Supplementary Material

Text S1. Evaluation datasets

China Meteorological Administration Land Data Assimilation System version 2.0 (CLDAS-V2.0) was used to evaluate the simulated 2 m air temperature and precipitation. CLDAS-V2.0 provides hourly gridded meteorological fields at a horizontal resolution of 0.0625° over China and surrounding regions (Sun et al., 2020). The product integrates surface meteorological observations, satellite retrievals, and numerical model background fields through multi-source data fusion and land data assimilation procedures. Depending on the meteorological variable, these procedures include the Space-Time Multiscale Analysis System, optimal interpolation, probability density function matching, and terrain correction. Previous evaluations against surface-station observations have shown that CLDAS-V2.0 performs well in reproducing the spatial and temporal variations of near-surface air temperature and precipitation across China, with particularly good agreement for air temperature (Sun et al., 2020). Some uncertainties remain over complex terrain and during localized heavy precipitation events.

Daily precipitation observations from 42 surface meteorological stations were obtained from the National Meteorological Science Data Center of the China Meteorological Administration and were used to evaluate the simulated precipitation-frequency distribution. The observations consist of daily accumulated precipitation measured by the operational surface rain-gauge network and subjected to the operational quality-control procedures of the China Meteorological Administration.

The daytime LST fields from the MOD21A2 and MYD21A2 Collection 6.1 land surface temperature products were used to evaluate the simulated skin temperature (Hulley et al., 2018). These products are derived from the Moderate Resolution Imaging Spectroradiometer instruments aboard the Terra and Aqua satellites and have spatial and temporal resolutions of 1 km and 8 days, respectively. The MOD21/MYD21 products apply a physics-based Temperature – Emissivity Separation algorithm to retrieve land surface temperature and spectral emissivity simultaneously from MODIS thermal infrared bands 29, 31, and 32 (Hulley et al., 2018). Validation over barren surfaces in northwestern China showed that MYD21 generally agreed well with in situ measurements (Li et al., 2021). Remaining uncertainties are mainly associated with residual cloud contamination and surface heterogeneity, particularly over arid regions. MODIS pixels flagged as cloudy were excluded prior to comparison.

Text S2. Effective-albedo experiment

S2.1 Experimental design

To directly compare the physically based WRF-PV model with the effective albedo (EA) method used in previous climate-modeling studies, we conducted an additional experiment referred to as WRF_EA. WRF_EA used the same model domains, horizontal and vertical resolutions, simulation periods, initial and lateral boundary conditions, atmospheric physical parameterizations, and annual PV spatial distributions as WRF_PV and WRF_CTL. The only difference was the representation of PV installations.

The simulations were conducted separately for the summers of 2018–2024. Each annual simulation started on 1 May and ended on 31 August. May was discarded as model spin-up, and June–August was used for evaluation and analysis. In WRF_EA, the physically based PV module was deactivated, and the original surface albedo of each grid cell containing PV installations was replaced by a constant effective albedo. All other model settings were retained.

S2.2 Effective-albedo formulation

The EA method represents reflected solar radiation and the fraction of solar energy converted into electricity as energy unavailable for surface heating (Li et al., 2018). In WRF_EA, a constant effective albedo of α_EA = 0.15 was applied to all PV grid cells. This value was selected using a PV panel reflectance of α_PV = 0.0436 and an electrical conversion efficiency of Eff_PV = 0.112. The two quantities were calculated from the actual reflected shortwave radiation and electrical power generation, respectively. Thus, α_EA represents the combined fraction of incoming solar energy reflected by the panels or converted into electricity.

S2.3 Evaluation results

WRF_EA substantially degraded the simulation of skin temperature over PV installations. It produced a mean TSK bias of +2.62 °C and an RMSE of 4.02 °C, both larger than those of WRF_PV and WRF_CTL. The positive bias indicates that the EA method systematically overestimated the spatially averaged TSK over the PV locations.

At the domain scale, the mean T2 bias in WRF_EA was comparable to those in WRF_PV and WRF_CTL. However, its T2 RMSE increased to 2.22 °C, compared with 1.78 °C in WRF_PV and 1.81 °C in WRF_CTL. The EA method therefore did not produce a clearly larger domain-mean T2 bias, but it reduced the overall agreement of the simulated T2 field with CLDAS.

WRF_EA also produced larger domain-scale precipitation errors. Its precipitation bias and RMSE were +0.14 and 1.06 mm day^{-1}, respectively. The precipitation RMSE was nearly twice those of WRF_PV and WRF_CTL, which were both approximately 0.55 mm day^{-1}. Overall, the EA method showed poorer performance in simulating TSK over PV installations and domain-scale precipitation.

Table S1. Evaluation statistics for WRF_CTL, WRF_PV, and WRF_EA during the summers of 2018–2024.

Variable and evaluation range	Experiment	Bias	RMSE
Panel TSK versus MODIS	WRF_CTL	+0.697 °C	3.071 °C
	WRF_PV	−0.340 °C	2.560 °C
	WRF_EA	+2.619 °C	4.021 °C
T2 versus CLDAS	WRF_CTL	+0.49 °C	1.81 °C
	WRF_PV	+0.38 °C	1.78 °C
	WRF_EA	+0.40 °C	2.22 °C
precipitation versus CLDAS	WRF_CTL	+0.05 mm day^{-1}	0.55 mm day^{-1}
	WRF_PV	+0.08 mm day^{-1}	0.55 mm day^{-1}
	WRF_EA	+0.14 mm day^{-1}	1.06 mm day^{-1}

References

Hulley, G. C., Malakar, N. K., Islam, T., and Freepartner, R. J.: NASA's MODIS and VIIRS Land Surface Temperature and Emissivity Products: A Long-Term and Consistent Earth System Data Record, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., 11, 522–535, https://doi.org/10.1109/JSTARS.2017.2779330, 2018.

Li, Y., Kalnay, E., Motesharrei, S., Rivas, J., Kucharski, F., Kirk-Davidoff, D., Bach, E., and Zeng, N.: Climate model shows large-scale wind and solar farms in the Sahara increase rain and vegetation, Science, 361, 1019–1022, https://doi.org/10.1126/science.aar5629, 2018.

Li, H., Li, R., Yang, Y., Cao, B., Bian, Z., Hu, T., Du, Y., Sun, L., and Liu, Q.: Temperature-based and radiance-based validation of the Collection 6 MYD11 and MYD21 land surface temperature products over barren surfaces in northwestern China, IEEE T. Geosci. Remote Sens., 59, 1794–1807, https://doi.org/10.1109/TGRS.2020.2998945, 2021.

Sun, S., Shi, C., Pan, Y., Bai, L., Xu, B., Zhang, T., Han, S., and Jiang, L.: Applicability Assessment of the 1998–2018 CLDAS Multi-Source Precipitation Fusion Dataset over China, J. Meteorol. Res., 34, 879–892, https://doi.org/10.1007/s13351-020-9101-2, 2020.