



1 **Comprehensive validation of MODIS atmospheric temperature** 2 **profile data across mainland China using sounding observations**

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13 **Abstract.** The vertical profile of atmospheric temperature is crucial for understanding energy transfer within the climate system.
14 The Moderate Resolution Imaging Spectroradiometer (MODIS) atmospheric profile product (MOD07_L2) provides vertical
15 temperature profiles at 5 km spatial resolution. However, comprehensive validation of its absolute accuracy—particularly for
16 lower tropospheric stability (LTS) and temperature inversion layer (TIL) detection—remains limited. Therefore, this study
17 conducted systematic evaluations using sounding data from 74 stations across mainland China spanning 2003–2020,
18 encompassing both daytime and nighttime periods. Results indicated that absolute retrieval accuracy was generally superior at
19 nighttime compared to daytime, with MOD07_L2 demonstrating better performance in upper layers (400–620 hPa) than in
20 lower layers (850–1000 hPa). Nonetheless, retrieval errors at the 700 hPa level exhibited a more pronounced bias (B) relative
21 to other pressure levels. In contrast, LTS accuracy was higher during daytime ($r = 0.74$, $B = 0.04^{\circ}\text{C}$, $\text{RMSE} = 4.52^{\circ}\text{C}$) than at
22 nighttime ($r = 0.57$, $B = 0.3^{\circ}\text{C}$, $\text{RMSE} = 6.78^{\circ}\text{C}$). For TIL, MOD07_L2 displayed limited detection capability, achieving an
23 overall detection rate of 6.6% during daytime and 13.1% at nighttime. This study provides essential data support for
24 atmospheric science, hydrology, and ecology fields that rely on high-resolution vertical temperature profiles.

25 **Keywords:** MODIS, Vertical atmospheric temperature profiles, Absolute accuracy, Lower tropospheric stability, Temperature
26 inversion layers

27 **1 Introduction**

28 The vertical distribution of atmospheric temperature constitutes a fundamental component of Earth's climate system,
29 profoundly influencing weather patterns, atmospheric circulation, and surface environmental processes. In recent years,
30 intensified global climate change has induced substantial alterations in this distribution. Notably, the pronounced tropospheric



31 warming juxtaposed against stratospheric cooling highlights the intricate energy exchanges and dynamic interactions among
32 atmospheric layers (Dessler & Davis, 2010; Seidel et al., 2016). These anomalous variations in temperature profiles have
33 consequently reconfigured global circulation patterns and heightened the frequency of extreme weather events (Seeley, 2021;
34 Galfi et al., 2021).

35 In recent years, rapid advancements in remote sensing technology and numerical simulations have greatly advanced the
36 observation and analysis of vertical temperature distributions from the surface to the stratosphere (Santer et al., 2018; Thorne
37 et al., 2016). The acquisition of vertical temperature data drawn from diverse sources, yet notable disparities existed among
38 datasets in spatial and temporal resolution, parameter coverage, and applicability. Reanalysis datasets, such as the National
39 Centers for Environmental Prediction (NCEP), European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA5),
40 and Climatic Research Unit (CRU), offered global coverage and long-term consistency but fell short in meeting the demands
41 of fields requiring high-resolution data (Hersbach et al., 2020; Gelaro et al., 2017; Saha et al., 2010). For instance, despite
42 optimizations in NCEP's boundary layer parameterization, its coarse spatial resolution (2.5°) remained inadequate for resolving
43 local-scale temperature details (Saha et al., 2010; Grimmond et al., 2010). Similarly, while the CRU dataset provided long-
44 term records, its 0.5° resolution constrained its utility in local-scale studies (Harris et al., 2020). Furthermore, although ERA5
45 excelled in global climate trend analysis, its 0.25° resolution still imposed limitations on regional-scale investigations (Zhao
46 et al., 2014). In contrast, the Moderate Resolution Imaging Spectroradiometer (MODIS) atmospheric profile product
47 (MOD07_L2) emerged as an optimal choice for regional studies, owing to its high spatial resolution of 5 km (Schwarz et al.,
48 2011; Chen et al., 2019). However, existing research has primarily focused on the retrieval accuracy of near-surface (2 m) air
49 temperatures, with systematic evaluations of vertical profiles in mid-to-upper atmospheric layers largely absent (Zhang et al.,
50 2021; Yuan et al., 2023). Additionally, some studies have employed MOD07_L2 vertical temperature profiles to examine
51 atmospheric structures and thermal stratification, albeit relying on limited station data (Huang et al., 2020; Barlow et al., 2015).
52 To date, no nationwide assessment of these profiles has been undertaken across complex terrains and diverse climatic zones.
53 Lower tropospheric stability (LTS) served as a pivotal factor influencing atmospheric vertical distributions and weather
54 patterns, governing air vertical mixing and convective activity intensity. Variations in LTS exhibited strong correlations with
55 atmospheric temperature profiles, particularly in modulating extreme weather events such as severe pollution episodes, air
56 humidity fluctuations, and precipitation extremes (Ning et al., 2018; Guo et al., 2016a; Guo et al., 2016b). Additionally, Li et
57 al. (2014) confirmed that in low-latitude oceanic regions, enhanced LTS is typically significantly associated with subsidence
58 at 700 hPa and increased low-level cloud cover, indicating that LTS serves as a crucial link connecting large-scale dynamical
59 processes with the vertical structure of clouds. As a high-resolution atmospheric vertical profile product, MOD07_L2 held
60 substantial potential for national-scale LTS analysis, yet its efficacy in this domain remained unvalidated. In addition,



61 temperature inversion layers (TIL) represented a key feature of atmospheric vertical temperature distributions, suppressing
62 vertical air mixing and thereby altering local climate conditions (Barlow et al., 2015; Li et al., 2019). Recent research further
63 revealed a close coupling between the inversion layer and the atmospheric boundary layer, jointly influencing the vertical
64 distribution and capture efficiency of aerosols (Liu et al., 2022). The MOD07_L2 dataset furnished temperature data across 20
65 vertical pressure levels, laying a robust foundation for inversion layer detection and analysis (Coll et al., 2012; Leng et al.,
66 2019). Existing validations have predominantly relied on radiosonde or lidar data, leaving the performance of MOD07_L2 in
67 inversion detection unevaluated on a systematic basis.

68 Therefore, this study makes several novel contributions to the field. First, it provides the first long-term (2003–2020) and
69 nationwide validation of MOD07_L2 vertical temperature profiles across China's diverse climatic and topographic regions
70 beyond previous site-specific assessments. Second, it represents the first systematic evaluation of the MOD07_L2 product's
71 capability to retrieve LTS and detect TIL, thereby extending validation beyond single-level temperatures to derived parameters
72 critical for boundary layer and climate studies. Third, the diagnostic analysis of retrieval errors—particularly the attribution of
73 the 700 hPa bias to a combination of atmospheric dynamics, topographic effects, and sensor characteristics—provides
74 actionable insights for both users of the MODIS archive and developers of future satellite missions.

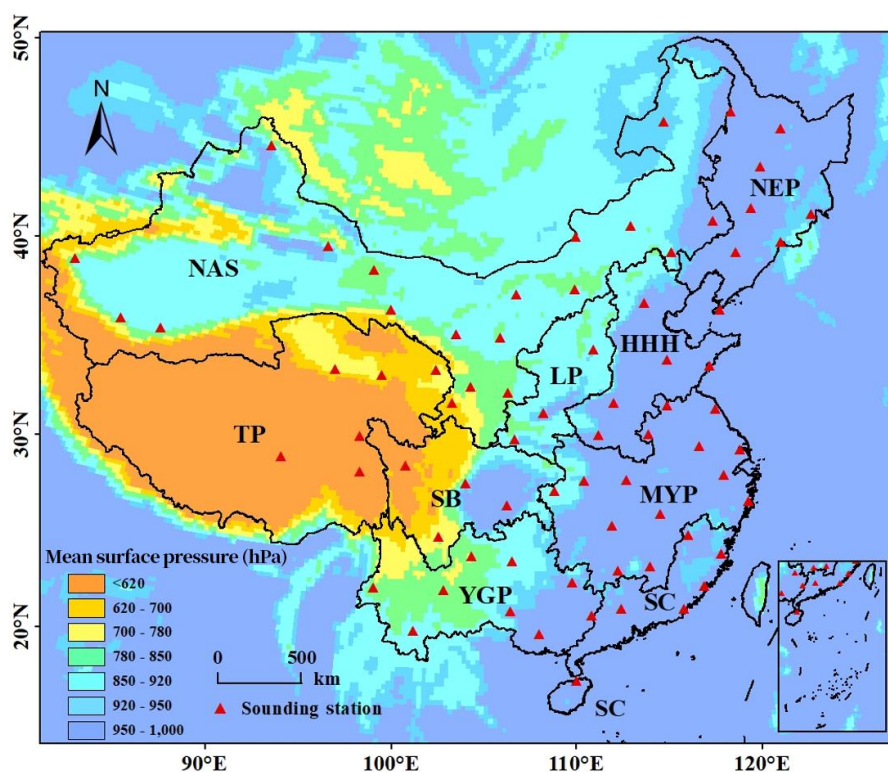
75 **2 Materials and methodology**

76 **2.1 Study area**

77 This study covered the entirety of China, characterized by complex and diverse geographical and climatic conditions. China's
78 topography ascended progressively from east to west, featuring low-lying plains and hills in the east and towering mountains
79 and plateaus in the west—most notably the Tibetan Plateau, with an average elevation surpassing 4,000 m. This configuration
80 established a pronounced topographical gradient. China encompassed a broad spectrum of climate types, spanning tropical
81 zones in the south to cold temperate regions in the north, complemented by alpine climates in the west, thereby engendering
82 substantial climatic diversity. Eastern coastal areas are predominantly humid, whereas western regions are largely arid or semi-
83 arid. These geographical and climatic characteristics amplified variations in surface temperature distributions and atmospheric
84 boundary layer features across regions. To delineate these regional distinctions more precisely, this study adopted China's
85 agricultural zoning framework (Fig. 1), comprising the Northeast China Plain (NEP), the Northern Arid and Semi-Arid Region
86 (NAS), the Huang-Huai-Hai Plain (HHH), the Loess Plateau (LP), the Qinghai-Tibet Plateau (TP), the Middle-Lower Yangtze
87 Plain (MYP), the Sichuan Basin and Surrounding Areas (SB), the Yunnan-Guizhou Plateau (YGP), and Southern China (SC).
88 This zoning scheme is accessible via the following link: <https://gitcode.com/open-source->



89 [toolkit/6b76d/commit/aab463c56bfbc7b0de5024ef53da43a634529ac?ref=main.](https://doi.org/10.5194/egusphere-2026-2290)



90

91 **Figure 1. Annual mean surface pressure and sounding stations distribution in China from 2003 to 2020.**

92 **2.2 Data**

93 **2.2.1 Sounding data**

94 The sounding data utilized in this study were provided by the China Meteorological Administration
95 (<http://weather.uwyo.edu/upperair/sounding.html>). This investigation employed vertical temperature profile data from 74
96 stations recorded from 2003 to 2020 across China. These data were collected using meteorological balloons that measure
97 atmospheric temperature, pressure, and other parameters at various altitudes, ranging from the surface to the upper atmosphere.
98 Sounding observations were conducted daily at 00:00 and 12:00 across more than 100 pressure levels, thereby enabling a
99 detailed characterization of the vertical temperature distribution. The sounding data used in this study adhere to the World
100 Meteorological Organization (WMO) Global Climate Observing System (GCOS) Upper-Air Network (GUAN) standards and
101 underwent rigorous quality control procedures. During the study period, the data completeness rate across all selected stations



102 exceeded 90%, providing a reliable foundation for statistical analysis.

103 **2.2.2 MOD07_L2 data**

104 This study utilizes the MOD07_L2 Collection 6.1 atmospheric profile product generated by NASA's Moderate Resolution
105 Imaging Spectroradiometer (MODIS) sensor. This version incorporates significant improvements in retrieval algorithms and
106 cloud detection, (<https://ladsweb.modaps.eosdis.nasa.gov/search/>). This product provided vertical atmospheric temperature
107 profiles at 20 pressure levels (5, 10, 20, 30, 50, 70, 100, 150, 200, 250, 300, 400, 500, 620, 700, 780, 850, 920, 950, and 1000
108 hPa) with a spatial resolution of 5 km. For this study, temperature data were selected at the 400, 500, 620, 700, 780, 850, 920,
109 950, and 1000 hPa levels, which can represented key temperature distribution characteristics, such as LTS and TIL. For clear
110 expression, the nine pressure levels were categorized into lower layers (850, 920, 950, and 1000 hPa), middle layers (700 and
111 780 hPa), and upper layers (400, 500, and 620 hPa). This classification aligned with standard isobaric surfaces in
112 meteorological studies and reflected the characteristic atmospheric processes at varying altitudes. Additionally, surface
113 pressure data were extracted from the MOD07_L2 product. This dataset shares the same 5 km spatial resolution as the
114 temperature profiles and will be used to calculate near-surface potential temperature for the assessment of lower tropospheric
115 stability.

116 **2.3 Methodology**

117 **2.3.1 Vertical interpolation of vertical temperature profiles**

118 To ensure the comparability between MOD07_L2 retrieved temperature profiles and sounding observation data, vertical
119 interpolation of pressure levels was carried out in this study. A linear interpolation method was employed to interpolate the
120 sounding temperature data onto the corresponding pressure levels of MOD07_L2. If a pressure level P_{modis} in MOD07_L2
121 exactly matched a pressure level in the sounding data, the corresponding sounding temperature T_{sod} was directly used without
122 interpolation. For pressure levels in MOD07_L2 (P_{modis}) that did not match any sounding pressure levels, the two adjacent
123 pressure levels in the sounding data (P_{lower} and P_{upper}) and the corresponding temperatures (T_{lower} and T_{upper}) were
124 searched to satisfy the following relationship:

$$125 \quad P_{\text{lower}} < P_{\text{modis}} < P_{\text{upper}} \quad (1)$$

126 Then, the vertical temperature lapse rate γ was calculated as follows:

$$127 \quad \gamma = \frac{T_{\text{upper}} - T_{\text{lower}}}{P_{\text{upper}} - P_{\text{lower}}} \quad (2)$$

128 This value indicated the amount of temperature change corresponding to a unit change in pressure between adjacent sounding



129 layers. By applying the calculated lapse rate γ , the temperature at the MOD07_L2 pressure level (P_{modis}) was interpolated to
130 obtain its equivalent sounding temperature value as below:

$$131 \quad T_{\text{modis}} = T_{\text{lower}} + \frac{T_{\text{upper}} - T_{\text{lower}}}{P_{\text{upper}} - P_{\text{lower}}} \times (P_{\text{modis}} - P_{\text{lower}}) \quad (3)$$

132 When P_{modis} fell outside the maximum or minimum pressure levels of the sounding data, the following approach was used
133 to handle boundary cases: If the pressure value corresponding to the MOD07_L2 pressure level (P_{modis}) was greater than the
134 maximum pressure value (P_{max} corresponding to the lowest altitude) in the sounding data, interpolation was performed using
135 the two sounding pressure levels with the highest pressure values, $P_{\text{max}-1}$ and P_{max} . Similarly, if the pressure value of
136 MOD07_L2 (P_{modis}) was less than the minimum pressure value (P_{min} corresponding to the highest altitude) in the sounding
137 data, P_{min} and $P_{\text{min}+1}$ were used.

138 2.3.2 Sensitivity analysis of temporal matching window

139 Sounding data are typically observed at 00:00 and 12:00 Beijing Time. However, due to the sun-synchronous orbit of the Terra
140 satellite carrying MODIS, the overpass times of MOD07_L2 data exhibit spatial variations within China, with earlier overpass
141 times in the eastern regions compared to the western regions. To ensure the comparability between satellite retrievals and
142 sounding observations, and to assess the impact of time deviations on retrieval accuracy, this study conducted a time-matching
143 sensitivity experiment. The time deviation ($|\Delta t|$) was divided into four intervals: 0–0.5 hours, 0.5–1 hour, 1–1.5 hours, and 1.5–
144 2 hours. Statistical metrics between MOD07_L2 temperature retrieval values and sounding data were calculated within each
145 interval to determine the optimal matching window. Detailed sensitivity analysis results are presented in the Results section of
146 this article.

2.3.3 Lower Tropospheric Stability Calculation

147 Lower tropospheric stability (LTS) was defined as the difference between the potential temperature at 700 hPa level and that
148 near the surface (Guo et al., 2016a; Ning et al., 2018). To accurately obtain the near-surface temperature from MOD07_L2
149 data, a linear interpolation method was employed. Based on the two pressure levels closest to the surface and their
150 corresponding temperature values, the temperature corresponding to the surface pressure was calculated. In the sounding data,
151 the near-surface layer was defined as the lowest pressure level and its corresponding temperature in the raw data. Subsequently,
152 the temperatures at 700 hPa level and near the surface were converted to potential temperatures using the standard formula.
153 The calculation formula for potential temperature (θ) is as follows:

$$154 \quad \theta = T \left(\frac{p_0}{p} \right)^{\frac{R}{\gamma_p}} \quad (4)$$

155 In this formula, T is the temperature (K), p is the pressure, p_0 is the reference pressure (usually taken as 1000 hPa), R is the



156 gas constant for dry air (R usually taken as $287.05 \text{ J}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$), and c_p is the specific heat at constant pressure for dry air (c_p
157 usually taken as $1004 \text{ J}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$). After obtaining the potential temperatures at the 700 hPa level and near the surface, LTS
158 was calculated as their difference:

$$159 \quad \text{LTS} = \theta_{700\text{hPa}} - \theta_{\text{surface}} \quad (5)$$

160 LTS represents atmospheric stability, higher values indicate greater stability.

161 **2.3.4 Temperature inversion layer detection**

162 The identification of TIL was based on analyzing the vertical temperature differences between neighboring pressure levels.
163 Under standard adiabatic conditions, temperature should decrease as pressure decreases. If adverse, temperature inversion was
164 defined. To evaluate the detection accuracy of temperature inversions in the MOD07_L2 data, its results were compared against
165 sounding observations. The number of inversion layers co-detected with the sounding data (N_{both}) was calculated. The ratio
166 of this number to the total number of inversions independently detected by the soundings (N_{SD}) defines the inversion detection
167 accuracy for that dataset:

$$168 \quad A = \frac{N_{\text{both}}}{N_{\text{SD}}} \quad (6)$$

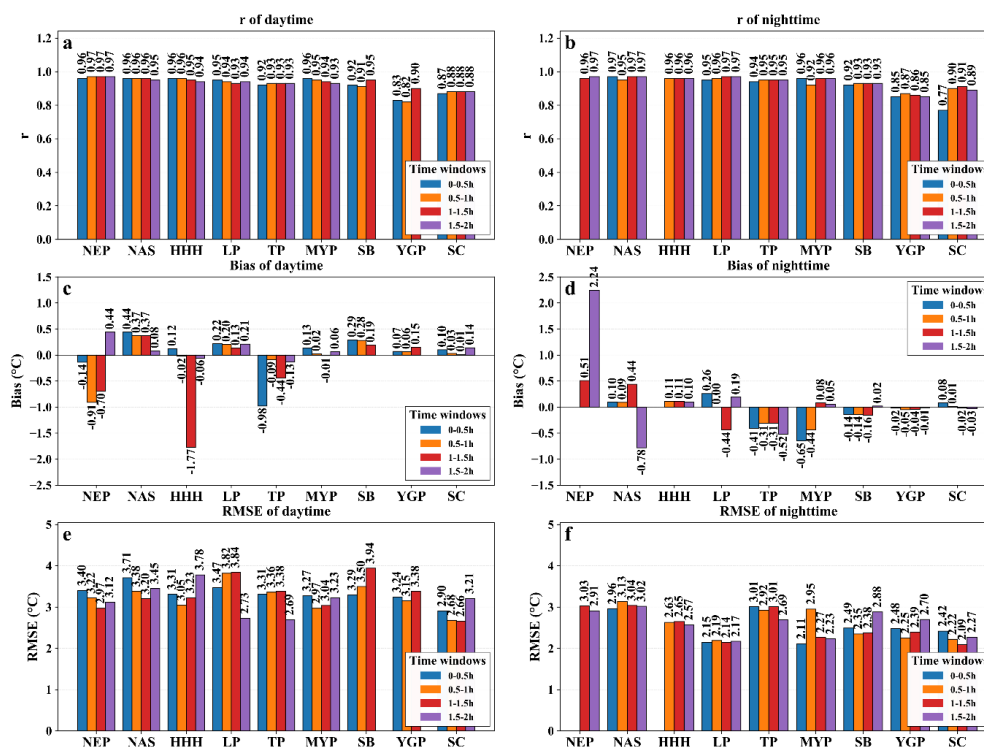
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170 **3 Results**

171 **3.1 Sensitivity analysis of time-matching window**

172 To determine the optimal time-matching window, we analyzed the variations in accuracy between MOD07_L2 temperature
 173 retrievals and sounding observations under different time deviations ($|\Delta t|$) (Fig. 2). The results indicate that when $|\Delta t| < 1$ hour,
 174 no effective matches were found in the NEP, and the sample size in the HHH was also limited, making it insufficient to support
 175 a national-scale evaluation. When the window was expanded to 1–1.5 hours and 1.5–2 hours, the sample size increased
 176 significantly, but the B in some regions became larger: during daytime, the bias in HHH reached -1.77°C under the 1–1.5 hour
 177 window (Fig. 2C); at night, under the 1.5–2 hour window, the bias in the NEP reached 2.24°C , and in the NAS increased to
 178 0.78°C (Fig. 2D). Nevertheless, the r at most sites remained above 0.9, and the increase in RMSE was within an acceptable
 179 range. Balancing sample coverage and retrieval accuracy, this study selected $|\Delta t| < 2$ hours as the final matching threshold.
 180 This threshold ensures sufficient sample size across the national scale while controlling the uncertainty introduced by temporal
 181 mismatch at a reasonable level, laying the foundation for subsequent validation of temperature profiles and derived parameters.



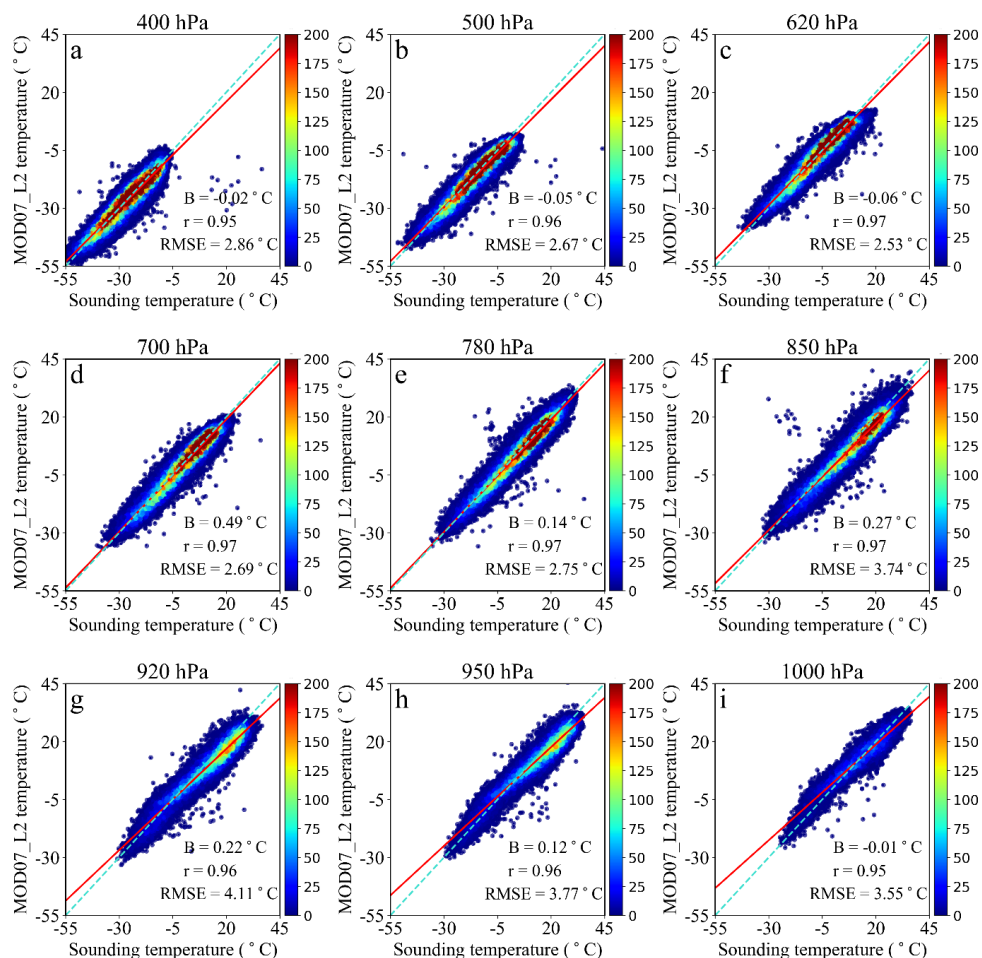
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183 **Figure 2. Sensitivity analysis of temperature retrieval accuracy to different temporal matching windows. (a), (c), and (e) show**



184 **daytime correlation coefficient (r), bias (B), and root mean square error (RMSE), respectively; (b), (d), and (f) show the**
185 **corresponding nighttime statistics.**

186 **3.2 The overall absolute retrieval accuracy during daytime and nighttime**

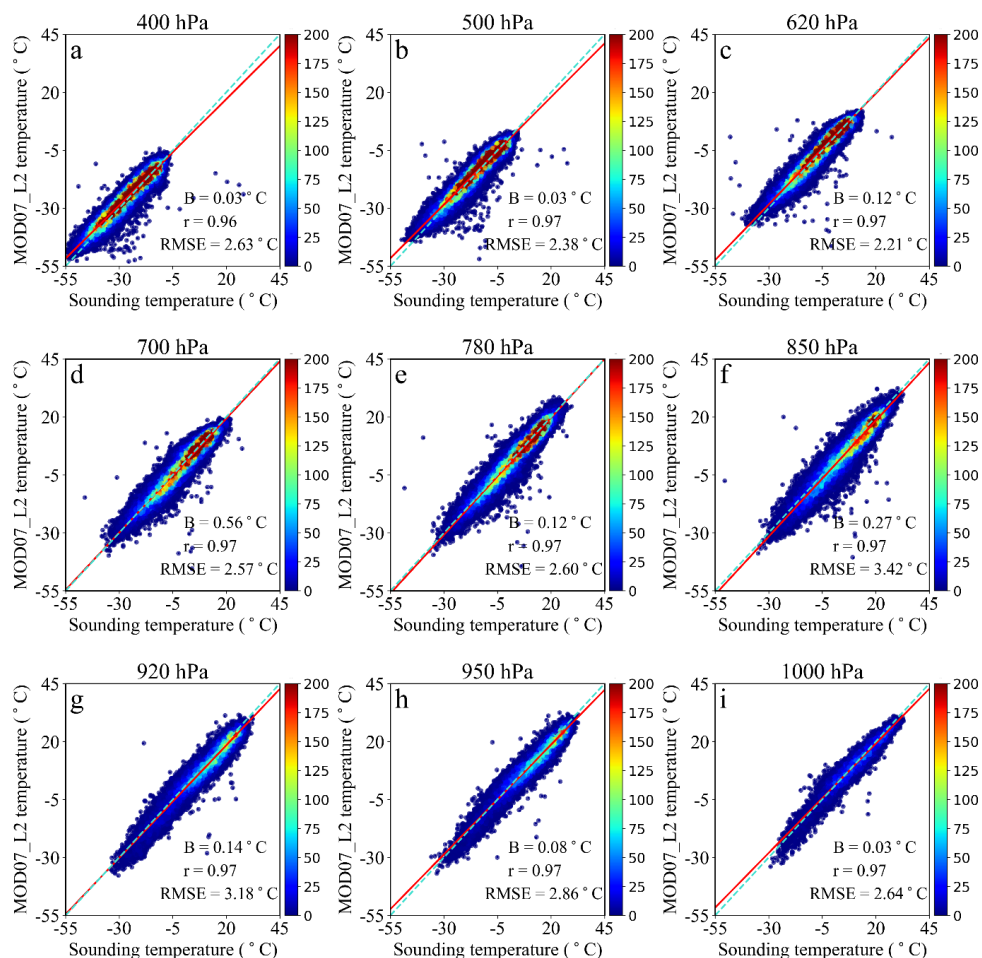
187 Figure 3 illustrated the density scatter distributions between MOD07_L2 instantaneous retrievals and sounding temperatures
188 at different pressure levels during daytime. Results indicated that the retrieval accuracy of MOD07_L2 data was high in the
189 upper layers (400, 500 , and 620 hPa). Specifically, at 400 hPa, the r was 0.95, the B was near 0°C, and the RMSE was around
190 2.8°C. Similar trends were observed at the 500 and 620 hPa levels, where the r remained above 0.95, the B approached 0°C,
191 and the RMSE ranged from 2.5°C to 2.7°C. These results demonstrated the good consistency between the retrievals and the
192 observations in the upper layers. However, the error increased in the lower layers (850, 920, 950 hPa and 1000 hPa).
193 Particularly at the 920 hPa, the r was 0.96, the B was near 0.2°C, and the RMSE reached approximately 4.1°C. This indicated
194 that the retrieval results of MOD07_L2 were unstable in the lower layers. In addition, the 700 hPa presented the high r of 0.97
195 and the RMSE of 2.69°C, but the B was 0.49°C, which was higher than that at other layers. Overall, MOD07_L2 exhibited
196 better retrieval accuracy in the upper layers during daytime conditions, but retrieval errors were larger than those in the lower
197 layers, especially near the surface.



198

199 **Figure 3. Overall accuracy of MOD07_L2 retrieved temperatures compared with sounding observed temperatures during daytime**
 200 **from 2003 to 2020.**

201 Figure 4 illustrated the density scatter distributions between MOD07_L2 instantaneous retrieved and observed atmospheric
 202 temperatures during nighttime. In general, the overall retrieval performance during nighttime was better than that during
 203 daytime. In the upper layers, the r was above 0.96, the B approached 0°C , and the RMSE was ranged from 2.2°C to 2.7°C .
 204 However, at the 700 hPa, the nighttime retrieval B reached 0.56°C , which was higher than other levels. In the lower layers, the
 205 RMSE remained lower than during the daytime. For example, at the 1000 hPa, the r increased from 0.95 during daytime to
 206 0.97, the B remained near 0°C , and the RMSE improved to approximately 2.6°C .



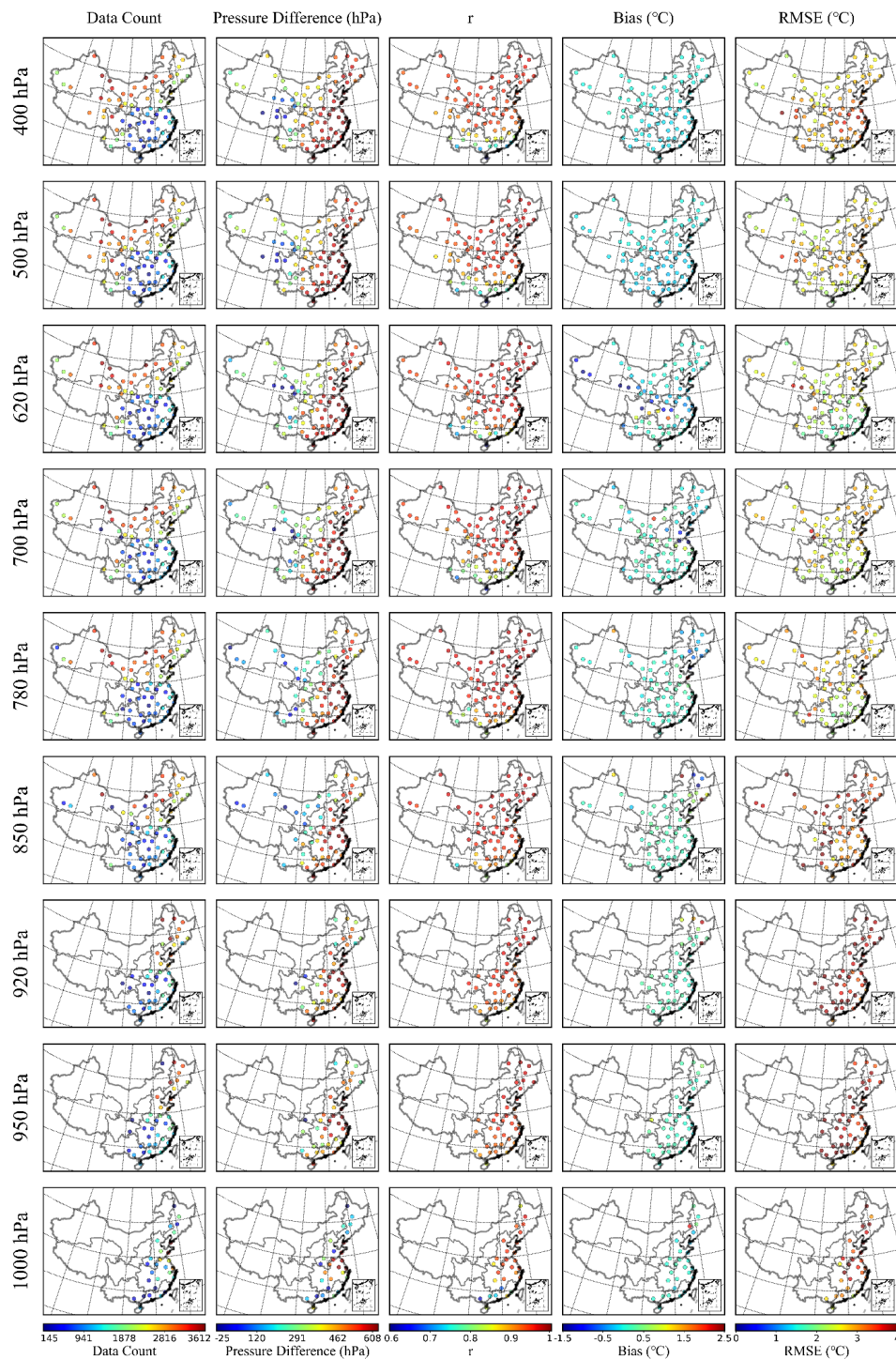
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208 **Figure 4. Overall accuracy of MOD07_L2 retrieved temperatures compared with sounding observed temperatures during nighttime**
 209 **from 2003 to 2020.3 The Spatial Distribution of the Absolute Retrieval Accuracy.**

210 Figure 5 presents the spatial distribution of MOD07_L2 retrieval accuracy metrics across various pressure levels during
 211 daytime. The first two columns display the effective matching sample size for each station and the pressure difference (ΔP)
 212 between the given level and the near-surface layer, respectively. The sample size generally exhibits a decreasing trend from
 213 northwest to southeast across China. The spatial pattern of the ΔP reflects the influence of topography, where a smaller value
 214 indicates that the selected standard isobaric surface is closer to the local ground surface in those regions. The retrieval accuracy
 215 of MOD07_L2 varies across different regions and atmospheric pressure levels. In the upper layers, retrieval performance was
 216 optimal in regions characterized by flat terrain, ample sample sizes, and a large ΔP from the surface, such as the NEP, NAS,
 217 and HHH. The r exceeded 0.95, the B was within $\pm 0.5^\circ\text{C}$, and the RMSE was around 2.5°C . Nevertheless, at some stations



218 over the TP and the MYP, the RMSE at these pressure levels increased to approximately 3.0°C. In the middle levels, the
219 retrieval accuracy improved over the MYP and SB compared with the upper layers. Conversely, in the lower layers, the retrieval
220 errors increased. Particularly over the SC, MYP, and YGP, where sample sizes are relatively small, despite favorable r and
221 minimal B , the RMSE was above 3.5°C. In contrast, retrievals over the NEP and the HHH at the lower layers indicated better
222 accuracy, with r greater than 0.9, the B near 0°C, and the RMSE stabilized near 3.0°C. Overall, under daytime conditions,
223 MOD07_L2 exhibited superior retrieval accuracy at upper-air pressure levels, particularly over flat terrain. In contrast, larger
224 retrieval errors were observed in the lower pressure layers, over complex terrain, and across southern regions with limited data
225 availability.



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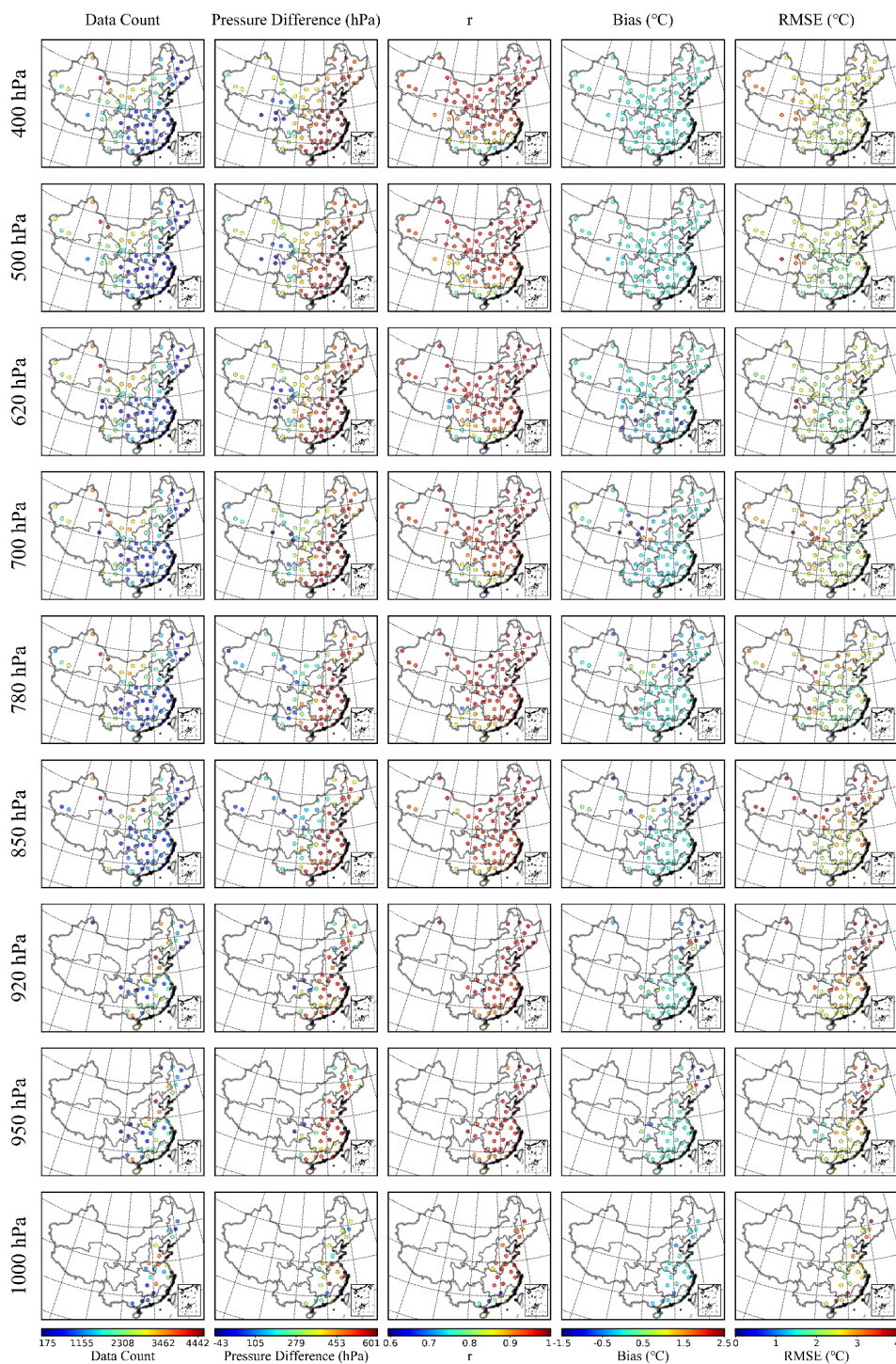
227 Figure 5. Spatial distribution of statistical indicators at each station for MOD07_L2 retrieved versus sounding temperatures at nine



228 **pressure levels during daytime from 2003 to 2020.**

229 Figure 6 illustrated the comparison between MOD07_L2 retrieved temperatures and sounding observations at different
230 pressure levels during nighttime. The first two columns present the effective matched sample size for each station and the ΔP
231 between the given atmospheric level and the near-surface layer, respectively. Spatially, the nighttime sample size exhibits a
232 decreasing gradient from northeast to southwest in the upper and middle layers, while lower counts are observed in the lower
233 layers over the NEP, SC, and the southeastern part of the YGP. Overall, the retrieval accuracy was higher during nighttime
234 than during daytime. In the upper layers, the retrieval accuracy was slightly higher than daytime accuracy over flat regions
235 such as the NEP, HHH, and NAS. The r was above 0.95, the B was close to 0°C , and the RMSE at most stations fell between
236 2.0°C and 2.5°C . In particular, the RMSE decreased by about 0.5°C compared to daytime over the TP and MYP regions. In
237 the middle layers, nighttime retrieval errors were generally lower than those during the daytime. Overall, the r remained above
238 0.95, and the B was close to 0°C . Regionally, the RMSE was about 2.5°C over the NEP and HHH, and about 3.0°C over the
239 NAS. All of these were lower than their daytime counterparts. In the lower layers, the retrieval accuracy at nighttime showed
240 improvement, especially in over the HHH and MYP. The r approached 0.9 and the B remained near 0°C at these regions and
241 the RMSE decreased to around 2.0°C . However, in the NEP region, where the sample size was relatively small, considerable
242 retrieval errors persisted in the lower atmospheric layers, where r decreased to around 0.9, the B exceeded $\pm 0.5^{\circ}\text{C}$, and the
243 RMSE ranged between 3.0°C and 4.0°C . In general, nighttime retrieval accuracy of MOD07_L2 was higher than that during
244 daytime in the upper layers, especially over flat regions. In contrast, the retrieval errors exhibited only a slight increase in
245 lower atmospheric levels, especially in regions characterized by both complex topography and data scarcity.

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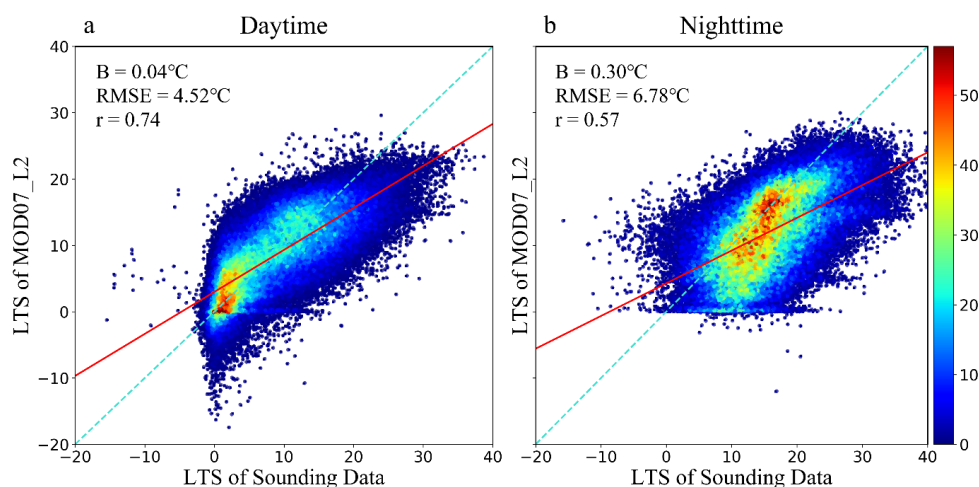
248 Figure 6. Spatial distribution of statistical indicators at each station for MOD07_L2 retrieved versus sounding temperatures at nine



249 pressure levels during nighttime from 2003 to 2020.

250 3.4 The accuracy of lower tropospheric stability

251 Figure 7 illustrated the ability of the MOD07_L2 product to capture lower tropospheric stability (LTS) during both daytime
252 and nighttime. During daytime, the r , B , and RMSE were 0.74, 0.04 °C, and 4.52 °C, respectively. In contrast, during nighttime,
253 r decreased to 0.57, the B increased to 0.30°C and the RMSE rose to 6.78°C. Furthermore, during nighttime, the red regression
254 line diverged more substantially from the cyan diagonal in the density scatter plot, indicating a pronounced systematic error.



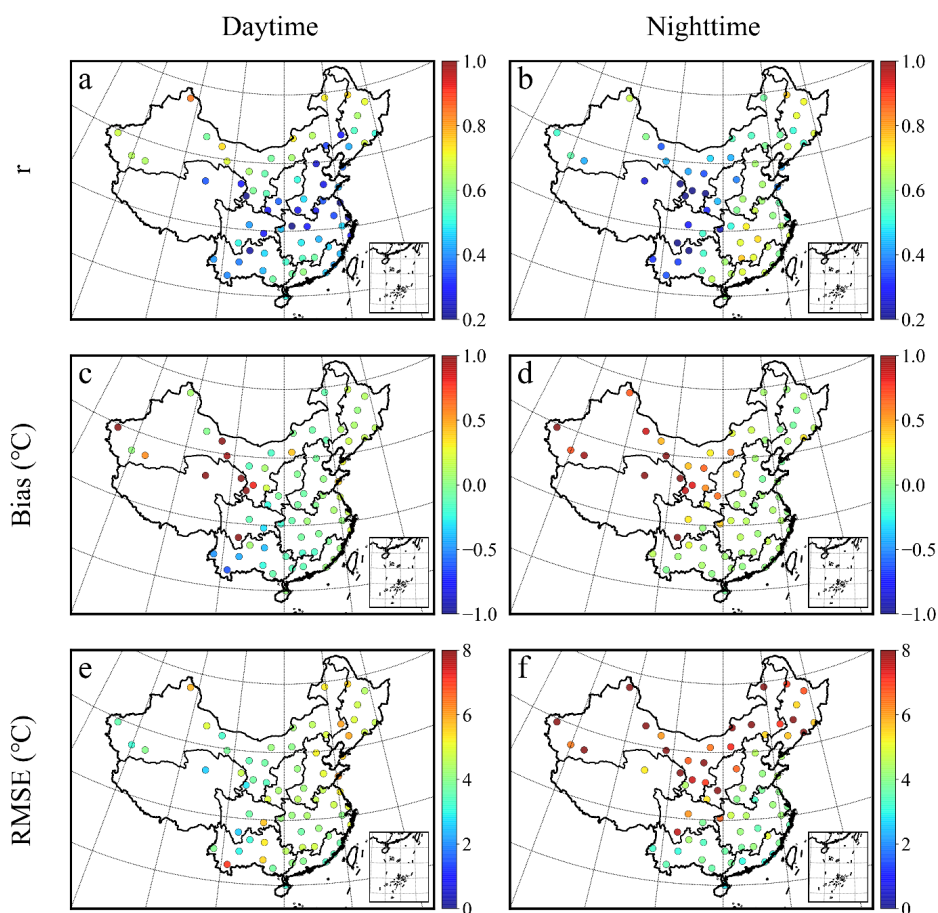
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256 **Figure 7. Heat map of lower tropospheric stability derived from sounding and MOD07_L2 observations during daytime and**
257 **nighttime from 2003 to 2020.**

258 In terms of spatial distribution, the retrieval accuracy of LTS exhibited pronounced regional variability during both daytime
259 and nighttime. During daytime, r values were lower in humid and topographically complex regions such as the SB, MYP, LP,
260 and HHH, with most values falling below 0.5. By contrast, the r values were higher in northern and southern regions,
261 particularly over the NAS where the mean approached 0.6. These results indicated that retrieval performances were superior
262 in arid and flat terrains. The mean RMSE during daytime was about 4°C nationwide, but that was lower along the margins of
263 the TP. Additionally, the large mean biases were evident at the margins of the TP, indicating a systematic error in this area. In
264 contrast, most other regions exhibited modest biases, with errors displaying patchy spatial variability. During nighttime, the
265 spatial distribution of r exhibited a distinct pattern. On the NAS and along the margins of the TP, the r fell below 0.6. In contrast,
266 the higher r values were observed over southeastern and northeastern China, suggesting that retrieval performance in humid
267 zones improved at nighttime compared with daytime. Nighttime RMSE values were lower over the YGP, SC, MYP, and HHH,



268 mostly ranging from 3°C to 4°C, reflecting greater retrieval stability. The RMSE values were elevated over eastern and
269 southern China, as well as along the TP margins, generally exceeding 5°C and thereby indicating greater uncertainty. In terms
270 of bias, eastern and southern China exhibited small deviations, whereas systematic biases persisted on arid and high-elevation
271 regions.



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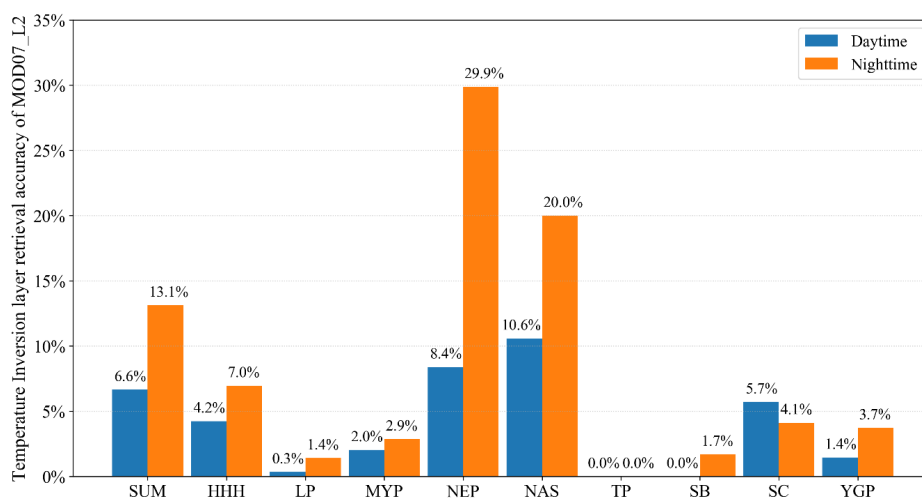
273 **Figure 8. Spatial distribution of MOD07_L2 lower tropospheric stability retrieval accuracy for daytime and nighttime from 2003 to**
274 **2020. (a), (c), and (e) show daytime r, B, and RMSE, respectively; (b), (d), and (f) show the corresponding nighttime metrics.**

275 3.5 The identification of temperature inversion layers

276 Figure 9 illustrated the detection results of TILs by MOD07_L2 over China and its nine agricultural zones during daytime and
277 nighttime. Overall, the proportion of TILs detected by MOD07_L2 was low, with 6.6% during daytime and 13.1% during
278 nighttime. Generally, regions with higher detection rates during the daytime also exhibited higher rates during the nighttime,



279 except for the SB. During the daytime, the detection rate of inversion layers by MOD07_L2 was below 6% in most regions,
 280 even no inversion layers were detected on the TP and in the SB. Only NAS and NEP showed respective 10.6% and 8.4%
 281 detection rates during daytime. During nighttime, the detection rate remained below 10% in most regions, with only NEP and
 282 NAS at 29.9% and 20.0%, respectively. No inversion layers were detected on the TP during nighttime. In general, the detection
 283 rates were higher during nighttime than during daytime across most regions.



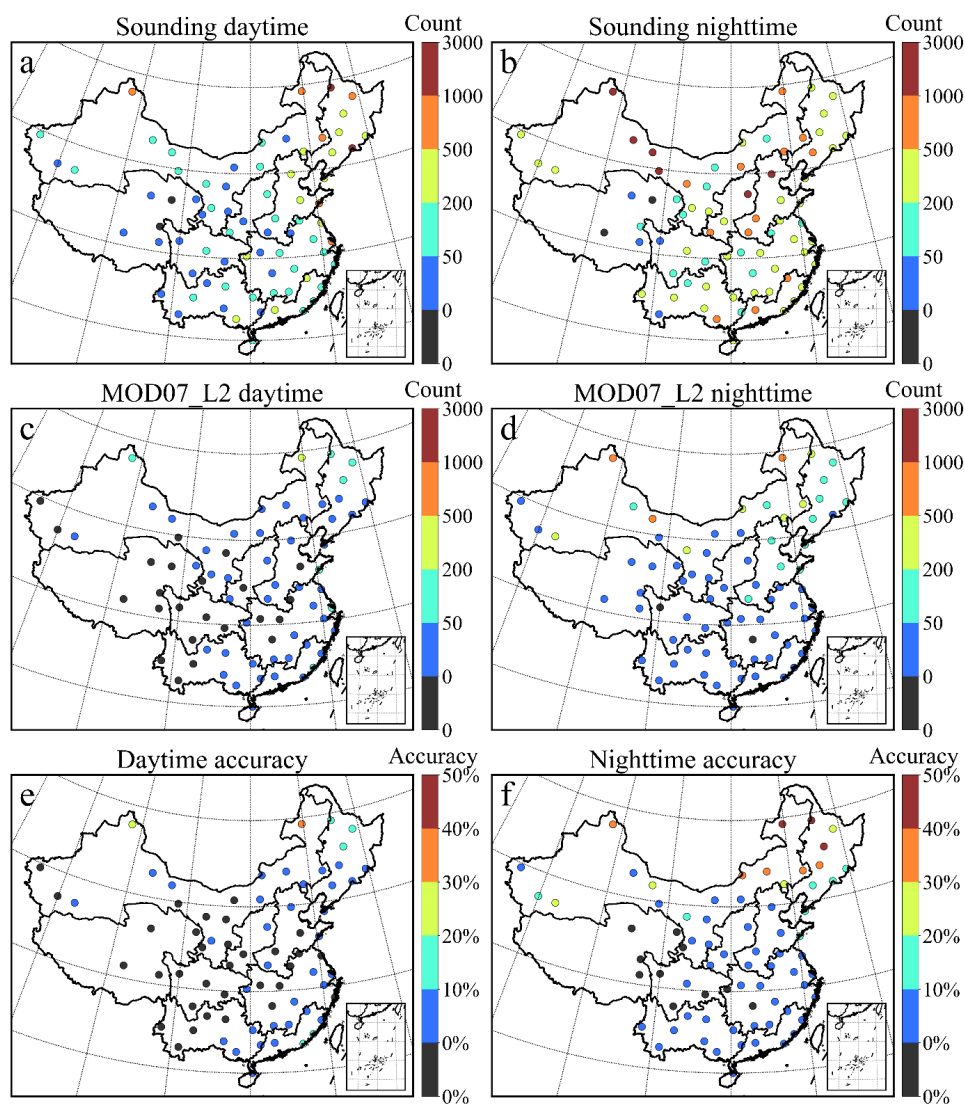
284

285 **Figure 9. The overall detection accuracy of MOD07_L2 for temperature inversion layers, as well as over nine agricultural regions**
 286 **during daytime and nighttime.**

287 As illustrated in Fig. 10, the spatial distributions and detection accuracies of temperature inversions derived from sounding
 288 data and MOD07_L2 exhibited marked discrepancies between daytime and nighttime. During daytime, sounding data recorded
 289 the highest inversion counts in the NEP, with two stations surpassing 1000 events. Most stations in the NEP and HHH region
 290 ranged from 200 to 500 counts, while those in other areas were predominantly below 200. Notably, two stations on the TP
 291 detected no inversions. In contrast, MOD07_L2 identified inversion counts between 50 and 500 solely in the northern portions
 292 of the NEP and in the NAS. The majority of stations elsewhere fell below 50 counts and no detections were detected in the SB.
 293 Only one northeastern station on the TP detected a minimal number. Furthermore, stations in the western portions of the YGP
 294 and on the MYP also failed to detect any inversions. Detection precision exceeded 10% at only a few isolated sites in the
 295 northern in the northern NAS and NEP regions. During nighttime, sounding data revealed that inversion events were more
 296 prevalent and frequent. Stations with inversion counts exceeding 1000 were primarily distributed in western NAS, northern
 297 LP, and northern HHH. Specifically, inversion counts in western NAS, NEP, HHH, and LP were relatively high, all surpassing



298 200. In contrast, the TP exhibited the fewest inversions, with two stations detecting none. The detection performance of
299 MOD07_L2 improved at night, identifying 500–1000 inversions at three stations in northern NAS and exceeding 50 counts in
300 NEP, northern NAS, and northern HHH. However, inversion counts at stations in other regions remained below 50. Detection
301 precision reached 10% only in northern NAS and northern NEP. Notably, MOD07_L2 failed to detect any inversions at stations
302 on the TP, as well as in parts of the SB and MYP.



303

304 **Figure 10.** Spatial distribution and precision of temperature inversion detection based on MOD07_L2 and sounding data during
305 daytime and nighttime from 2003 to 2020. (a) and (b) show the daytime and nighttime distributions derived from sounding data, (c)



306 and (d) show the corresponding distributions from MOD07_L2, (e) and (f) show the detection precision at each station for daytime
307 and nighttime.

308 4 Discussion

309 4.1 Uncertainty of the absolute temperature retrieval

310 This study reveals that the retrieval accuracy of MOD07_L2 satellite temperature profiles significantly decreases as pressure
311 levels approach the Earth's surface. This phenomenon primarily arises from stronger interference by surface longwave radiation
312 in the lower atmosphere, greater variability in surface thermal inertia, and more intense local circulation and temperature
313 fluctuations induced by complex terrain near the surface (Xue et al., 2023; Cheng et al., 2025; Song et al., 2024). Retrieval
314 accuracy is higher in the upper layers, whereas errors increase in the lower layers, with the largest errors occurring in levels
315 close to the surface. Additionally, overall retrieval accuracy is higher at night than during the daytime, mainly because
316 nighttime surface radiative cooling reduces diurnal variations in thermal infrared signals (He et al., 2023).

317 Spatially, the retrieval errors exhibit pronounced regional heterogeneity. In the TP, errors in the middle and lower layers are
318 high, primarily attributable to high elevation and complex terrain causing standard pressure levels to be closer to the surface,
319 as well as extreme diurnal temperature variations that amplify fluctuations in thermal infrared signals (Zhao et al., 2020; Ma
320 et al., 2023). Additionally, the MOD07_L2 product integrates multi-channel infrared brightness temperatures with global
321 reanalysis and sounding data through statistical regression and physical retrieval algorithms (Sobrino et al., 2014; Zhang et al.,
322 2025). In high-elevation regions, the limited number of meteorological stations and sounding observations increases errors in
323 numerical simulations (Zhang et al., 2023). The SB and MYP, experience significantly larger lower-layer errors due to humid
324 climate, frequent stratiform cloud cover, and topographic enclosure (Zhang et al., 2019; Feng et al., 2020). In the NAS, sparse
325 vegetation cover weakens near-surface energy exchange, thereby increasing retrieval errors in the lower layers (Meier et al.,
326 2022). Dust storms and aerosols with high optical thickness further interfere with atmospheric transmittance (Huang et al.,
327 2020).

328 It is particularly noteworthy that MOD07_L2 exhibits substantial systematic biases at the 700 hPa level. The causes of this
329 bias are complex. First, the 700 hPa level serves as a key interface in the mid-troposphere, commonly used to characterize
330 mid-level humidity, vertical motion, and weather system structures such as fronts and shear lines. Its temperature field displays
331 strong spatial heterogeneity, making retrieval or assimilation challenging (Hersbach et al., 2020; Li et al., 2021). Second, in
332 high-elevation regions of China, the 700 hPa standard pressure level lies closer to the surface, rendering this layer susceptible
333 to contamination by surface influences during retrieval (Ma et al., 2023; Zhao et al., 2020). Additionally, the weighting



334 functions of MODIS infrared channels typically peak near the 700 hPa level in the mid-troposphere. This makes them sensitive
335 to temperature but highly susceptible to interference from clouds, water vapor, and aerosols, resulting in cloud contamination
336 or weakened signals in absorption bands (Menzel et al., 2019; Platnick et al., 2003).

337 **4.2 Uncertainty of lower tropospheric stability and temperature inversion layer**

338 This study revealed that the accuracy of LTS retrieved by MOD07_L2 was higher during the daytime than at nighttime, which
339 appears inconsistent with the superior absolute retrieval accuracy of atmospheric temperature observed at night. This
340 discrepancy arose from the nature of LTS as a derived parameter, whose accuracy hinges not only on the absolute retrieval
341 precision of individual layer temperatures but also on the fidelity of vertical temperature gradient retrieval. At night, although
342 atmospheric temperature retrieval accuracy may be enhanced, the frequent occurrence of strong near-surface inversion layers
343 heightened vertical structural complexity (Kaushal et al., 2022; Tan et al., 2021). Furthermore, clouds further complicate
344 nighttime boundary layer structure. A ground-based study at the Southern Great Plains site showed that during cloudy nights,
345 clouds absorb surface longwave radiation and re-radiate it downward, reducing surface radiative cooling rates and thereby
346 enhancing atmospheric instability and turbulence intensity (Liu et al., 2025). This leads to more complex vertical temperature
347 gradients at night, increasing the difficulty of LTS retrieval using MOD07_L2. The limited vertical resolution of MOD07_L2
348 thus struggled to resolve sharp temperature gradients within thin inversion layers, leading to underestimation of near-surface
349 potential temperature via linear interpolation. Moreover, nighttime thermal infrared remote sensing exhibited diminished
350 sensitivity to subtle thermal variations in the boundary layer (He et al., 2023). In humid regions such as SB and MYP, prevalent
351 cloud cover and elevated water vapor further attenuate infrared signal sensitivity to the lower atmosphere (Zhang et al., 2019),
352 thereby degrading LTS retrieval accuracy. Additionally, in areas like the TP edges and NAS, intense nighttime radiative cooling
353 induced rapid temperature gradient shifts, exacerbating LTS retrieval errors (Tian et al., 2023; Chen et al., 2022).

354 In addition, MOD07_L2 identified only a limited number of TILs, possibly due to its 5 km spatial resolution, which may
355 average out thin inversion structures (Seemann et al., 2016). Furthermore, the limited vertical sampling of only 20 standard
356 pressure levels in MOD07_L2 hindered the resolution of shallow near-surface inversions. MOD07_L2 data indicated that
357 nighttime inversions were more frequent than those during the daytime, attributable to nighttime surface longwave cooling
358 that readily initiates and sustains near-surface inversions. This mechanism aligned with findings from multi-site radiosonde
359 observations (Zhang et al., 2022; Zeng et al., 2022). The present study further demonstrates that MOD07_L2 exhibited a higher
360 detection rate and accuracy for nighttime inversions compared to daytime ones, primarily owing to the enhanced boundary
361 layer stability and reduced atmospheric turbulence, which improve the reliability of satellite-based inversion detection (Tan et
362 al., 2021). On a regional scale, the frequency of temperature inversion detection over the Tibetan Plateau is relatively low. This



363 finding aligns with recent evaluations of reanalysis products over the TP, which have also revealed substantial challenges in
364 capturing low-level temperature inversions due to complex terrain and surface–atmosphere interactions (Luo et al.,
365 2025). Furthermore, MOD07_L2 provided fewer effective pressure levels at high-altitude regions, thereby reducing its
366 inversion detection capabilities (Che et al., 2021; Chen et al., 2016). At the SB, the humid and enclosed terrain promoted
367 inversion formation. However, the multi-layered structure and moist air impeded thermal infrared profile retrieval, resulting
368 in lower accuracy (Feng et al., 2020; Feng et al., 2023). At high latitude areas, despite the greater temporal mismatch between
369 the datasets at northern NEP and NAS, MOD07_L2 demonstrated superior accuracy in inversion layer detection in these
370 regions. This finding aligned with long-term radiosonde climatology, underscoring that colder, higher-latitude areas were prone
371 to forming thicker and stronger near-surface inversions (Guo et al., 2020). In humid southern regions such as MYP and YGP,
372 abundant moisture and thin inversion layers impeded effective detection by MOD07_L2. Furthermore, Huang et al. (2021)
373 reported that humid southern China predominantly featured thin, weak elevated inversions, which posed significant challenges
374 for reliable infrared profile retrievals.

375 **4.3 Future effort**

376 Based on the systematic validation of the high-resolution MOD07_L2 satellite product conducted in this study, the performance
377 characteristics and regional applicability of this dataset in terms of vertical temperature profile absolute accuracy, lower
378 tropospheric stability (LTS), and temperature inversion layer (TIL) detection have been clarified. Future work can be deepened
379 in the following directions. First, optimize the spatiotemporal matching scheme by developing more refined interpolation
380 methods or incorporating atmospheric model corrections to reduce boundary layer evolution errors potentially introduced by
381 the $|\Delta t| < 2$ -hour window. Second, deepen error attribution analysis by integrating auxiliary data such as cloud cover, aerosol
382 optical depth, water vapor, and terrain, combined with radiative transfer simulations or machine learning methods, to
383 quantitatively diagnose the formation mechanisms of systematic biases at 700 hPa and regional differences. Finally, further
384 improve the retrieval algorithm performance of the MOD07_L2 product and explore feasible pathways for integrating multi-
385 source observational data, with the aim of generating higher-accuracy temperature profile products, thereby significantly
386 enhancing their application value in regional high-impact weather mechanism analysis, local climate monitoring, and
387 environmental assessment.

388 **5 Conclusion**

389 While the MOD07_L2 atmospheric temperature profile product provides important information at high spatial resolution, there
390 is still a lack of comprehensive evaluation in terms of its absolute retrieval accuracy and its capability to assess boundary layer



391 stability and detect temperature inversions. Therefore, we conducted a comprehensive assessment by comparing it with 74
392 geographically dispersed sounding stations from 2003 to 2020 across China. The absolute retrieval accuracy of MOD07_L2
393 showed clear differences across pressure layers during both daytime and nighttime, with nighttime accuracy generally better
394 than that during daytime. Meanwhile, the upper layers (400–620 hPa) demonstrated higher accuracy, whereas the lower layers
395 (850–1000 hPa) exhibited larger errors in humid and topographically complex regions. However, the retrieval errors at the 700
396 hPa level showed a more significant bias than those in other pressure levels. In contrast, the retrievals of lower tropospheric
397 stability were more reliable during daytime than nighttime. Moreover, there were limitations in detecting temperature inversion
398 layers during both daytime and nighttime. The findings of this study enhance the utility of MODIS's long-term data archive
399 for climate applications and provide a valuable reference for the development and validation of similar products from current
400 and future satellite missions, such as the VIIRS instrument.

401 **CRedit authorship contribution statement**

402 Zhang Wenjie: Conceptualization, Methodology, Supervision, Funding acquisition, Resources, Writing – review & editing. Qu
403 Mengxi: Methodology, Supervision, Data curation, Formal analysis, Writing - Original Draft. Sun Ranhao and Zhao Jiarui:
404 Validation, Supervision. Ning Guicai: Conceptualization, Investigation, Writing – review & editing. Aziz Inamov, Zokhid
405 Mamatkulovd and Zhou Di: Validation, Methodology. Bakhtiyor Pulatov: Methodology. Yang Yuanjian: Conceptualization,
406 Methodology, Supervision, Resources, Writing – review & editing.

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411 **Data availability**

412 The shapefile data of agricultural zones is accessible from [https://gitcode.com/open-source-](https://gitcode.com/open-source-toolkit/6b76d/commit/aab463c56bfbc7b0de5024ef53da43a634529ac?ref=main)
413 [toolkit/6b76d/commit/aab463c56bfbc7b0de5024ef53da43a634529ac?ref=main](https://gitcode.com/open-source-toolkit/6b76d/commit/aab463c56bfbc7b0de5024ef53da43a634529ac?ref=main). The MOD07_L2 data are available
414 from <https://doi.org/10.5067/MODIS/MOD07L2.061>. The sounding data are available
415 from <http://weather.uwyo.edu/upperair/sounding.html>. These data are openly accessible, and no permissions are required to
416 download them. The corresponding data citations have been included in the reference list of this manuscript.

417 **Declaration of competing interest**

418 Some authors are members of the editorial board of *Atmospheric Measurement Techniques*.



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