



29 (Tave), and minimum temperature (Tmin) from approximately 17,000 global sites, with
30 daily data amounts reaching about 10,000 entries per day in the current decade. When
31 compared to the Global Summary of the Day (GSOD) dataset, GLBD-FED exhibits more
32 temperate performance over the last 40 years, showing a slightly lower daily Tmax
33 (around -0.3°C) and a higher daily Tmin (around $+0.3^{\circ}\text{C}$), with a nearly identical daily
34 Tave (approximately $+0.1^{\circ}\text{C}$). GLBD-FED identifies records that could or almost could
35 represent the highest or lowest temperature in the 24-hour period as daily Tmax or Tmin,
36 while GSOD selects the highest or lowest records within the 24 hours. This variance in
37 definitions, combined with different preferences for meteorological and airport report
38 sources, contributes to these observed biases. The database and associated data can be
39 found at <https://doi.org/10.5281/zenodo.17895292> (Su et al., 2025).

40

41 **2. Introduction**

42 Global in-situ daily temperature measurements are essential data resources for assessing
43 living environments, agricultural systems, and climate-related studies (IPCC, 2021). They
44 play critical roles in monitoring extreme weather, detecting climate change, and validating
45 satellite observations and reanalysis products. (Beck et al., 2017, 2019; Dietzsch et al.,
46 2017; Harris et al., 2014, 2020; Jones and Hulme, 1996; Jones and Moberg, 2003; Mitchell
47 and Jones, 2005; New et al., 1999, 2000; Schneider et al., 2018).

48

49 Multiple research institutions and National Hydrometeorological Services (NMHSs) have
50 developed global observational datasets (Adler RF, Huffman GJ, Chang A, Ferraro R, Xie
51 P, Janowiak J, Rudolf B, Schneider U, Curtis S, Bolvin D, Gruber A, Susskind J, 2003;
52 Daly, 2002; Harris et al., 2014; Hulme, 1991, 1992; Janowiak et al., 1998; Kamiguchi et
53 al., 2010; Klein Tank et al., 2002; Menne et al., 2012; Rudolf, 1993; Schamm et al., 2014;
54 Schneider, 1993; Xie et al., 2007; Yatagai et al., 2012). Recent advancements have
55 progressed from monthly aggregates to daily and sub-daily products (Blenkinsop et al.,
56 2018; Schamm et al., 2014; Westra1 et al., 2014). The Global Summary of the Day (GSOD)



57 released by the National Centers for Environmental Information (NCEI, 2017) is one of
58 the most widely-used global quasi-real-time daily products. It relies on the Integrated
59 Surface Database (ISD) published by NCEI (Smith et al., 2011) as its main data source
60 utilizing the hourly average temperature (T_{ave}), 12 and 24-hours (h) cumulative
61 maximum (T_{max}) and minimum temperature (T_{min}) to creates daily T_{ave} , T_{max} , T_{min}
62 values.

63

64 Similar to the processing of precipitation data, temperature records also include
65 cumulative data for specific durations, such as T_{max}/T_{min} over 12 and 24 hours, which
66 are recorded on a non-uniform observation schedule worldwide (WMO, 2015).
67 Consequently, global daily temperature data, particularly for T_{max} and T_{min} , face
68 temporal representation issues akin to those encountered with precipitation data. To
69 address this, GSOD defines the maximum and minimum records occurring within a day
70 as the daily T_{max} and T_{min} , respectively. While this method generally performs well, it
71 presents challenges due to the non-standardized and unstable nature of global observations.

72

73 This study aims to produce a global daily dataset representing the maximum, minimum,
74 and average temperatures over a 24-hour period, effectively encapsulating one day. To
75 achieve this, we developed new algorithms for optimally utilizing the irregularly timed
76 sub-daily measurements in the ISD and harmonizing them under consistent temporal
77 references. The data sources and methodology are detailed in Sections 3 and 4, followed
78 by a comparative evaluation against the daily temperature dataset defined by different
79 methods (GSOD) in Section 5. Finally, conclusions from this study are presented in
80 Section 6.

81

82 **3. Data Sources**

83 **3.1. Near-real time sub-daily meteorological measurements**

84 Hourly surface temperature observations spanning 1981-2024 were compiled through the



85 Integrated Surface Database (ISD), a global database that consists of hourly and synoptic
86 surface observations compiled from numerous sources into a single common ASCII
87 format and common data model (Smith et al., 2011).

88

89 The ISD-derived temperature parameters encompass five temporal resolution components:
90 hourly mean temperature (T_{ave}), 24-hour maxima and minima ($T_{max-24h}$ and $T_{min-24h}$),
91 and 12-hour maxima and minima ($T_{max-12h}$ and $T_{min-12h}$). Fig.1 illustrates their global
92 temporal distributions from 2011 to 2024, with panels a-c corresponding to T_{ave} , $T_{max-24h}$ /
93 $T_{min-24h}$, and $T_{max-12h}$ / $T_{min-12h}$, respectively. Analysis reveals two dominant
94 regimes for T_{ave} observations with 6-hour cadences: 0000/0600/1200/1800 UTC
95 (approximately 95×10^6 records per hour) and 0300/0900/1500/2100 UTC (approximately
96 70×10^6 records per hour). This four-peak temporal distribution supports the computational
97 efficiency of deriving daily T_{ave} through quad-hourly sampling at 6-hour intervals,
98 offering an optimized solution for global temperature averaging.

99

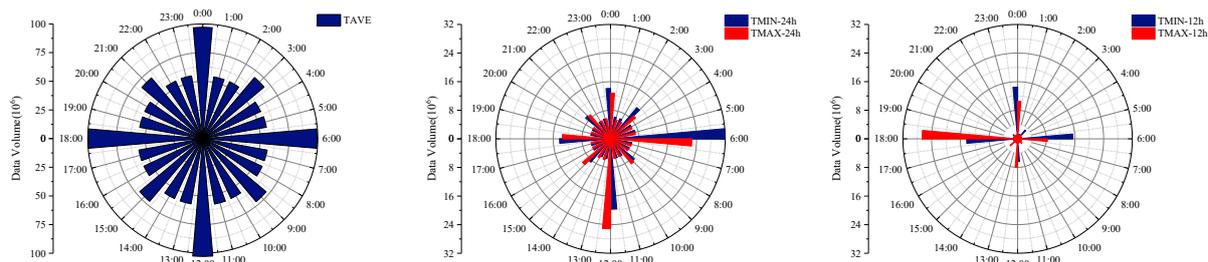
100 $T_{max}/T_{min-24h}$ (Fig.1 panel b) show significantly fewer records compared to T_{ave} . Eight
101 synoptic times (0000/0300/0600/0900/1200/1500/1800/2100 UTC) exhibit uniform data
102 densities for T_{max} and $T_{min-24h}$, with peaks at 0000 and 0600 UTC (approximately 27
103 $\times 10^6$ records per hour) containing three times the volume of adjacent times (around $9 \times$
104 10^6 records per hour). This suggests a potential date shift or inhomogeneity between daily
105 T_{max} and T_{min} records from different regions if T_{max} and $T_{min-24h}$ are treated as global
106 daily data directly. In contrast, $T_{max}/T_{min-12h}$ do not exhibit a similar distribution to the
107 24-hour records (Fig.1 panel c), being predominantly clustered at 0000/0600/1200/1800
108 UTC with 6 to 26×10^6 records per hour.

109

110 In summary, T_{max} and T_{min} display weaker temporal regularity compared to T_{ave} .
111 Moreover, T_{max} and T_{min} do not always appear in pairs as expected, indicating that date
112 shifts and inhomogeneities may not only exist between regions but also between the raw



113 Tmax and Tmin records themselves.



114

115 Figure 1 The distribution of sub-daily temperature data amounts at each o'clock during 2011-2024

116

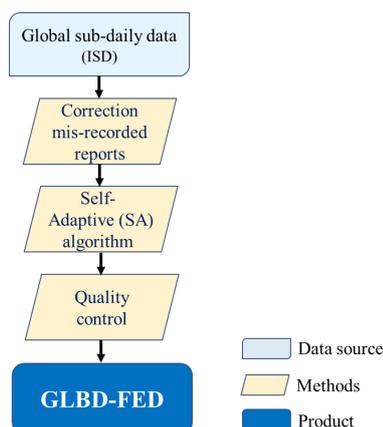
117 3.2. GSOD in-situ daily data

118 The Global Surface Summary of the Day (GSOD; accessible at
119 <https://data.noaa.gov/dataset/dataset/groups/global-surface-summary-of-the-day-gsod>),
120 maintained by the U.S. National Centers for Environmental Information (NCEI),
121 generates daily meteorological summaries from over 9,000 global weather stations.
122 Derived through systematic processing of the ISD, this product provides continuous
123 records spanning 1929 to present, with post-1973 data exhibiting optimal completeness.

124

125 4. Methods

126 Fig.2 illustrates the main procedures involved in the production of the Global Base
127 Dataset-First Estimate Daily Data (GLBD-FED). The Integrated Surface Database (ISD)
128 served as the data source, from which daily Tmax, Tave, and Tmin were derived using
129 new methods after correcting for misrecorded data. All daily data underwent quality
130 control and were assigned a quality code and date boundary code.



131

132

Figure 2 Main procedures of GLBD-FED production

133

134 4.1. Correction for Mis-recorded sub-daily Tmax/Tmin in data source

135 The quality of the data source is one of the most critical factors influencing the final data
136 product. Notably, there were numerous misrecorded values for Tmax and Tmin over 12-
137 hour and 24-hour periods in the global hourly data, particularly in South America.

138

139 Fig.3 presents a case study from San Antonio Oeste, Argentina (877840-99999), covering
140 January 5 to January 12, 2023. The red and green lines represent the hourly upper limits
141 of temperature derived from Tmax-12h and Tmax-24h, respectively, while the black
142 circles indicate hourly Tave. Panel (a) displays results from the raw data, revealing that
143 San Antonio Oeste tends to record Tmax-24h at 1200 UTC and Tmax-12h at 0000 and
144 1200 UTC. Although the hourly temperature upper limits derived from these records
145 sometimes overlap, they differ significantly at other times. The green lines (derived from
146 Tmax-24h) are consistently lower than the hourly Tave, suggesting that these Tmax-24h
147 values are likely erroneous due to incorrect recording.

148 In this study, these data were not simply labeled with an 'error' quality code; efforts were
149 made to restore them through the following procedures:

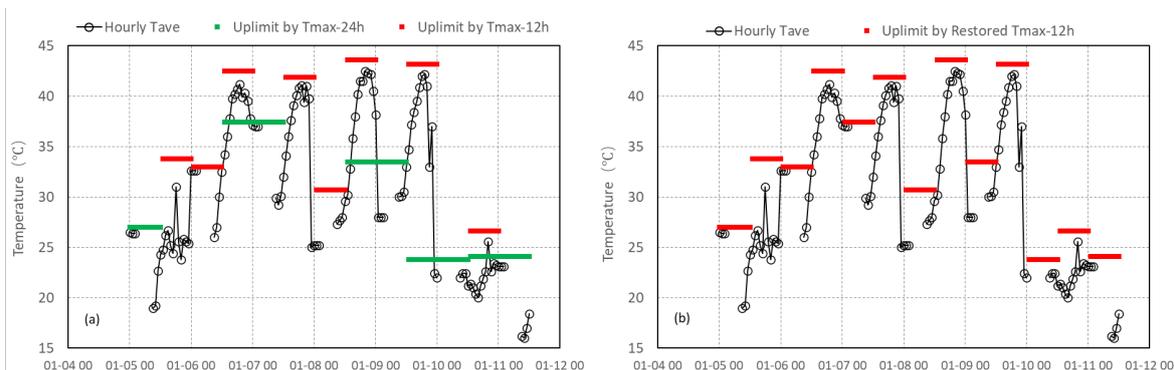
- 150 1. Tmax-24h records at hh:00 were compared with the highest hourly Tave from the
151 previous 12 hours (Tave-12hhigh) and 24 hours (Tave-24hhigh). If Tmax-24h < Tave-



152 24hhigh - 0.5°C and $T_{\max-24h} \geq T_{\text{ave-12hhigh}}$, it indicates that the $T_{\max-12h}$ at hh:00
153 was incorrectly recorded as $T_{\max-24h}$ and should be corrected.
154 2. $T_{\max-12h}$ records at hh:00 were similarly compared with the highest hourly Tave from
155 the previous 12 hours and 24 hours. If $T_{\max-12h} > T_{\text{ave-12hhigh}} + 0.5^\circ\text{C}$ and $T_{\max-12h} \leq T_{\text{ave-24hhigh}}$, it suggests that the $T_{\max-24h}$ at hh:00 was inaccurately recorded
156 as $T_{\max-12h}$ and should also be corrected.
157
158 3. The corrections for $T_{\min-24h}$ and $T_{\min-12h}$ followed a similar approach, but
159 comparisons were made with the lowest hourly Tave from the previous 12 hours and
160 24 hours.

161

162 Fig.3 panel (b) displays the corrected results. The misrecorded $T_{\max-24h}$ values were
163 restored to $T_{\max-12h}$, and the derived hourly upper limit temperatures now align closely
164 with the hourly Tave.



166 Figure 3 The hourly average temperature and the hourly up-limit of temperature derived from $T_{\max-12h/24h}$
167 during 5th Jan to 12th Jan 2023 at San Antonio Oeste, Argentina. Panel a and b represent the
168 results from raw and restored data, respectively. The red and green lines are hourly up limit of temperature
169 derived from $T_{\max-12h}$ and $T_{\max-24h}$, respectively, and the black cycles are hourly Tave.

170

171 4.2. New algorithms for in-situ daily temperature calculation

172 Aiming to obtain a set of global daily temperature data standing for the air temperature
173 status under prospective dateline, new algorithms were developed.

174



175 **4.2.1. Dateline management for daily data calculation**

176 The standardized and preferred dateline for calculating daily Tmax, Tave, and Tmin is set
177 at 0000-2400 UTC. When standard 0000-2400 UTC calculations are unfeasible, a
178 graduated adjustment protocol ($\pm hh$ offsets in 1-hour increments, up to ± 12 hours) is
179 employed to maximize data retention while maintaining temporal consistency. All
180 adjustments made are systematically recorded in the final metadata outputs, ensuring
181 comprehensive data inclusion and maximal uniformity in dateline across the dataset.

182

183 **4.2.2. Equidistant sampling for daily Tave calculation**

184 As discussed in Section 3.1, deriving daily Tave from the average of four hourly Tave
185 records at 6-hour intervals proves to be both effective and efficient. The daily average
186 temperature is calculated as the following formulae

187
$$Tave_{daily}^1 = (Tave_{hh} + Tave_{hh+6hours} + Tave_{hh+12hours} + Tave_{hh+18hours})/4 \quad (1)$$

188
$$hh = 0000, 0100, \dots, 0600 \text{ UTC}$$

189 In this context, Tave represents the average temperature, with the subscript "daily"
190 indicating data for the day and "hh" denoting the hour. The value of hh ranges from 0000
191 to 0600 UTC.

192

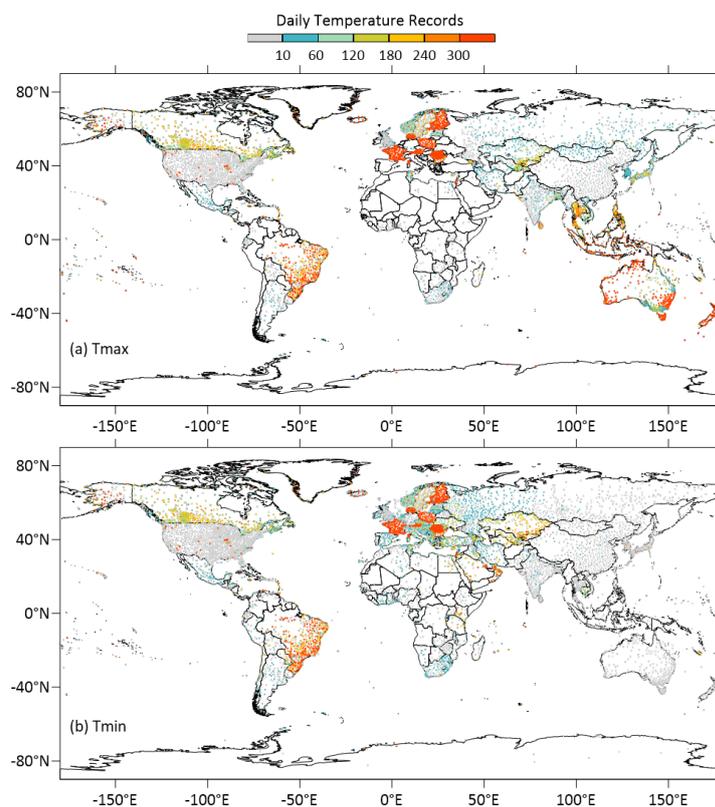
193 **4.2.3. Reaggregation for daily Tmax and Tmin calculation**

194 Sub-daily Tmax and Tmin records were temporally decomposed into finer intervals,
195 following the precipitation data processing protocols established by Yang et al. 2020. This
196 approach facilitated probabilistic recombination into daily Tmax and Tmin values under
197 prospective dateline. Fig.4 illustrates a case of daily Tmin calculation using the
198 reaggregation algorithm at False Pass, US (700638-99999) on October 11, 2024. During
199 the period from October 11 to October 12, False Pass recorded Tmin-12h at 1200 UTC
200 and Tmin-24h at 0900 UTC. Initially, a less apparent Tmin-15h at 0000 UTC on October
201 12 (-1.7°C , indicated by the dashed deep green arrow) was derived from the Tmin-24h at
202 0900 UTC (4.4°C , light blue arrow) and Tmin-12h at 1200 UTC on October 12 (-1.7°C ,
203 deep blue arrow). This value was then combined with the Tmin-12h at 1200 UTC on
204 October 11 (-1.1°C , light blue arrow) to produce the daily Tmin value for October 11 (-



225 regions such as America, Australia, western Europe, and southern Asia. Tmax exhibits a
226 more notable increase than Tmin, likely due to the scarcity of Tmax-12h and Tmax-24h
227 records, particularly in Australia.

228



229

230 Figure 6 The spatial distribution of the increasing Tmax (panel a) and Tmin (panel b) data improved by
231 reaggregated algorithm in 2023. The color represents increasing data volume.

232

233 Similar to GSOD, if the reaggregation algorithm fails, the maxima and minima records in
234 hourly Tave serve as supplementary estimators for Tmax and Tmin, respectively, provided
235 that there is at least 21 hours of temporal coverage.

236

237 4.3. Data quality controls

238 Quality controls were implemented for both the input hourly data and the produced daily



239 data. Global hourly temperature data quality tests include a spike value test, a stuck value
240 test (which identifies prolonged sequences of the same value in the data series), and an
241 inner consistency test (assessing the relationships between T_{max} , T_{ave} , and T_{min}). The
242 daily data underwent these same tests, along with additional temporal and spatial
243 consistency tests. Details of these tests for daily data are provided in the Appendix.

244

245 Data quality results are flagged at each step and categorized into three groups: credible,
246 suspicious, and erroneous. The quality test results at each stage are compiled into a final
247 assessment of data quality levels. A final quality level is flagged as credible if there is no
248 more than one suspicious test result and no erroneous test results. Conversely, a value is
249 flagged as erroneous if more than one erroneous test result is found; otherwise, the final
250 quality level is classified as suspicious.

251

252 **5. Results**

253 In this section, we first present the temporal changes and spatial coverage of the global
254 in-situ daily temperature data volume of GLBD-FED. This is followed by comparisons of
255 data values between GLBD-FED and GSOD, along with further discussions.

256

257 **5.1. In-situ Data Volume and Spatial Coverage**

258 Fig.7 presents the spatial distribution (panels a1, a2, and a3) and temporal changes (panels
259 b1, b2, and b3) of global daily T_{max} , T_{ave} , and T_{min} data from 1981 to 2024. The colorful
260 dots in panel a indicate the duration of daily data at each site, while the gray and black
261 curves represent the daily data volume and the 15-point smoothing results, respectively.

262

263 T_{max} , T_{ave} , and T_{min} exhibit very similar spatial distributions and temporal changes over
264 the last four decades. Panel a1, a2, and a3 show approximately 17,000 sites with at least
265 one year of daily T_{max} data. Sites in China, Japan, and central Europe have extensive
266 time series of daily T_{max} (≥ 40 years, indicated by red dots). Western Europe and the US



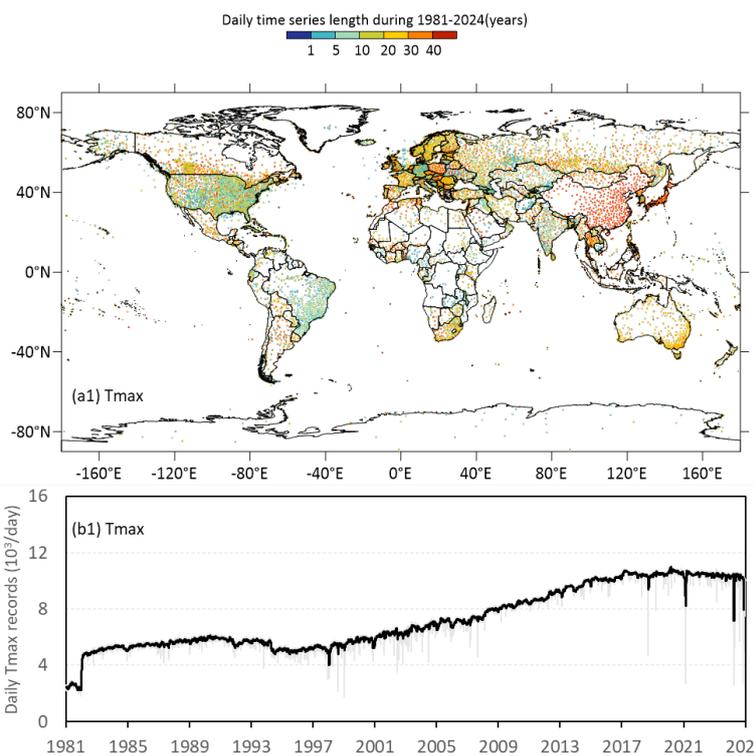
267 demonstrate a high spatial density of daily Tmax data. Notably, inconsistencies in U.S.
268 station metadata (e.g., station 72200654926 [43.617°N, 96.217°W] post-2005 vs.
269 72200699999 [43.621°N, 96.216°W] pre-2005) have resulted in many short time series
270 (green and blue dots, <20 years of records). Brazil also displays a high spatial density of
271 data, with most stations beginning temperature observations in the last decade. Substantial
272 sites with at least 20 years of daily temperature data can be found in southern Canada,
273 coastal Australia, Russia, and southern Asia. Although the Antarctic and Arctic regions are
274 among the most challenging for meteorological observation globally, dozens of sites have
275 commenced measurements in the current century.

276

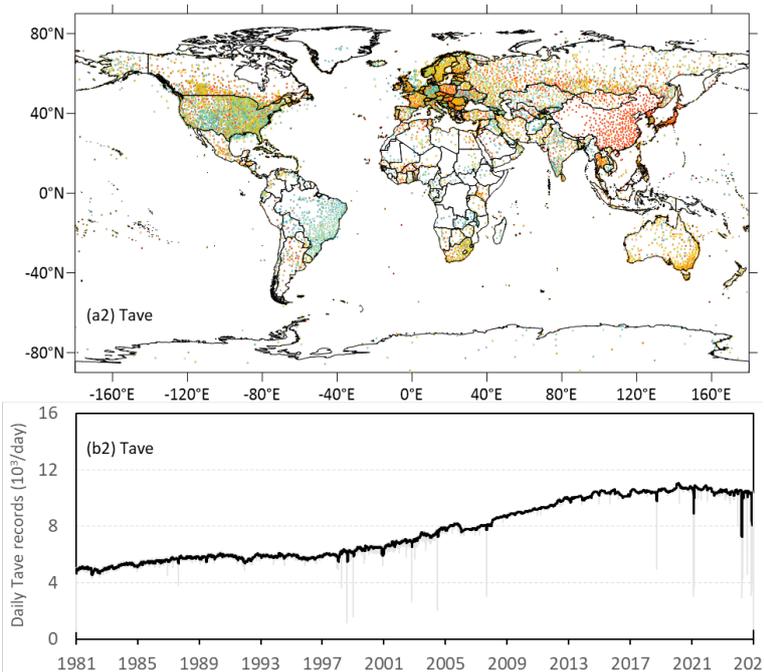
277 The global daily data volume for Tmax, Tave, and Tmin has increased significantly over
278 the last four decades. As shown in panels b1, b2, and b3, the global daily data volume rose
279 from approximately 3,000 entries per day in the 1980s to around 10,000 entries per day in
280 recent years.



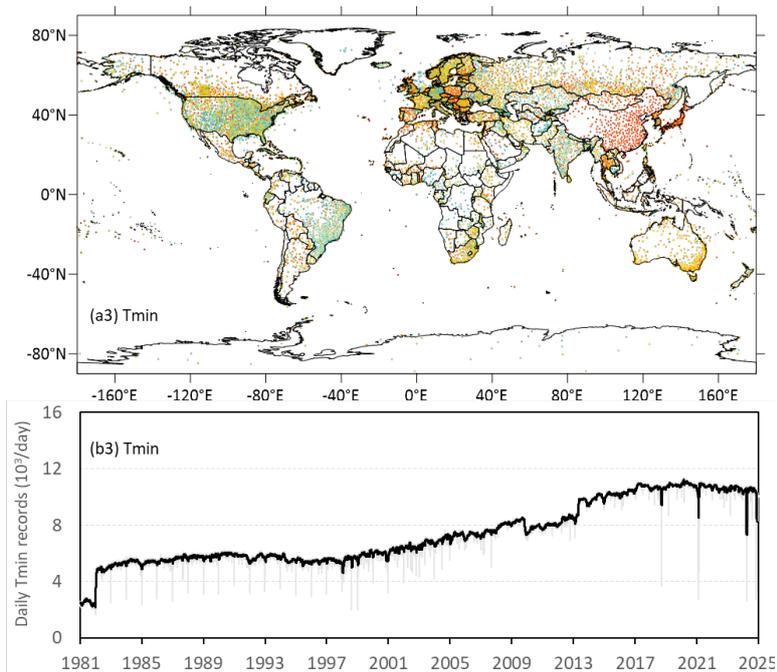
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291

Figure 7 The spatial distribution (panel a1, a2, and a3) and temporal changes (panel b1, b2 and b3) of global daily temperature data during 1981-2024. Panel a1 and b1 represent the Tmax, panel a2 and b2 represent the Tave, panel c1 and c2 represent the Tmin. The colorful dots in panel a represent the length of the daily data at sites; the gray and black curves stand for the daily data volume and the 15 points-smoothing result, respectively.

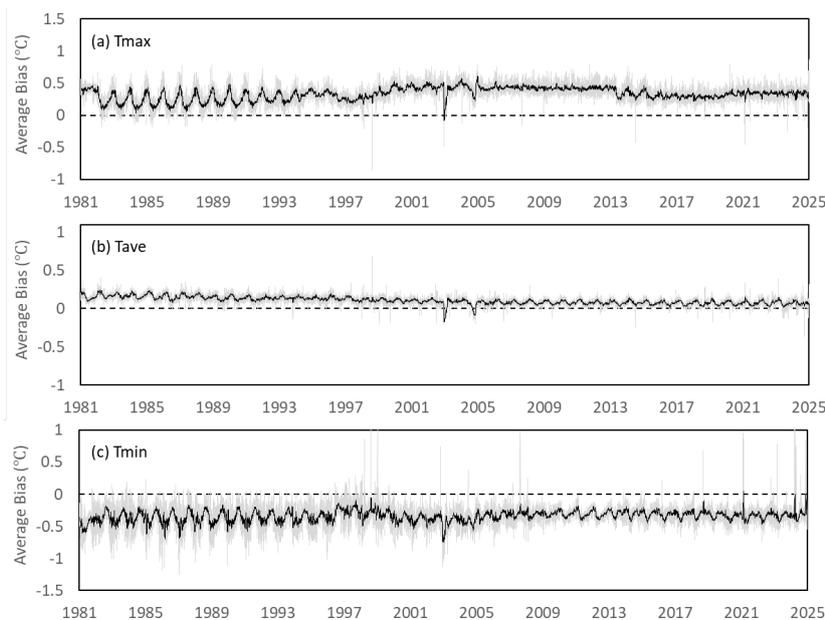


292 **5.2. Comparison of daily temperature with GSOD**

293 Fig.8 presents the multi-decadal time series (1981-2024) of global daily temperature
294 differences between GSOD and GLBD-FED. Nearly all records of GLBD-FED shown in
295 Fig.7 were compared. It is clear that GSOD manifest warmer daily Tmax (around +0.3°C),
296 colder Tmin (around -0.3°C) and nearly same daily Tave (around +0.1°C) relative to
297 GLBD-FED in the whole period. That mean the research based on GSOD daily
298 temperature data probably produce more remarkable climate extreme events than that
299 based on GLBD-FED.

300

301 The difference in daily data definitions between GLBD-FED and GSOD is the primary
302 cause of the systematic variability in Tmax and Tmin. GLBD-FED considers records that
303 could or almost represent the highest or lowest temperature during the 24-hour period as
304 daily Tmax and Tmin data, while GSOD selects the highest and lowest records within the
305 24 hours. This means that in GSOD, accumulated Tmax and Tmin records covering two
306 days that represent the high or low values from the previous day (e.g., Tmax/Tmin-24h at
307 0300 UTC) may be treated as the daily Tmax and Tmin data for the following day if they
308 are the highest or lowest values. The impact of this daily data definition is discussed in
309 detail in Section 5.3.1.



310

311 Figure 8 The daily time series of average difference in global in-situ daily temperature between GLBD-
312 FED and GSOD (1981-2024) (GSOD minus GLBD-FED). The gray and black lines are the daily and 15
313 points-smoothing results, respectively. Panel (a), (b), and (c) stand for the results of Tmax, Tave and Tmin,
314 respectively.

315

316 Fig.9 illustrates the spatiotemporal heterogeneity of daily temperature discrepancies
317 between GSOD and GLBD-FED from 1981 to 2024. The sites in GSOD with higher daily
318 Tmax ($\geq 0.5^{\circ}\text{C}$) relative to GLBD-FED are primarily located in Southern Africa, Brazil,
319 Argentina, Canada, and the western United States (panel a1), accounting for 21.4% of all
320 sites (approximately 17,000) (panel a2).

321

322 Interestingly, GSOD shows lower Tmax values in China compared to GLBD-FED. This
323 discrepancy arises from several types of reports labeled with the same ID in the ISD. The
324 Metar and Synoptic reports in China are independent and measured at different sites.
325 Metar temperature reports tend to be lower than Synoptic temperature reports since the
326 latter are mostly recorded in urban areas. GSOD prioritized Metar reports as data sources,
327 while GLBD-FED optimized Synoptic reports, leading to the observed negative bias in

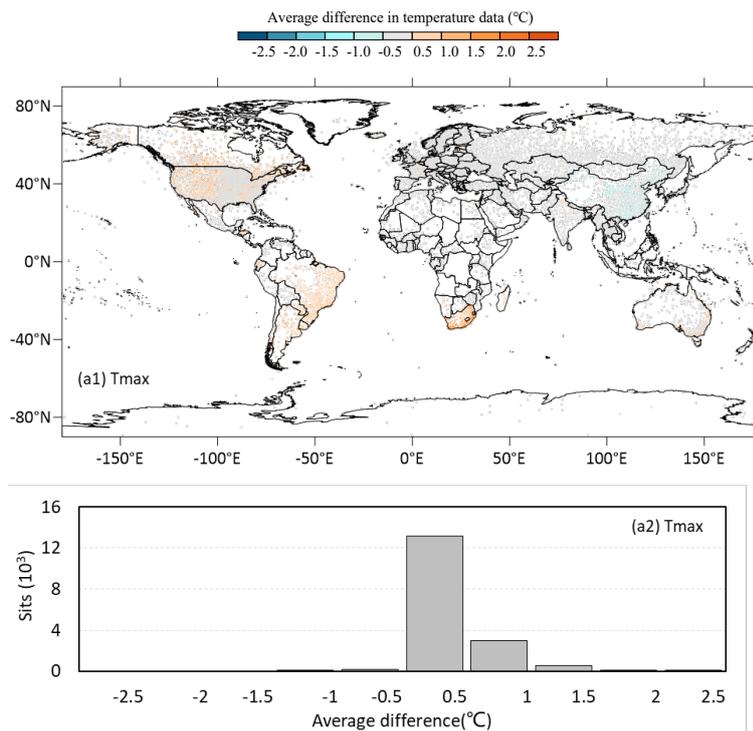


328 China. This issue is discussed in more detail in Section 5.3.2.

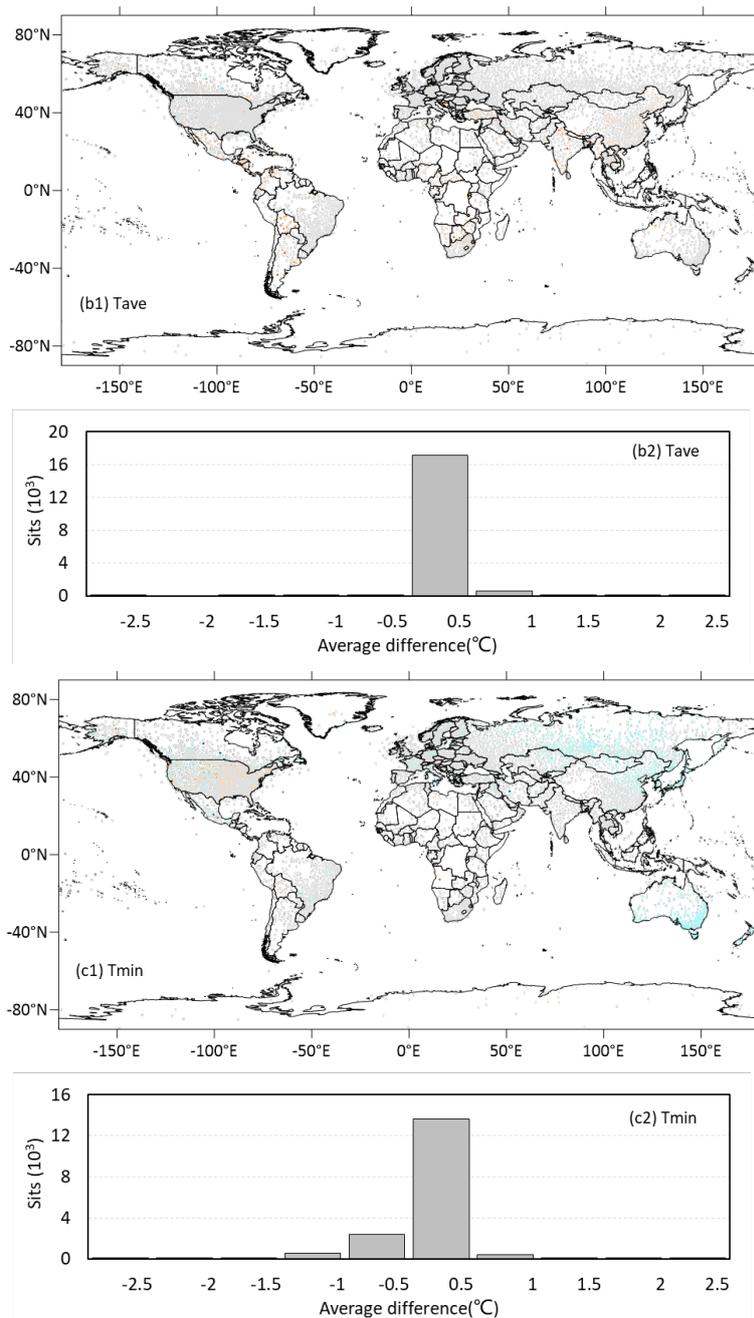
329

330 Meanwhile, sites in GSOD with lower daily Tmin ($\leq -0.5^{\circ}\text{C}$) compared to GLBD-FED are
331 predominantly found in Australia, Russia, and Northeast Asia (panel c1), representing
332 17.4% of all sites. Daily Tave from GSOD and GLBD-FED exhibits much greater
333 consistency compared to Tmax and Tmin (panel b1), with 95.3% of sites maintaining
334 differences within $\pm 0.5^{\circ}\text{C}$ (panel b2).

335



336



337

338

339

340

341

342

Figure 9 Spatial distribution of the difference in-situ daily temperature data between GLBD-FED and GSOD during 1981-2024 (GSOD minus GLBD-FED). Panel a1, b1, c1 show the difference in Tmax, Tave and Tmin at each site, respectively. Panel a2, b2, c2 represent the sites number distribution with diversities.



343 **5.3. The causes for the discrepancy in daily temperature data**

344 GLBD-FED and GSOD employ different algorithms to produce daily temperature data,
345 resulting in discrepancies in data properties and biases between the two datasets,
346 particularly for Tmax and Tmin. Table 1 outlines three main differences in the key
347 processes of daily Tmax and Tmin data production between GLBD-FED and GSOD.

348

349 First, GLBD-FED and GSOD have distinct definitions for daily Tmax and Tmin data.
350 GLBD-FED considers records that could or almost represent the highest or lowest
351 temperature in a 24-hour period as daily Tmax and Tmin, while GSOD selects the highest
352 and lowest records within the 24 hours.

353

354 Second, although both GLBD-FED and GSOD utilize sub-daily data shared globally
355 through the Global Telecommunication System (GTS) as their data source, they apply this
356 data differently. GLBD-FED prefers Synoptic reports over Meteorological Aerodrome
357 (Metar) and other reports when multiple types of sub-daily reports share the same ID,
358 whereas GSOD does the opposite.

359

360 Third, GLBD-FED makes efforts to adjust the daily temperature boundary to 0000 UTC
361 whenever possible, while GSOD retains the highest and lowest values as they appear
362 within the 24-hour period.

363

364 Table 1 the comparison of the key processes in daily Tmax/Tmin calculation between GBLD-FED and
365 GSOD

No	Key processes	GLBD-FED	GSOD
1	The definition of the daily Tmax/Tmin data	The records could/almost represent the highest/lowest temperature over the 24h.	The highest/lowest records in the 24h.
2	The preference about the data source as there are several types of sub-daily reports labeled by the same ID	Synoptic reports	Meteorological Aerodrome Reports



3 The date boundary for global daily data Adjust the daily boundary of the daily temperature value to 00:00 UTC as much as possible. /

366

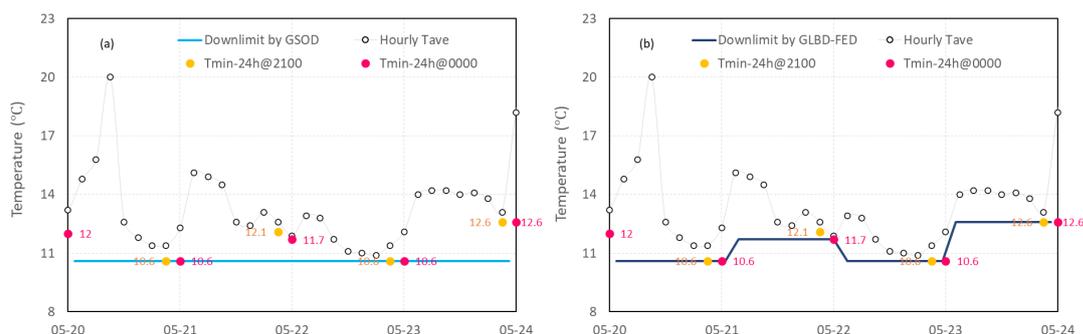
367 **5.3.1. The influence of the daily data definition**

368 Fig.10 displays the variations in air temperature at the SINPO station (470460) in North
 369 Korea from May 20 to May 23, 2014. The hollow black dots represent hourly average air
 370 temperatures recorded at fixed observation times, while the red and yellow dots indicate
 371 the Tmin-12h and Tmin-24h values recorded at 0000 and 2100 UTC, respectively. The
 372 light blue curve in panel (a) and the dark blue curve in panel (b) denote the lower-bound
 373 estimates of air temperature derived from the daily Tmin values based on GSOD and
 374 GLBD-FED data, respectively.

375

376 In the GSOD dataset (panel a), the daily Tmin value for the SINPO station was recorded
 377 as 10.6°C for four consecutive days. This occurred because the Tmin-24h recorded at 0000
 378 UTC on May 21, which was the lowest value during the period from May 21 to May 22,
 379 was treated as the daily Tmin for both May 21 and May 22. Similarly, the Tmin-24h
 380 recorded at 0000 UTC on May 23 was adopted as the daily Tmin for both May 22 and
 381 May 23. As a result, the derived daily Tmin values for May 21 and May 23 are evidently
 382 underestimated and duplicated.

383



385 Figure 10 Variations in air temperature at the SINPO station (470460) in North Korea to
 386 May 23, 2014. The hollow black dots represent hourly average air temperatures recorded at fixed



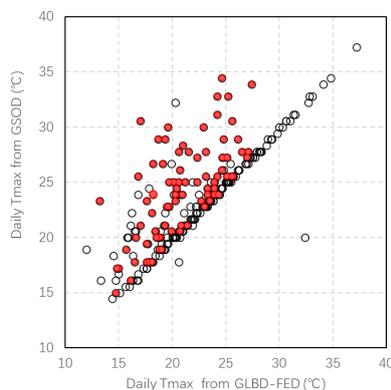
387 observation times, while the red and yellow dots indicate the Tmin-12h and Tmin-24h values recorded at
388 0000 and 2100UTC, respectively. The light blue curve in panel (a) and the dark blue curve in panel (b)
389 denotes the lower-bound estimate of air temperature derived from the daily Tmin values based on GSOD
390 and GLBD-FED data, respectively.

391

392 Fig.11 presents a comparison of daily Tmax values at the Plettenberg Bay station (689310).
393 The abscissa and ordinate represent the daily values from the GLBD-FED and GSOD
394 datasets, respectively. The red solid dots indicate data points that are repeated from
395 previous values, while the black hollow dots represent non-repeating values. The mean
396 difference between the two sets of daily Tmax values shown in the figure is 1.3°C,
397 indicating that GSOD generally reports warmer temperatures compared to GLBD-FED.

398

399 The data points are further categorized into two groups based on the presence of
400 consecutive identical values in GSOD: red points (repeated GSOD values) and black
401 points (non-repeated GSOD values). Interestingly, approximately one-third of the Tmax
402 daily values from GSOD this year were likely duplicated records, showing a significantly
403 positive bias of about 3.2°C. Excluding these red points results in a roughly 70% reduction
404 in the mean bias, decreasing it to 0.4°C. This suggests that GSOD's definition of daily
405 Tmax and Tmin data may lead to repeated records, resulting in more extreme temperature
406 results (higher Tmax and lower Tmin) compared to GLBD-FED.



407

408 Figure 11 A comparison of daily Tmax values at the Plettenberg Bay station (689310), South Africa,
409 for the year 2024. The abscissa and ordinate represent the daily values from the GLBD-FED and GSOD



410 datasets, respectively. The red solid dots indicate the data that are repeated with their previous ones (86
411 points), while the black hollow dots represent non-repeating values (172 points).

412

413 **5.3.2. The influence of the choice of data source**

414 There are several types of sub-daily reports labeled with the same ID in the ISD, and these
415 reports are not always measured at the same location. Both GLBD-FED and GSOD treat
416 these reports independently based on their types, but they have different preferences.
417 Given the more uniform observation mechanisms in meteorological stations compared to
418 airports, GLBD-FED prioritizes synoptic reports over Metar reports as data sources.

419

420 Table 2 presents a case study for Ulan Bator, Mongolia, where two types of sub-daily
421 reports labeled as 442920-99999 originate from different sites in the ISD. GSOD shows
422 significantly lower daily T_{min} values for Ulan Bator compared to GLBD-FED, which
423 uses synoptic reports (Fig. 12 panel a), with an average bias of -4.5°C. These values nearly
424 overlap with the daily T_{min} derived from Metar reports (Figure 12 panel b). This indicates
425 that the daily T_{min} data for Ulan Bator produced from sub-daily temperature reports at
426 airports are much lower than those from meteorological sites. Thus, the choice of data
427 source has a substantial impact on the data quality.

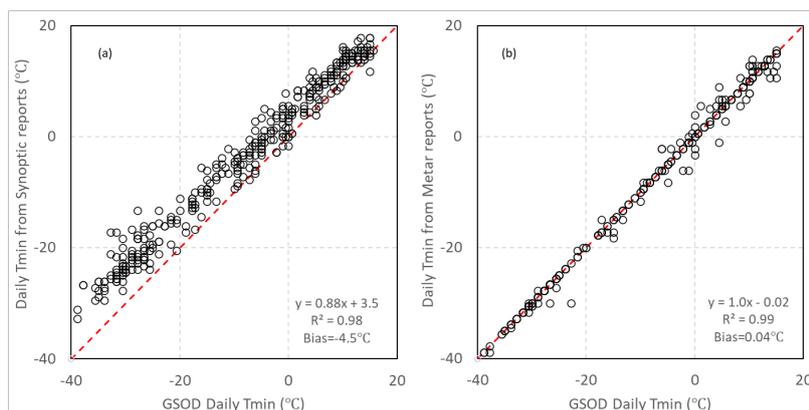
428

429

Table 2 Ulan Bator, Mongolia (442920-99999) sub-daily reports

Reports Type	Longitude	Latitude	Altitude
Synoptic Report (FM-12)	36.067°N	120.333°E	77m
Metar Report (FM-15)	36.266°N	120.374°E	10.05m

430



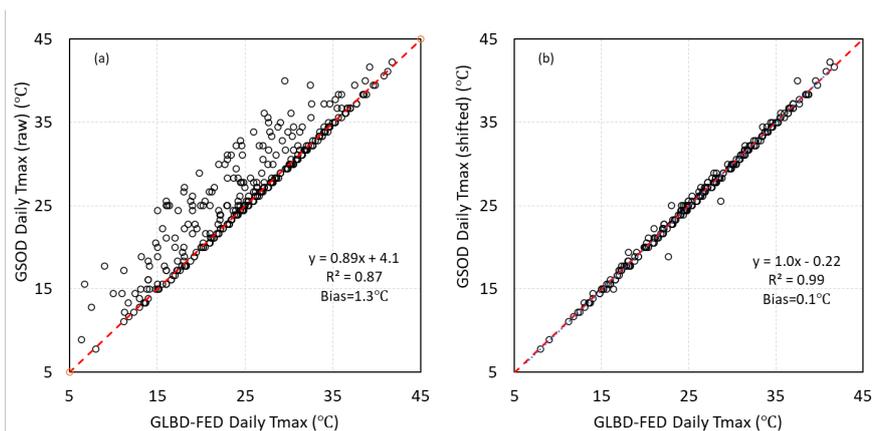
431

432 Figure 12 The comparison of daily Tmin at Ulan Bator, Mongolia (442920-99999) between GLBD-FED
433 and GSOD in 2024. Panel a is the comparison between GLBD-FED (Synoptic reports) and GSOD data,
434 while panel b is similar to panel a but with GLBD-FED (Metar reports).
435

436 5.3.3. The influence of the date boundary treatment

437 The systematic discrepancies identified in Fig.8 originate from methodological
438 divergences between GLBD-FED and GSOD, specifically in temporal alignment
439 frameworks. Fig.13 (a) illustrates this mechanism through a case study at Villa Reynolds,
440 Argentina (31.96°S, 65.13°W), where GSOD exhibits a systematic Tmax warm bias of
441 +1.6°C relative to GLBD-FED. This deviation occurs because GSOD attributes maximum
442 temperatures to calendar days using the 1200 UTC Tmax-24h (0900 local time), in
443 contrast to GLBD-FED's UTC-aligned approach, which reconstructs diurnal extremes by
444 integrating next-day 1200 UTC observations with contemporaneous measurements.
445 Temporal recalibration experiments (Fig.13 (b)) effectively mitigate this discrepancy,
446 achieving inter-dataset convergence at 0.1°C with improved correlation ($R^2=0.99$
447 compared to the original $R^2=0.87$).

448



449

450 Figure 13 The comparison of daily Tmax at Villa Reynolds Argentina between GLBD-FED and GSOD in
451 2022. Panel a is the comparison between GLBD-FED and original GSOD data, while panel b is the
452 comparison between GLBD-FED and date shifted (forward moving) GSOD data.

453

454 6. Data availability

455 The global in-situ temperature daily data are publicly available at
456 <https://zenodo.org/records/17895292>

457

458 7. Conclusion

459 This study develops GLBD-FED, a global in situ daily temperature dataset encompassing
460 maximum (Tmax), average (Tave), and minimum (Tmin) temperatures, constructed using
461 quasi-real-time sub-daily observations from ISD. The main results of this study show that:

- 462 1. To produce a global daily dataset representing maximum, minimum, and average
463 temperatures over a 24-hour period (i.e., one day), we developed a new algorithm
464 that decomposes sub-daily Tmax and Tmin records into finer intervals and then
465 reagggregates them into daily Tmax and Tmin under prospective dateline. Compared
466 to the original method (which relied on two consecutive Tmax/Tmin records over 12
467 hours or one Tmax/Tmin record over 24 hours), the new method increased daily
468 Tmax and Tmin by 64% and 45%, respectively. A correction for misrecorded Tmax
469 and Tmin records was also implemented.



470 2. GLBD-FED includes Tmax, Tave, and Tmin data from approximately 17,000 global
471 sites covering the period from 1981 to 2024. The daily temperature volume of GLBD-
472 FED increased from 3,000 records per day in the 1980s to 10,000 records per day in
473 the 2020s. America and Asia show high spatial densities of daily temperature data,
474 especially in recent years. In comparison to GSOD, Tmax and Tmin from GLBD-
475 FED exhibit more temperate performance, with slightly lower daily Tmax
476 (approximately -0.3°C) and higher daily Tmin (approximately $+0.3^{\circ}\text{C}$), resulting in
477 nearly the same daily Tave (around $+0.1^{\circ}\text{C}$). These differences are primarily
478 attributed to the diversity in daily data definitions and the choice of data sources.

479

480 **8. Author contributions**

481 SY designed and carried out the study, performed the analyses, and drafted the
482 manuscript. PMZ and XBZ contributed to the development of the manuscript
483 framework, provided scientific guidance throughout the research process, and
484 critically reviewed and revised the manuscript. ZJZ reviewed and edited the paper.

485

486 **9. Competing interests**

487 The contact authors have declared that none of the authors has any competing
488 interests.

489

490 **10. Acknowledgements**

491 This work is supported by the National Natural Science Foundation of China
492 (42475152) and The Joint Research Project for Meteorological Capacity
493 Improvement (24NLTSZ005).

494

495 **11. Appendix: Formulae used for Daily Data Quality**

496 **Data Quality Tests**

497 **Spike test**

$$498 \quad q_c = \left\{ \begin{array}{l} \text{credible, } x_{lowerlimit} \leq x_i \leq x_{upperlimit} \\ \text{wrong, } x_i \geq x_{upperlimit} \text{ or } x_i \leq x_{lowerlimit} \end{array} \right\}$$



$$499 \quad x_{upperlimit} = \min[\max(\bar{x}) + 5^{\circ}\text{C}, 80^{\circ}\text{C}]$$

$$500 \quad x_{lowerlimit} = \max[\min(\bar{x}) - 5^{\circ}\text{C}, -80^{\circ}\text{C}]$$

501 Where the subscript i stands for the measurement on the i -th day; $x_{upperlimit} / x_{lowerlimit}$
 502 is the upper/lower threshold value for the record and is the smaller/higher value between
 503 $\max(\bar{x}) + 5^{\circ}\text{C}$ and 80°C , where \bar{x} represents the subset of the historic measurements in
 504 the month (Jan, Feb,...Dec) which removes the smallest and largest 1% of values.

505

506 **Inner consistency test**

$$507 \quad qc = \begin{cases} \text{credible}, T_{max} \geq T_{ave} \geq T_{min}, \\ \text{wrong}, T_{max} \leq T_{ave} \leq T_{min} \\ \text{doubtful}, \text{else} \end{cases}$$

508 Where the T_{max} , T_{ave} , T_{min} stand for the daily T_{max} , T_{ave} , T_{min} data, respectively

509 **Temporal consistency test**

$$510 \quad qc = \begin{cases} \text{credible}, x_i \leq \mu + 2.5\sigma \\ \text{wrong}, x_i > \mu + 5\sigma \\ \text{doubtful}, \mu + 2.5\sigma < x_i \leq \mu + 5\sigma \end{cases}$$

$$511 \quad \mu = \text{median}(\bar{x})$$

$$512 \quad \sigma = \text{std}(\bar{x})$$

513 Where the μ and σ are the median value and standard deviation of \bar{x} , respectively.

514

515 **Spatial consistency test**

$$516 \quad qc = \begin{cases} \text{credible}, \delta_i \leq \min [\bar{\delta} + 2.5\nabla\delta, 10^{\circ}\text{C}] \\ \text{doubtful}, \min [\bar{\delta} + 2.5\nabla\delta, 10^{\circ}\text{C}] < \delta_i < \min [\bar{\delta} + 3.5\nabla\delta, 15^{\circ}\text{C}] \\ \text{wrong}, \delta_i \geq \min [\bar{\delta} + 3.5\nabla\delta, 15^{\circ}\text{C}] \end{cases}$$

$$517 \quad \delta_i = \sqrt{\frac{\sum_{j=1}^m (x_j - x_i)^2}{m}}$$

$$518 \quad \bar{\delta} = \text{median}(\delta_i)$$

$$519 \quad \nabla\delta = \text{std}(\delta_i)$$

520 Where the subscript j stands for the j -th neighbouring sites (within the 100km radius
 521 around the candidate site) and m is the total number of neighbouring sites.

522



523 **Stuck values test**

524
$$qc = \begin{cases} \text{wrong}, & \sigma = 0 \\ \text{credible}, & \text{else} \end{cases}$$

525
$$\sigma = \text{std}(x_{i-1}, x_i, x_{i+1})$$

526
$$\mu = \text{mean}(x_{i-1}, x_i, x_{i+1})$$

527 where σ and μ are the standard deviation and smoothing average of 3 days
528 measurements, respectively.

529

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