



1 **Benchmarking and evaluating the NASA Land Information System (version 7.5.2) coupled**
2 **with the refactored Noah-MP land surface model (version 5.0)**

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16 **Abstract**

17 We integrate the refactored community Noah-MP version 5.0 model with the NASA Land
18 Information System (LIS) version 7.5.2 to streamline the synchronization, development, and
19 maintenance of Noah-MP within LIS and to enhance their interoperability and applicability. We
20 evaluate and compare 5-year (2018-2022) global and regional benchmark simulations of
21 LIS/Noah-MPv5.0 and LIS/Noah-MPv4.0.1 for a set of key land surface variables. Both models
22 capture the spatial and seasonal distributions of observed soil moisture, latent heat (LH), snow
23 water equivalent (SWE), snow depth, snow cover, and surface albedo, with similar bias patterns.
24 Both models tend to have negative soil moisture bias over wet soil regimes and positive bias over
25 dry soil regimes, with slightly higher ($\leq \sim 0.01 \text{ m}^3/\text{m}^3$ for global mean) soil moisture in LIS/Noah-
26 MPv5.0 than LIS/Noah-MPv4.0.1 across most regions. The model bias patterns of LH overall
27 follow those of soil moisture, while LIS/Noah-MPv5.0 has a lower LH across most non-polar
28 regions than LIS/Noah-MPv4.0.1, which reduces the global mean LH bias from 0.99 W/m^2 to -
29 0.39 W/m^2 . The model SWE bias patterns are dominated by the precipitation and temperature
30 forcing uncertainties, with slightly lower SWE values in LIS/Noah-MPv5.0 (global mean bias of
31 -13.2 mm) than LIS/Noah-MPv4.0.1 (global mean bias of -10.1 mm). The model bias patterns of



32 snow depth generally follow those of SWE. LIS/Noah-MPv4.0.1 consistently overestimates snow
 33 cover globally with a mean bias of 0.11, while LIS/Noah-MPv5.0 effectively reduces the
 34 overestimates across the global snowpacks with a mean bias of 0.07 because of updated snow
 35 cover parameters. Both models show widespread overestimates of surface albedo over mid-latitude
 36 and high-latitude regions but significant underestimates in the Sahara Desert and Antarctica. This
 37 study reveals possible model deficiencies, motivates future improvements in coupled canopy-
 38 snowpack-soil processes and input soil data, and points to the importance of considering
 39 observational and forcing data uncertainties in model evaluation.

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42 1. Introduction

43 Land processes play a profound role in the Earth and climate systems through altering
 44 surface water and energy balances and feedback to the atmosphere (Fisher and Koven, 2020; Blyth
 45 et al., 2021). Earth's land surface provides important boundary conditions for atmospheric
 46 processes and climate/weather predictions particularly at the subseasonal-to-seasonal (S2S) time
 47 scale (Koster and Walker, 2015; Benson and Dirmeyer, 2023). Furthermore, as climate changes,
 48 increasing climate/weather extremes (e.g., drought, flood, heatwave, and fire) and food-water
 49 security issues (e.g., agricultural production and irrigation management) are happening at the land
 50 surface, triggering key crises for the society (Sillmann et al., 2017; AghaKouchak et al., 2020). To
 51 tackle these critical land-related environmental issues, accurate land modeling systems are needed.

52 There have been substantial efforts in the past decades to develop and improve various land
 53 modeling systems (e.g., Dickinson et al., 1993; Liang et al., 1994; Chen et al., 1997; Ek et al.,
 54 2003; Oleson et al., 2010; Best et al., 2011; Niu et al., 2011; Haverd et al., 2018). Among them,
 55 the NASA Land Information System (LIS) is a widely used, established open-source framework
 56 for high performance land surface and terrestrial hydrology modeling as well as data assimilation
 57 (DA) of satellite and ground-based observations (Kumar et al., 2006; Peters-Lidard et al., 2007;
 58 Kumar et al., 2008a). The LIS system integrates different land surface models (LSMs), satellite
 59 and ground observations, and advanced computing and data management tools, to enable an
 60 interoperable environment that is applicable across different spatial and temporal scales. Various
 61 model developments and applications using LIS have been conducted in the past decade, such as
 62 coupling with atmospheric models to improve weather predictions (Kumar et al., 2008b; Wu et al.,



63 2016), DA of observed vegetation, snow, terrestrial water storage, albedo, and soil conditions to
 64 improve land surface modeling (Liu et al., 2015; Santanello et al., 2016; Kumar et al., 2016; Kumar
 65 et al., 2019; Kumar et al., 2020), and applications for hydrological predictions (Arsenault et al.,
 66 2020), food security (Hazra et al., 2023), and land analysis (Nie et al., 2024).

67 LIS allows the use of an ensemble of LSMs, such as Noah (Chen et al., 1997; Ek et al.,
 68 2003), Noah-MP (Niu et al., 2011), CLM (Oleson et al., 2010), VIC (Liang et al., 1994), JULES
 69 (Best et al., 2011), and CABLE (Haverd et al., 2018). Among them, Noah-MP is one of the most
 70 commonly used state-of-the-art LSMs in the world (He et al., 2023a). Built upon the Noah LSM,
 71 Noah-MP has significant enhancements in representations of canopy-snow-soil-hydrology
 72 processes and interactions as well as capabilities of modeling human activity impacts (e.g., crop
 73 dynamics, irrigation dynamics, tile drainage, and urbanization). The multi-parameterization
 74 options of Noah-MP further allow for uncertainty analysis and model performance
 75 optimization/calibration based on multi-physics model ensembles (Li et al., 2020). Noah-MP has
 76 been serving as a key land component of various research and operational weather and
 77 hydroclimate models, such as the NOAA Unified Forecast System (UFS), the Weather Research
 78 and Forecasting (WRF) model, the U.S. National Water Model (NWM), the Model for Prediction
 79 Across Scales (MPAS), the Korean Integrated Model (KIM), and the Chinese Global-to-Regional
 80 Integrated Forecast System (GRIST). Because of its advantages, Noah-MP has been applied in
 81 numerous applications, including high-resolution climate modeling (Liu et al., 2017; Rasmussen
 82 et al., 2023), vegetation and soil DA (Kumar et al., 2019; Xu et al., 2021), climate extremes
 83 (Arsenault et al., 2020; Kumar et al., 2021; Abolafia-Rosenzweig et al., 2022, 2023, 2024a),
 84 snowpack and hydrology (He et al., 2019; Jiang et al., 2020; Hazra et al., 2023), agriculture and
 85 groundwater (Barlage et al., 2021; Zhang et al., 2023, 2025), and urban climate (Xue et al., 2024,
 86 2025).

87 Recently, the community Noah-MP has undergone a substantial code modernization effort
 88 (version 5.0) to improve its modularity and interoperability (He et al., 2023b), with many physics
 89 updates and bug fixes compared to the versions 3.6 and 4.0.1 in LIS. These two earlier Noah-MP
 90 versions in the current LIS (version 7.5.2) were implemented by manually replicating the Noah-
 91 MP source code and updating LIS/Noah-MP interface and drivers, which does not allow easy
 92 model upgrades and hence leads to a long-delayed version update compared to the community
 93 Noah-MP. Thus, in this effort, we describe the streamlining of the development and maintenance



94 of Noah-MP in LIS to enable the seamless integration between LIS and the community Noah-MP
 95 version to further enhance the interoperability and applicability of both models. Specifically, we
 96 couple the refactored community Noah-MPv5.0 with the LIS framework through the GitHub
 97 submodule mechanism accompanied by developing a new LIS/Noah-MP interface, which
 98 provides a direct, automatic link between the two models' source codes. This integration will allow
 99 easy code updates, synchronization, and maintenance for the coupled LIS/Noah-MP framework.
 100 The second goal of this study is to evaluate and compare global and regional benchmark
 101 simulations between LIS/Noah-MPv5.0 and LIS/Noah-MPv4.0.1 for key land surface conditions.
 102 Such systematic benchmarking is needed to examine the realism of LIS/Noah-MP model
 103 simulations, quantify the gaps between modeling and observations, and identify key processes for
 104 future model enhancements. This study is a step toward establishing a 'scorecard' type of practice
 105 for LSMs.

106

107 **2. Model descriptions and simulations**

108 **2.1 NASA LIS**

109 The LIS system is a land surface hydrology digital twin environment, with the development
 110 led by the Hydrological Sciences Laboratory at NASA's Goddard Space Flight Center. Because of
 111 its extensible and flexible software infrastructure, LIS allows customized land DA systems and
 112 multiple LSMs to be integrated, assembled, and reconfigured easily using shared plugins and
 113 standard interfaces. Currently, LIS is the land component for several Earth system models, such
 114 as the NASA Unified WRF (NU-WRF) model, and the key component of several land DA system
 115 (LDAS) such as Global LDAS (GLDAS), North American LDAS (NLDAS), the Famine Early
 116 Warning Systems Network (FEWS NET) LDAS (FLDAS), and the operational land DA analysis
 117 environment at the U.S. Air Force Weather (Eylander et al., 2022).

118 Specifically, the LIS software suite consists of three main components: (1) Land Data
 119 Toolkit (LDT; Arsenault et al., 2018), which handles the data-related requirements of LIS
 120 including land surface parameter processing, geospatial transformations, consistency checks, data
 121 assimilation preprocessing, and forcing bias correction; (2) Land Information System (LIS), which
 122 is the modeling system that encapsulates land and hydrological models, DA algorithms,
 123 optimization and uncertainty estimation algorithms, and high performance computing (HPC)
 124 support; and (3) Land Verification Toolkit (LVT; Kumar et al., 2012), which is a model



125 verification and benchmarking environment that can be used for enabling rapid prototyping and
 126 evaluation of model simulations by comparing against a large suite of in-situ, remote sensing, and
 127 model and reanalysis data products. More details can be found at the LIS website:
 128 <https://lis.gsfc.nasa.gov/> (last access: November 25, 2024). In this study, we use the LIS version
 129 7.5.2 (latest version at the time of this work) coupled with Noah-MP in benchmark simulations
 130 and the LVT for model evaluation.

131

132 **2.2 Integration of refactored Noah-MPv5.0 with LIS**

133 In this study, we couple the LIS system with the refactored community Noah-MPv5.0
 134 model through the GitHub submodule mechanism to streamline the synchronization of Noah-MP
 135 between the community version and the LIS version, which will simplify future code updates and
 136 maintenance of Noah-MP within LIS. Compared to the Noah-MPv4.0.1 model in LIS, the
 137 community Noah-MPv5.0 model includes several important updates and new features: (1)
 138 improved modularization with modern Fortran code structures, (2) new hierarchical model data
 139 types and structures, (3) enhanced subroutine interface and calling workflow based on the
 140 modularization and new data types, (4) new self-explanatory model variable and module names,
 141 and (5) model bug fixes and new physics schemes. The key bug fixes include updates in vegetation
 142 properties (e.g., bug fixes in vegetation fraction scaling treatments) and processes (e.g., bug fixes
 143 in canopy wind absorption parameters) as well as snowpack processes. The new physics schemes
 144 include improved parameters related to various snowpack processes, a new wet-bulb temperature-
 145 based snow-rain partitioning scheme, a new snow meltwater retention process, a new dynamic
 146 irrigation scheme, updated crop growth parameters, a new tile drainage scheme, a new canopy heat
 147 storage treatment, additional runoff schemes, and new capabilities to control soil process timestep.
 148 More details of Noah-MPv5.0 features can be found in He et al. (2023b). The detailed Noah-MP
 149 physics and formulations are described in He et al. (2023c). The major code changes from Noah-
 150 MPv4.0.1 to Noah-MPv5.0 are described in the model release notes available at:
 151 https://github.com/NCAR/noahmp/blob/master/RELEASE_NOTES.md (last access: November
 152 25, 2024). The key components we modify to couple LIS and Noah-MPv5.0 are the LIS/Noah-MP
 153 land model driver interface to create new input/output variable mapping, and the LIS initialization
 154 and master driver parts to leverage new modularized Noah-MP code modules. By taking advantage



155 of the plugin and standard interfaces in LIS, the Noah-MPv5.0 model is also connected to other
 156 components of LIS, such as data assimilation, river routing, etc.

157

158 **2.3 LIS/Noah-MP benchmark simulations**

159 We conduct and evaluate two sets of coupled LIS/Noah-MP benchmark simulations,
 160 including one set of regional simulations over the contiguous U.S. (CONUS) and one set of global
 161 simulations. Each set of the simulations includes one LIS/Noah-MPv4.0.1 simulation and one
 162 LIS/Noah-MPv5.0 simulation to compare their performance and quantify differences between
 163 versions. The regional simulations are conducted for 10 years (2013-2022) with a 5-year spin-up,
 164 which are driven by the hourly 0.125° North American Land Data Assimilation System (NLDAS-
 165 2) atmospheric forcing data (i.e., precipitation, surface temperature, surface pressure, surface
 166 specific humidity, wind speed, downward surface shortwave and longwave radiation). More
 167 details of NLDAS-2 data are described in Xia et al. (2012). The global simulations are conducted
 168 for 5 years (2018-2022) with a 5-year spin-up, and are driven by the global hourly ~10-km U.S.
 169 Air Force (USAF) atmospheric forcing reanalysis data (Kemp et al., 2022). More details of the
 170 forcing data (formerly known as AGRMET, AGRiculture METeorology) are described in
 171 Eylander et al. (2022). For all the simulations, the static land type map is from the Moderate
 172 Resolution Imaging Spectroradiometer (MODIS) satellite data (Figure 1), while the MODIS
 173 monthly climatological (2000-2008) leaf area index (LAI) and stem area index (SAI) are used
 174 (Yang et al., 2011). The static soil type map is from the State Soil Geographic (STATSGO)/Food
 175 and Agriculture Organization (FAO) soil database (FAO, 1991). For both LIS/Noah-MPv4.0.1 and
 176 LIS/Noah-MPv5.0 simulations, we adopt the same default Noah-MP physics options (see
 177 Appendix Table A1), which have been commonly used in previous Noah-MP applications to
 178 produce skilled model performance (He et al., 2023b). Model evaluations for both the regional and
 179 global simulations are focused on the 5-year period of 2018-2022.

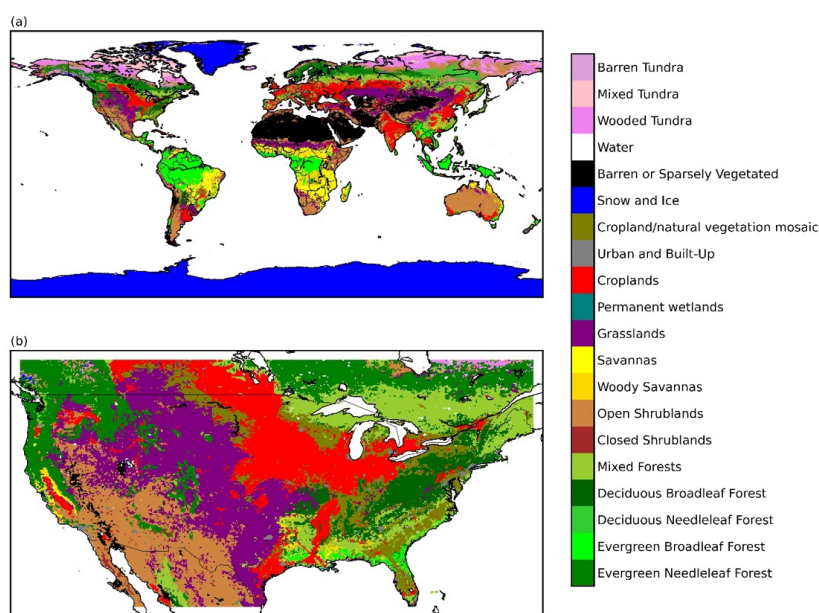


Figure 1. MODIS land cover maps used for LIS/Noah-MP (a) global and (b) CONUS benchmark simulations.

3. Reference data for model evaluation

We use a suite of reference datasets to evaluate the LIS/Noah-MP simulations of key land surface variables over the globe and CONUS, including soil moisture, latent heat flux (LH), snow water equivalent (SWE), snow depth, snow cover fraction, and surface albedo. Specifically, for surface soil moisture, we use the global daily 36-km Soil Moisture Active Passive (SMAP) version 8 Level 3 satellite data (O'Neill et al., 2021; <https://nsidc.org/data/spl3smp/versions/8>, last access: November 25, 2024). We also use the surface and root-zone soil moisture from the International Soil Moisture Network (ISMN) ground station hourly measurements (Dorigo et al., 2021; <https://ismn.earth/en/>, last access: November 25, 2024). The data quality control is done via LVT. For LH, we use the global 0.25° daily Global Land Evaporation Amsterdam Model (GLEAMv3.8a) reanalysis data (Miralles et al., 2011; <https://www.gleam.eu/>, last access: November 25, 2024). For SWE and snow depth, we use the daily 1-km NOAA National Weather Service's National Operational Hydrologic Remote Sensing Center (NOHRSC) Snow Data Assimilation System (SNODAS) data (Barrett, 2003; <https://nsidc.org/data/g02158/>, last access: November 25, 2024) and the global 0.1° ERA-5 land (ERA5-Land) reanalysis data (Muñoz-Sabater et al., 2021;



199 <https://www.ecmwf.int/en/era5-land>, last access: November 25, 2024). For snow cover fraction,
 200 we use the global daily 500-m MODIS Terra Snow Cover version 6 data (Hall and Riggs, 2016;
 201 <https://nsidc.org/data/mod10a1/versions/6>, last access: November 25, 2024). For surface albedo,
 202 we use the global daily 0.05° MODIS Terra/Aqua merged data (Schaaf and Wang, 2021;
 203 <https://lpdaac.usgs.gov/products/mcd43c3v061/>, last access: November 25, 2024). For model
 204 evaluation, we re-map the reference gridded datasets to the LIS/Noah-MP model grids or bilinearly
 205 interpolate model values to in-situ measurement locations via LVT, which will likely introduce
 206 uncertainties to model evaluations. We also note that those reference datasets have their own
 207 uncertainties, which may impact model evaluation results.

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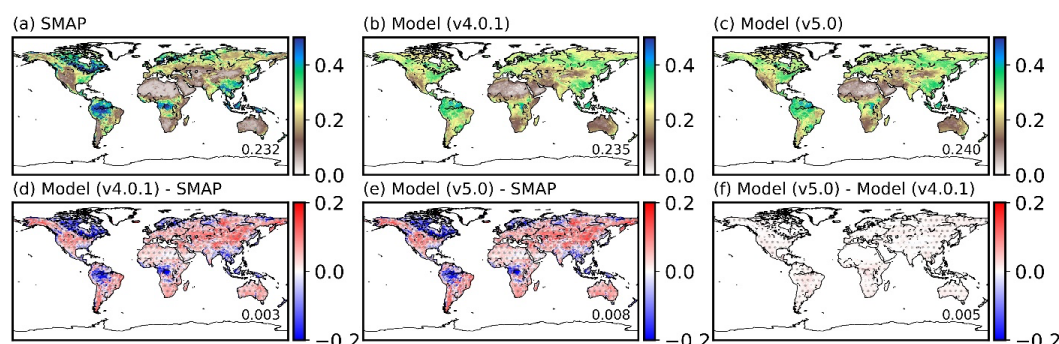
209 **4. Results and discussions**

210 **4.1 Soil moisture**

211 Figure 2 shows the global 5-year (2018-2022) mean surface soil moisture comparison
 212 between SMAP retrievals and LIS/Noah-MP simulations driven by the USAF forcing. Both
 213 LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0 simulations capture the spatial and seasonal
 214 distributions of surface soil moisture globally (Figures 2 and S1), with similar bias patterns. Both
 215 simulations tend to have negative biases over wet soil regimes (e.g., northern and eastern Canada,
 216 Amazon forests, northern Europe, tropical Africa, and southeast Asia) and positive biases over dry
 217 soil regimes (e.g., western US, west and east coasts of South America, southern and northern
 218 Africa, mid-latitudinal Eurasia, and Australia), partially caused by the USAF precipitation forcing
 219 bias except for northern and eastern Canada (Figure S2). We note that SMAP data quality is less
 220 reliable over regions with thick vegetation (e.g., Southeast US, Amazon rainforest, Congo Basin).
 221 The evapotranspiration (ET) biases caused by model deficiencies in plant hydraulics and root water
 222 uptake processes may also contribute to the soil moisture bias, as revealed by previous Noah-MP
 223 studies (Niu et al., 2020; Li et al., 2021). These global model bias patterns are consistent across all
 224 seasons (Figure S1). Due to the offset of positive and negative biases across different regions, the
 225 global annual mean model bias is small ($0.003 \text{ m}^3/\text{m}^3$ for LIS/Noah-MPv4.0.1 and $0.008 \text{ m}^3/\text{m}^3$
 226 for LIS/Noah-MPv5.0). Overall, LIS/Noah-MPv5.0 shows consistently higher surface soil
 227 moisture than LIS/Noah-MPv4.0.1 but the difference is small (Figure 2f), which is expected since
 228 there is no direct soil physics update but changes in vegetation processes (e.g., vegetation fraction
 229 scaling treatments) from Noah-MPv4.0.1 to Noah-MPv5.0.



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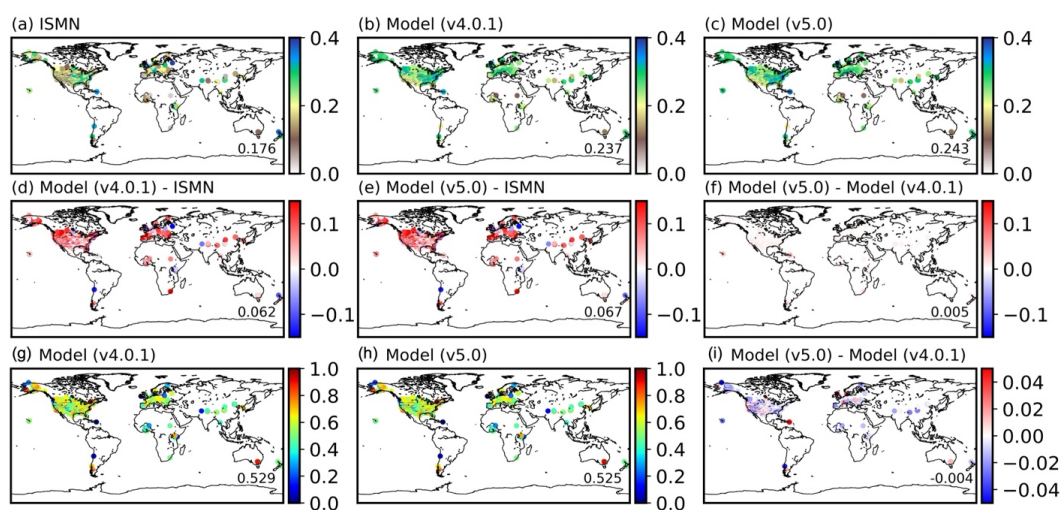
232 **Figure 2.** Surface soil moisture (m^3/m^3) comparison between SMAP retrievals and LIS/Noah-MP
 233 simulations driven by USAF forcing globally averaged during 2018-2022: (a) SMAP data, (b)
 234 LIS/Noah-MPv4.0.1 simulation, (c) LIS/Noah-MPv5.0 simulation, (d) LIS/Noah-MPv4.0.1 biases
 235 (model minus SMAP), (e) LIS/Noah-MPv5.0 biases (model minus SMAP), and (f) differences
 236 between LIS/Noah-MPv5.0 and LIS/Noah-MPv4.0.1 simulations. Grids with statistically
 237 significant differences ($p < 0.05$) are shown with gray dots in panels (d)-(f). The global mean value
 238 is also provided in the lower right of each panel. See Figure S1 for seasonal plots.

239

240 Further model evaluation with the ISMN global in-situ measurements indicates systematic
 241 model overestimates of surface soil moisture at most sites (Figure 3), particularly over the CONUS
 242 and Europe that have very dense measurement networks, with global mean biases of $0.062 \text{ m}^3/\text{m}^3$
 243 and $0.067 \text{ m}^3/\text{m}^3$ for LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0, respectively. This bias pattern
 244 is consistent with the SMAP comparisons (Figure 2). LIS/Noah-MPv5.0 shows slightly (0.005
 245 m^3/m^3) higher mean surface soil moisture than LIS/Noah-MPv4.0.1 across all sites (Figure 3f).
 246 We further compute the soil moisture anomaly correlation between the model simulations and
 247 ISMN observations following Navari et al. (2024), where the anomaly is computed as daily
 248 anomaly by subtracting monthly mean values. Both models show similar anomaly correlation
 249 spatial patterns (Figure 3g-h), with a mean value of ~ 0.53 and higher values in North America and
 250 Europe than in Asia and Africa. Compared to the surface soil moisture, the root-zone soil moisture
 251 shows similar spatial distributions (Figure 4a-c), model bias patterns (Figure 4d-e), and anomaly
 252 correlation patterns (Figure 4g-i) across most ISMN sites, with global annual mean biases of 0.039
 253 m^3/m^3 and $0.050 \text{ m}^3/\text{m}^3$ for LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0, respectively.



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Figure 3. Surface soil moisture (m^3/m^3) comparison between ISMN station measurements and LIS/Noah-MP simulations driven by USAF forcing globally averaged during 2018-2022: (a) ISMN data, (b) LIS/Noah-MPv4.0.1 simulation, (c) LIS/Noah-MPv5.0 simulation, (d) LIS/Noah-MPv4.0.1 biases (model minus ISMN), (e) LIS/Noah-MPv5.0 biases (model minus ISMN), (f) differences between LIS/Noah-MPv5.0 and LIS/Noah-MPv4.0.1 simulations, (g) LIS/Noah-MPv4.0.1 anomaly correlation, (h) LIS/Noah-MPv5.0 anomaly correlation, and (i) differences between LIS/Noah-MPv5.0 and LIS/Noah-MPv4.0.1 anomaly correlation. The global mean value is also provided in the lower right of each panel.

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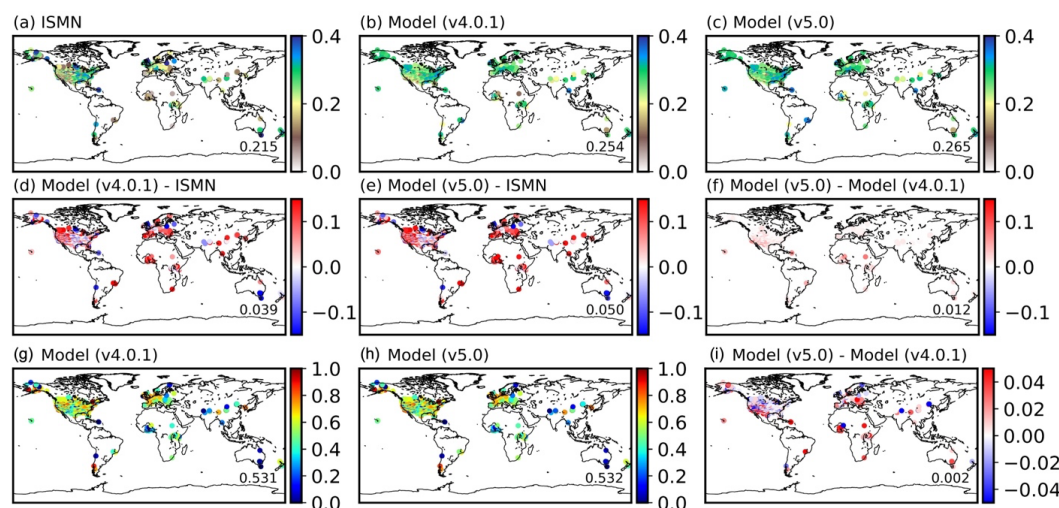
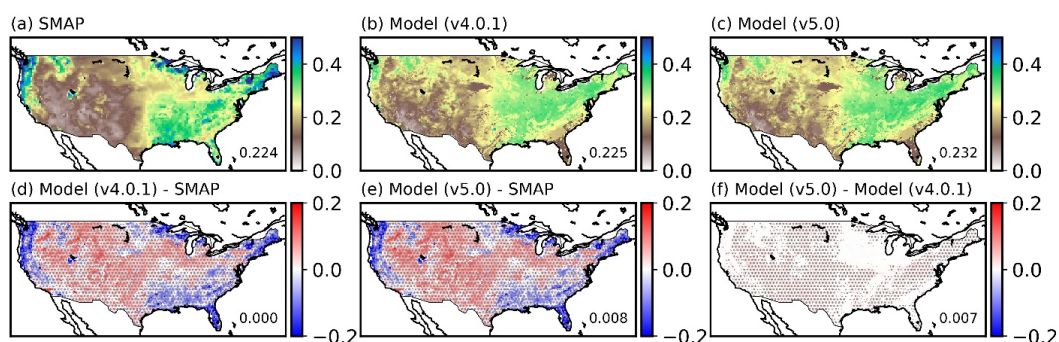


Figure 4. Same as Figure 3, but for root-zone soil moisture (m^3/m^3) evaluation.

Over the CONUS, both LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0 simulations driven by the NLDAS-2 forcing capture the spatial distribution of SMAP surface soil moisture with similar spatial bias patterns (Figure 5), which show model underestimates over wet soil regimes (e.g., the northwest coast and southeast and northeast U.S.) and overestimates over dry soil regimes (e.g., western and central U.S.). This is consistent with the global evaluation albeit using a different forcing dataset. LIS/Noah-MPv5.0 also produces consistently but slightly ($0.007 \text{ m}^3/\text{m}^3$) higher soil moisture than LIS/Noah-MPv4.0.1 using the NLDAS-2 forcing (Figure 5f), similar to the results using the USAF forcing, revealing a robust difference pattern between the two model versions. The comparison with ISMN surface soil moisture data over the CONUS shows similar model bias patterns with those evaluated against SMAP (Figure 6), except for the northwest coast and Florida, where ISMN indicates dry soil regimes that are opposite to SMAP. This points to the importance of considering observational data uncertainty in model evaluation. The CONUS mean biases across all ISMN sites are $0.041 \text{ m}^3/\text{m}^3$ and $0.047 \text{ m}^3/\text{m}^3$ for LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0, respectively. The CONUS mean anomaly correlation is about 0.6 for both models (Figure 6g-h), with slightly lower values particularly over many western U.S. sites for LIS/Noah-MPv5.0 than LIS/Noah-MPv4.0.1 (Figure 6i). The model bias pattern of root-zone soil moisture is similar to that of surface soil moisture but with larger underestimates at some central U.S. sites (Figure 7).



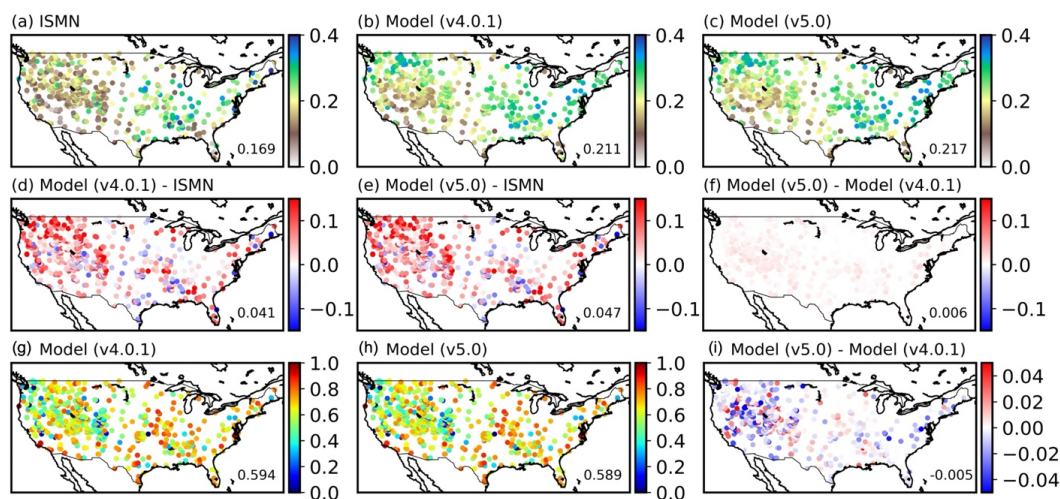
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288 **Figure 5.** Same as Figure 2, but for evaluation of LIS/Noah-MP simulations driven by the
 289 NLDAS-2 forcing over the CONUS averaged during 2018-2022.

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292 **Figure 6.** Same as Figure 3, but for evaluation of LIS/Noah-MP simulated surface soil moisture
 293 (m^3/m^3) driven by the NLDAS-2 forcing over the CONUS averaged during 2018-2022.

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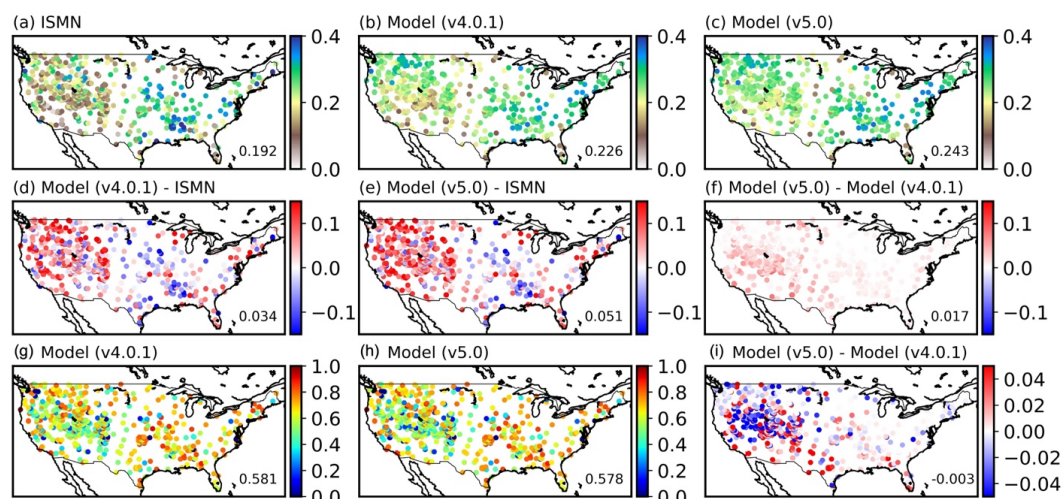


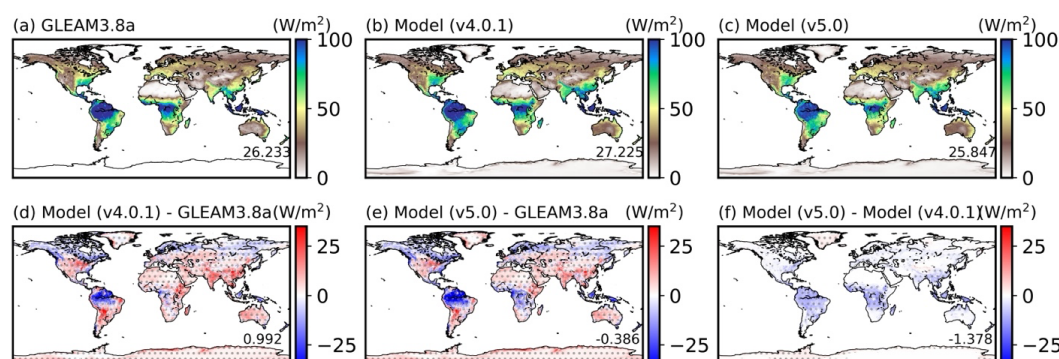
Figure 7. Same as Figure 4, but for evaluation of LIS/Noah-MP simulated root-zone soil moisture (m^3/m^3) driven by the NLDAS-2 forcing over the CONUS averaged during 2018-2022.

4.2 Latent heat flux

Figure 8 shows the global 5-year (2018-2022) mean latent heat (LH) flux comparison between GLEAM data and LIS/Noah-MP simulations driven by the USAF forcing. Both LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0 simulations capture the spatial and seasonal LH distributions with similar bias patterns (Figures 8 and S3). The model LH biases are generally consistent with the surface soil moisture bias patterns (Figure 2), with negative (positive) LH biases over regions with negative (positive) soil moisture biases, except for northern Eurasia and northwest North America (Alaska and west Canada). Although LIS/Noah-MPv5.0 has a slightly higher soil moisture than LIS/Noah-MPv4.0.1 (Figures 2-4), it shows a lower LH (by up to $\sim 15 \text{ W/m}^2$) across most non-polar regions with the largest difference in the tropics, which reduces the global mean LH bias from 0.99 W/m^2 (LIS/Noah-MPv4.0.1) to -0.39 W/m^2 (LIS/Noah-MPv5.0). This difference in the two Noah-MP versions is mainly due to the code updates related to vegetation properties (e.g., bug fixes in vegetation fraction scaling treatments) and processes (e.g., bug fixes in canopy wind absorption parameters), which alters ET and LH. The minor LH difference (up to $\sim 5 \text{ W/m}^2$) between the two model versions over the Antarctica and Greenland is mainly caused by updates in the glacier scheme that uses consistent snowpack physics as other land snowpacks in LIS/Noah-MPv5.0.



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Figure 8. Latent heat flux (W/m^2) comparison between the GLEAM data and LIS/Noah-MP simulations driven by USAF forcing globally averaged during 2018-2022: (a) GLEAM3.8a data, (b) LIS/Noah-MPv4.0.1 simulation, (c) LIS/Noah-MPv5.0 simulation, (d) LIS/Noah-MPv4.0.1 biases (model minus GLEAM), (e) LIS/Noah-MPv5.0 biases (model minus GLEAM), and (f) differences between LIS/Noah-MPv5.0 and LIS/Noah-MPv4.0.1 simulations. Grids with statistically significant differences ($p < 0.05$) are shown with gray dots in panels (d)-(f). The global mean value is also provided in the lower right of each panel. See Figure S3 for seasonal plots.

325

Further CONUS evaluation of model simulations driven by the NLDAS-2 forcing also reveals that model LH bias patterns (Figure 9) generally follow the soil moisture bias patterns (Figure 5) except for many western U.S. mountainous regions, where both model simulations have very small LH biases albeit with overestimated soil moisture (Figures 5-7). Compared to LIS/Noah-MPv4.0.1, LIS/Noah-MPv5.0 shows a lower LH over southwest U.S. and eastern U.S. by up to about 10 W/m^2 , which degrades the CONUS-mean model bias from -0.21 W/m^2 to -2.30 W/m^2 . We note that GLEAM is a model-based reanalysis data that has its own uncertainty.

333

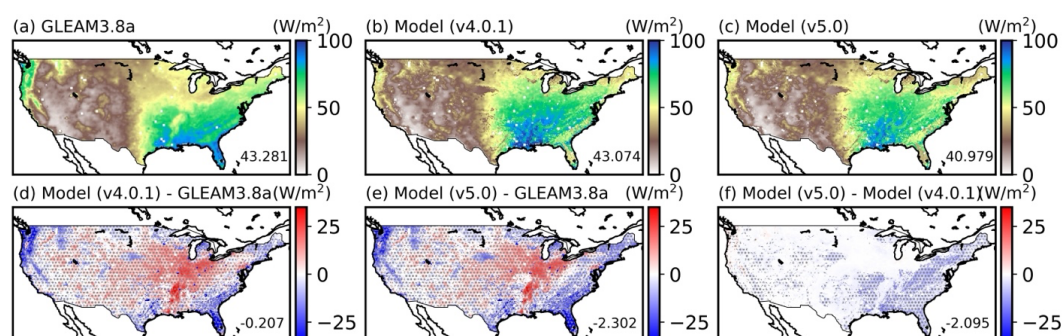


Figure 9. Same as Figure 8 but for evaluation of LIS/Noah-MP simulations driven by the NLDAS-2 forcing over the CONUS averaged during 2018-2022.

4.3 Snow water equivalent (SWE)

Figure 10 shows the global 5-year (2018-2022) mean SWE comparison for seasonal snowpack between ERA5-Land data and LIS/Noah-MP simulations driven by the USAF forcing. Both LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0 simulations capture the spatial and seasonal SWE distributions with similar bias patterns (Figures 10 and S4). Both simulations tend to have much lower SWE (by up to 50 mm) in the Himalayas and west Canada than ERA5-Land, with slightly less SWE in eastern Russia, partially driven by overestimated surface temperature (Section 4.7). Both simulations have higher SWE than ERA5-Land in most other mid-latitude and high-latitude snowpacks, mainly driven by overestimated precipitation (Figure S2) and underestimated surface temperature (Figure S8). The global annual mean SWE biases are -10.1 mm and -13.2 mm for LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0, respectively. Overall, LIS/Noah-MPv5.0 shows lower SWE than LIS/Noah-MPv4.0.1, particularly in spring when differences reach up to 25 mm (Figures 10f and S4) due to the updated snow cover and compaction parameters (He et al., 2021) that reduces snow cover fraction (Section 4.5) and enhances snow ablation particularly in spring through the positive surface albedo feedback. We note that the ERA5-Land SWE data also has uncertainties, which tends to overestimate SWE over mountainous areas (Monteiro and Morin, 2023).

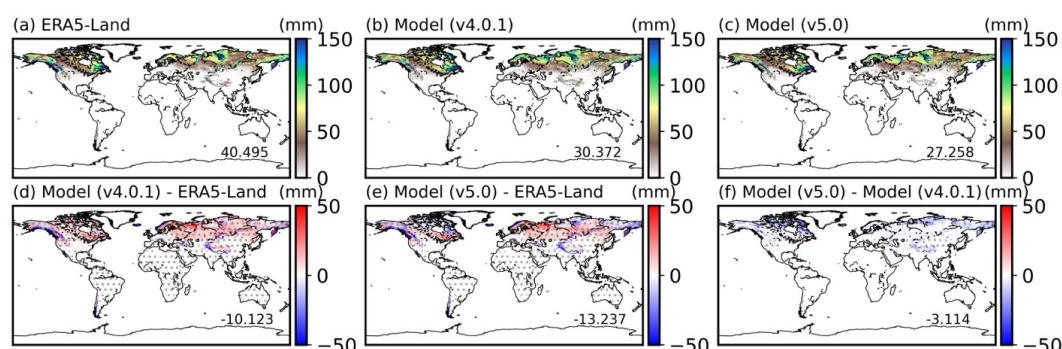


Figure 10. SWE (mm) comparison between ERA5-Land and LIS/Noah-MP simulations driven by USAF forcing globally averaged during 2018-2022: (a) ERA5-Land data, (b) LIS/Noah-MPv4.0.1 simulation, (c) LIS/Noah-MPv5.0 simulation, (d) LIS/Noah-MPv4.0.1 biases (model minus ERA5-Land), (e) LIS/Noah-MPv5.0 biases (model minus ERA5-Land), and (f) differences between LIS/Noah-MPv5.0 and LIS/Noah-MPv4.0.1 simulations. Grids with statistically significant differences ($p < 0.05$) are shown with gray dots in panels (d)-(f). The global mean value is also provided in the lower right of each panel. See Figure S4 for seasonal plots.

The CONUS-wide regional evaluation between SNODAS and LIS/Noah-MP simulations driven by the NLDAS-2 forcing indicates large SWE underestimates by up to 50 mm or more in high-elevation mountains in the western U.S. and very small biases across other CONUS regions (Figure 11), mainly due to the underestimated mountain precipitation in NLDAS-2 (He et al., 2019). The CONUS mean SWE biases are -4.2 mm and -5.0 mm for LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0, respectively, with slightly lower SWE in LIS/Noah-MPv5.0 than LIS/Noah-MPv4.0.1 over most CONUS snowpacks (Figure 11f).

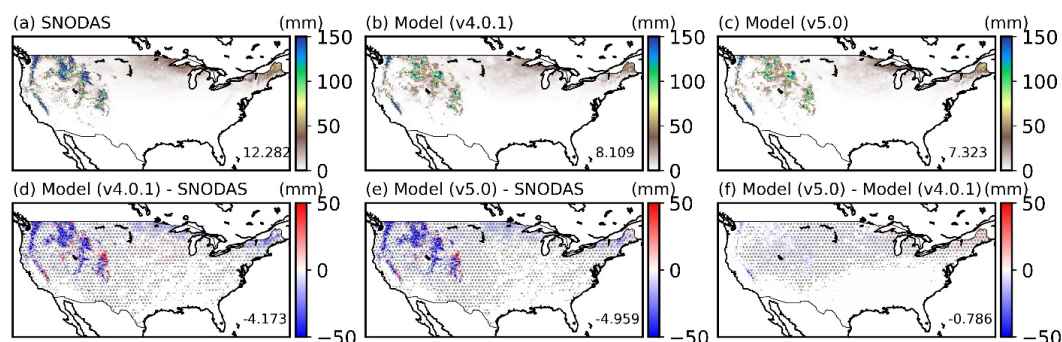




Figure 11. Same as Figure 10 but for SWE (mm) comparison between SNODAS and LIS/Noah-MP simulations driven by the NLDAS-2 forcing over the CONUS averaged during 2018-2022.

4.4 Snow depth

Figure 12 shows the global 5-year (2018-2022) mean snow depth comparison for seasonal snowpack between ERA5-Land data and LIS/Noah-MP simulations driven by the USAF forcing. Both LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0 simulations reproduce the spatial and seasonal snow depth distributions with similar bias patterns (Figures 12 and S5). The snow depth bias pattern generally follows the SWE bias pattern (Figure 10) with global annual mean biases of ~ 0.06 m for both simulations, except for the lower snow depth over some regions with higher SWE in northern Canada and northern Russia compared to ERA5-Land. The snow depth difference (global mean of 0.003 m) between LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0 is small (Figure 12f).

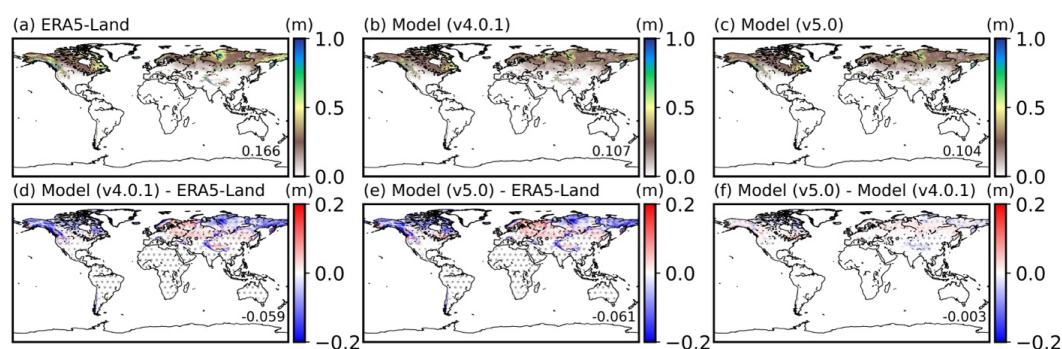
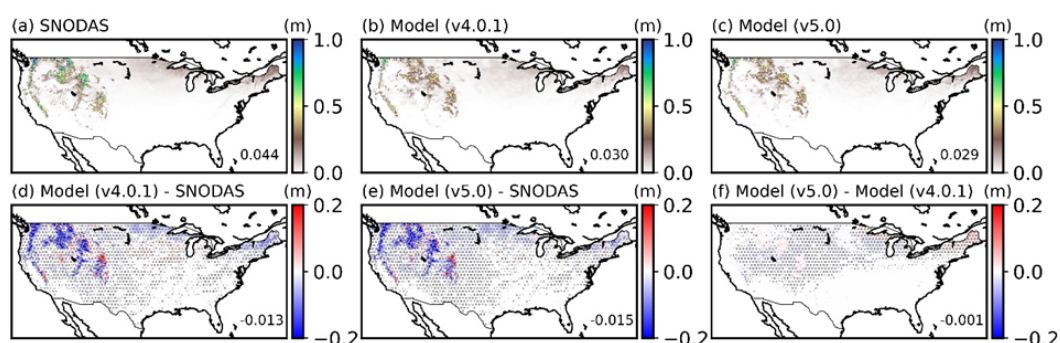


Figure 12. Snow depth (m) comparison between ERA5-Land and LIS/Noah-MP simulations driven by USAF forcing globally averaged during 2018-2022: (a) ERA5-Land data, (b) LIS/Noah-MPv4.0.1 simulation, (c) LIS/Noah-MPv5.0 simulation, (d) LIS/Noah-MPv4.0.1 biases (model minus ERA5-Land), (e) LIS/Noah-MPv5.0 biases (model minus ERA5-Land), and (f) differences between LIS/Noah-MPv5.0 and LIS/Noah-MPv4.0.1 simulations. Grids with statistically significant differences ($p < 0.05$) are shown with gray dots in panels (d)-(f). The global mean value is also provided in the lower right of each panel. See Figure S5 for seasonal plots.



397 The CONUS-wide regional snow depth evaluation between SNODAS and LIS/Noah-MP
 398 simulations driven by the NLDAS-2 forcing also reveals a similar bias pattern (Figure 13) as the
 399 SWE evaluation, with largely underestimated snow depth over most western U.S. high mountains
 400 due to the underestimated SWE. The CONUS mean snow depth biases are -0.013 m and -0.015 m
 401 for LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0, respectively, with very minor differences
 402 between the two simulations (Figure 13f).

403



404

405 **Figure 13.** Same as Figure 12, but for snow depth (m) comparison between SNODAS and
 406 LIS/Noah-MP simulations driven by the NLDAS-2 forcing over the CONUS averaged during
 407 2018-2022.

408

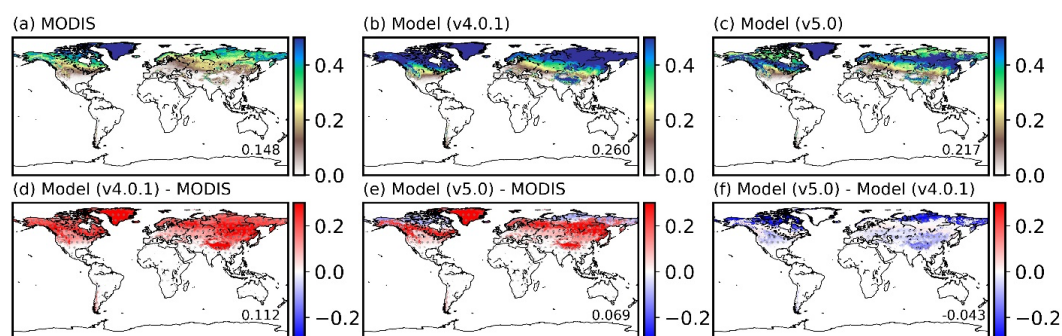
409 4.5 Snow cover fraction

410 Although LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0 simulations capture the spatial and
 411 seasonal snow cover distributions, they systematically overestimate snow cover globally relative
 412 to MODIS observations (Figures 14 and S6). This high bias in snow cover is particularly
 413 outstanding considering the underestimated SWE and snow depth (Figures 10 and 12), which has
 414 been a long-standing problem in Noah-MP (He et al., 2019; Jiang et al., 2020; Zhou et al., 2023).
 415 Specifically, LIS/Noah-MPv4.0.1 tends to overestimate snow cover across the global snowpack
 416 by up to 0.3 with a global mean bias of 0.11, while LIS/Noah-MPv5.0 reduces the snow cover
 417 overestimate particularly in northern high-latitudes and the Tibetan Plateau, which effectively
 418 reduces the global mean bias to 0.07. This bias reduction is attributable to the updated snow cover
 419 parameters in LIS/Noah-MPv5.0 (He et al., 2021). However, LIS/Noah-MPv5.0 still
 420 systematically overestimates snow cover over most mid-latitude and high-latitude snowpacks,



421 which suggests the need for improved snowpack physics in Noah-MP (see Section 5 for
 422 discussion).

423



424

425 **Figure 14.** Snow cover fraction comparison between MODIS and LIS/Noah-MP simulations
 426 driven by the USAF forcing globally averaged during 2018-2022: (a) MODIS data, (b) LIS/Noah-
 427 MPv4.0.1 simulation, (c) LIS/Noah-MPv5.0 simulation, (d) LIS/Noah-MPv4.0.1 biases (model
 428 minus MODIS), (e) LIS/Noah-MPv5.0 biases (model minus MODIS), and (f) differences between
 429 LIS/Noah-MPv5.0 and LIS/Noah-MPv4.0.1 simulations. Grids with statistically significant
 430 differences ($p < 0.05$) are shown with gray dots in panels (d)-(f). The global mean value is also
 431 provided in the lower right of each panel. See Figure S6 for seasonal plots.

432

433 The CONUS-wide regional evaluation between MODIS and LIS/Noah-MP simulations
 434 driven by the NLDAS-2 forcing also reveals a consistently high bias in snow cover in LIS/Noah-
 435 MPv4.0.1, particularly over western U.S. mountains, with a CONUS mean bias of 0.055 (Figure
 436 15). LIS/Noah-MPv5.0 effectively removes the snow cover overestimates in snowpacks outside
 437 high-elevation mountains in the western U.S., which halves the CONUS mean bias. The remaining
 438 snow cover overestimate in western U.S. high mountains, which notably correspond to the regions
 439 with underestimated SWE and snow depth (Figures 11 and 13), needs further investigation.

440

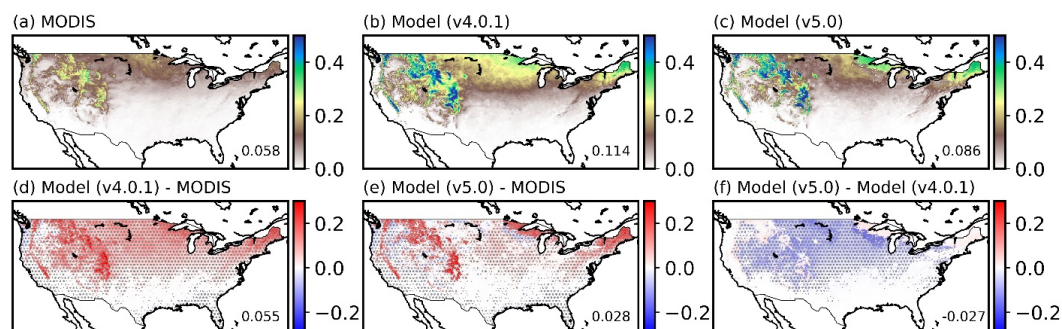


Figure 15. Same as Figure 14, but for evaluation of LIS/Noah-MP simulations driven by the NLDAS-2 forcing over the CONUS averaged during 2018-2022.

4.6 Surface albedo

Figure 16 shows the global 5-year (2018-2022) mean surface albedo comparison between MODIS and LIS/Noah-MP simulations driven by the USAF forcing. Both LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0 simulations capture the spatial and seasonal surface albedo distributions with similar bias patterns (Figures 16 and S7). LIS/Noah-MPv4.0.1 shows consistently overestimated surface albedo over most global regions by up to 0.05 or more, except for significant underestimates in the Sahara Desert and Antarctica which dominate the global mean bias (-0.02). This bias pattern is consistent across different seasons (Figure S7). Compared to LIS/Noah-MPv4.0.1, LIS/Noah-MPv5.0 shows an overall reduction of surface albedo across mid-latitudes and high-latitudes due to lower snow cover (Section 4.5), which reduces the high bias of surface albedo particularly in the midlatitudes (Figure 16). The remaining albedo overestimates in LIS/Noah-MPv5.0 in the mid-latitude and high-latitude snowpacks are partially caused by the overestimated snow cover (Figure 14e) and also likely by the soil and vegetation albedo uncertainties. The systematic surface albedo underestimates in the Sahara Desert, Antarctica, and Greenland further indicate model biases in the background albedo for desert soil and glacier ice/snow albedo.

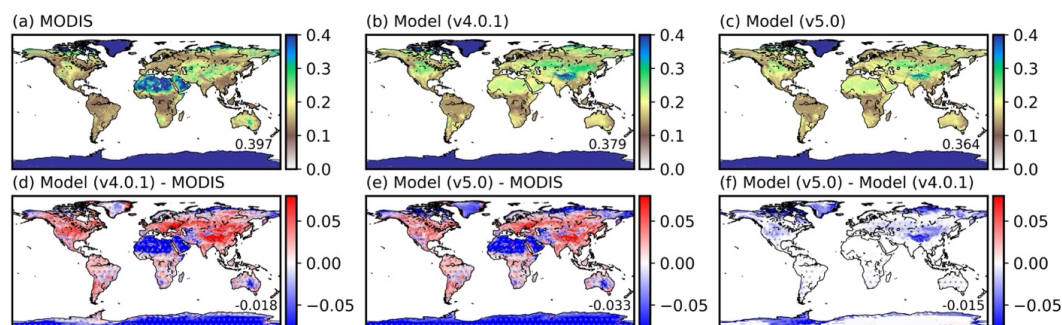


Figure 16. Surface albedo comparison between MODIS and LIS/Noah-MP simulations driven by USAF forcing globally averaged during 2018-2022: (a) MODIS data, (b) LIS/Noah-MPv4.0.1 simulation, (c) LIS/Noah-MPv5.0 simulation, (d) LIS/Noah-MPv4.0.1 biases (model minus MODIS), (e) LIS/Noah-MPv5.0 biases (model minus MODIS), and (f) differences between LIS/Noah-MPv5.0 and LIS/Noah-MPv4.0.1 simulations. Grids with statistically significant differences ($p < 0.05$) are shown with gray dots in panels (d)-(f). The global mean value is also provided in the lower right of each panel. See Figure S7 for seasonal plots.

The CONUS-wide regional evaluation between MODIS and LIS/Noah-MP simulations driven by the NLDAS-2 forcing also reveals a consistently high bias in surface albedo in LIS/Noah-MPv4.0.1 across the CONUS, except in some parts of southwest US (Figure 17), with a CONUS mean bias of 0.031. LIS/Noah-MPv5.0 effectively reduces the mean albedo bias to 0.023 due to improved snow cover simulations (Figures 15f and 17f). The remaining albedo overestimates in the western U.S. is partially due to the snow cover bias (Figure 15e) and snow albedo bias (He et al., 2019; Abolafia-Rosenzweig et al., 2022). The albedo overestimates in the rest of CONUS may be related to the model uncertainty in background soil and vegetation albedo (see Section 5 for discussion).

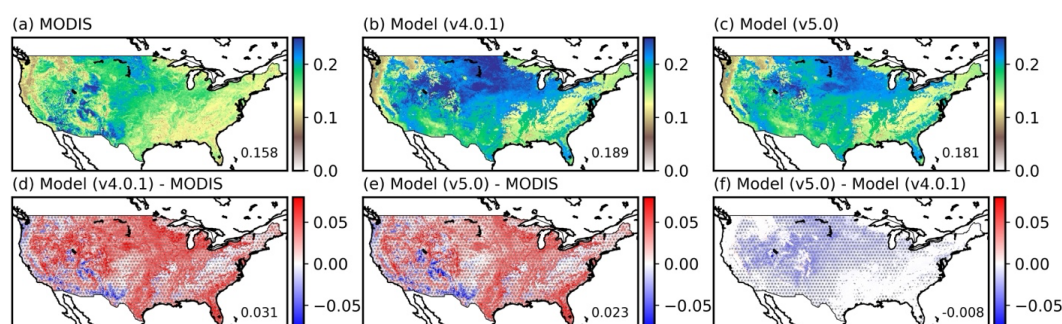


Figure 17. Same as Figure 16, but for evaluation of LIS/Noah-MP simulations driven by the NLDAS-2 forcing over the CONUS averaged during 2018-2022.

5. Discussions for model improvements

The evaluation of global and regional benchmark simulations (Section 4) reveals several important Noah-MP model uncertainties and deficiencies, which calls for future model improvements.

First, the model biases in soil moisture and LH (Sections 4.1 and 4.2) partially reflect the inadequate representation of plant hydraulics and root schemes and/or too shallow soil column configuration (e.g., in the Amazon), which have also been highlighted by a few previous studies (e.g., Niu et al., 2020; Li et al., 2021; Bieri et al., 2024). Recently, Li et al. (2021) developed a new whole-plant hydraulics scheme for Noah-MP with observation-constrained parameters (Sun et al., 2024), which largely improves simulations of ET and terrestrial water storage (TWS) compared to the default soil hydraulics scheme in Noah-MP. Other studies (e.g., Niu et al., 2020; Bieri et al., 2024) developed dynamic root uptake schemes in Noah-MP that improve modeled soil moisture, ET, and TWS. These model updates have not been included in the community Noah-MPv5.0, which needs to be done in the future. Another possible model deficiency that could result in the LH bias is the canopy turbulence scheme. Noah-MP uses the Monin–Obukhov (M–O) similarity theory to compute momentum and heat exchange coefficients above and through the canopy, which however does not account for the canopy-induced turbulence in the roughness sublayer (RSL) and hence fails above and within dense forests (Bonan et al., 2018). Abolafia-Rosenzweig et al. (2021) implemented and evaluated a unified RSL turbulence scheme throughout the canopy in an earlier Noah-MP version, which demonstrates the potential of improving modeled surface heat fluxes. We are currently working on a comprehensive assessment of this RSL canopy



506 turbulence scheme in Noah-MPv5.0 across global FLUXNET sites. However, we note that the
 507 satellite soil moisture data has large uncertainties over dense forests. In addition, the input soil
 508 texture data could also impact the modeled soil moisture and hence ET. Li et al. (2024) recently
 509 developed a global 1-km high-quality datasets for key land surface parameters (including soil
 510 texture), and we plan to test the effect of using this new dataset in Noah-MP simulations in our
 511 next step.

512 Second, the model biases in snowpack, including SWE, snow depth, and snow cover,
 513 reveal inadequate treatments of snow physics. For example, the SWE underestimates over
 514 midlatitude mountains (e.g., the Himalayas and western U.S. high mountains) could be caused by
 515 the snow ablation bias in the model, in addition to the precipitation and temperature forcing
 516 uncertainty (Section 4.3). He et al. (2021) found that Noah-MP tends to melt snow faster than
 517 observations in some western US mountain areas, likely due to wind and solar radiation forcing
 518 biases and/or model deficiencies in above-snowpack turbulence, canopy radiative transfer, and
 519 snow albedo. Recently, Lin et al. (2025) coupled Noah-MPv5.0 with a widely used physical snow
 520 albedo scheme, SNICAR-ADv3 (Flanner et al., 2021; He et al., 2024a), and found improved snow
 521 albedo relative to the default semi-empirical snow albedo scheme in Noah-MP. This snow albedo
 522 physics update will be included in the next Noah-MP major version release. The snow depth bias
 523 is not only driven by the SWE bias but also by uncertainty in snow compaction processes. A recent
 524 study (Abolafia-Rosenzweig et al., 2024b) enhanced the Noah-MP snow compaction
 525 parameterization constrained by in-situ measurements across ~800 SNOTEL sites in the western
 526 U.S., which is currently being transferred to the Noah-MPv5.0
 527 (<https://github.com/NCAR/noahmp/pull/148>; last access: November 24, 2024). In addition, a new
 528 flexible framework was recently developed to couple the LSMs (including Noah-MPv4.0.1) in LIS
 529 with a physical snow model, Crocus, which shows promising improvements in modeling snow
 530 depth and SWE (Navari et al., 2024). The systematically overestimated snow cover fraction in
 531 Noah-MP is a long-standing model problem, which has been investigated by several studies over
 532 different mountain regions (He et al., 2019; Jiang et al., 2020; Zhou et al., 2023). A number of
 533 improvements in the model snow cover parameterization have been proposed for the Tibetan
 534 Plateau (Jiang et al., 2020; Zhou et al., 2023) and the western U.S. (Abolafia-Rosenzweig et al.,
 535 2024c). These solutions, however, need to be tested for global applications.



536 Third, the model biases in surface albedo, particularly over the Sahara Desert and glaciers,
 537 suggest possible deficiencies in background desert soil albedo and glacier albedo. Currently, Noah-
 538 MPv5.0 assumes a uniform medium soil color everywhere, whereas using a spatially-varying soil
 539 color map (Lawrence and Chase, 2007) tends to reduce Noah-MP surface albedo particularly over
 540 the desert (Michael Barlage, personal communication), which will be tested in NoahMPv5.0
 541 together with the aforementioned Li et al. (2024) global 1-km input datasets. To improve glacier
 542 modeling, Eidhammer et al. (2021) coupled the Crocus snow/ice model with Noah-MP within the
 543 WRF-Hydro framework, which reproduces the observed glacier surface albedo and mass balance
 544 in Norwegian glaciers. Future Noah-MP model improvements need to also focus on glacier regions,
 545 which were less studied in previous Noah-MP applications. In addition, vegetation albedo (and
 546 canopy radiative transfer) may also contribute to the surface albedo biases in Noah-MP, which
 547 however lacks systematic assessments in the literature and hence needs more future investigations.

548

549 **6. Conclusions**

550 In this study, we integrated the refactored community Noah-MPv5.0 model with the NASA
 551 LIS system (version 7.5.2) through the GitHub submodule mechanism to streamline the
 552 synchronization, development, and maintenance of Noah-MP within LIS and to enhance the
 553 interoperability and applicability of both models. The GitHub submodule mechanism also allows
 554 for more rapid implementation of bug fixes as well as new versions of Noah-MP (such as including
 555 the new physics detailed in Section 5) into the LIS software framework. We systematically
 556 evaluated multi-year (2018-2022) global and regional (CONUS) LIS/Noah-MP benchmark
 557 simulations driven by the USAF and NLDAS-2 atmospheric forcing, respectively, for a set of key
 558 land surface variables.

559 Specifically, both LIS/Noah-MPv4.0.1 and LIS/Noah-MPv5.0 simulations capture the
 560 spatial and seasonal distributions of observed surface and root-zone soil moisture, LH, SWE, snow
 561 depth, snow cover, and surface albedo, with similar bias patterns. For surface and root-zone soil
 562 moisture, model simulations tend to have negative biases over wet soil regimes and positive biases
 563 over dry soil regimes, with slightly higher soil moisture in LIS/Noah-MPv5.0 than LIS/Noah-
 564 MPv4.0.1 across most regions. Due to the offset of positive and negative soil moisture biases
 565 across different regions, the global mean biases of both models are relatively small.



566 For LH, the model bias patterns generally follow those of soil moisture, with negative
 567 (positive) LH biases over areas with negative (positive) soil moisture biases across most global
 568 regions. Although LIS/Noah-MPv5.0 has a slightly higher soil moisture than LIS/Noah-MPv4.0.1,
 569 it shows a lower LH across most non-polar regions, which reduces the global mean LH bias from
 570 0.99 W/m^2 (LIS/Noah-MPv4.0.1) to -0.39 W/m^2 (LIS/Noah-MPv5.0).

571 For snowpack conditions, the model SWE bias patterns are dominated by the precipitation
 572 and temperature forcing uncertainties, with large SWE underestimates in the Himalayas, west
 573 Canada, and western U.S. mountains and overestimates in most other mid-latitude and high-
 574 latitude snowpacks. The SWE biases are similar for both models, with slightly larger
 575 underestimates in LIS/Noah-MPv5.0 (global mean bias of -13.2 mm) than LIS/Noah-MPv4.0.1
 576 (global mean bias of -10.1 mm). The model bias patterns of snow depth generally follow those of
 577 SWE, with a global mean bias of $\sim 0.06 \text{ m}$ for both simulations. For snow cover, LIS/Noah-
 578 MPv4.0.1 has a systematic large overestimate across the globe, even over regions with
 579 underestimated SWE, which is a long-standing Noah-MP problem. LIS/Noah-MPv5.0 with
 580 updated snow cover parameters effectively reduces the snow cover overestimates globally,
 581 decreasing the global mean bias from 0.11 to 0.07 .

582 For surface albedo, both models show widespread overestimates over most mid-latitude
 583 and high-latitude regions partially due to the snow cover overestimate, and significant
 584 underestimates in the Sahara Desert, Greenland, and Antarctica, which dominate the global mean
 585 bias. Because of the reduced snow cover, LIS/Noah-MPv5.0 shows consistently lower surface
 586 albedo than LIS/Noah-MPv4.0.1, which degrades the global mean bias from -0.018 to -0.033 .

587 The model evaluation in this study reveals several important Noah-MP uncertainties and
 588 deficiencies and motivates future improvements in model processes/components including plant
 589 hydraulics and dynamic root uptake, canopy turbulence and interaction with snowpack, input soil
 590 texture and color data, snow cover and albedo, glacier ice, and vegetation albedo (canopy radiative
 591 transfer).

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Appendix

Table A1. Default Noah-MP physics options used in this study

Noah-MP Physics	Option	Description
dynamic vegetation option	4	use table LAI and maximum vegetation fraction
rain-snow partition option	1	Jordan (1991) scheme
soil moisture factor for stomatal resistance option	1	Noah (soil moisture) (Ek et al., 2003)
ground resistance option	1	Sakaguchi and Zeng (2009) scheme
surface drag coefficient option	1	Monin-Obukhov (M-O) Similarity Theory (Brutsaert, 1982)
canopy stomatal resistance option	1	Ball-Berry scheme (Bonan, 1996)
snow surface albedo option	1	BATS snow albedo (Dickinson et al., 1993)
canopy radiation transfer option	3	two-stream applied to vegetated fraction (Niu and Yang, 2004)
snow/soil temperature time scheme option	1	semi-implicit; flux top boundary condition (Niu et al., 2011)
snow thermal conductivity option	1	Stieglitz scheme (Yen, 1965)
lower boundary of soil temperature option	2	Deep soil boundary temperature read from input file (Niu et al., 2011)
soil supercooled liquid water option	1	No iteration (Niu and Yang, 2006)
runoff option	3	Schaake scheme (Schaake et al., 1996)
frozen soil permeability option	1	linear effects, more permeable (Niu and Yang, 2006)
soil configuration option	1	use input dominant soil texture
glacier treatment option	1	include phase change of glacier ice
tile drainage option	0	No tile drainage
irrigation option	0	No irrigation
dynamic crop model option	0	No dynamic crop model

Code and data availability

1. The data and scripts produced in this study is available at <https://doi.org/10.5281/zenodo.14567219> (He et al., 2025).
2. The LIS/Noah-MPv5.0 model code produced and used in this study is available at <https://doi.org/10.5281/zenodo.14567646> (He et al., 2024b).



610 **Author contribution**

611 CH, JW, and SK proposed research idea. CH performed technical coding and model coupling with
 612 help of DM. TL performed model simulations and evaluations with contribution from CH, DM,
 613 and RA. CH drafted the paper with contribution from TL, DM, RA, JW, and SK.

614

615

616 **Competing interests**

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

618

619

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 626 findings, conclusions, or recommendations expressed in this publication are those of the authors
 627 and do not necessarily reflect the views of the National Science Foundation or NASA.

628

629

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