GENERATION AND VALIDATION OF A DAILY 1KM ALL-WEATHER LAND SURFACE TEMPERATURE DATASET FOR CHINA'S LANDMASS AND SURROUNDING AREAS

Wenbin Tang[1], Ji Zhou[1,*], Jin Ma[1], Ziwei Wang[1], Lirong Ding[1], Xiaodong Zhang[2,3], and Xu Zhang[1]

[1] School of Resources and Environment, University of Electronic Science and Technology of China, Chengdu 611731, China

[2] Shanghai Aerospace Electronic Technology Institute, Shanghai 201109, China

[3] Shanghai Spaceflight Institute of TT&C and Telecommunication, Shanghai 201109, China

ABSTRACT

In this study, we generated a daily (four observations per day) 1 km all-weather LST dataset for China's landmass and surrounding areas, the Thermal and Reanalysis Integrating Moderate-resolution Spatial-seamless (TRIMS) LST, which begins on the first day of the new millennium (1 January 2000). We used the enhanced reanalysis and thermal infrared remote sensing merging (E-RTM) method to generate the TRIMS LST dataset with the temporal gaps being filled, which had not been achieved by the original RTM method. Specifically, we developed two novel approaches, i.e., the random-forest-based spatiotemporal merging (RFSTM) approach and the time-sequential LST-based reconstruction (TSETR) approach, respectively, to produce Terra/MODIS-based and Aqua/MODIS-based TRIMS LSTs during the temporal gaps. We also conducted a thorough evaluation of the TRIMS LST. A comparison with the Global Land Data Assimilation System (GLDAS) and ERA5-Land LST demonstrates that the TRIMS LST has similar spatial patterns but a higher image quality, more spatial details, and no evident spatial discontinuities. The results outside the temporal gap show consistent comparisons of the TRIMS LST with the MODIS LST and the Advanced Along-Track Scanning Radiometer (AATSR) LST, with a mean bias deviation (MBD) of 0.09/0.37K and a standard deviation of bias (STD) of 1.45/1.55 K. Validation based on the in situ LST at 19 ground sites indicates that the TRIMS LST has a mean bias error (MBE) ranging from -2.26 to 1.73K and a root mean square error (RMSE) ranging from 0.80 to 3.68 K. There is no significant difference between the clear-sky and cloudy conditions. For the temporal gap, it is observed that RFSTM and TSETR perform similarly to the original RTM method. Additionally, the differences between Aqua and Terra remain stable throughout the temporal gap. The TRIMS LST has already been used by scientific communities in various applications such as soil moisture downscaling, evapotranspiration estimation, and urban heat island modeling.

INTRODUCTION

➢Significance to China and surrounding areas

- **Since the beginning of the new millennium (post-2000), accompanied by rapid economic development and the implementation of a series of environmental protection measures, there has been a significant impact on land use/cover in this region.**
- **Since LST is highly sensitive to land cover change, heat waves, droughts, and vegetation information, making it an important indicator of global climate change. Therefore, it is important to investigate the spatial and temporal variations of LST for these areas, which requires a long-term, high-quality, and spatio-temporally continuous LST dataset.**

DATASETS

➢Study area

China's landmass and its surrounding areas (19–55° N, 72–135° E)

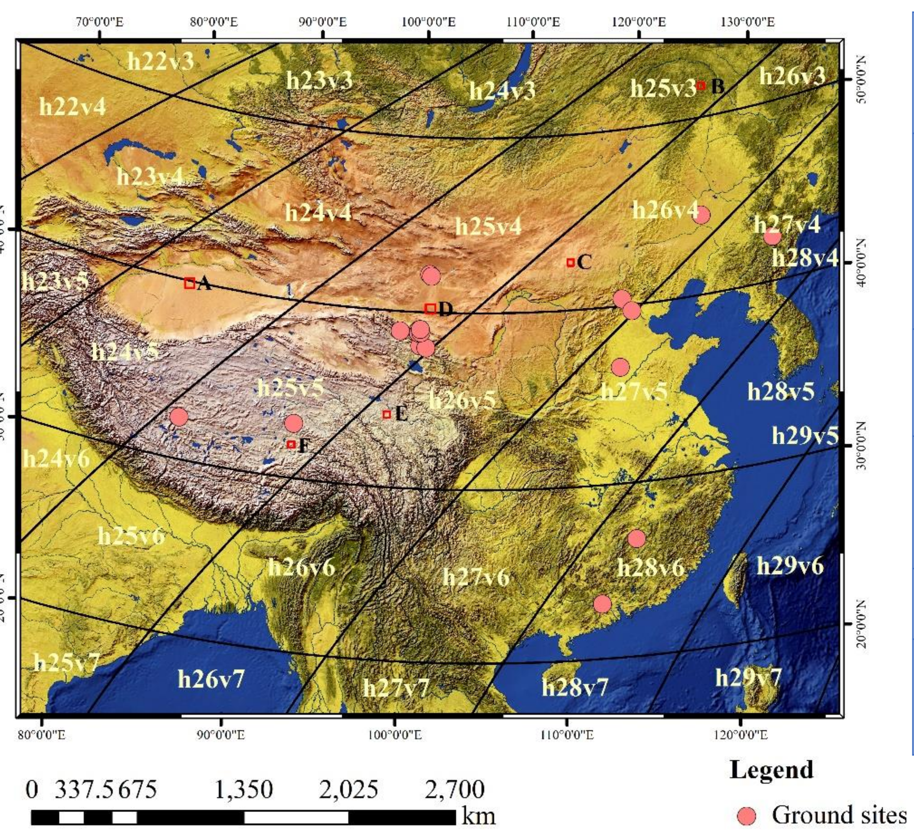

Figure 1: The study area and the selected 19 ground sites.

Table I: Satellite data, reanalysis data and ground measurement.

Datatypes	Satellite data	Reanalysis data	Ground measurements
Details	Terra/Aqua MODIS LST	GLDAS	*In-situ* LST
Spatial resolution	1 km	~25 km	/
Temporal resolution	4 observations per day	3 hour	10 min
Period	2000-2022		
Application	Modelling		Validation

METHODOLOGY

➢Module I: the RTM method

$$LST(t_d, t_{avg}, t_{ins}) = LFC(t_d, t_{avg}) + HFC(t_d, t_{avg}, t_{ins}) + HFC_{cld}(t_d, t_{ins})$$

Module I runs the original RTM method to merge MOD11A1 (MYD11A1) and GLDAS LST, producing daily all-weather LST at the Terra (Aqua) satellite overpass time from DOY 55 of 2000 (DOY 185 of 2002) to DOY 365 of 2022.

➢Module II: the RFSTM approach

- the temporal stage, the daily LST ($\mathbf{LST}_T$) of a pixel Q in a certain period is modeled as:

$$\mathbf{LST}_T = f_T(\mathbf{X}_T)$$

$$\mathbf{X}_T = [\mathbf{P}_{T,1}\ \mathbf{P}_{T,2}\ \dots\ \mathbf{P}_{T,m}]^T = \begin{bmatrix} p_{T,1}(t_{d,1}) & p_{T,1}(t_{d,2}) & \dots & p_{T,1}(t_{d,n}) \\ p_{T,2}(t_{d,1}) & p_{T,2}(t_{d,2}) & \dots & p_{T,2}(t_{d,n}) \\ \dots & \dots & & \dots \\ p_{T,m}(t_{d,1}) & p_{T,m}(t_{d,2}) & \dots & p_{T,m}(t_{d,n}) \end{bmatrix}$$

- the spatial stage, the LST (LSTS) at td in the prediction period is expressed as:

$$\mathbf{LST}_S = f_S[N_{S,1}(t_d)\ N_{S,2}(t_d)\ \dots\ N_{S,k}(t_d)]$$

The RFSTM approach was developed to predict the all-weather LST during the period of DOY 1–54 2000, during which the Terra MODIS LST was not available. It is based on the fact that (i) the LST of a pixel in the temporal dimension is strongly affected by the meteorological conditions as well as the underlying surface and that (ii) the LST of many pixels at a certain time are closely related to their underlying surfaces. Therefore, RFSTM has two stages, i.e., the temporal stage and the spatial stage.

➢Module III: the TSETR approach

$$\begin{cases} LFC_{\text{M-Aqua-T1}}(t_d, t_{avg}) = LFC_{\text{M-Terra-T1}}(t_d, t_{avg}) + \Delta LFC_M(t'_d, t_{avg}) \\ \Delta LFC_M(t'_d, t_{avg}) = LFC_{\text{M-Aqua-T2}}(t'_d, t_{avg}) - LFC_{\text{M-Terra-T2}}(t'_d, t_{avg}) \end{cases}$$

$$\begin{cases} HFC_{\text{M-Aqua-T1}}(t_d, t_{\text{ins-Aqua-T1}}) = HFC_{\text{M-Terra-T1}}(t_d, t_{\text{ins-Terra-T1}}) + \\ \Delta HFC_{\text{M-Terra-Aqua-T1}} \\ \Delta HFC_{\text{M-Terra-Aqua-T1}}(t_d, t_{ins}) = f_{\text{M-T2}}(g_M, DEM_M, NDVI_M(t_d), \\ slp_M(t_d), \alpha_M(t_d), v_M(t_d), \Delta LFC_M, \Delta DTC_M) \\ \Delta DTC_M = \Delta DTC_{\text{M-Aqua}}(t_d, t_{ins}, t_{avg}) - \Delta DTC_{\text{M-Terra}}(t_d, t_{ins}, t_{avg}) \end{cases}$$

$$HFC_{\text{cld-M-G-Auqa-T1}}(t_d, t_{ins}) = LST_{\text{M-G-Auqa-T1}}(t_d, t_{ins}) - LFC_{\text{M-Auqa-T1}}(t_d, t_{avg}) - HFC_{\text{M-Auqa-T1}}(t_d, t_{ins})$$

The TSETR approach was developed to estimate the all-weather LST during the period from DOY 1 of 2000 to DOY 184 of 2002 during which the Aqua/MODIS LSTs were not available (with a temporal gap of 915 days). Terra/MODIS LST from 2000-2002 could be transformed into Aqua/MODIS LST. Since the Terra/MODIS LST (MOD11A1) is available as a reference in the temporal gap, we generated an all-weather LST based on the TSETR approach, which is reconstruction rather than prediction.

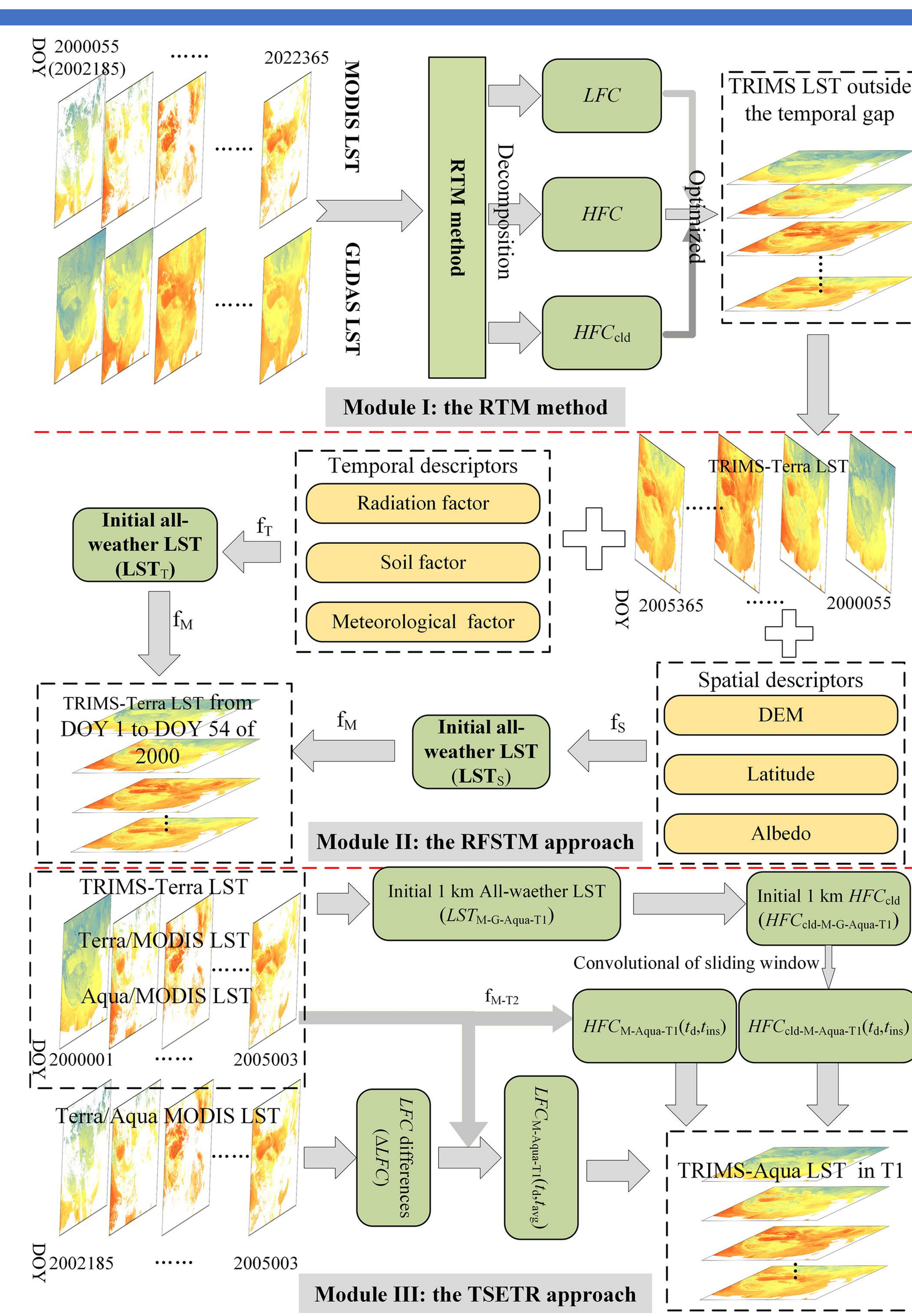

Figure 2: Flowchart of the E-RTM method.

RESULTS

➢Comparison of the TRIMS LST with reanalysis data and satellite TIR LST

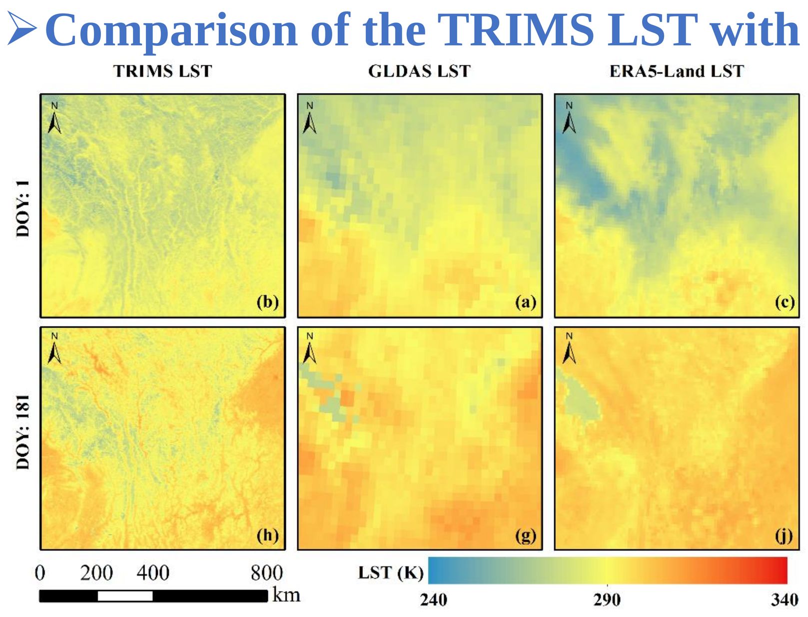

Figure 3: Spatial patterns of the daytime LST.

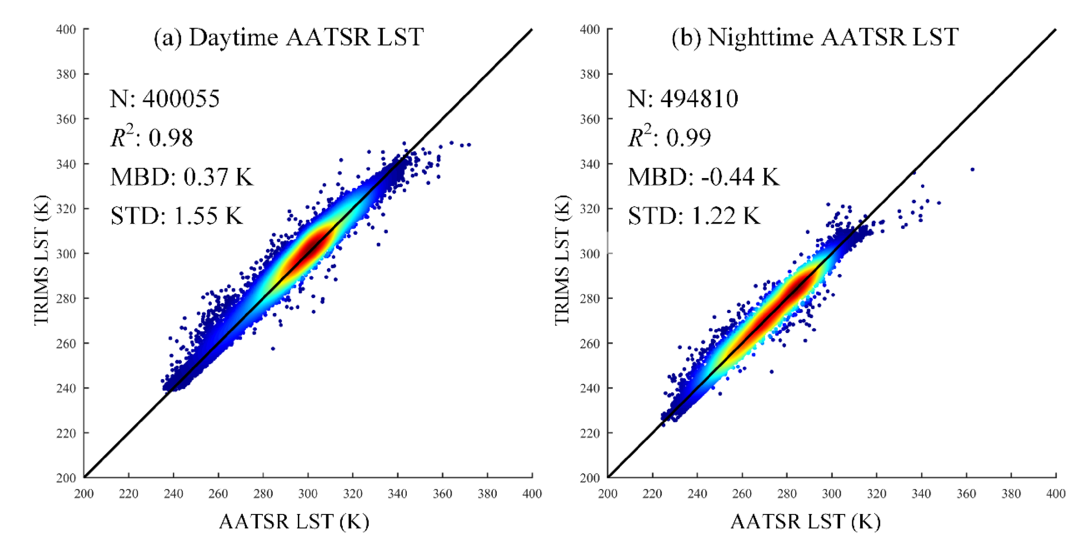

Figure 4: Density plots between the TRIMS LST and the AATSR LST.

➢Validation against *in-situ* LST

Table II: R^2, MBE, and RMSE of the daytime validation for different groups.

Group	LC	Condition	Amounts	TRIMS LST			MODIS LST		
				MBE (K)	RMSE (K)	R^2	MBE (K)	RMSE (K)	R^2
I	Grassland	Clear-sky	5370	0.26	2.15	0.95	0.61	2.37	0.95
		Cloudy	6972	0.41	2.18	0.96	–	–	–
II	Desert or barren land	Clear-sky	5930	0.46	2.30	0.98	0.79	2.53	0.98
		Cloudy	5698	0.43	2.26	0.98	–	–	–
III	Cropland	Clear-sky	5738	0.02	2.11	0.97	-0.21	2.52	0.95
		Cloudy	7570	0.04	2.11	0.97	–	–	–
IV	Forest	Clear-sky	3170	0.55	2.46	0.97	0.72	2.38	0.98
		Cloudy	3655	0.68	2.27	0.98	–	–	–

CONCLUSION

- **TRIMS LST agrees well with the original MODIS and GLDAS LST and the independent ERA5 and AATSR LST but with more spatial details and better spatiotemporal completeness.**
- **TRIMS LST has a mean bias error (MBE) ranging from -2.26 K to 1.73 K and a root mean square error (RMSE) ranging from 0.80 K to 3.68 K. There is no significant difference between the clear-sky and cloudy conditions.**

KEY REFERENCES

Tang, W., Zhou, J., Ma, J., Wang, Z., Ding, L., Zhang, X., and Zhang, X.: TRIMS LST: a daily 1 km all-weather land surface temperature dataset for China's landmass and surrounding areas (2000–2022), Earth Syst. Sci. Data, 16, 387–419, https://doi.org/10.5194/essd-16-387-2024, 2024.

Zhang, X., Zhou, J., Liang, S., and Wang, D.: A practical reanalysis data and thermal infrared remote sensing data merging (RTM) method for reconstruction of a 1-km all-weather land surface temperature, Remote Sensing of Environment, 260, 112437, https://doi.org/10.1016/j.rse.2021.112437, 2021.