^{est}})}{\sqrt{\sum_{t=1}^n (X_t^{obs} - \overline{X^{obs}})^2} \sqrt{\sum_{t=1}^n (X_t^{est} - \overline{X^{est}})^2}} \quad (6)$$

where N denotes the number of data points. For the evaluation of upscaled in-situ SMST data, X_t^{obs} represents the mean SMST of the largest number of available monitoring sites in a certain year for each in-situ network (see Section 3.1), and X_t^{est} represents the upscaled SMST based on the monitoring sites that provide the longest continuous measurements as input. For the assessment of model-based products, X_t^{obs} represents the upscaled SMST for each in-situ network, and X_t^{est} represents the SMST simulations derived from each product.

3.4 Trend analysis

The Mann Kendall trend test reported by Richland (1987) is used in this study to determine whether a trend is presented within the long-term SMST time series derived either from the upscaled in-situ measurements or from the model-based products. The trend analysis is also performed for the precipitation and air temperature data for comparison purposes. The trend analysis is respectively carried out over the warm season, the cold season, and the full year. Therefore, the data points are monthly mean values of each year for calculating seasonal statistics instead of annual mean value, and all missing data points are assigned an equal value smaller than existed valid data points. If the trend test results show a significant upward or downward tendency, the Sen's slope estimate method is adopted to quantify the magnitude of the tendency. A detailed description of the trend analysis process can be found in Appendix C.

4 Results

Section 4.1 gives the uncertainty analysis results for the upscaled SMST profile data. Section 4.2 presents the upscaled SMST profile data for the Maqu and Shiquanhe networks spanning the 10-year period from 2010 to 2019 (see Section 3.1), as well as the analysis results for the SMST seasonal dynamics, trend test, detection of F/T state and soil freezing characteristics at different depths. Application of the upscaled data to evaluate the performance of model-based products is presented in Section 4.3 to demonstrate its suitability for the evaluation of readily available SMST profile products.

4.1 Uncertainty analysis of the upscaled SMST profile dataset

The spatial upscaling data is inevitably subject to uncertainty as a result of the SMST spatial variabilities. Therefore, in this section we quantify the uncertainties of the long-term upscaled SMST profile dataset for the Maqu and Shiquanhe networks via comparisons to the mean of SM and ST measurements collected during the year with the largest number of active monitoring sites that is considered as the "ground truth" (hereafter SM_{tru} and ST_{tru}) as shown in Zhang et al. (2021) (see Section 3.1). The selected validation periods are from 16 May 2010 to 15 May 2011 and from 1 September 2017 to 31 August 2018 for the Maqu and Shiquanhe networks, respectively.

305 Fig. 3a shows the comparisons between the time series of SM_{ups} and SM_{tru} at soil depths of 5, 20, and 40 cm with 15-min
306 interval for the Maqu network from 16 May 2010 to 15 May 2011, and the comparisons between the ST_{ups} and ST_{tru} profile
307 dynamics are shown in Fig. 3b. The statistical performance metrics, i.e., bias, RMSD, ubRMSD, and R, computed between
308 the upscaled SMST and the ground truth are shown in the figure as well. In general, the variations of SM_{ups} and SM_{tru} are
309 consistent with each other at every depth as indicated by very high R values (≥ 0.985), yielding RMSD values of 0.025, 0.019,
310 and 0.030 $\text{m}^3 \text{m}^{-3}$ at the depths of 5, 20, and 40 cm, respectively. These RMSD values are comparable and even better than the
311 measurement accuracy (see Section 2.1), indicating the good performance for the SM_{ups} profile data. The consistency between
312 the ST_{ups} and ST_{tru} variations is even better as indicated by higher R values (≥ 0.995) for each soil depth, yielding RMSD values
313 of 0.7, 0.2, and 0.3 $^{\circ}\text{C}$ at the depths of 5, 20, and 40 cm, respectively. These RMSD values are also better than the reported
314 accuracy of temperature measurements (see Section 2.1), implying the good performance for the ST_{ups} profile data as well.
315 Table 4 presents further the FSD, TED, and F/T duration for 5, 20, and 40 cm soil depths estimated based on the upscaled
316 SMST profile data and ground truth, respectively. The estimated FSD, TED, and F/T duration are close to each other especially
317 at upper soil layers (e.g., 5 and 20 cm), and the noted differences for the FSD and TED are generally less than 3 days except
318 that of TED at 40 cm, leading to differences of not more than 4 days for the F/T duration.

319 Fig. 4a shows the comparisons between the time series of SM_{ups} and SM_{tru} at soil depths of 5, 20, and 40 cm with 15-min
320 interval for the Shiquanhe network from 1 September 2017 to the 31 August 2018, and the comparisons between the ST_{ups} and
321 ST_{tru} profile dynamics are shown in Fig. 4b. The statistical performance metrics are shown in the figures as well. Similar to the
322 Maqu network, the variations of SM_{ups} and SM_{tru} are consistent with each other for each soil depth as indicated by high R
323 values (> 0.92), yielding RMSD values of 0.011, 0.009, and 0.010 $\text{m}^3 \text{m}^{-3}$ at the depths of 5, 20, and 40 cm, respectively. These
324 RMSD values are much better than the measured accuracy of adopted SM sensor (see Section 2.1), indicating the good
325 performance for the SM_{ups} profile data. The consistence between the ST_{ups} and ST_{tru} variations is even better as indicated by
326 higher R value (≥ 0.97) for every soil depth. Table 4 presents further the FSD, TED, and F/T duration for 5, 20, and 40 cm soil
327 depths estimated based on the upscaled SMST profile data and ground truth, respectively. The estimated FSD, TED, and F/T
328 duration are close to each other especially at upper soil layers (e.g., 5 and 20 cm), and there is little difference for the FSD and
329 TED except that of TED at 40 cm, leading to differences of not more than 8 days for the F/T duration.

330 4.2 Analysis of the upscaled SMST profile measurements

331 4.2.1 Maqu network

332 Figs. 5a and 5c show the time series of upscaled daily SM (SM_{ups}) and ST (ST_{ups}) at depths of 5, 20, 40, and 80 cm from
333 January 2010 to December 2018 for the Maqu network, respectively. The daily precipitation (P) and air temperature (T_a)
334 collected from the Maqu weather station (Fig. 1b) are also shown for comparison purposes. The time series of the SM_{ups} at
335 different depths shows similar seasonal variations, with high values in warm summer with larger amounts of precipitation and
336 low values in cold winter with soil freezing and much smaller amounts of precipitation. The amplitudes of SM_{ups} variations

337 generally decrease with increasing soil depth, with larger variations noted for soil layers above 20 cm, and smallest one at the
338 deepest depth of 80 cm. The soil layers below 20 cm are dryer than the upper layers in the warm season, whereas the soil at
339 depth of 80 cm is wetter than 40 cm that might be attributed to absence of evapotranspiration and existence of shallow
340 groundwater (Li et al., 2021). The time series of the ST_{ups} at different depths also show similar seasonality with peak values in
341 summer and lowest values in winter that is in agreement with the seasonal T_a dynamics. The soil layers above 40 cm generally
342 drop below 0 °C in winter, while the ST_{ups} of 80 cm is always greater than 0 °C throughout the year, indicating that the
343 maximum freezing depth in the Maqu network is shallower than 80 cm. The magnitude of ST_{ups} variations also diminishes
344 with increasing soil depth.

345 Figs. 5b and 5d further show the SM_{ups} and ST_{ups} profile dynamics with 15-min interval for a single year between May 2010
346 and May 2011, which confirm that amplitudes of both SM_{ups} and ST_{ups} variations decrease with depth. The SM_{ups} variations at
347 5 and 20 cm are comparable to each other and larger than those at 40 and 80 cm, which also show better response to the
348 precipitation in rainy season. Obvious diurnal cycles can be noted for the ST_{ups} at 5 cm, which diminish with depth and are
349 virtually absent at 40 cm. The ST_{ups} at 5 cm starts to drop below 0 °C around mid-November, leading to a sharp decrease of
350 surface SM_{ups} due to freezing of the soil. The deeper layers gradually freeze as time progresses, and the freezing depths reach
351 its peak around mid-February. Later on, the soil starts thawing with a sharp increase of SM_{ups} as the ST_{ups} rises above 0 °C,
352 and the entire soil profile is totally thawed around the mid-April. In general, both start date of soil freezing and end date of soil
353 thawing increase with increasing soil depth. To further explore the characteristics of F/T cycle in the Maqu network, Fig. 5e
354 shows the freezing start day (FSD), thawing end day (TED), and F/T duration of each year for the depths of 5, 20 and 40 cm
355 during the study period, and the 80 cm layer does not freeze (see Figs. 5c and 5d). The FSD is defined as the first day that the
356 daily ST drops below 0 °C along with sharp SM decrease in current year, and the TED is the last day of ST below 0 °C in next
357 year. The number of days between the FSD and TED is referred to as the F/T duration. There is no specific information of the
358 FSD and TED in 2017 for the depths of 5 and 20 cm due to missing data of in-situ ST measurements in this period, and the
359 same holds for the soil depth of 40 cm between 2015 and 2018 (see Figs 2a and A1). It can be observed that the inter-annual
360 variabilities of the FSD, TED, and F/T duration for each depth are within 30 days, and no significant trend is found. It also
361 confirms that the deeper layer generally shows late onset of freezing and an earlier start of thawing every year leading to
362 shorter F/T duration.

363 Figs. 6a and 6b show the Mann Kendall trend test and Sen's slope estimate for the 9-year (2010-2018) SM_{ups} and ST_{ups} at
364 depths of 5 and 20 cm for the Maqu network in the warm season, cold season, and full year. The trend analysis for the depth
365 of 40 cm is not presented since there is not long enough (< 7 years) continuous $SMST$ time series due to missing data. The
366 trends of the P and T_a are also shown in Figs. 6a and 6b, respectively. As described in Section 3.4, the time series would present
367 a significant trend if the absolute value of statistic Z is greater than 1.96 in this study. The results show that no significant trend
368 is found for the SM_{ups} at 5 and 20 cm in the warm season like the P . For the cold season, the SM_{ups} at depths of 5 and 20 cm
369 show a drying trend despite the absence of a P trend. Consequently, the SM_{ups} at 5 and 20 cm in the full year also show a
370 drying trend with the Sen's slopes of -0.004 ($m^3 m^{-3}/yr$) and -0.002 ($m^3 m^{-3}/yr$), respectively, which is in agreement with the P

371 trend. The full year trend analysis results are consistent with the results reported by Shi et al. (2021) using the ESA CCI SM
372 product, since the precipitation is the dominant driver of SM variation which shows significant negative trend in the humid area
373 on the TP. The ST_{ups} at depth of 5 cm shows a decreasing trend in the warm season while no significant trend is found for the
374 T_a and ST_{ups} at 20 cm. In the cold season, there is no significant trend found for the T_a and ST_{ups} at 5 and 20 cm. For the full
375 year, the ST_{ups} at 5 cm shows a decreasing trend with a Sen's slope of -0.08 ($^{\circ}C/yr$) while no significant trend found for the
376 ST_{ups} at 20 cm like the T_a .

377 Fig. 7 shows the soil freezing characteristics for the depths of 5, 20 and 40 cm for the Maqu network by plotting the ST_{ups}
378 against corresponding measured unfrozen SM for all subzero temperatures during the freezing and thawing periods in the cold
379 season. The freezing period defined in this study spans from the first date of ST falling below zero to the date of lowest ST
380 occur, whereby the SM value is generally decreasing in this period. Later on the thawing period starts and ends when the ST
381 rise above zero, whereby the SM value is increasing during this period. The power function fitting curves to the soil freezing
382 characteristics and corresponding fitting parameters are given in figure for both freezing and thawing periods. The difference
383 between the soil freezing characteristics of freezing and thawing periods is much smaller at the surface layer (i.e., 5 cm), which
384 increases with increasing soil depth. At the deeper soil layers (e.g., 20 and 40 cm), the freezing rate (i.e., the amount change
385 of unfrozen SM with temperature) of unfrozen SM with decreasing ST in the freezing period is larger than the thawing rate of
386 ice content with increasing ST during the thawing period. As such, the obtained parameter values of the power function fitting
387 curves are identical to each other at the surface layer for the freezing and thawing periods, which are different for the deeper
388 soil layers. The obtained parameter values are also distinct from each other at different soil layers, indicating the layering
389 characteristics of frozen soil in the Maqu network.

390 4.2.2 Shiquanhe network

391 Figs. 8a and 8c show the time series of daily SM_{ups} and ST_{ups} at depths of 5, 10, 20, and 40 cm from January 2011 to December
392 2018 for the Shiquanhe network, respectively. The daily P and T_a collected from the Shiquanhe weather station (Fig. 1d) are
393 also shown for comparison purposes. The SM_{ups} time series at different depths display the similar seasonality to that found for
394 the Maqu network. The amplitudes of SM_{ups} variations generally decrease with increasing soil depth, with slightly larger
395 variations noted for soil layers above 10 cm, and smallest one at the deepest depth of 40 cm. The layers above 10 cm are dryer
396 than the deeper layers in the warm season except for the rainy period. The time series of the ST_{ups} at different depths also show
397 the similar seasonality to that found for the Maqu network, whereas the amplitudes of ST_{ups} variations are larger than those of
398 the Maqu network and diminish with soil depth. The soil layers above 40 cm generally drop below 0 $^{\circ}C$ in winter, indicating
399 that the maximum freezing depth in the Shiquanhe network is deeper than 40 cm.

400 Figs. 8b and 8d further show the SM_{ups} and ST_{ups} profile dynamics with 15-min interval for a single year between August 2017
401 and August 2018, which confirm that amplitudes of both SM_{ups} and ST_{ups} variations decrease with depth. The SM_{ups} variations
402 at 5 and 10 cm are comparable to each other and larger than those at 20 and 40 cm, which also show better response to the
403 precipitation. Obvious diurnal cycles can be noted for the ST_{ups} at 5, 10, and 20 cm, which diminish with depth and are almost

404 absent at 40 cm. The ST_{ups} at 5 and 10 cm starts to drop below 0 °C around early November, leading to a decrease of SM_{ups}
405 due to soil freezing. The deeper layers freeze as time progresses, and the freeze depths reach its maximum around early January.
406 Later on, the soil starts thawing with an increase of SM_{ups} when the ST_{ups} rises above 0 °C, and the entire soil profile is totally
407 thawed around mid-March. To further explore the characteristics of F/T cycles in Shiquanhe, Fig. 8e shows the FSD, TED,
408 and F/T duration of each year for the depths of 5, 10, 20, and 40 cm during the study period. There is no specific information
409 of the FSD and TED in 2011 and 2013 for the depth of 5 cm due to missing data of in-situ ST measurements in this period,
410 and the same holds for the soil depths of 20 and 40 cm in 2018 (see Figs 2b and A2). In general, the FSD increases with
411 increasing soil depth whereas the TED is comparable at each depth. It can be observed that the inter-annual variabilities of the
412 FSD, TED, and F/T duration for each depth are within 20 days, and there is no significant trend found for them. It also confirms
413 that the F/T cycles at 5 and 10 cm are almost the same with each other, and the deeper layers (i.e., 20 and 40 cm) generally
414 show late onset of freezing, leading to shorter duration.

415 Figs. 9a and 9b show the trend analysis results for the 8-year (2011-2018) SM_{ups} and ST_{ups} at depths of 5, 20, and 40 cm for the
416 Shiquanhe network in the warm season, cold season, and full year. The trends of the P and T_a are also shown in Fig. 9a and
417 9b, respectively. The results show that no significant trend is found for the SM_{ups} at all three depths in the warm season, which
418 is in agreement with the P trend. Meanwhile, the SM_{ups} at 5 and 20 cm also do not show a significant trend in the cold season
419 like the P , whereas the SM_{ups} at 40 cm shows a wetting trend. Consequently, the SM_{ups} at 40 cm shows a wetting trend with a
420 Sen's slope of 0.001 ($m^3 m^{-3}/yr$) while no trend found for the P and SM_{ups} at 5 and 20 cm for the full year. The result is slightly
421 different from Shi et al. (2021) that might be attributed to the different time span. Nevertheless, it is in agreement with the
422 conclusion of spatial-temporal trend changes of surface SM generally decreasing from southeast to northwest over the TP
423 comparing to the trend analysis result of Maqu network area. The ST_{ups} at all three depths do not show a significant trend in
424 the warm season, while an increasing trend is found in the cold season, which is in agreement with T_a trend. For the full year,
425 no trend is found for the ST_{ups} at depths of 5 and 20 cm like T_a , while an increasing trend is found for ST_{ups} of 40 cm.

426 Fig. 10 shows the soil freezing characteristics for the depths of 5, 20 and 40 cm for the Shiquanhe network. The fitted power
427 functions to the soil freezing characteristics and the corresponding parameters are also given for the freezing and thawing
428 periods. It is observed that there is no notable difference between the soil freezing characteristic of freezing and thawing
429 periods at each depth. As such, the obtained parameter values of the power function fitting curves are identical for the freezing
430 and thawing periods. However, the obtained parameter values are distinct from each other at different soil layers, indicating
431 the layering characteristics of frozen soil in the Shiquanhe network.

432 4.3 Application of the upscaled SMST profile dataset to validate model-based products

433 To demonstrate the uniqueness of the upscaled SMST profile dataset for validating existing products for a long-term period,
434 the performance of five model-based products is investigated in this section, including the ERA5, MERRA2, GLDAS-2.1
435 CLSM (hereafter CLSM), GLDAS-2.1 Noah (hereafter Noah), and GLDAS-2.1 VIC (hereafter VIC) (see Section 2.3). The
436 performance of these model-based products in capturing the SMST seasonal variations, long-term trend changes, and the F/T

437 cycle at depths of 5, 20, and 40 cm in the Maqu and Shiquanhe networks is evaluated. The cold season SM data of the ERA5,
438 CLSM, and VIC products are excluded for the analysis since their values represent the total soil water content while in-situ
439 sensors measure the liquid soil water content in frozen soil, and the MERRA2 and Noah SM products can provide liquid soil
440 water content (Gelaro et al., 2017; Zheng et al., 2017).

441 4.3.1 Maqu network

442 Figs. 11a-11c show the time series of daily average SM at soil depths of 5, 20, and 40 cm derived from the SM_{ups} and the five
443 model-based products from January 2010 to December 2018 for the Maqu network. The error metrics, i.e., bias, RMSD,
444 ubRMSD, and R, computed between the five model-based SM data and the SM_{ups} for the warm and cold season are listed in
445 Table 5. Among the five model-based products, the ERA5 SM product agrees best with the SM_{ups} at 5 and 20 cm in the warm
446 season with the lowest RMSD values of 0.053 and 0.032 $m^3 m^{-3}$ and the largest R values of 0.76 and 0.74, but it tends to
447 overestimate the SM_{ups} at 40 cm with a bias of 0.108 $m^3 m^{-3}$. Similarly, the VIC SM product is also able to capture the magnitude
448 of SM_{ups} dynamics at 5 and 20 cm in the warm season with slightly larger RMSD values of 0.060 and 0.049 $m^3 m^{-3}$, but also
449 overestimates the SM_{ups} at 40 cm with a bias of 0.088 $m^3 m^{-3}$. The other three products tend to considerably underestimate the
450 SM_{ups} at 5 and 20 cm in the warm season, but they yield better estimates of the SM at 40 cm as indicated by smaller biases and
451 RMSD values. In general, the modelling uncertainties may be caused by many factors, such as model structure, model
452 parameterization and parameters, and meteorological forcing data. The underestimation of surface SM noted for the Noah,
453 CLSM and MERRA2 can be related to fact that the impact of organic matter on soil hydraulic parameters is ignored (Yi et al.,
454 2011; Chen et al., 2013; Zheng et al., 2015a). The better performance of ERA5 can be associated with the better estimation of
455 precipitation and assimilation of ASCAT SM product (Shi et al., 2021; Hersbach et al., 2020). In the cold season, the Noah
456 SM product generally captures well the SM_{ups} variations at surface layer (i.e., 5 cm) but overestimates the SM_{ups} at deeper
457 layers (e.g., 20 and 40 cm), and overestimations are also found for the MERRA2 products at all the depth. The overestimation
458 can be related to the inappropriate parameterization of soil freezing characteristics as shown in Fig. 7 (Zheng et al., 2017). The
459 trend analysis results for the five model-based SM data are also presented in Fig. 6a. The results show that no significant trend
460 is found for any of five model-based SM products at every depth in the warm season, which is in agreement with the trend of
461 SM_{ups} . Both Noah and MERRA2 SM products are able to reproduce the drying trend noted for the SM_{ups} in the cold season
462 and full year except for the Noah SM product of 5 cm.

463 Figs. 11d-11f show the time series of monthly average ST at soil depths of 5, 20, and 40 cm derived from the ST_{ups} and the
464 five model-based products for the Maqu network. The corresponding error metrics computed by daily ST_{ups} are listed in Table
465 5 as well. In general, the five model-based ST products have similar performance and can well capture the seasonal variations
466 of ST_{ups} at every depth. However, they tend to underestimate the ST_{ups} across the entire study period, and the magnitude of
467 underestimations generally increases with increasing soil depths. Similar findings have recently been reported by Ma et al.
468 (2021). The underestimation can be due to the i) underestimation of downward shortwave or longwave radiation (Chen et al.,
469 2011; Wang et al., 2016), ii) inappropriate parameterization of diurnally varying roughness length for heat transfer (Chen et

470 al., 2011; Zheng et al., 2015b; Reichle et al., 2017), and iii) overlook of the impact of organic matter on soil thermal parameters
471 (Zheng et al., 2015b). The trend analysis results for the five model-based ST data are also presented in Fig. 6b. At the surface
472 layer (i.e., 5 cm), only the VIC ST product shows a decreasing trend in the warm season like the ST_{ups} , while no significant
473 trend is found for other products. In the cold season, there is no significant trend presented for the CLSM, Noah, and MERRA2
474 ST products at surface layer that is consistent with ST_{ups} , while the other two products show a decreasing trend. For the full
475 year, the Noah and VIC ST products are able to reproduce the decreasing trend found for the ST_{ups} of 5 cm, whereas no
476 significant trend is found for other products. The trends for the deeper soil layers (i.e., 20 and 40 cm depths) are consistent
477 with each other for each model-based ST product, and there is no significant trend found for the products in both warm and
478 cold season like that ST_{ups} , except the VIC ST product shows a decreasing trend. Consequently, the ERA5, CLSM, and
479 MERRA2 ST products do not show significant trend at deeper layers in the full year, that is consistent with ST_{ups} , whereas the
480 VIC product of two depths and Noah product of 20 cm show a decreasing trend for the full year.

481 To further investigate the performance of five model-based products in capturing the characteristics of F/T cycle in the Maqu
482 network, Fig. 12 shows the FSD, TED, and F/T duration derived from the five model-based products and upscaled dataset for
483 each year during the study period. It can be observed that all the five model-based products underestimate the FSD especially
484 at deeper depths. The FSD estimated based on the upscaled dataset generally increases with increasing depth, while those
485 estimates using the model-based products are close to each other at different depth. In contrast to the FSD, all the products
486 overestimate the TED at deeper depths. In other words, all the model-based products tend to produce earlier onset of freezing
487 and later onset of thawing, leading to longer F/T duration in comparison to the upscaled dataset. [This can be related to the](#)
488 [underestimation of ST noted for all the model-based products](#). The soil freezing characteristics for depths of 5, 20 and 40 cm
489 obtained based on the Noah and MERRA2 products are shown in Fig. 7 as well. It can be observed that the difference between
490 the soil freezing characteristics of freezing and thawing periods generally decreases with increasing soil depth for the two
491 models that is inconsistent with the upscaled dataset. In comparison to the upscaled dataset, both Noah and MERRA2 products
492 tend to produce higher unfrozen SM values at the same subzero ST in the freezing period, and overestimations are also found
493 in the thawing period except that of Noah model at 5 cm. This can explain why the two models overestimate the SM_{ups} in the
494 cold season especially at deeper depths as shown in Fig. 11.

495 **4.3.2 Shiquanhe network**

496 Figs. 13a-13c show the time series of daily average SM at soil depths of 5, 20, and 40 cm derived from the SM_{ups} and the five
497 model-based products from January 2011 to December 2018 for the Shiquanhe network. The error metrics computed between
498 the five model-based SM data and the SM_{ups} for the warm and cold season are listed in Table 6. Among the five model-based
499 SM products, the ERA5 product agrees best with the SM_{ups} at 5 cm in the warm season with the lowest RMSD of $0.06 \text{ m}^3 \text{ m}^{-3}$
500 and largest R value of 0.80, while other products tend to overestimate the SM_{ups} especially for the VIC product. [As in the Maqu](#)
501 [network, the better performance of ERA5 can be associated with the better estimation of precipitation and assimilation of](#)
502 [ASCAT SM product \(Hersbach et al., 2020; Shi et al., 2021\)](#). The overestimation noted to other products can be associated

503 with the overestimations of precipitation (Yang et al., 2020) and uncertainty of soil texture and thus overestimation of soil
504 porosity (Su et al., 2013; Shangguan et al., 2013; Bi et al., 2016). Both the Noah and MERRA2 products also overestimate the
505 SM_{ups} of 5 cm in the cold season, which is related to the inappropriate parameterization of soil freezing characteristics as shown
506 in Fig. 10. For the 20 and 40 cm deeper depths, all the products systematically overestimate the SM_{ups} due to uncertainty of
507 soil texture, among which the ERA5 product shows the lowest bias while the VIC product presents the largest bias. The trend
508 analysis results for the five model-based SM data are also presented in Fig. 9a. The results show that no significant trend is
509 found for the MERRA2 product at every depth throughout the year, that is consistent with the SM_{ups} of upper layers (i.e., 5 and
510 20 cm), whereas both CLSM and VIC products show a drying trend at each depth. At soil depths of 5 cm, there is also no
511 significant trend found for the ERA5 and Noah products like the SM_{ups} , while the ERA5 product shows a drying trend at
512 deeper layers (i.e. 20 and 40 cm) in the warm season, and Noah product also presents a drying trend at deeper layers for the
513 cold season and full year, both of which are inconsistent with those of SM_{ups} .

514 Figs. 13d-13f show the time series of monthly average ST at soil depths of 5, 20, and 40 cm derived from the ST_{ups} and the five
515 model-based ST products from January 2011 to December 2018 for the Shiquanhe network. The corresponding error metrics
516 computed by daily ST_{ups} are also listed in Table 6. Similar to the Maqu network, all the five model-based products well capture
517 the seasonal variations of ST_{ups} at every depth, but they tend to underestimate the ST_{ups} throughout the entire study period, and
518 the magnitude of underestimations also increases with increasing soil depth. [The reason for the underestimation can be the](#)
519 [same as the Maqu network.](#) Among all the products, the Noah and CLSM products yields the lowest bias and RMSD in the
520 warm and cold seasons, respectively, while the VIC product presents the largest bias for both seasons. It should be noted that
521 the Noah product is slight worse than the CLSM product in the cold season. The trend analysis results for the five model-based
522 ST data are also presented in Fig. 9b. The results show that all products do not show significant trend at every depth in the
523 warm season that is consistent with the ST_{ups} . In the cold season, the ERA5, CLSM, and MERRA2 products show an increasing
524 trend at every depth that is consistent with the ST_{ups} , while no significant trend is found for the VIC product. An increasing
525 trend is also noted for the Noah product of 5 and 20 cm despite no trend is found at 40 cm. For the full year, only the ERA5
526 and MERRA2 products capture the trends of ST_{ups} at all three depths. At the depth of 5 and 20 cm, except the CLSM product,
527 no significant trend is found for other products that is consistent with the ST_{ups} . For the depth of 40 cm, besides the Noah and
528 VIC products, an increasing trend is found for other products and the ST_{ups} .

529 To further investigate the performance of five model-based products in capturing the characteristics of F/T cycle in the
530 Shiquanhe network, Fig. 14 shows the FSD, TED, and F/T duration derived from the five model-based products and upscaled
531 dataset for each year during the study period. [Similar as the Maqu network, all the model-based products tend to produce](#)
532 [earlier onset of freezing and later onset of thawing at every depth due to the underestimation of ST, leading to underestimation](#)
533 [of FSD and overestimation of TED and thus longer F/T duration in comparison to the upscaled dataset.](#) Among the five model-
534 based products, the CLSM product provides the closet estimates of TED and F/T duration compared to the upscaled dataset,
535 while the VIC product presents the worst performance. The soil freezing characteristics for the depths of 5, 20, and 40 cm
536 obtained from the Noah and MERRA2 products are shown in Fig. 10 as well. Similar to the Maqu network, both Noah and

537 MERRA2 products tend to produce higher unfrozen SM values at the same subzero ST in both freezing and thawing periods,
538 leading to the overestimation of SM in the cold season in comparison to the upscaled dataset (see Fig. 13), and the magnitude
539 of overestimation increases with increasing soil depth.

540 **5 Data availability**

541 A long-term (2008-2019) dataset of SMST at multiple depths on the TP is freely available from the 4TU.ResearchData
542 repository at <https://doi.org/10.4121/20141567.v1> (Zhang et al., 2022). The original in-situ SMST data, the upscaled SMST
543 data, and the supplementary data are stored in .xlsx files. A user guide document is given to introduce the content of the dataset
544 and to provide the method to download online datasets used in this paper.

545 **6 Conclusions**

546 The Tibet-Obs is a long-term SMST observatory in the TP covering different representative climatic and land surface
547 conditions, which includes the Maqu, Naqu, and Ngari (including Ali and Shiquanhe) networks. The three networks are located
548 in the cold humid area covered by [grassland](#), the polar area dominated by tundra, and the cold arid area dominated by desert,
549 respectively. Each network includes various numbers of in situ SMST monitoring sites, and each monitoring site is configured
550 with one Decagon (now: METER group) EM50 data logger and several Decagon SMST probes (i.e., EC-TM and 5TM) to
551 monitor SMST dynamics at multiple depths (e.g., 5, 10, 20, 40, and 60/80 cm underground) every 15-minute, which have
552 generally been in operation for over a decade. This paper presents a long-term (~10 years) SMST profile dataset collected from
553 the Tibet-Obs, which includes original in-situ measurements collected between 2008 and 2019 from all the three networks and
554 the spatially upscaled data (SM_{ups} and ST_{ups}) for the Maqu and Shiquanhe networks. The uncertainty of the spatially upscaled
555 dataset are first quantified via comparison to the average of SMST measurements collected at a certain year having the largest
556 number of available valid monitoring sites, i.e., ground truth (SM_{tru} and ST_{tru}). The results show that the SM_{ups} and SM_{tru} are
557 consistent with each other at every depth for both Maqu and Shiquanhe networks, yielding RMSD values that are better than
558 the measured accuracy of adopted SM sensor. The variations of ST_{ups} also agree well with the ST_{tru} , and the obtained RMSD
559 value is also better than the measured accuracy of adopted ST sensor in the Maqu network. Therefore, it can be concluded that
560 the quality of the upscaled dataset is generally good.

561 Based on the upscaled dataset, the analysis on the seasonal variations and inter-annual trend changes of profile SMST
562 dynamics, as well as the characteristics of F/T cycle in an approximately 10-year period is carried out for the two
563 hydrometeorologically contrasting networks. The results show that the time series of both SM_{ups} and ST_{ups} at each depth display
564 notable seasonality with peak values in warm summer and lowest values in cold winter, and the amplitudes of their variations
565 generally decrease with increasing soil depth for both networks. It can be noted that the amplitudes of the seasonal SM_{upas}
566 variations in the cold-humid Maqu network area are larger than those of the cold-arid Shiquanhe network, whereas the ST_{ups}

567 seasonality is generally stronger within the Shiquanhe measurements. The Mann Kendall trend analysis results demonstrate
568 that no significant trend is found for the SM_{ups} profile in the warm season (from May to October) for both networks that is
569 consistent with the precipitation (P) trend. A similar finding is also found for the ST_{ups} profile and air temperature T_a for the
570 Shiquanhe network during the warm season. For the cold season (from November to April) and the full year, a drying trend is
571 noted for the SM_{ups} above 20 cm in the Maqu network, while no significant trend is found for those in the Shiquanhe network.
572 In general, the deeper soil layers in both networks present later onset of freezing and earlier thawing and thus shorter F/T
573 duration in comparison to the surface layer. The obtained parameter values of the power function fitting curves to the soil
574 freezing characteristics are distinct from each other at different soil layers in both networks, confirming the layering
575 characteristics of frozen soil on the TP.

576 To demonstrate the uniqueness of the upscaled SMST profile dataset for validating existing products for a long-term period,
577 the performance of five model-based products is investigated. The results show that none of the model-based products can
578 reproduce the seasonal variations and inter-annual trend changes of profile SMST dynamics, and the characteristics of F/T
579 cycle obtained based on the upscaled dataset. Among the five products, only the ERA5 product captures well the seasonal
580 variations and trend changes of SM_{ups} dynamics at surface layer (i.e., 5 cm) during the warm season in both networks, which
581 also provides the lowest bias for the estimations of SM above 20 cm during the warm season. All the products underestimate
582 the ST_{ups} at every depth in both networks, whereby the Noah and ERA5 products provide better estimations in the warm season,
583 and the CLSM and Noah products yield better simulations for the cold season. Consequently, all the model-based products
584 tend to produce earlier onset of freezing and later start of thawing at every depth, leading to underestimation of FSD and
585 overestimation of TED and thus longer F/T duration than observed on the ground.

586 Overall, the Tibet-Obs SMST observatory has greatly advanced the evaluation and improvement of satellite- and model-based
587 SM and ST products for their applications to the TP over the past decade (see Table 1). Development of the long-term (~10
588 years) SMST profile dataset collected from the Tibet-Obs is urgently needed to further strengthen relevant research and could
589 be of value for calibration and validation of long-term satellite- or/and model-based SMST products, improving the
590 representation of TP hydrometeorological processes in current land surface model and satellite-based SM retrieval algorithms,
591 and other applications across scientific disciplines such hydrology, meteorology and climatology.

592 **Author contribution**

593 Pei Zhang, Donghai Zheng, Rogier van der Velde and Zhongbo Su designed the framework of this work. Pei Zhang performed
594 the computations and data analysis, and wrote the manuscript. Donghai Zheng, Rogier van der Velde, and Zhongbo Su
595 supervised the progress of this work and provided critical suggestions, and revised the manuscript. Zhongbo Su, Jun Wen, and
596 Yaoming Ma designed the setup of Tibet-Obs, Yijian Zeng, XinWang and Zuoliang Wang involved in maintaining the Tibet-
597 Obs and downloading the original measurements. Pei Zhang, Zuoliang Wang, and Jiali Chen organized the data.

598 **Competing interests**

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

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777 **Table 1. Summary of the applications of Tibet-Obs SMST data and corresponding findings.**

Literature	In-situ data	Satellite- and/or model-based products/simulations	Key findings
Simultaneous usage of SM and ST			
Zheng et al. (2016)	SMST at 5, 10, 20, 40, and 80 cm depths from the Maqu network, period between 2009 and 2010.	SMST simulations by the Noah model including three sets of augmentations.	The augmentations for the turbulent and soil heat transport improved the ST profile simulations, while the augmentations for the soil water flow mitigated deficiencies of SM profile simulations by Noah model.
Deng et al. (2020)	SMST at 5, 10, 20, and 40 cm depths from the Maqu network, period between 2010 and 2011.	SMST simulations by two versions of the Community Land Model (CLM), i.e., versions 4.5 and 5.0.	The ST simulations from both CLM model versions coincided with the in-situ measurements, while the SM simulations showed large biases.
Deng et al. (2021)	SMST at 5 cm depth from the Maqu network during period of 2011 and from the Ngari network during period between 2013 and 2014.	SMST simulations by the CLM5.0 that include nine experiments evaluating soil water and heat transfer parameterizations.	(i) At the Ngari network, ST simulations in all experiments generally coincided with the observations yielding RMSE within 3°C, while SM simulations in Experiment 6 (i.e., replaced soil property data, adopted virtual temperature scheme and dry surface scheme) showed the best performance. (ii) At the Maqu network, ST simulations in Experiment 5 (i.e., replaced soil property data, adopted Balland and Arp scheme and dry surface scheme) showed the best performance, while SM simulations in Experiment 1 (i.e., replaced soil property data) showed the best performance.
Usage of SM at multiple depths			
Su et al. (2013)	SM at 5, 10, 20, 40, and 80 cm depths from the Maqu network, period between 2008 and 2009; SM around 5, 10, 20, 40, and 60 cm depths from the Naqu network, period of 2008.	SM simulations by the European Centre for Medium-Range Weather Forecasts (ECMWF) based on optimum interpolation scheme and point-wise extended Kalman filter scheme, respectively.	(i) At the Naqu network, both ECMWF's SM products showed significant overestimations in the monsoon season, indicating the ECMWF model and soil texture parameter need to be improved for the cold-semiarid area on the TP. (ii) At the Maqu network, both ECMWF's SM products generally showed good and comparable performance in the humid monsoon period.
Bhatti et al. (2013)	SM at 5, 10, 20, 40, and 80 cm depths from the Maqu network, period of 2009.	Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) SM product generated by the Vrije University Amsterdam and NASA.	The in-situ SM measurements at 10 cm are more suitable to validate the AMSR-E SM product.
Bi et al. (2016)	SM at 5, 10, 20, 40, and 80 cm depths from the Maqu network, period between 2008 and 2010.	SM products generated by CLM, Noah, Mosaic, and VIC models implemented in Global Land Data Assimilation System V1 (GLDAS-1) and Noah model adopted in GLDAS-2.	(i) The GLDAS-2 SM product did not show better performance than the GLDAS-1 products. (ii) All four models can capture well the temporal variations of in-situ SM measurements but underestimated the SM values, and the Mosaic model yielded the largest bias.

Ju et al. (2020)	SM at 5 and 40 cm depths from the Maqu network, period between 2011 and 2012.	SM simulations by Variable Infiltration Capacity (VIC) model with assimilation of brightness temperature (T_B) data from the Soil Moisture and Ocean Salinity (SMOS) mission.	Assimilation of SMOS T_B data improved the performance of VIC SM product indicated by reducing the root mean square difference (RMSD) for the SM at 5 cm from 0.126 to 0.087 $m^3 m^{-3}$, which however, had a slight positive impact for the SM at 40 cm.
Zhuang et al. (2020)	SM at 5, 10, 20, 40, and 60/80 cm depths from the Maqu, Naqu, and Ngari networks, period between 2013 and 2016.	Surface SM (SSM) data generated by using the blend method, and then rootzone SM (RZSM) data generated by Cumulative Distribution Function (CDF) matching approach and Soil Moisture Analytical Relationship (SMAR) model based on the blended SSM data.	(i) The blended SSM product constrained by in-situ SM measurements can eliminate the influence of different LSM simulations. (ii) Both SMAR model and CDF matching approach can give reliable RZSM estimates, but the performances varied from different regions, e.g., the SMAR model provided better estimates in the semi-arid area while the CDF matching approach performed slightly better in the arid area.
Liu et al. (2021)	SM at 5, 10, 20, and 40 cm depths from the Maqu and Ngari networks, period between 2013 and 2015.	China Meteorological Administrational Land Data Assimilation System (CLDAS) and GLDAS SM products	The CLDAS and GLDAS SM data can capture the temporal dynamics with favorable performances, expect for the GLDAS SM data at the layer of 10-40 cm
Usage of ST			
Wang et al. (2016)	ST at 5 cm depth from the Maqu network, period between 2008 and 2009.	ST simulations by Noah and CLM models from GLDAS-1, and by Noah model from GLDAS-2	GLDAS-1 CLM product overestimated the ST, while both GLDAS-1 and GLDAS-2 Noah products showed underestimations although they can replicate the daily variability of in-situ ST measurements.
Li et al. (2019)	ST at 5 m depth from the Maqu and Ngari networks, period between 2010 and 2011.	ST simulations by Common Land Model (CoLM) implementing three different fractional vegetation cover (FVC) schemes.	(i) At the Ngari network dominated by sparse grassland or desert, ST simulations were not sensitive to FVC scheme. (ii) At the Maqu network dominated by grass, ST simulations were improved by implementing a new FVC scheme.
Cao et al. (2020)	ST at 5, 10, 20, and 40 cm depths from the Maqu network, period between 2008 and 2016	ERA5-land ST product.	ERA5-land ST data showed a negative bias in the TP, and it matched better to in-situ ST measurements in permafrost regions than in non-permafrost regions.

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779 **Table 2. Information of the Tibet-Obs networks**

Networks	Climate zone	Land cover	Altitude (m)	Annual Precipitation (mm)	Monitoring sites
Maqu	Cold humid	Grassland	3400-3800	600	26
Shiquanhe	Cold arid	Desert	4200-4700	100	20
Ali					4
Naqu	Cold semiarid	Tundra	Around 4500	400	11

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783 **Table 3. Information for the selected model-based products.**

Product	Spatial Resolution	Temporal Resolution	Temporal Coverage	SM Stratification (cm)	ST Stratification (cm)
ERA5	0.25°×0.25°	Hourly	1979 ongoing	0-7, 7-28, 28-100, 100-289	
Noah				0-10, 10-40, 40-100	
CLSM	1°×1°	3 Hours	2000 ongoing	0-2, 0-100	0-10, 10-29, 29-68, 68-144
VIC				0-30, 30-130*, 130-150*	
MERRA2	0.5°×0.625°	Hourly	1980 ongoing	0-5*, 0-100*	0-10*, 10-30*, 30-70*, 70-146*

784 * The depth of this layer varies with region, and the value shown here is for our study area.

785 **Table 4. Estimation of FSD, TED, and F/T duration at soil depths of 5, 20, and 40 cm using the upscaled SMST profile dataset and**
 786 **ground truth in the selected single year for the Maqu and Shiquanhe networks.**

	SMST _{ups}			SMST _{tru}		
	5 cm	20 cm	40 cm	5 cm	20 cm	40 cm
Maqu network						
FSD	19 Nov	10 Dec	23 Dec	16 Nov	8 Dec	26 Dec
TED	24 Mar	5 Mar	3 Mar	23 Mar	7 Mar	10 Mar
F/T duration	125	85	70	127	89	74
Shiquanhe network						
FSD	14 Nov	17 Nov	23 Nov	14 Nov	18 Nov	23 Nov
TED	18 Mar	18 Mar	13 Mar	18 Mar	18 Mar	21 Mar
F/T duration	124	121	110	124	120	118

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795 **Table 5. Statistical indicators of model-based SMST products at soil depths of 5, 20, and 40 cm for the Maqu network in the warm**
 796 **and cold season, respectively.**

		Warm season				Cold season			
		Soil moisture							
		Bias (m ³ m ⁻³)	RMSD (m ³ m ⁻³)	ubRMSD (m ³ m ⁻³)	R (-)	Bias (m ³ m ⁻³)	RMSD (m ³ m ⁻³)	ubRMSD (m ³ m ⁻³)	R (-)
5cm	ERA5	0.036	0.053	0.039	0.76	-	-	-	-
	CLSM	-0.081	0.098	0.056	0.35	-	-	-	-
	Noah	-0.102	0.116	0.055	0.42	-0.047	0.088	0.075	0.52
	VIC	0.000	0.060	0.060	0.38	-	-	-	-
	MERRA2	-0.092	0.104	0.049	0.58	0.009	0.089	0.088	0.05
20cm	ERA5	0.016	0.032	0.027	0.74	-	-	-	-
	CLSM	-0.102	0.108	0.038	0.32	-	-	-	-
	Noah	-0.122	0.127	0.037	0.49	-0.031	0.085	0.079	0.46
	VIC	-0.013	0.049	0.047	0.39	-	-	-	-
	MERRA2	-0.113	0.118	0.034	0.50	-0.016	0.089	0.087	0.13
40cm	ERA5	0.108	0.111	0.025	0.69	-	-	-	-
	CLSM	-0.018	0.028	0.022	0.44	-	-	-	-
	Noah	-0.040	0.049	0.028	0.54	0.042	0.075	0.062	0.06
	VIC	0.088	0.093	0.029	0.45	-	-	-	-
	MERRA2	-0.025	0.034	0.024	0.50	0.047	0.074	0.057	0.34
		Soil temperature							
		Bias (°C)	RMSD (°C)	ubRMSD (°C)	R (-)	Bias (°C)	RMSD (°C)	ubRMSD (°C)	R (-)
5cm	ERA5	-3.5	3.7	1.1	0.96	-2.4	3.0	1.8	0.84
	CLSM	-3.1	3.4	1.3	0.94	-2.0	2.8	2.0	0.91
	Noah	-3.5	3.9	1.8	0.89	-2.4	3.6	2.7	0.89
	VIC	-4.3	4.4	1.2	0.95	-2.7	3.1	1.6	0.87
	MERRA2	-3.5	3.8	1.4	0.93	-2.6	3.3	2.0	0.91
20cm	ERA5	-5.0	5.0	0.7	0.98	-3.2	3.5	1.4	0.84
	CLSM	-4.8	4.9	1.1	0.95	-3.0	3.4	1.7	0.87
	Noah	-5.9	6.3	2.1	0.84	-2.9	3.3	1.6	0.88
	VIC	-5.5	5.6	1.3	0.92	-3.8	4.1	1.5	0.85
	MERRA2	-5.1	5.2	1.0	0.95	-3.6	4.0	1.8	0.86
40cm	ERA5	-5.3	5.4	0.8	0.97	-2.8	3.0	1.2	0.79
	CLSM	-5.1	5.2	0.8	0.97	-2.8	3.2	1.6	0.77
	Noah	-6.2	6.5	1.9	0.85	-2.8	3.1	1.4	0.82
	VIC	-5.7	5.8	1.1	0.93	-3.7	4.0	1.7	0.74
	MERRA2	-5.9	6.0	0.9	0.95	-3.3	3.8	1.8	0.70

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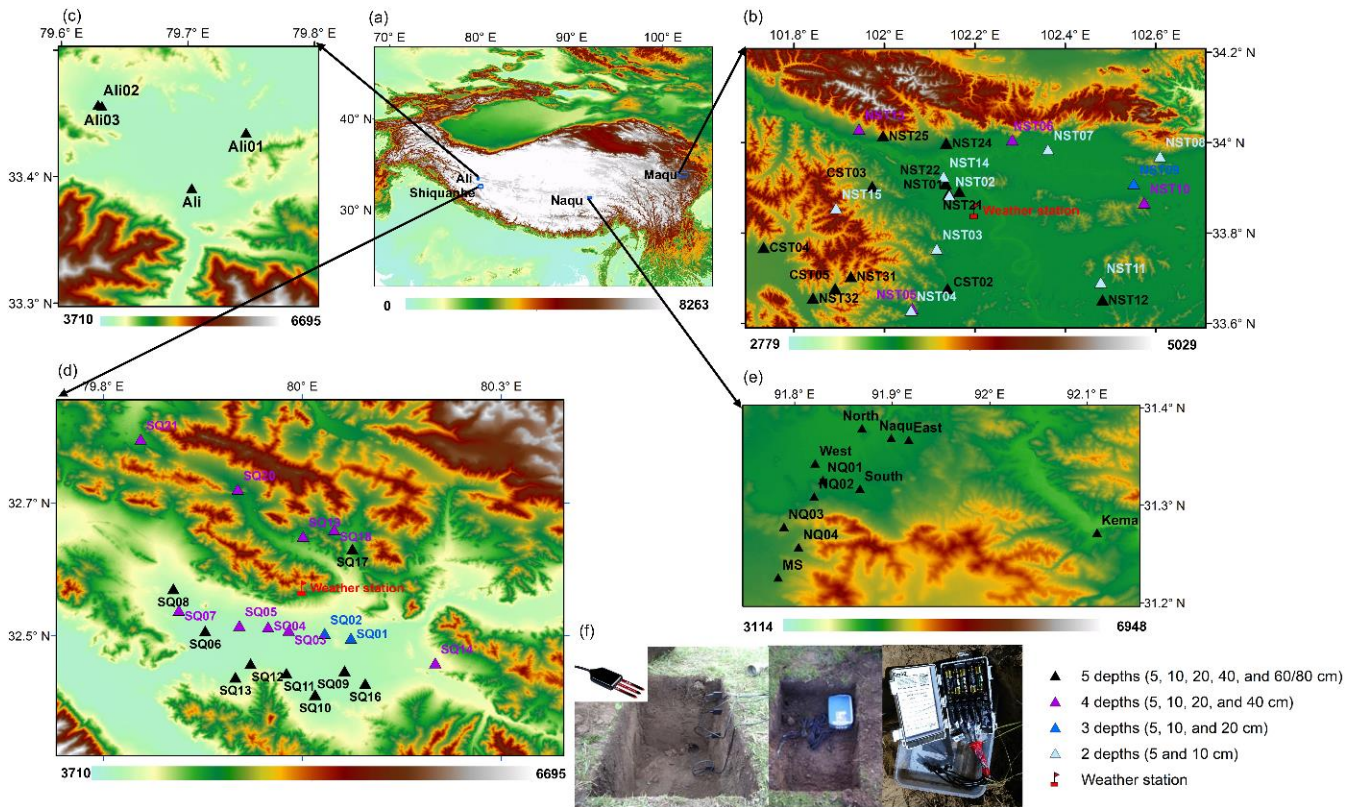
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804 **Table 6. Same as Table 5 but for the Shiquanhe network.**

		Warm season				Cold season			
		Soil moisture							
		Bias (m ³ m ⁻³)	RMSD (m ³ m ⁻³)	ubRMSD (m ³ m ⁻³)	R (-)	Bias (m ³ m ⁻³)	RMSD (m ³ m ⁻³)	ubRMSD (m ³ m ⁻³)	R (-)
5cm	ERA5	-0.001	0.060	0.060	0.80	-	-	-	-
	CLSM	0.156	0.158	0.027	0.53	-	-	-	-
	Noah	0.134	0.142	0.046	0.64	0.072	0.075	0.023	0.12
	VIC	0.256	0.259	0.042	0.38	-	-	-	-
	MERRA2	0.070	0.082	0.042	0.73	0.060	0.065	0.024	0.13
20cm	ERA5	0.084	0.088	0.026	0.55	-	-	-	-
	CLSM	0.152	0.153	0.021	0.56	-	-	-	-
	Noah	0.159	0.161	0.025	0.66	0.145	0.146	0.008	0.28
	VIC	0.256	0.259	0.042	0.31	-	-	-	-
	MERRA2	0.087	0.092	0.028	0.70	0.086	0.087	0.016	0.10
40cm	ERA5	0.107	0.110	0.021	0.30	-	-	-	-
	CLSM	0.154	0.155	0.019	0.39	-	-	-	-
	Noah	0.173	0.174	0.020	0.49	0.174	0.175	0.010	-0.19
	VIC	0.272	0.274	0.032	0.29	-	-	-	-
	MERRA2	0.117	0.118	0.015	0.62	0.123	0.124	0.009	0.08
		Soil temperature							
		Bias (°C)	RMSD (°C)	ubRMSD (°C)	R (-)	Bias (°C)	RMSD (°C)	ubRMSD (°C)	R (-)
5cm	ERA5	-5.5	5.8	1.8	0.95	-6.2	7.0	3.3	0.83
	CLSM	-5.9	6.2	1.6	0.96	-3.0	3.8	2.2	0.93
	Noah	-4.7	5.0	1.6	0.96	-3.8	4.8	3.0	0.86
	VIC	-11.8	12.2	3.1	0.84	-6.6	7.9	4.4	0.69
	MERRA2	-8.2	8.4	1.8	0.95	-5.5	5.8	1.9	0.95
20cm	ERA5	-6.6	6.8	1.7	0.94	-5.8	6.7	3.3	0.76
	CLSM	-7.1	7.2	1.4	0.96	-3.2	3.8	2.1	0.92
	Noah	-5.5	5.6	1.4	0.96	-2.9	4.1	2.9	0.83
	VIC	-12.0	12.2	2.2	0.89	-7.2	8.1	3.7	0.71
	MERRA2	-9.2	9.4	1.6	0.95	-5.6	5.9	1.6	0.95
40cm	ERA5	-7.5	7.7	1.5	0.93	-6.1	6.8	2.9	0.75
	CLSM	-8.9	9.0	1.3	0.96	-3.3	3.8	1.8	0.92
	Noah	-6.6	6.7	1.4	0.95	-2.9	4.0	2.8	0.77
	VIC	-12.8	12.9	1.7	0.92	-7.7	8.2	3.0	0.72
	MERRA2	-10.8	11.0	1.6	0.95	-5.9	6.0	1.4	0.95

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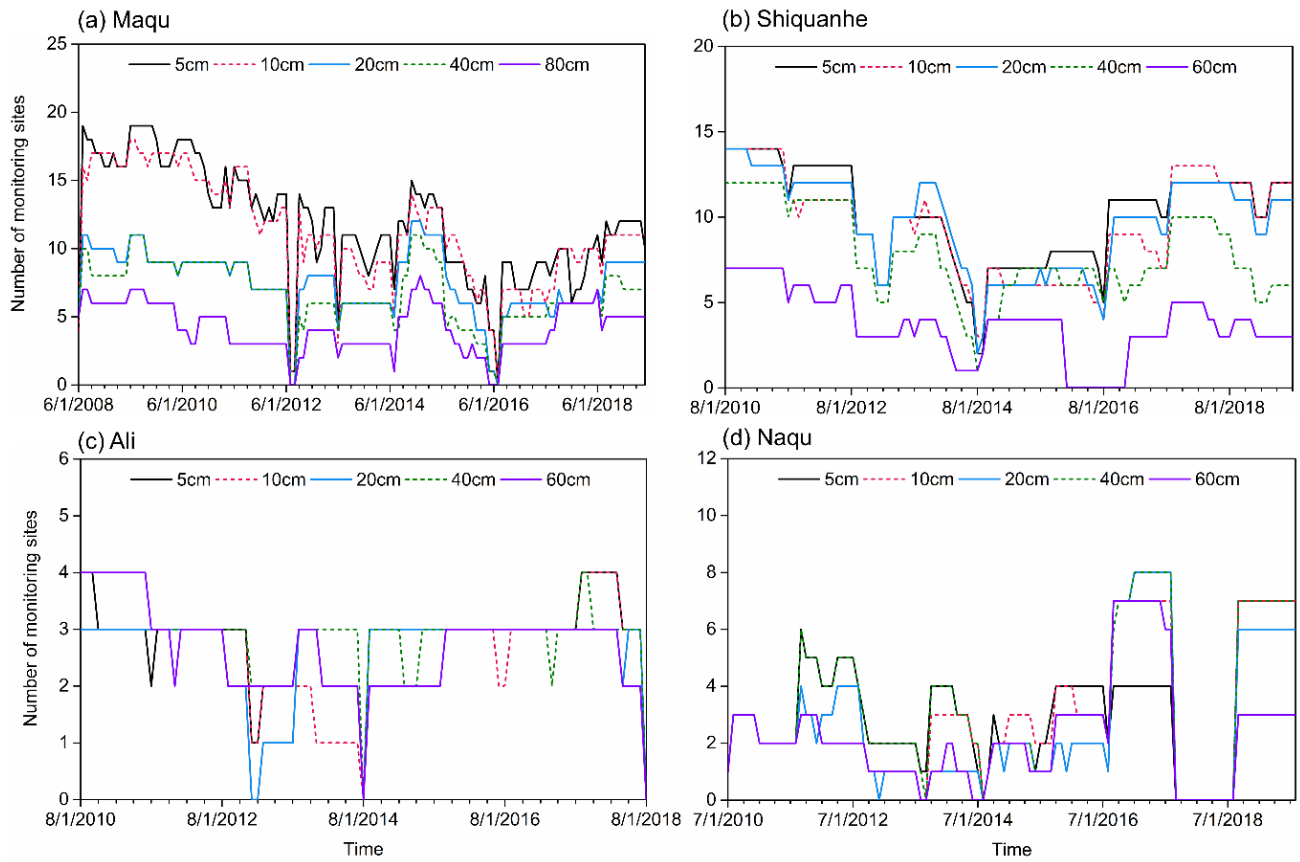
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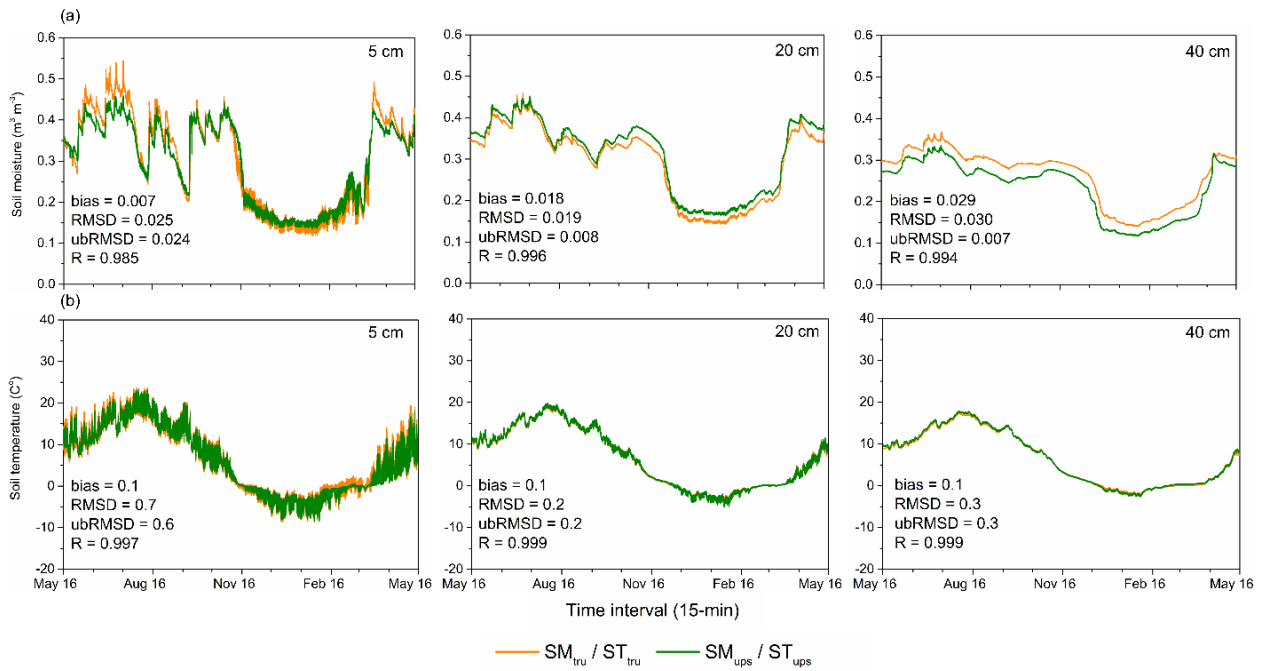
808 **Figure 1. (a) Location of the Tibet-Obs network over the TP; Spatial distributions of SMST monitoring sites and weather station**
 809 **within the (b) Maqu, (c) Ali, (d) Shiquanhe, and (e) Naqu networks; and (f) an example of instruments configured for each SMST**
 810 **monitoring site. The triangles with different colours represent the SMST measured at different depths. (Base map is from EROS,**
 811 **Copyright: © EROS)**

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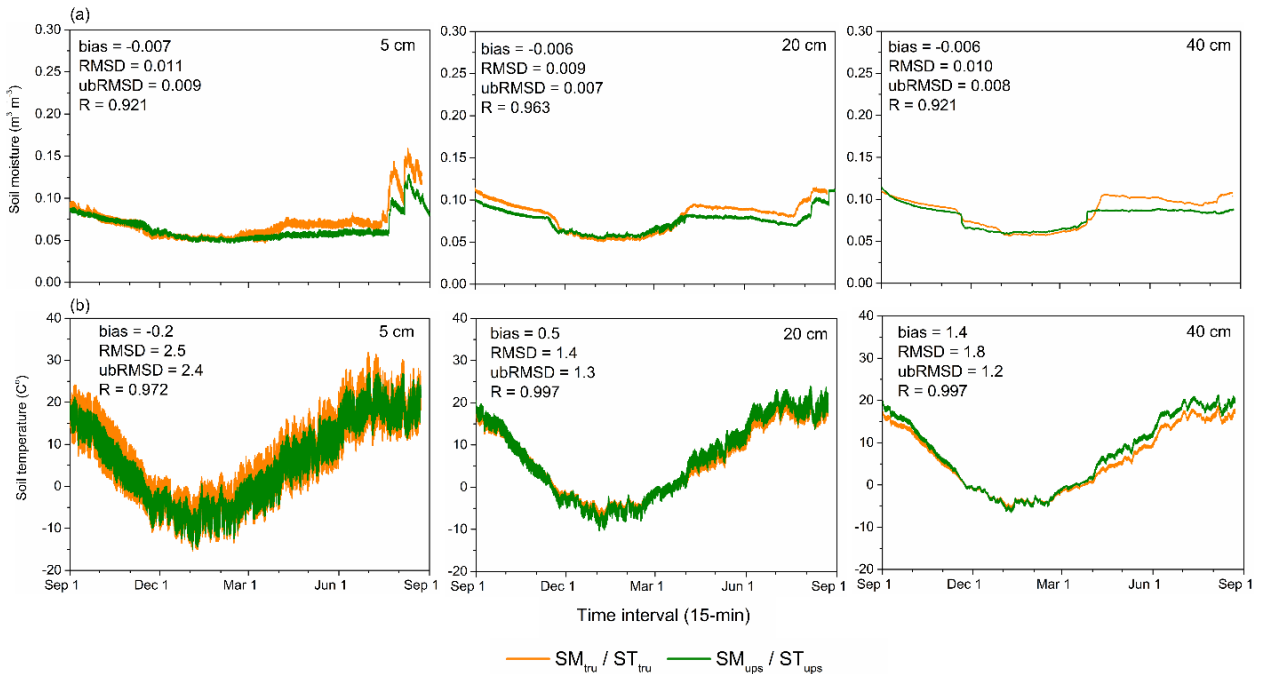
814 **Figure 2. Number of available SMST monitoring sites for different depths at each month for the (a) Maqu, (b) Shiquanhe, (c) Ali**
 815 **and (d) Naqu networks.**



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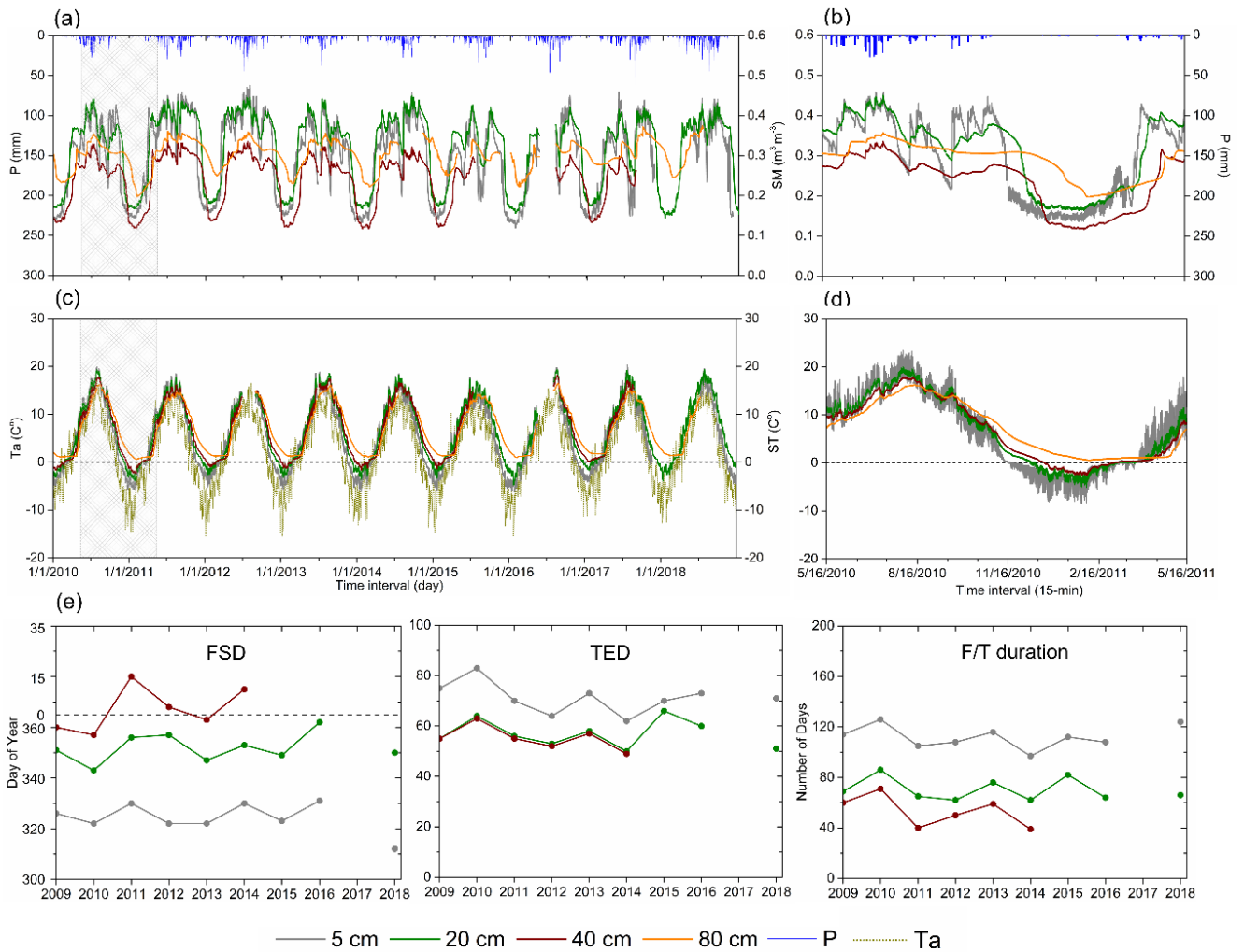
817 **Figure 3. Comparisons between the time series of (a) SM_{ups} and SM_{tru} , and (b) ST_{ups} and ST_{tru} at soil depths of 5, 20, and 40 cm with**
 818 **15-min interval from 16th May 2010 to 16th May 2011 for the Maqu network.**

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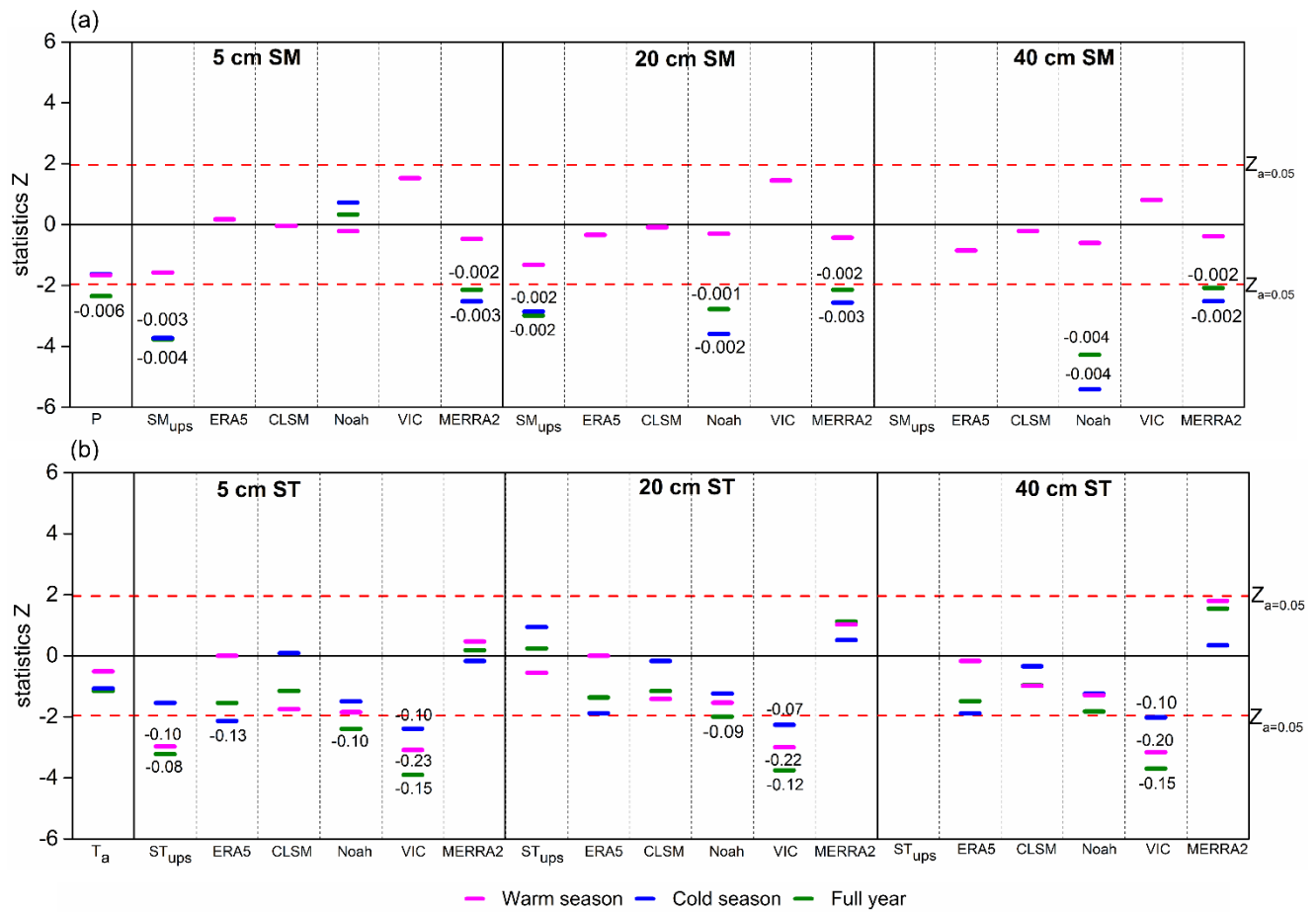
820

821 **Figure 4. Same as Figure 3 but for the Shiquanhe network from 1st Sep 2017 and 31st Aug 2018.**



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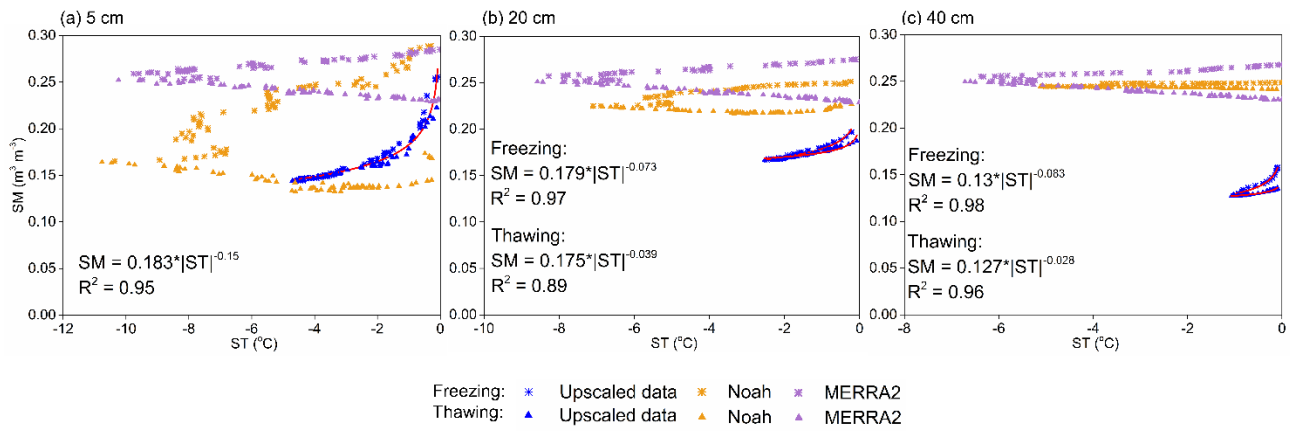
824 **Figure 5. Time series of upscaled daily (a) SM_{ups} and (c) ST_{ups} at depths of 5, 20, 40, and 80 cm for the Maqu network between**
 825 **January 2010 and December 2018; the subplots highlight the time series of upscaled (b) SM_{ups} and (d) ST_{ups} with interval of 15-min**
 826 **between 16-5-2010 and 16-5-2011; and (e) annual variations of TSD, TED, and F/T duration at 5, 20, and 40 cm depths. The time**
 827 **series of daily precipitation and air temperature are shown in (a) and (c) as well.**



828

829 **Figure 6. Mann Kendall trend test and Sen's slope estimate for the long-term (a) SM and (b) ST at depths of 5, 20 and 40 cm from**
 830 **2010 to 2018 obtained from the upscaled dataset and different model-based products for the Maqu network. The trend analysis**
 831 **results for the precipitation and air temperature are also shown in (a) and (b), respectively. The digits in the figure represent the**
 832 **values of Sen's slope estimate.**

833

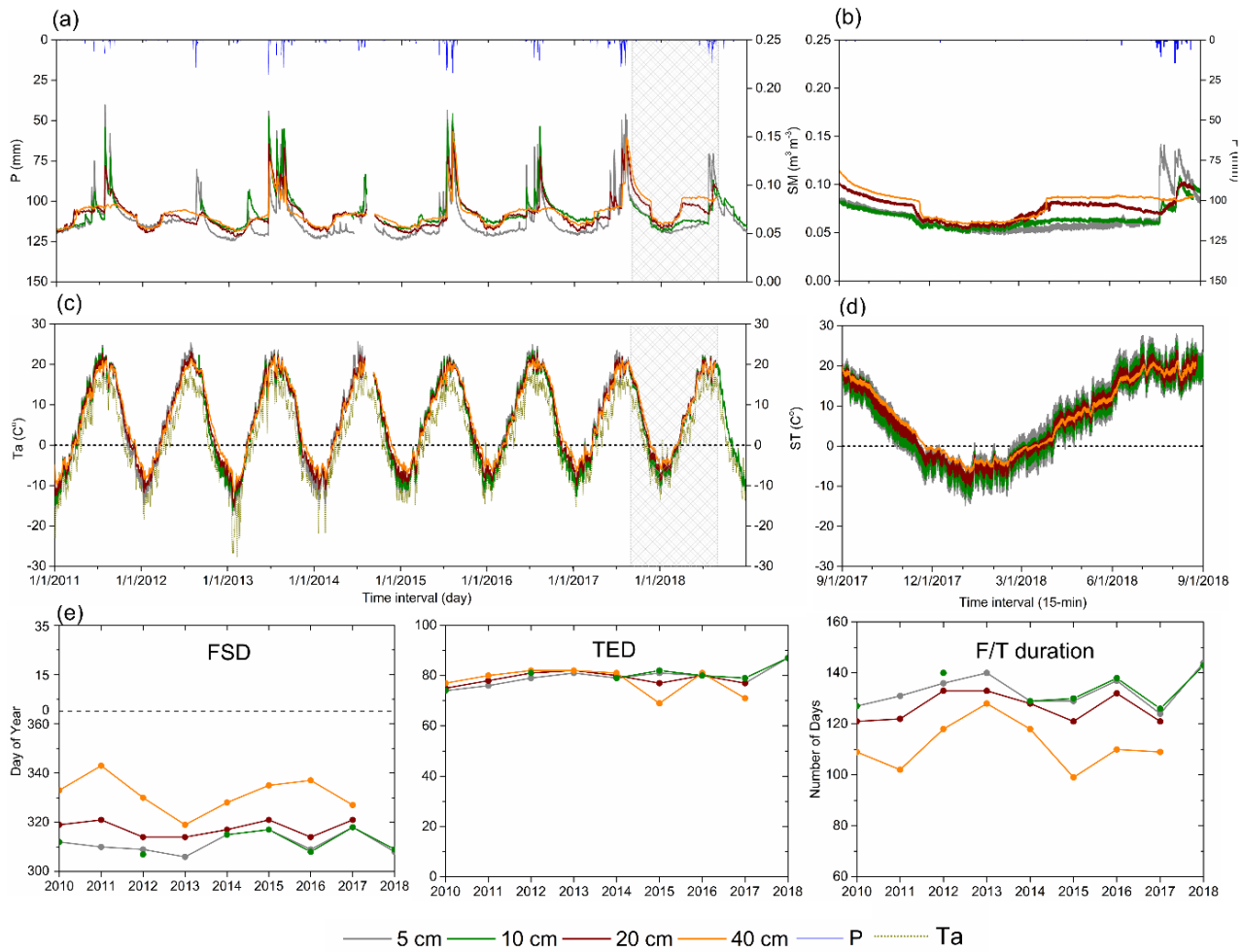


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835 **Figure 7. Soil freezing characteristics for depths of (a) 5, (b) 20 and (c) 40 cm determined from the measured and simulated unfrozen**
 836 **SM and subzero ST obtained from the upscaled dataset, GLDAS Noah and MERRA2 products for the Maqu network.**

837

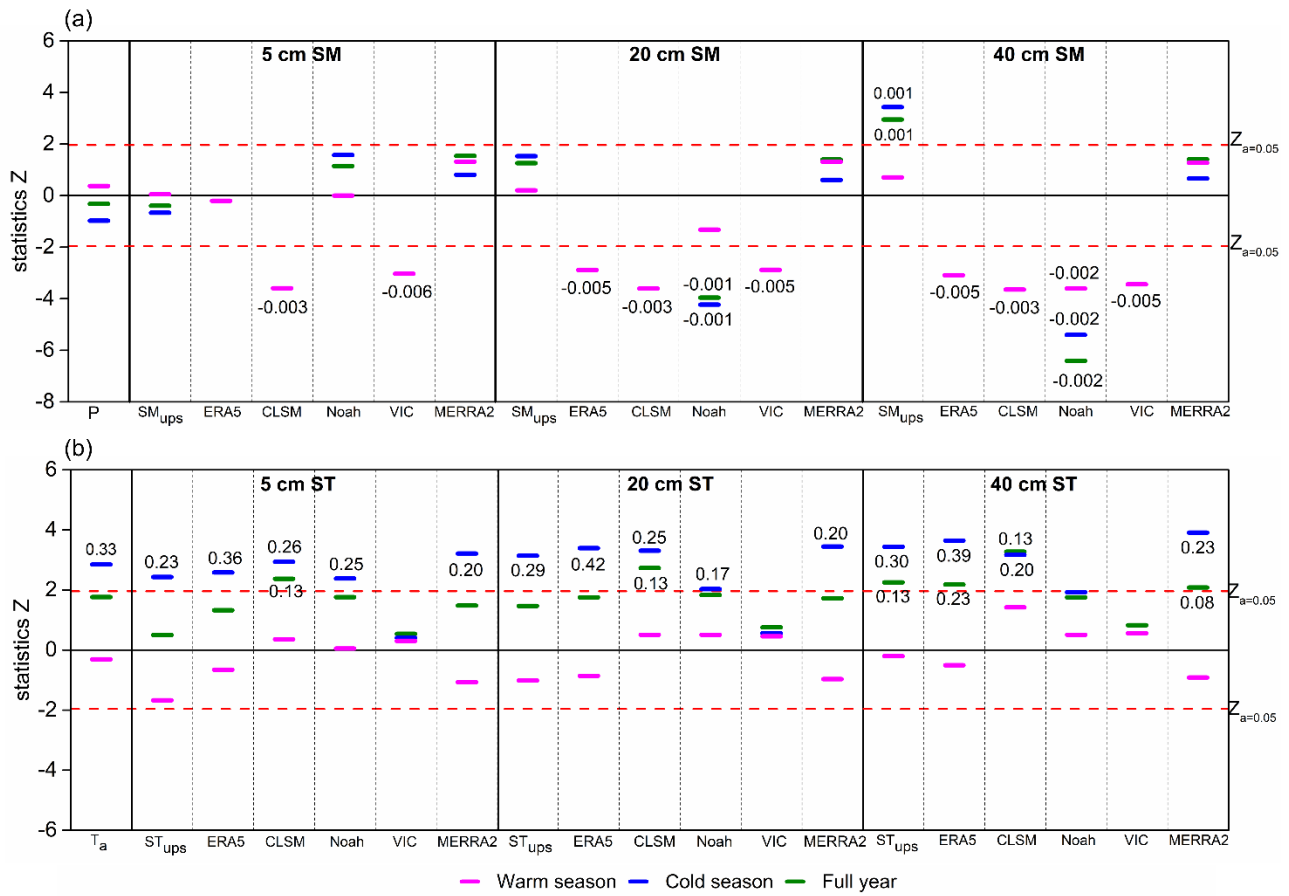
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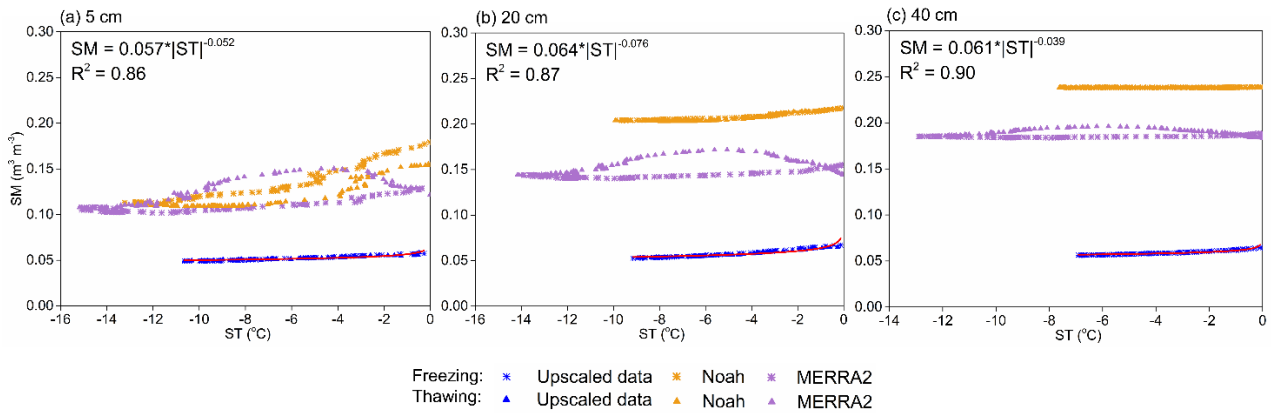
840 **Figure 8.** Time series of upscaled daily (a) SM_{ups} and (c) ST_{ups} at depths of 5, 10, 20, and 40 cm for the Shiquanhe network between
 841 January 2011 and December 2018; the subplots highlight the time series of upscaled (b) SM_{ups} and (d) ST_{ups} with interval of 15-min
 842 between 9-1-2017 and 8-31-2018; and (e) annual variations of TSD, TED, and F/T duration at 5, 10, 20, and 40 cm depths. The time
 843 series of daily precipitation and air temperature are shown in (a) and (c) as well.

844



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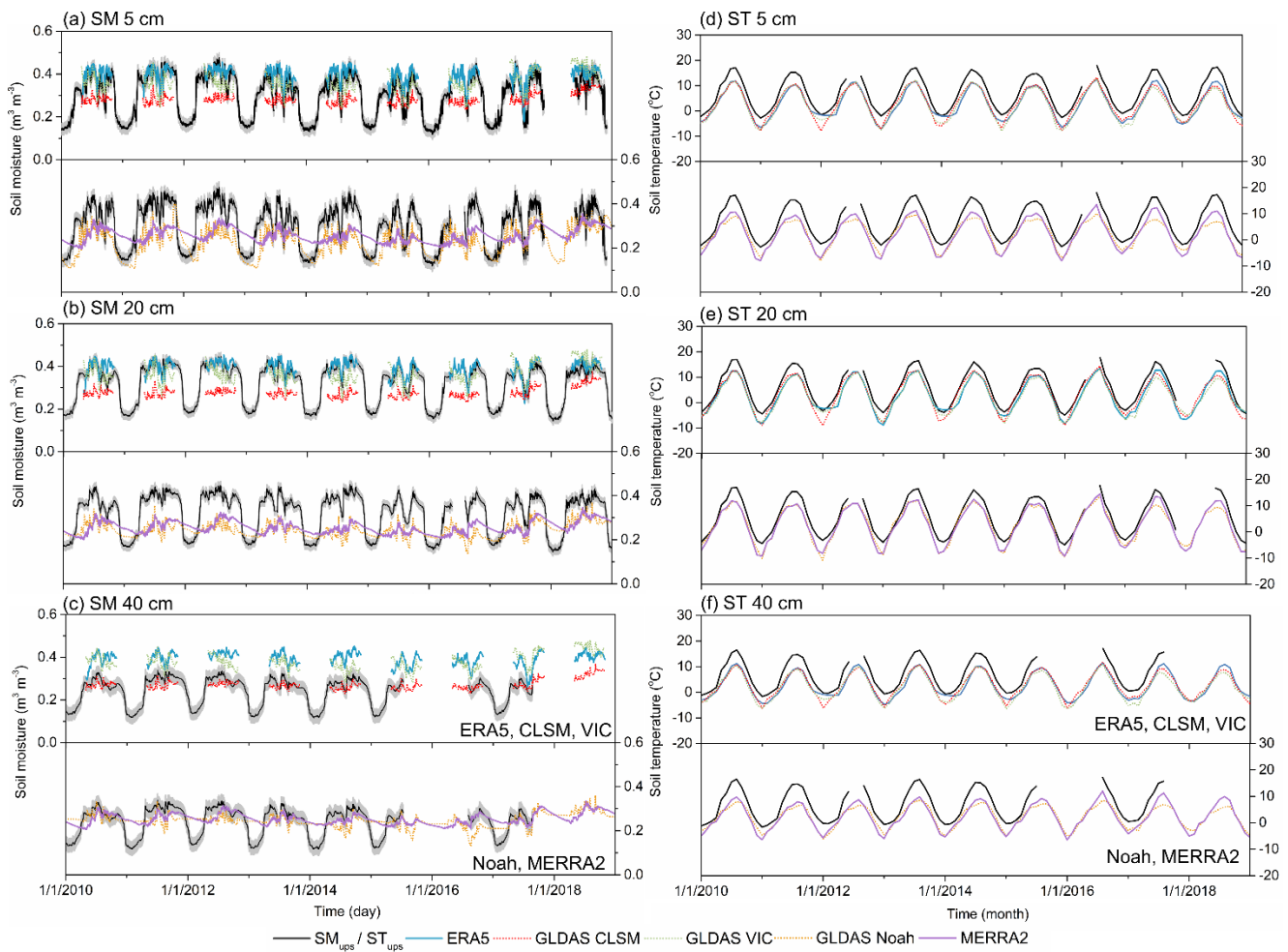
846 **Figure 9.** Same as Figure 6 but for the Shiquanhe network from 2011 to 2018.



847

848 **Figure 10.** Same as Figure 7 but for the Shiquanhe network.

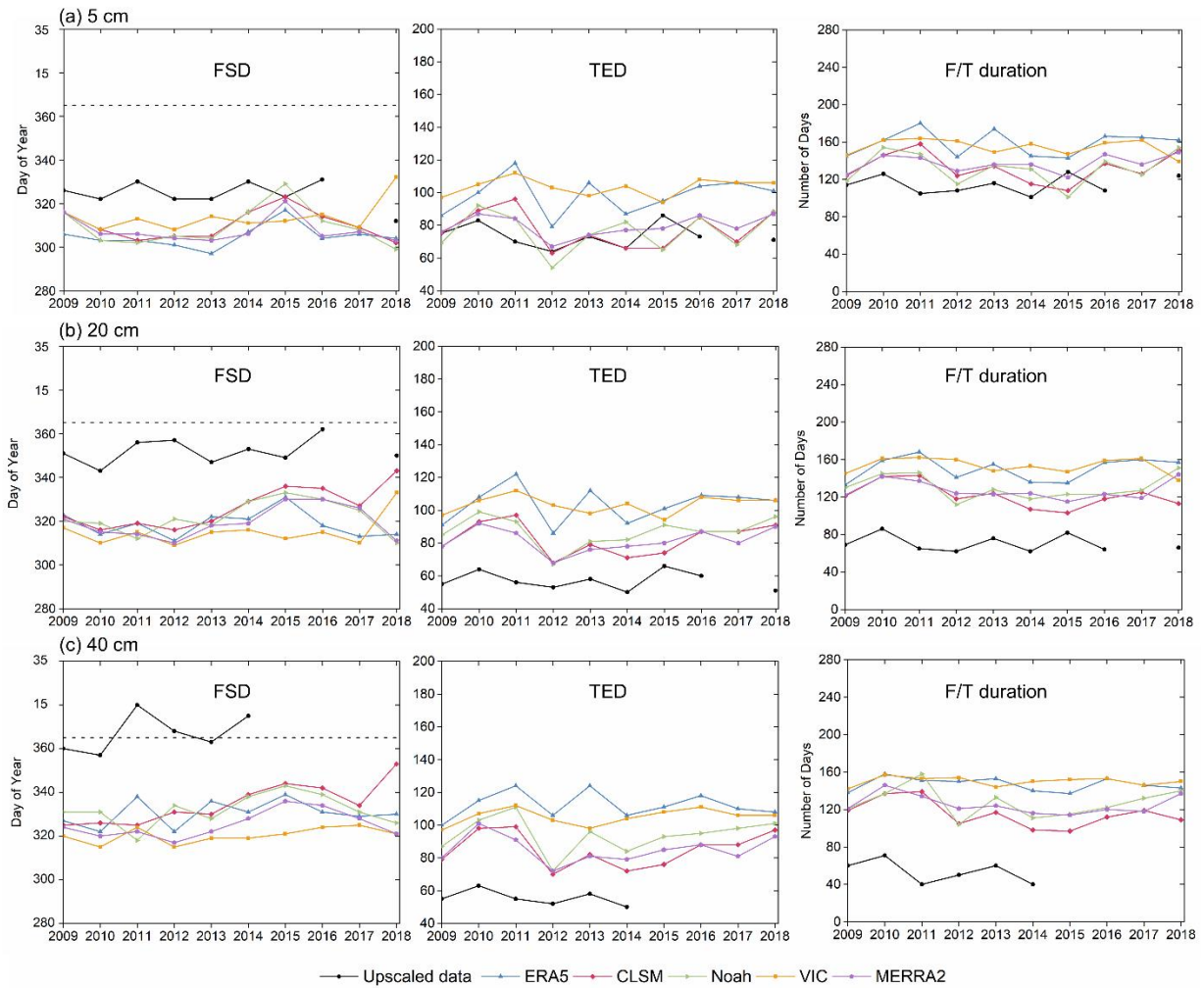
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850

851 **Figure 11. Time series of daily average SM (a-c) and monthly mean ST (d-f) at soil depths of 5 (a, d), 20 (b, e), and 40 cm (c, f) derived**
 852 **from the upscaled SMST dataset and five model-based products from January 2010 to December 2018 for the Maqu network.**

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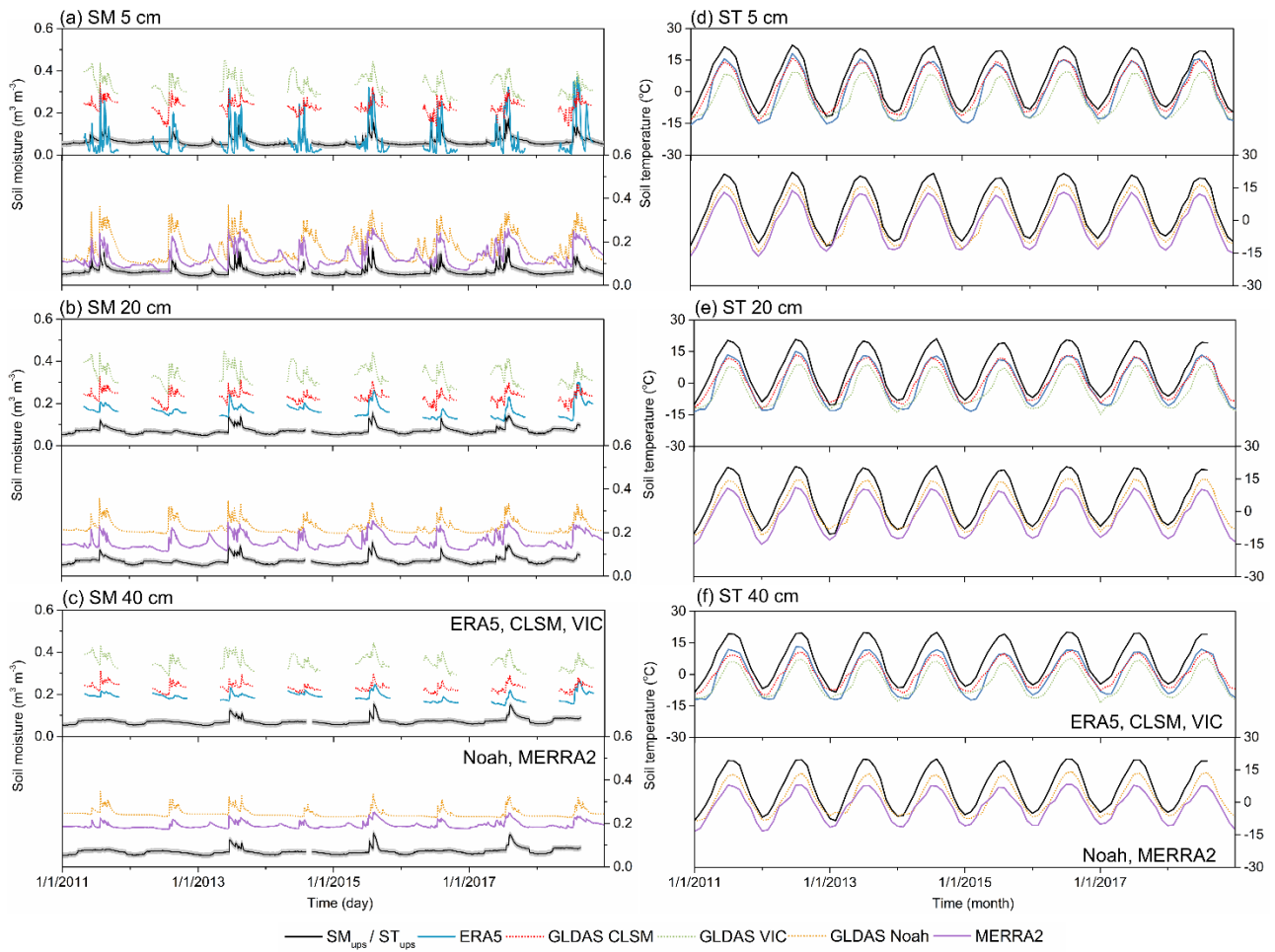


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855 **Figure 12. The annual variations of FSD, TED and F/T duration at the depth of (a) 5, (b) 20, and (c) 40 cm obtained from the**
 856 **upscaled dataset and five model-based products for the Maqu network.**

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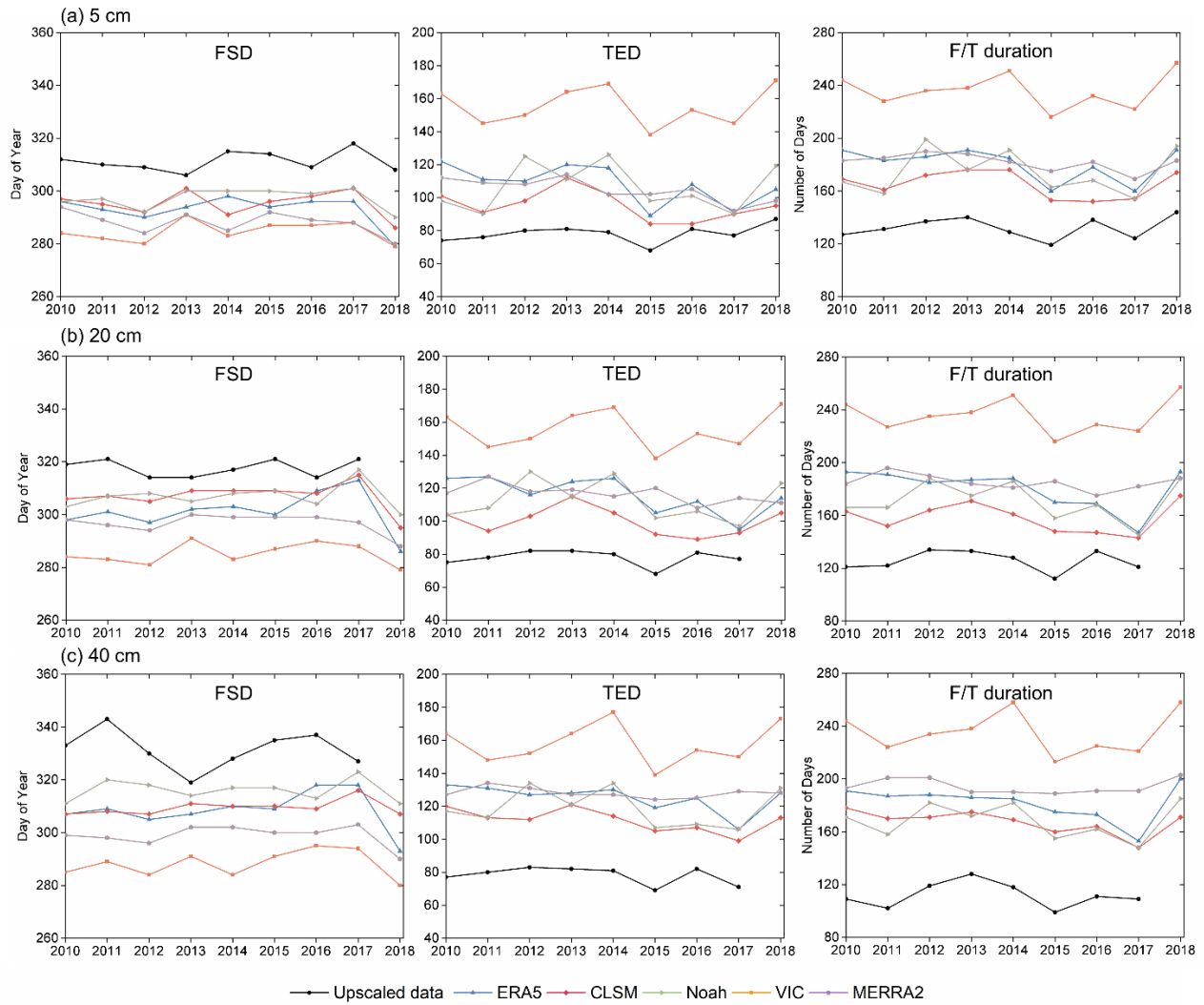
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859

860 **Figure 13. Same as Figure 11 but for the Shiquanhe network from January 2011 to December 2018.**

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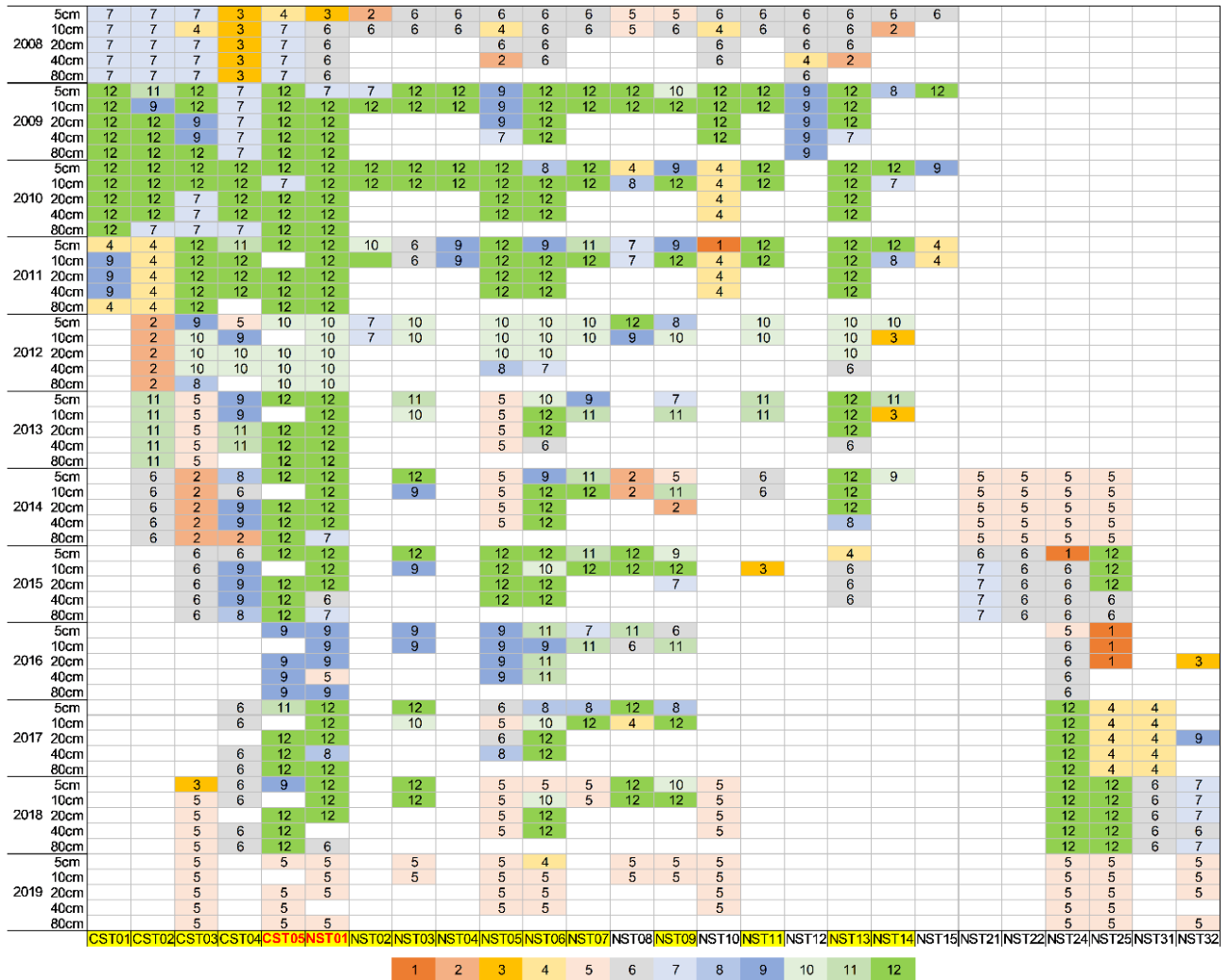


862

863 **Figure 14. Same as Figure 12 but for the Shiquanhe network.**

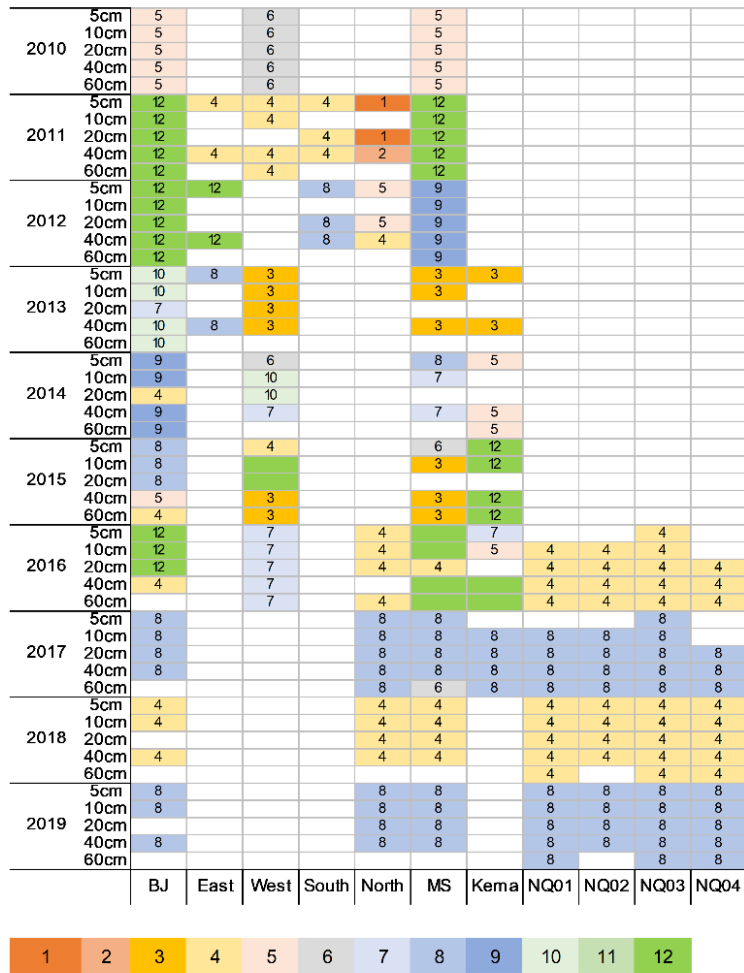
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865 Appendix A: SMST data records of the Tibet-Obs



866 Figure A1. Data records of the SMST measured at different depths with temporal persistence from May 2008 to May 2019 (Y-axis)
 867 for all the monitoring sites in the Maqu network (X-axis). Cells with different colours and digits represent different number of
 868 months that contain valid SMST data in each year. Blank cells indicate that there are no measurements performed. Site names with
 869 highlight and red font represent the sites used for producing the long-term (May 2009 ~ May 2019) upscaled SMST dataset, and site
 870 names only with highlight represent the sites used for generating “ground truth” for a selected year (May 2010 ~ May 2011).

871



878

879 **Figure A3. Same as Table A1 but for the Naqu network with temporal persistence from June 2010 to August 2019.**

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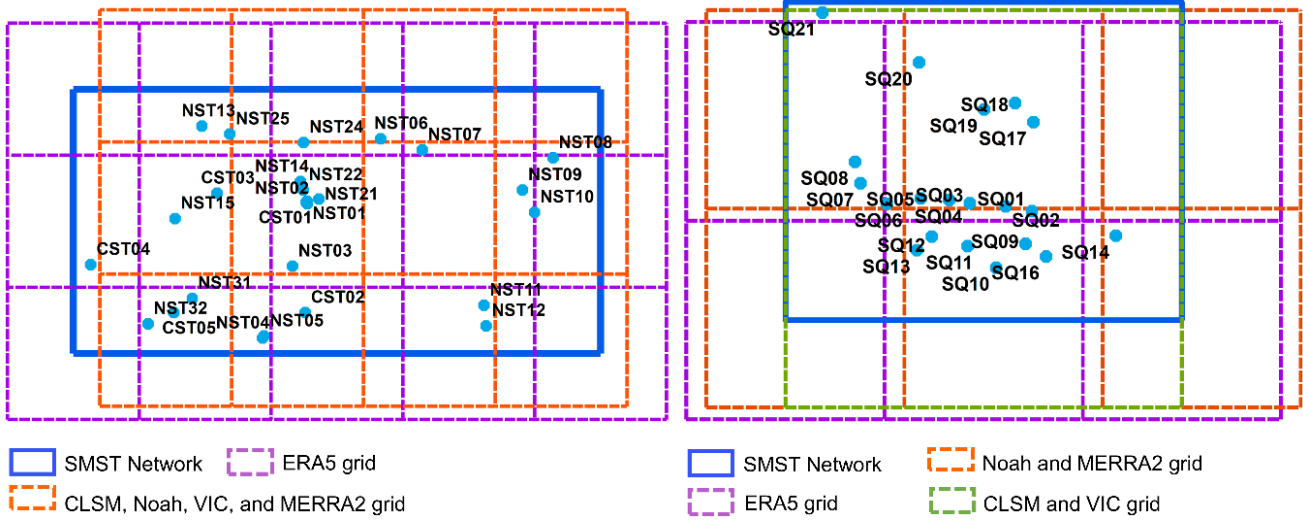
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884

885

(a) Maqu

(b) Shiquanhe



887

888 **Figure B1: Grids of the model-based products falling into the (a) Maqu and (b) Shiquanhe network areas (denoted by the colourful**
 889 **dashed rectangles).**

890 **B1 ERA5 SMST data**

891 The SMST derived from the ERA5 product for the depths of 5, 20, and 40 cm are calculated as:

892
$$X_{5,ERA5} \approx X_{0-7,ERA5}$$

893
$$X_{20,ERA5} \approx X_{7-28,ERA5} + (X_{28-100,ERA5} - X_{7-28,ERA5}) * (20 - 17.5)/(64 - 17.5)$$

894
$$X_{40,ERA5} \approx X_{7-28,ERA5} + (X_{28-100,ERA5} - X_{7-28,ERA5}) * (40 - 17.5)/(64 - 17.5)$$

895 where $X_{5,ERA5}$, $X_{20,ERA5}$, and $X_{40,ERA5}$ represent the interpolated SMST values at 5, 20, and 40 cm depths for the ERA5 product,
 896 and $X_{0-7,ERA5}$, $X_{7-28,ERA5}$, and $X_{28-100,ERA5}$ represent the SMST values for layers of 0-7, 7-28, 28-100 cm derived from the
 897 ERA5 product.

898

899 **B2 GLDAS-2.1 CLSM SMST data**

900 The SM derived from GLDAS-2.1 CLSM product for the depths of 5, 20, and 40 cm are calculated as:

901
$$X_{5,GLDAS\ CLSM} \approx X_{0-2,GLDAS\ CLSM}$$

902
$$X_{20,GLDAS\ CLSM} \approx X_{0-2,GLDAS\ CLSM} + (X_{0-100,GLDAS\ CLSM} - X_{0-2,GLDAS\ CLSM}) * (20 - 1)/(50 - 1)$$

903
$$X_{40,GLDAS\ CLSM} \approx X_{0-2,GLDAS\ CLSM} + (X_{0-100,GLDAS\ CLSM} - X_{0-2,GLDAS\ CLSM}) * (40 - 1)/(50 - 1)$$

904 The ST derived from GLDAS-2.1 CLSM product for the depths of 5, 20, and 40 cm are calculated as:

905
$$X_{5,GLDAS\ CLSM} \approx X_{0-10,GLDAS\ CLSM}$$

$$906 \quad X_{20,GLDAS\ CLSM} \approx X_{10-29,GLDAS\ CLSM} + (X_{29-68,GLDAS\ CLSM} - X_{10-29,GLDAS\ CLSM}) * (20 - 19.5)/(48.5 - 19.5)$$

$$907 \quad X_{40,GLDAS\ CLSM} \approx X_{10-29,GLDAS\ CLSM} + (X_{29-68,GLDAS\ CLSM} - X_{10-29,GLDAS\ CLSM}) * (40 - 19.5)/(48.5 - 19.5)$$

908

909 **B3 GLDAS-2.1 Noah SMST data**

910 The SMST derived from the GLDAS-2.1 Noah product for the depths of 5, 20, and 40 cm are calculated as:

$$911 \quad X_{5,GLDAS\ Noah} \approx X_{0-10,GLDAS\ Noah}$$

$$912 \quad X_{20,GLDAS\ Noah} \approx X_{0-10,GLDAS\ Noah} + (X_{10-40,GLDAS\ Noah} - X_{0-10,GLDAS\ Noah}) * (20 - 5)/(25 - 5)$$

$$913 \quad X_{40,GLDAS\ Noah} \approx X_{10-40,GLDAS\ Noah} + (X_{40-100,GLDAS\ Noah} - X_{10-40,GLDAS\ Noah}) * (40 - 25)/(70 - 25)$$

914

915 **B4 GLDAS-2.1 VIC SMST data**

916 The SMST derived from the GLDAS-2.1 VIC product for the depths of 5, 20, and 40 cm are calculated as:

$$917 \quad X_{5,GLDAS\ VIC} \approx X_{0-30,GLDAS\ VIC}$$

$$918 \quad X_{20,GLDAS\ VIC} \approx X_{0-30,GLDAS\ VIC} + (X_{30-130,GLDAS\ VIC} - X_{0-30,GLDAS\ VIC}) * (20 - 15)/(80 - 15)$$

$$919 \quad X_{40,GLDAS\ VIC} \approx X_{0-30,GLDAS\ VIC} + (X_{30-130,GLDAS\ VIC} - X_{0-30,GLDAS\ VIC}) * (40 - 15)/(80 - 15)$$

920

921 **B5 MERRA2 SMST data**

922 The SM derived from MERRA2 product for the depths of 5, 20, and 40 cm are calculated as:

$$923 \quad X_{5,MERRA2} \approx X_{0-5,MERRA2}$$

$$924 \quad X_{20,MERRA2} \approx X_{0-5,MERRA2} + (X_{0-100,MERRA2} - X_{0-5,MERRA2}) * (20 - 2.5)/(50 - 2.5)$$

$$925 \quad X_{40,MERRA2} \approx X_{0-5,MERRA2} + (X_{0-100,MERRA2} - X_{0-5,MERRA2}) * (40 - 2.5)/(50 - 2.5)$$

926 The ST derived from MERRA2 product for the depths of 5, 20, and 40 cm are calculated as:

$$927 \quad X_{5,MERRA2} \approx X_{0-10,MERRA2}$$

$$928 \quad X_{20,MERRA2} \approx X_{10-30,MERRA2}$$

$$929 \quad X_{40,MERRA2} \approx X_{10-30,MERRA2} + (X_{30-70,MERRA2} - X_{10-30,MERRA2}) * (40 - 20)/(50 - 20)$$

930

931 **Appendix C: Mann Kendall trend test and Sen's slope estimate**

932 Trend analysis for each time series is carried out as following steps:

933 1. Calculate month statistics (S_i)

934 For the i^{th} month (1~12), S_i is calculated as:

$$935 S_i = \sum_{K=1}^{Y-1} \sum_{L=K+1}^Y sgn(X_{i,L} - X_{i,K})$$

$$936 sgn(X_{i,L} - X_{i,K}) = \begin{cases} 1 & X_{i,L} > X_{i,K} \\ 0 & X_{i,L} = X_{i,K} \\ -1 & X_{i,L} < X_{i,K} \end{cases}$$

937 where $X_{i,L}$ and $X_{i,K}$ represent the monthly value of the data (e.g., SMST at different depths, precipitation, air temperature) for
 938 the K^{th} and L^{th} year (satisfied $1 \leq K \leq Y-1$, $K \leq L \leq Y$), Y represents the total number of years (e.g., 9 for the Maqu network
 939 and 8 for the Shiquanhe network).

940 2. Calculate the variance of S_i ($VAR(S_i)$)

941 For the i^{th} month (1~12), $VAR(S_i)$ is calculated as:

$$942 VAR(S_i) = \frac{1}{18} [Y(Y-1)(2Y+5) - \sum_{p=1}^{g_i} t_{i,p}(t_{i,p}-1)(2t_{i,p}+5)]$$

943 where g_i is the total number of equal-value data point group, and $t_{i,p}$ is the number of equal-value data point in the p th group.

944 3. Calculate the seasons statistic and its variance (S and $VAR(S)$)

945 For the fully year, cold seasons, and warm seasons, S and $VAR(S)$ are calculated as:

$$946 S = \sum S_i$$

$$947 VAR(S) = \sum VAR(S_i)$$

948 where i denotes 1~12 for the full year, 5~10 for the warm season, and 1~4, 11, and 12 for the cold seasons.

949 4. Calculate the final statistic (Z)

950 The final statistics Z for the full year, cold seasons, and warm seasons is calculated as:

$$951 Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{Var(S)}} & \text{if } S < 0 \end{cases}$$

952 If the final statistics Z is positive (negative) and its absolute value is greater than $Z_{1-\alpha/2}$ (here $\alpha = 0.05$, $Z_{1-\alpha/2} = 1.96$), the
 953 time series showed uptrend (downtrend) at the significance level of α . Otherwise, there is no significant trend existed.

954 5. Sen's slope estimate

955 If there is a trend existed, we will further estimate the trend slope using Sen's method. For the i^{th} month, individual slope Q_i is
 956 calculated as:

$$957 Q_i = \frac{X_{i,L} - X_{i,K}}{L - K}$$

958 where i denotes 1~12 for the full year, 5~10 for the warm season, and 1~4, 11, and 12 for the cold seasons. The median value
 959 of the Q_i is considered as the Sen's trend slope.

960