A comprehensive evaluation of soil moisture and soil temperature from third-generation atmospheric and land reanalysis data sets

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Abstract
Soil moisture and soil temperature, reflecting a synthetic climate regime, are vitally important for climate change assessments and adaptation. As historical in situ measurements of soil states are extremely scarce and spatially uneven, reanalysis products play an increasingly important role in filling these gaps. The focus of this paper is on water–heat covariations in reanalysis products and a joint evaluation of soil moisture and soil temperature in five widely used atmospheric and land reanalyses is presented using in situ observations from 25 networks during various periods from 1979 to 2017. At the network scale, the five reanalyses show statistically significant correlations with observations, and the European Centre for Medium-Range Weather Forecasts ERA5 shows higher skills than the other four products and a significant improvement over its predecessor. The National Centers for Environmental Prediction Climate Forecast System Reanalysis performs better in terms of long-term trends. The most skilful signals in the five reanalyses are the seasonal cycles, with correlation coefficients of over 0.9. However, long-term trends are substantially weaker than the observed trends and still tend to perform poorly over the high latitudes during cold seasons. Soil temperature reanalyses show even better skills, with mean correlation coefficients over 0.9 between anomalies; ERA5 shows enhanced annual ranges toward the high latitudes and altitudes. A joint evaluation of soil temperature and soil moisture showed physically consistent water–heat covariations in the soil in conjunction with atmospheric fluxes during the growing season over the Northern Hemisphere. This report suggests a good future for reanalysis products and their potential role in land surface climate change assessments.

Keywords
atmospheric and land reanalysis, climate change, soil moisture, soil temperature, water–heat covariation
1 | INTRODUCTION

Soil moisture and soil temperature states synthetically reflect the climatology of water–heat balances between the land and atmosphere and hence fundamentally shape the region-specific terrestrial ecosystems and environments (Hirschi et al., 2011; Wang and Dickinson, 2012). However, in the past, owing to the large labour costs and the complexity of measurements, in situ observations of soil states have been conducted less often than those of precipitation and surface air temperature. The lack of observations is currently hampering the urgently needed assessments of the impacts of climate change on our living environments (Seneviratne et al., 2010). Over recent decades, reanalysis systems that assimilate satellite and ground observations have made encouraging progress, and the resulting data sets play increasingly important roles in filling data gaps in the studies of climate change and environmental impacts. However, the interpretation of these applications lies in the reliability of the reanalysis data (Thorne and Vose, 2010). Although a host of efforts have been dedicated to evaluating reanalysis products (Stillman et al., 2016; Zhou et al., 2017), with the accumulation of observations and the use of new methods, further evaluations are still necessary to offer insights into effective and the efficient use of reanalysis data sets.

Compared with the previous systems, the third-generation atmospheric and land reanalyses provide the following key advancements: the transition of land surface analysis schemes from semicoupled to offline mode, advancements in assimilation schemes, land surface models, and coupled models, and the augmentation of input observational data. In part of the reanalyses, the land analysis is forced directly using observed precipitation analyses instead of simulations by a background atmospheric model or adjustments with observations (Saha et al., 2010; Dee et al., 2011; Kobayashi et al., 2015; Gelaro et al., 2017). Thus, land processes are less influenced by precipitation errors in atmospheric models, which in turn improves bottom-boundary initializations for atmospheric models. Building on predecessor models, third-generation reanalysis systems improved physical parameterizations, with considerably increased horizontal resolution, vertical height and levels in atmospheric models, and implemented data assimilation techniques (Evensen, 1994; Yin et al., 2015). These make effective use of land data and the assimilation of atmospheric observations (Fujiiwara et al., 2017). In addition to accumulated conventional observations, the increased satellite data from 1979 onward are assimilated (Bronnimann et al., 2018). Together, these processes improve the budgets and balances of land water and heat variations in third-generation reanalyses (Reichle et al., 2011; Lorenz and Kunstmann, 2012; Kang and Ahn, 2015).

There have been many efforts made to assess the third-generation reanalysis products of soil states based on limited observations. In terms of soil moisture, the evaluation of the European Centre for Medium-Range Weather Forecasts Interim Re-Analysis (ECMWF, ERA-Interim) indicated that the reanalysis makes considerable progress in reproducing observed spatial and temporal characteristics, especially in the surface-layer soil (Albergel et al., 2012). The interannual variations in ERA-Interim also agree well with those in regional observations, with enhanced precipitation-evapotranspiration balances (Liu et al., 2014). In a semiarid climate, the ability of ERA-Interim to reproduce annual variations in the surface soil layer is comparable to that of retrievals from remote sensing, in terms of mean biases and trends (Stillman et al., 2016). In the permafrost regions of the Tibetan Plateau, the National Centers for Environmental Prediction Climate Forecast System produces similar temporal patterns to those of in situ soil moisture observations, but ERA-Interim underestimates the temporal dynamics of soil moisture and fails to capture the observed dynamics during the thawing season (Zeng et al., 2015; Qin et al., 2017). These evaluations suggest that the ability of a reanalysis to simulate soil moisture varies with region.

There have been fewer regional evaluations of soil temperature reanalyses, because of a lack of in situ measurements. However, a comparison of observations at 700 stations, but only for 2012, showed that the ECMWF system, which used the same models as ERA-Interim, accurately regenerates the annual and diurnal cycles in observed soil temperature (Albergel et al., 2015). The land surface temperatures from eight reanalyses (two included in this study) are skilful in determining the interannual variations in the China region, except over the Tibetan Plateau, and ERA-Interim performs better (Zhou et al., 2017). In the 40-cm soil layer, reanalyses reasonably reproduce the spatial patterns of observed soil temperature, especially in eastern China, despite underestimating their magnitudes (Yang and Zhang, 2018). However, evaluations of the soil temperature from third-generation reanalyses currently remain scarce.

The limited previous evaluations are mainly focused on a single variable (soil moisture or soil temperature). However, in the soil, the processes of water and heat transport interact with each other within a soil thermal-hydraulic regime (Cahill and Parlange, 1998; Parlange et al., 1998). These interactions are tightly linked to the processes of soil evaporation, soil moisture content changes, surface energy partitioning, and land geochemical and planetary boundary layer dynamics (Bittelli et al.,...
2008). Over the high-latitude and high-altitude cold regions, in particular, the soil freeze–thaw cycles strengthen the water–heat coupling; soil temperature determines the timing of the phase changes in soil water, and the heat consumed (released) over the course of thawing (freezing) affects the variations in soil temperature (Wang and Yang, 2018). In addition, soil water–heat states regulate the physiological processes of vegetation, inducing changes in carbon and nitrogen budgets on regional and global scales (Raich and Schlesinger, 1992; Agehara and Warncke, 2005; Anderson et al., 2008). Therefore, the joint evaluation of soil moisture and soil temperature considering water–heat interactions, facilitates understanding of the physical consistency in the soil and the appropriate application of reanalyses in the studies of terrestrial environments.

With the advancement of reanalysis systems, these products have been extensively used; however, more detailed evaluations are more urgently required, especially for the latest ECMWF reanalysis (ERA5), which uses improved historical observations and is at a finer resolution than its predecessor ERA-Interim. Moreover, the joint evaluations of soil states in reanalyses, from the perspective of water–heat interactions, needs further research to shed light on the improvement and application of reanalysis products. In the present study, we focus on the further evaluation of soil moisture and soil temperature in such reanalysis products, particularly in ERA5, through a combined assessment using augmented in situ observations of soil moisture and soil temperature throughout recent decades. The reality of water–heat interaction regimes is also assessed against the variabilities in precipitation and surface air temperature. The aim is to deepen the understanding of soil state representations in third-generation reanalyses and to assist in their effective application.

2 DATA AND METHODS

2.1 The Reanalyses

Five reanalysis products were evaluated: (a) the Japanese 55-year reanalysis (JRA-55), (b) the National Centers for Environmental Prediction Climate Forecast System Reanalysis (CFSR), (c) the Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2), (d) ERA-Interim, and (e) the latest ECMWF reanalysis ERA5. Currently, these reanalyses are playing increasingly important roles in the assessment of climate change, as well as in applications of terrestrial environmental studies (Seneviratne et al., 2010; Gallego-Elvira et al., 2016).

Among them, CFSR has the highest horizontal resolution (~0.31° × 0.31° for 1979–2010 and ~0.20° × 0.20° for version 2, 2011–2017); ERA-Interim has the coarsest resolution (~0.70° × 0.70°), whereas its successor ERA5 has a finer resolution (~0.28° × 0.28°); the other two data sets are in between. These data sets cover the period from 1979 (1980 MERRA-2) to present. In JRA-55 land analyses are conducted using an offline land model with a 3-hr forcing from an atmospheric model. In ERA-Interim, soil moisture and soil temperature simulations are corrected by the 2-m analysis increments of air temperature and relative humidity, according to an empirical approach. Building upon its predecessor, ERA5 combines more historical observations and runs on finer horizontal and vertical resolutions. In CFSR and MERRA-2, land reanalyses are generated using coupled atmosphere-land systems but with observation-corrected precipitation. Furthermore, the two reanalyses both use fully coupled and semicoupled systems to make first-guess simulations and land reanalyses. In addition, soil temperature products from the five reanalyses are also evaluated as a cross-examination to ensure water–heat consistency. Further details of the reanalysis data sets are presented in Table 1 and the references therein.

2.2 In situ observations and data quality

In situ soil moisture observations were taken from the international soil moisture network (ISMN, https://ismn.geo.tuwien.ac.at) and the China Meteorological Administration (CMA, http://www.cma.gov.cn/2011qxfw/2011qjxj). The ISMN is a soil moisture database maintained through international cooperation, and many available observations have been collected around the world through coordination by the Global Energy and Water Exchanges Project (Dorigo et al., 2011). To date, the database consists of measurements from 2,328 sites in 58 networks. These in situ observations play an increasingly substantial role in evaluating satellite and model products, for example, (Robock et al., 2000; Dorigo et al., 2011; De Lannoy et al., 2014; Wang-Erlandsson et al., 2016). Further details about observational instruments and rigorous data quality control can be found in the network reports and references therein (available from https://ismn.geo.tuwien.ac.at).

Regarding quality control and data selection of soil moisture in this study, to efficiently use these valuable observations and expand their spatial coverage, we used all available observations with efficient records over more than 36 months from all 2,328 sites. There were 842 qualified sites covering 25 networks from low to high latitudes during the study period (1979–2017). The details on the
25 networks are presented in Table 2. According to Dorigo et al. (2011), the ratios of records with ‘good’ quality to the totals are shown in Figure 1. The low-quality records are mainly wintertime observations from the SNOTEL network of the United States and parts of mid- to high latitude or high altitude networks, such as in Alaska of the United States, Finland, and the Tibetan Plateau of China (Figure 1 and Table 2). With respect to these sites, we filtered out some records of less than ‘good’ quality and excluded the frozen periods in wintertime according to Dorigo et al. (2013) due to the inconsistency in water contents in measurements (liquid water) and reanalyses (liquid water and ice) (Bi et al., 2016). Finally, all the records from the 842 sites have ‘good’ quality ratios of over 85% during selected periods (more than 36 months). These more than 3-year records can represent the local climate and meet the statistical requirements of the large sample theory ($n > 30$). These measurements were obtained at various depths ranging from 5 to 50 or 100 cm below the soil surface using sensors for high-frequency records, and the oven-drying method was used for those of lower frequencies in China, Mongolia, and the former Soviet Union region (Table 2).

The in situ observations of soil temperature herein were available only in parts of the networks (Table 2), which were measured concurrently with soil moisture. In

| Data sets | Analysis methods | Data period | Spatial resolution | Soil layer depths (cm) | Land model | Unit | References |
|-----------|------------------|-------------|--------------------|------------------------|------------|------|------------|
| JRA-55    | Offline with forcing by the atmospheric model | 1979–2017 | ~0.56° × 0.5° | Three layers, depths vary with vegetation types: 2–100, 17–148, 30–200 | JMA SiB (Sellars et al., 1986; Sato et al., 1989) | Proportion | Kobayashi et al. (2015) |
| CFSR      | Fully coupled and semicoupled analysis | | ~0.31° × 0.31° for 1979–2010; ~0.2° × 0.2° for 2011–2017 | 5, 30, 100, 250 | Noah land surface model (Ek et al., 2003) | Volumetric fraction | Saha et al. (2010), Saha et al. (2014) |
| ERA-interim | Empirical correction by 2-m atmospheric analysis increments | | ~0.7° × 0.7° | 7, 28, 100, 289 | TESSEL (Van den Hurk et al., 2000; Van den Hurk and Viterbo, van den Hurk and Viterbo, 2003) | | Douville et al. (2000); Dee et al. (2011) |
| ERA5      | Higher resolution (9-km) simulation, with thermo dynamical orographic adjustment | | ~0.28° × 0.28° | | HTESSEL (Balsamo et al., 2015) | | Hersbach et al. (2018) |
| MERRA-2   | Precipitation corrections within the coupled atmosphere–land modelling system | 1980–2017 | ~0.5° × 0.625° | 5, 100, depth to bedrock, nested depths | Catchment model (Koster et al., 2000) | | Gelaro et al. (2017) |

Abbreviations: HTESSEL, hydrology tiled ECMWF scheme for surface exchanges over land; JMA SiB, Japan meteorological agency simple biosphere model; TESSEL, tiled ECMWF scheme for surface exchanges over land.
particular, the data in China were available over a longer time, and these data were measured by CMA according to the requirements for meteorological observations by the World Meteorological Organization using soil thermometers at depths of 15, 20, and 40 cm below the soil surface. The observational frequency is four times (2, 8, 14, and 20, UTC + 8) per day. The data from 79 sites were used herein according to the data completeness with less than 5 and 30 days of consecutive missing and total missing records, respectively, during the study period of 1980–2000.

### 2.3 The precipitation and surface air temperature

To reduce uncertainties, we used two sets of precipitation and surface air temperature data to investigate the responses of soil states to atmospheric constraints. These data were taken from the Climate Prediction Center (CPC, taken from ftp.cdc.noaa.gov) of the National Oceanic and Atmospheric Administration in the United States and the Climatic Research Unit (CRU, http://www.cru.uea.ac.uk/data) at the University of East Anglia in the United Kingdom. The CPC data set is an analysis product that uses records from over 30,000 sites managed by international agencies. These records are also used in quality control, along with concurrent radar/satellite observations and numerical model forecasts. The daily mean data sets are globally available on a 0.5°C × 0.5°C latitude × longitude grid for the period from 1979 to present (Xie et al., 2007). The CRU data used herein were taken from the CRU TS v. 4.01 version of the gridded time-series data set, which was also produced based on site records. The monthly data sets are available on a
0.5° × 0.5° latitude × longitude grid covering all land between 60°S and 80°N during the period of 1901–2016 (Harris et al., 2014; Harris and Jones, 2017).

2.4 Methods

We performed the observation-reanalysis comparisons between the sites and the model grid cells that the sites were in. We did not conduct an interpolation to zoom in from model grid cells to locate sites owing to inevitably introduced errors. In the case of sites located at model grid borders (vertices), the means of two (four) grid cells were used to represent the reanalysis outputs. Because of the inconsistency between the observation-reanalysis soil layers (Tables 1 and 2), the reanalysis data were interpolated to meet the observational depths for all 25 networks by converting volumetric soil moisture to total soil water (Li et al., 2005; Albergel et al., 2013), which was then estimated using soil layer thicknesses as weights. For 0–30 cm soil moisture, which is not available in MERRA-2, we generated the data by weighted interpolation using values in the surface (0–5 cm) and root (0–100 cm) layers according to Li et al. (2005). In addition, comparisons were also conducted between the China network 0–100 cm layer versus 0–100 cm layer in CFSR, ERA-Interim, and ERA5, as well as versus the root layers in MERRA-2 and the ‘middle’ layer in JRA-55.

To derive the volumetric soil moisture contents of JRA-55, we used its soil wetness in fraction form and a soil constant of saturated volumetric soil moisture (field capacity) according to soil-water relationships (Clapp and Hornberger, 1978; Cosby et al., 1984; Wang-Erlandsson et al., 2016) as follows:

\[ S_v = F_C \times S_R, \]

where \( S_v, F_C, \) and \( S_R \) denote the volumetric soil moisture, field capacity, and relative soil moisture (fraction), respectively. The constant field capacity that is related to soil porosity was taken from the Community Land Model (Lawrence et al., 2019, from http://www.cesm.ucar.edu/models/cesm2/land/). For soil temperature in the 0–40 cm soil layer, we used the arithmetic average of the ground temperature and soil temperature (for all depths).

Given that each site observation has short durations to varying degrees and was conducted over various periods, we integrated these observations into a time series as a subset for the statistical population of climate during the whole period to conduct assessments on multiple time scales. The sequence of observational soil moisture was integrated from all 842 sites (Figure 1) along the timeline from 1979 to 2017, and a reanalysis sequence was generated with the corresponding timings and grid cells. The resulting time series may not represent a real climate, but it is sufficiently robust and more informative to assess the consistency between observations and reanalyses. To quantify the consistency of time multiscale signals, we then decomposed the integrated monthly time series into long-term, seasonal, and residual signals using a method of seasonal trend decomposition based on
Loess (Cleveland et al., 1990) in an additive model as follows:

\[ Y_t = T_t + S_t + R_t, \]  \hspace{1cm} (2)

where \( Y_t \) denotes the integrated soil moisture time series of observations or reanalyses. This equation additively consists of long-term (\( T_t \)), seasonal (\( S_t \)), and the remaining (\( R_t \)) components at time \( t \). The long-term component can be further decomposed into linear and nonlinear signals by linear least squares regression. The nonlinear signal reflects repeated but nonperiodic fluctuations. Seasonal variations occur over a fixed period (e.g., monthly). The residual component represents subseasonal signals and noise.

To assess the ability to regenerate extreme variations in soil temperature reanalyses, we adopted the quantile regression method (QR) to estimate the functional relationships between reanalyses and observations for all portions of a probability distribution rather than the mean (e.g., by ordinary least squares regression). QR is a collection of statistical methods for estimating and making inferences about conditional quantile functions (Koenker and Bassett, 1978). QR is suitable for modelling the heterogeneous variance in nonstationary change rates in heterogeneous data and has been widely used in studies of ecology and climate change (Barbosa et al., 2011; Cozzoli et al., 2013).

The other adopted statistics of comparison include the Pearson correlation coefficient and ordinary least squares linear trend, root-mean-square error, and \( SD \).

The correlation coefficients at site grid scales were estimated using raw data (with an annual cycle) because it remains a challenge for most land models to capture the accurate annual cycle of soil moisture in various layers. At regional scales, the annual cycles were removed to offer more rigorous evaluations of variations. The significance was tested using a Student's \( t \) test. The estimation of hemispheric means for land and atmospheric variables (Section 3.3) was weighted using the cosines of the central latitudes of each grid cell.

3 | RESULTS

3.1 | Evaluation of soil moisture and soil temperature of the latest ECMWF reanalysis ERA5

At the site scale, the correlation coefficients (\( r \)) of monthly soil moisture between reanalysis and observations (at depths from 5 to 50 cm or to 100 cm, Figure 2) illustrate that across 842 site grid pairs, 705 (83.7%) are significantly correlated (\( p < .05, n > 36 \)), with strong positive relationships for 589 pairs (70.0%, \( r > .5 \)) and 307 (36.5%) coefficients over 0.7. ERA5 soil moisture

![Geographical distribution of 842 in situ observational sites and correlation coefficients between the monthly observations and ERA5 reanalysis, with various sample sizes of each observation-reanalysis pairs (see Tables 1 and 2, 36 < n < 312) over 1979–2017. The colour bar denotes the distribution of correlation coefficients and the value of 0.349 indicates a significant correlation (p < .05) at the minimum sample size (n = 30).](image-url)
reasonably regenerates the observational monthly dynamics and annual cycles at most sites, especially the timings of the strong dry-wet transition. The spatial distribution of significant correlations indicates that the reanalysis also captures the spatial structure of variations in the observed soil moisture. However, the low correlations (16.3%) still account for a considerable portion, and their distributions depend on the observational networks, such as China summer, Mongolia, and SNOTEL in the United States. In parts of the high-latitude sites, particularly in Alaska, United States, ERA5 misses the main characteristics in the observed monthly evolutions. Notably, the mismatched representativeness between sites and model grid cells has likely degraded their correlations, especially in the regions with complex topography and landforms because the grid cell represents an averaged state within the latitude-longitude grids (~31 × 31 km), whereas site measurements are point-specific. In parts of the former Soviet Union, Mongolia, and China, the lower correlations are partly accounted for by a lower frequency of observations (Table 2).

At network scales, the annual cycles for 25 networks (Figure 3) illustrate overall good agreement between ERA5 and observations during various study periods over the 1979–2017 period. The temporal patterns for the observed dry-wet variations are regenerated by the reanalysis in all networks except for the high-latitude networks Alaska, United States, and Poland (Figure 3c, x), in addition to the much stronger aridity in June in Mongolia. The consistency in the CTP_SMTMN network (Figure 3l), which is set up in a 10,000 km² fairly smooth area at 4500 m above mean sea level on the central Tibetan Plateau (Yang et al., 2013), indicates that ERA5 regenerates the effects of low temperature on soil moisture at high altitudes but with homogeneous topography. Despite the reasonable annual cycles in most networks, substantial biases in absolute soil moisture remain, which are partly related to the mismatch of soil layer depths in observations and the reanalysis (Tables 1 and 2). In addition, it is worth noting that the mean annual cycles of soil moisture for the 25 networks represent the subsets of the climates during various study periods (to a varying

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**FIGURE 3** Annual cycles of site-averaged soil moisture over the 25 observational networks and corresponding ERA5 reanalysis. The serial numbers (a–y) of panels correspond to those of Table 2.
degree, not representing the real climatological features) due to the limitations of the available observations.

Considering the limitation of observations at site and network scales, we integrate all available observations into a time series that represents a subset for the statistical population of global soil moisture over 1979–2017. Then, we conducted a seasonal trend decomposition analysis (Figure 4) to assess the soil moisture consistency on multiple time scales, especially the long-term trends, on a global scale. ERA5 can considerably reproduce the observed fluctuations at a global scale, with a significant correlation coefficient of 0.79 ($p < .01$, $n = 468$, Figure 4a). The correlation coefficients for the trend, seasonal, and residual components are 0.73, 0.94, and 0.64 (all significant at $p < .01$, $n = 468$), respectively, suggesting that ERA5 reproduces the observational signals at various periodic scales. Linear trends in trend components (Figure 4b) are $-6.0$ and $-2.1$ percentage points during the 39 years of observations and the reanalysis, respectively, revealing high consistency in the linear parts of the two soil moisture trends. However, for nonlinear signals, the intensity of the reanalysis is characterized by decadal variability compared to observations. The seasonal variations (Figure 4c) show good agreement with each other, although the amplitudes are stronger in ERA5 than in the observations. The subseasonal signals and noise (Figure 4d) in ERA5 still have high fidelity to the high-frequency fluctuations. The seasonal trend decomposition analysis demonstrates that the ERA5 reanalysis reasonably regenerates the fluctuations at various periodic scales from the perspective of the global average.

To examine the water–heat consistency in ERA5, the soil temperature is also examined in regions where in situ observations are available (Figure 5). Correlation coefficients (annual cycles removed, Figure 5a) between 79 site grid pairs are all significant ($p < .01$, $n = 252$) during 1980–2000, and the values all exceed 0.9 in the case of the annual cycles retained. In total, 91.1% of the pairs show correlation coefficients over 0.5, and 74.7% of them are greater than 0.7. Low values appear at sites in mountainous areas in western China. The correlation coefficient between regional mean anomalies (Figure 5b) reaches 0.94 for the study period. Meanwhile, ERA5 accurately regenerates the traits of annual variations in observational soil temperature on a regional scale, with a slightly cooler bias (Figure 5c). This suggests, together with reasonable variations in soil moisture, that the ERA5 reanalysis is well constrained by water-energy interactions, and it is especially robust in regions with homogenous topography.

### 3.2 Comparisons of soil moisture and soil temperature between the five reanalyses

We place the latest ERA5 in the context of the other four reanalyses (ERA-Interim, CFSR, MERRA-2, and JRA-55)
to compare the level of fidelity in the soil states of the third-generation reanalyses. At the site scale, the five reanalysis soil moistures generally show high skill levels (Figure 6). The correlation statistics (Figure 6) show that 83.7% of sites are significant, 70.0% of R-values are over 0.5, and 36.5% are greater than 0.7 in ERA5. MERRA-2 has similar correlations, with a slightly higher ratio of significant correlations but a lower ratio of strong correlations ($r > 0.7$); the other three reanalyses show similar correlation levels, but they are distinctly lower than the former two. Regarding the spatial patterns of correlations (Figure S1), ERA5 performs better in Mongolia and western China and improves in the SNOTEL network, United States; over these regions, the other four reanalyses show relatively low consistencies with observations. MERRA-2 performs better in the mountainous regions in the SNOTEL network. JRA-55 shows a higher correlation than the others in not only the high latitudes of Eurasia but also Alaska, United States.

At the observational network scale, the statistics of site-averaged sequences from five reanalyses for 25 networks over the period of 1979–2017 show that the performances of reanalyses vary among networks (Figure 7a–c). In terms of average statistics (Figure 7d–f), ERA5 has the greatest correlation coefficients between anomalies, followed by ERA-Interim, MERRA-2, CFSR, and JRA-55, with medians of 0.63, 0.49, 0.46, and 0.48, respectively. Regarding SD, ERA5 is also statistically closest to the observations with medians of 3.2 and 3.1% points, respectively; the other four generally show lower intensities. With respect to linear trends, CFSR shows a stronger increase, but the others are all weaker than the observations; meanwhile, ERA5 shows improvement compared with its predecessor, ERA-Interim. Overall, the statistics vary considerably among networks. The correlation is much higher over those with homogenous terrain (e.g., USCRN, United States, China summer, and OZNET, Australia) than the others. Skills in capturing the variations on the Tibetan Plateau by ERA5, ERA-Interim and MERRA-2 are more encouraging (0.75, 0.69, and 0.64, respectively; significant at $p < .01$, $n = 84$). Over four networks of 1 m observational depths (Table 2), ERA5 is more skilful with significant correlation coefficients ($p < .05$). The annual cycles and monthly series of 25 networks (Figures S2 and S3) have larger spreads in absolute soil moisture between the five reanalyses. Overall, at the various network scales, ERA5 performs statistically better than the other four reanalyses.
On the global scale, the seasonal trend decomposition analysis of the time series, integrated with all available observations of 842 sites and corresponding grid cells of five reanalyses over 1979–2017, shows that the reanalyses generally agree well with observations ($p < .01$, $n = 486$, Figure 8, see statistics in Table 3). The trend terms are significantly in line with observations, with the largest correlation coefficient of 0.73 (ERA5, $p < .01$, $n = 468$) and the lowest value of 0.14 (JRA-55, $p < .05$, $n = 468$). Although there is substantially lower intensity in the linear trends in all the reanalyses than in the observations, CFSR shows a more proximate slope with the same sign, followed by ERA5, while JRA-55 presents the opposite sign. Regarding seasonal terms,
the five reanalyses all skilfully yield annual cycles, with correlation coefficients over 0.9. The subseasonal signals and noise (residual terms) show reasonable skill levels, and ERA5 still performs considerably better than the other reanalyses except for a larger root-mean-square error. Overall, with the expanded spatial scales, the reanalysis is increasingly skilful for various periods in the regeneration of the observed regional soil moisture.
variability, albeit with a lower intensity for long-term trends.

Given the close interactions between water and heat in the soil, soil temperature variations are also compared with in situ observations across 14 available networks (Table 2). At all 362 sites, the five reanalyses perform remarkably well, with 98–99% of sites having correlations over 0.8 ($p < .01$, with various sample numbers, but over 30). In other words, the sites of correlations less than 0.8 are 6, 6, 5, 3, and 3 for JRA-55, ERA-Interim, ERA5, MERRA-2, and CFSR, respectively (Figure S4). At observational network scales, five reanalyses capture the observed annual cycles. The 14-network averaged annual soil temperature ranges are 14.5, 10.0, 14.29, 17.6, 18.6, and 19.4 K for the observations, CFSR, MERRA-2, ERA5, ERA-Interim, and JRA-55, respectively (Figure S5). Further comparisons between ERA-Interim and ERA5 against observations (Figure S6) suggest that ERA5 outperforms its predecessor, ERA-Interim, in terms of annual soil temperature ranges in part of the networks (e.g., Figure S6f,l,m,n), which are mainly located at high latitudes and high altitudes. The improvement may be partly associated with the enhanced snowpack parametrization and the improved snow depth analysis (Hersbach et al., 2018).

In particular, we separately compared soil temperatures with in situ observations from the network of China because of their longer data series and operations according to the World Meteorological Organization (Section 2.2). From 1980 to 2000, the anomalies (Figure 9a) illustrate that reanalyses agree remarkably with observational variations, with all correlation coefficients over 0.9, and with similarly larger values of 0.97 for ERA-Interim and ERA5 (Table 4). High fidelity is observed in seasonal variations and multianual fluctuations, except for the cooler biases in all reanalyses (Figure 9a,b, with the smallest bias in ERA5 followed by its predecessor, ERA-interim). The mean soil temperature in ERA-Interim is closer to that of observations than its successor ERA5 and the other three reanalyses over China during the study period, although all of them show high skill levels (Table 4). Since the reanalysis soil temperature is skilful in reproducing the observed evolutions, we conducted a quantile regression analysis to validate their ability to generate extreme variability. The soil temperature distributions and regressions at quantiles of 0.05 and 0.95 illustrate that reanalyses can similarly generate the extremes at high and low quantiles, especially ERA-Interim, which shows more robust regressions and closer proximity to observations and is even better than its successor ERA5 (Figure 10). Soil temperature is higher at the high ends and lower at low ends in ERA-Interim, ERA5, CFSR, and JRA-55, with increased biases in turn, whereas in MERRA-2, the distribution is the opposite. The quantile regression slopes in ERA-Interim, ERA5, CFSR, and JRA-55 are ~3–1%, ~6–3%, ~10%, and ~18–22% greater than those in observational high and low ends, respectively, while slopes in

![Figure 9](https://example.com/figure9.png)

**Figure 9** Soil temperature (ST) anomalies (a) and annual cycles (b) for regionally averaged observations and the five reanalyses during 1980–2000

| Statistics                      | JRA-55 | ERA-Interim | ERA5       | MERRA-2       |
|---------------------------------|--------|-------------|------------|---------------|
| Correlation coefficients       | 0.90** | 0.97**      | 0.97**     | 0.92**        |
| Root mean square error (K)     | 0.38   | 0.15        | 0.18       | 0.27          |
| Standard deviation (K)         | 0.85   | 0.79        | 0.71       | 0.67          |
| Linear trends (K per dec.)     | 0.44** | 0.38**      | 0.50**     | 0.49**        |
| Linear trends (K per dec.)     | 0.32 for Obs. |            |            |               |

Note: * and ** denote significances at $p < .05$ and .01 levels, respectively, $n = 252$.
MERRA-2 are ~5–12% smaller than those in the observational variations at high and low ends during the study period. Although the various biases can be seen in terms of statistics, the five reanalyses of soil temperature are quite capable of representing the observed variations at regional scales.

### Covariations in soil moisture and soil temperature constrained by precipitation and surface air temperature

It is impractical to compare the covariations in the in situ soil moisture and temperature observations with those in...
**FIGURE 12**  Linear trend patterns of soil moisture and temperature means of CFSR, ERA-interim, ERA5, and MERRA-2, in relation to those of precipitation and air temperature means of CPC and CRU, in the growing season (May–September) over the period 1979–2017. The black dotted lines denote significance at the $p < .05$ level, $n = 468$.

**FIGURE 13**  Running correlation coefficients between zonal-averaged soil moisture and soil temperature (SM-ST), soil moisture and precipitation (SM-P), soil temperature and surface air temperature (ST-T), and precipitation and surface air temperature (P–T) in the growing season (May–September) from 1979 to 2017 over land in the Northern Hemisphere. Herein, SM and ST are the means of CFSR, ERA-interim, ERA5, and MERRA-2, P and T are the means of CPC and CRU, and the running-window width is 10° latitude; *denotes significance at the $p < .05$, $n = 468$ level.
reanalyses owing to short and various observational times and spatial inconsistencies. We examine the covariations in reanalyses in the context of observational precipitation and surface air temperature. The root-layer (0–1 m) soil moisture and temperature values of the four reanalyses with complete data (CFSR, ERA-Interim, ERA5, and MERRA-2, excluding JRA-55 due to its varying root layer depths) are used to estimate the variation range of the reanalyses. During the growing seasons (May–September) over the Northern Hemisphere, there is a significant warming and wetting trend in terms of atmospheric climate change (Figure 11). The surface air temperature increases by 1.2 K, and precipitation increased by 11.3 mm during 1979–2017; in contrast, the trends in the root-layer soil are considerably flat, with rates of 0.8 K and 1.2 mm, respectively, during the same period. The covariations in water–heat in the root-layer soil are also well constrained by atmospheric processes in terms of seasonal averages, with correlation coefficients of 0.63 and 0.97 for soil moisture versus precipitation and soil temperature versus air temperature, respectively. The interannual water–heat fluctuations are reasonable, with standard deviations of 1.99 and 8.73 (mm·a⁻¹) for soil moisture and precipitation and 0.28 and 0.35 (K·a⁻¹) for soil temperature and air temperature, respectively.

Regarding the spatial patterns of soil water–heat variations against those of atmospheric variables, the linear trends (Figure 12) show nearly consistent warming from the surface air to the root-layer soil in the growing season (May–September). The trends are similar in the root-layer soil to those in the surface air, except in parts of the Amazon Basin and northern Africa. Near the Arctic, the soil temperature shows quicker increases, which is consistent with the finding of Arctic amplification in air temperature (Serreze and Francis, 2006). Regarding soil moisture, the variation pattern agrees with that of precipitation in terms of strong dry-wet variations. However, substantial discrepancies are observed over the regions of dry-wet transitions and moderate trends. For instance, the soil moisture drying trends are much stronger and more extensive than the precipitation decreases over Eurasia. Over North America, the co-occurrence of increased precipitation but decreased soil moisture is observed in the northern parts. These discrepancies require specific observations and modelling experiments to understand the potential causalities. However, from the view of the physical processes of land-atmosphere interactions, these trend variations qualitatively agree with the observations and balances of water and heat between the land and atmosphere (Delworth and Manabe, 1993; Seneviratne et al., 2010). Overall, the land processes respond

**FIGURE 14** Evolution of the linear trend in zonally averaged soil moisture (SM), precipitation (P), soil temperature (soil T) and air temperature (air T) from low to high latitudes in the Northern Hemisphere in the growing season (May–September) for the period 1979–2017. The means of the four variables are estimated as in Figure 13. The dark blue lines denote linear trends in the averages of various variables; the light blue and red lines denote the minimum and maximum linear trends, respectively; and the black dashed lines are reference lines.
reasonably to atmospheric climate change, with remarkable regional diversity under the constraints of land-atmosphere interactions, especially viewed in the direction from low to high latitudes.

From low to high latitudes over the Northern Hemisphere, the meridionally running correlations between the zonally averaged variables in the soil and atmosphere (Figure 13) show that soil moisture and soil temperature generally interact with a negative correlation at the monthly scale; the significant positive correlations mainly occur at high latitudes approximately 70°N, along with the distinctly changed relationships between soil moisture and precipitation. At low latitudes, negative correlations between the soil moisture and soil temperature are contributed by two pathways: the atmospheric and land pathways. Soil moisture increases as precipitation increases, while the accompanying increased cloud cover and hence decreased solar radiation lead to decreases in both soil temperature and surface air temperature; meanwhile, increases in soil moisture in response to increased precipitation lead to intensified evapotranspiration of soil water, which then cools the soil temperature. At high latitudes, for the climate regime of rain-heat over the same period, soil moisture and soil temperature increase concurrently at the monthly time scale during the growing seasons. Additionally, warmed air and soil lead to melting of snowpack (if any), which contributes to the concurrency of variations in soil moisture and soil temperature. However, the dynamics of water and heat in soil vary with soil properties, topography, and climate, according to region-specific regimes. The physical causalities are complicated and require validation at even higher temporal resolution. However, the meridional variations in correlations reveal reasonable changes in constraints of topography and climate on soil water and heat transport in the reanalyses.

Figure 14 shows the rates of soil moisture and soil temperature variations, along with those in precipitation and surface air temperature (Figure 14). The linear trends show that strong variability and contrast occur in zonally averaged soil moisture over low latitudes, and they are largely consistent with the variations in precipitation trends. Over middle latitudes, soil moisture and precipitation trends are remarkably depressed, and they both increase over high latitudes, especially those of soil moisture. Regarding soil temperature and surface air temperature, closer associations occur over middle to lower-high latitudes. The strongest responses in soil temperature to the Arctic amplification of warming appear at approximately 75°N. Over high latitudes, the variations in soil moisture and temperature are progressively more complicated with accelerated increases in surface air temperature. The meridional evolutions of the variations in both land and atmospheric processes highlight the consistency in water–heat balances in the reanalyses against the observed atmospheric precipitation and temperature.

4 | DISCUSSION

4.1 | Realism of reanalysis soil moisture varies with region and time scale

The reanalysis soil moisture showed skill in seasonal evolutions but notably weaker long-term linear trends although with the same varying directions. At the site scale, most reanalyses (76–86% site grid cell pairs) significantly capture the observed monthly variations, which overall also depict the spatial structure of soil climate change. With respect to long-term variability, the observed nonperiodic fluctuations are reasonably regenerated in the reanalyses, particularly in ERA5. On the other hand, skills in reanalyses vary regionally, with good skills in the areas of homogeneous topography and landforms. These are mainly due to advances in data assimilation, model resolutions (finer than 1° × 1°), and input observations (Saha et al., 2010; Hersbach et al., 2018), which in turn enhance the accuracy of global climate and constraints in the analysis (Chen et al., 2014; Auger et al., 2018). Compared with their previous generation, reanalyses are noticeably improved (Albergel et al., 2013; Peng et al., 2015; Stillman et al., 2016). The present validations, along with the land hydrology and energy valuations (Liu et al., 2014; Reichle et al., 2017; Li et al., 2017a), support the high accuracy of the soil moisture reanalysis, especially in seasonal variations.

The biases of weaker variations in soil moisture are associated with multiple processes of water cycles between the land and atmosphere. In land surface models of reanalysis systems, deficient representations, such as soil water transport (Decker and Zeng, 2009), and exchanges of water between the soil and aquifers partly account for these biases (Niu et al., 2007). Moreover, the meteorological forcing that denote grid cell-averaged values tend to be weaker than those at sites and hence weaken the variations in simulated soil moisture compared with observations (Nadine et al., 2015). However, the use of in situ observations in the model evaluations requires further research, considering the mismatches in representativeness, which makes direct comparisons somewhat unfair for reanalysis products (Li et al., 2005; Dorigo et al., 2011; Albergel et al., 2013; Dorigo et al., 2013; Zeng et al., 2014; Notz, 2015; Xu et al., 2015; Zeng et al., 2015; Bi et al., 2016; Ma et al., 2019).

There are larger discrepancies in soil moisture during cold seasons compared with the observations, which may
be caused by the failure of reanalyses to capture the moisture peaks observed around May. Such a deficiency was also reported in previous studies (e.g., Li et al., 2005). It is partly associated with lower soil temperature biases (Figures 5 and 9), since moisture is coupled with temperature by water phase changes in the soil in land surface models (Wang and Yang, 2018). The lower soil temperature is likely to cause a failure in generating a moisture peak in spring and hence lower or even opposing correlations between the reanalyses and observations.

Over the regions from western China to Mongolia and to the eastern former Soviet Union, the correlations of all five reanalyses against the observations decrease substantially compared with the other regions. Over those regions, by targeting agricultural practices, observations are conducted once per 10 days (Robock et al., 2000; Li and Ma, 2015). The monthly mean with only three records deviates from those with daily records to varying degrees. In-depth comparisons will be conducted in the future as daily reanalyses become available.

In addition, soil moisture variability is forced by the combination of land water–heat processes and atmospheric climate (Bittelli et al., 2008; Baur et al., 2018; Zhong et al., 2018). Soil moisture generally correlates positively with precipitation on a monthly scale. However, as precipitation is in the form of snowfall, such as in high latitudes, the positive sign of correlations changes with the timing of snowmelt (Harms and Chanasyk, 1998). Precipitation variability and preceding soil moisture can also lead to changes in the directions of soil moisture and precipitation dynamics (Wei et al., 2008). Moreover, the water exchange between surface reservoirs (e.g., river channels, lakes, wetlands, and glacier meltwater) and aquifers can substantially change soil moisture–precipitation interactions (Chen and Hu, 2004; Tamea et al., 2009). These various mechanisms behind soil–climate coupling further contribute to the varying practicality of reanalysis soil moisture with regions and time scales (Seneviratne et al., 2010; Li et al., 2017b).

4.2 Limitations in observational data and evaluations

The present evaluation, despite considerable augmentation of the observations and hence the representativeness in space and time, showed that more observations are required over high latitudes for a more rigorous validation. The assessment of water–heat interactions facilitates our understanding of the physical consistency behind soil moisture and soil temperature reanalyses. However, the available soil temperature observations are particularly limited compared with those of soil moisture. In the future, validations beyond the present study regions are required with an accumulation of observational records. Moreover, the limited available observations further undermine the quality control, and quality control is crucial to accurate evaluations (Liu et al., 2011; Dorigo et al., 2013; Bi et al., 2016). Considering the quality and availability of in situ observations, the remarkable discrepancy in high latitude areas is partly attributed to in situ observations and not only the reanalyses. The evaluations were conducted using monthly data of both in situ observations and reanalyses, but it would be fairer and more informative to conduct evaluations based on daily data because monthly observations are partly estimated from 10-day observations. Additionally, the regionally integrated soil moisture is a subsample of soil moisture variations, which cannot rigorously represent the regional climatology. Notably, these limitations in the presently available observations somehow undermine the robustness of the statistics in the validations. This finding suggests the complexity of both reanalysis and in situ observation data and the necessity of making further efforts to validate reanalyses and effectively use in situ observations.

5 CONCLUSIONS

Using in situ observations from 25 monitoring networks over the period of 1979–2017, a joint evaluation of soil moisture and soil temperature from five reanalyses (JRA-55, CFSR, ERA-Interim, ERA5, and MERRA-2) is presented in this study. Overall, we found that the reanalyses are encouraging in the regeneration of observed soil states. In terms of a global average, both soil moisture and soil temperature are reasonably consistent with the available observations from seasonal to interannual variations. Joint evaluations of soil moisture and temperature show physically consistent water–heat balances on regional scales.

At individual sites, the latest ERA5 shows considerable fidelity in the annual cycles in soil moisture and soil temperature, with reasonable water–heat consistency. Compared with its predecessor ERA-Interim, ERA5 shows significant improvements in soil moisture. Despite encouraging skills in soil temperature both in ERA5 and ERA-Interim, there is no substantial advancement in ERA5 compared with its predecessor, except for the improved annual ranges toward high latitudes and high altitudes.

For network averages, ERA5 soil moisture shows a higher consistency and closer intensity, followed by ERA-Interim, MERRA-2, CFSR, and JRA-55. In terms of linear trends, MERRA-2 is closer to the observations. However,
the differences in statistics are small. ERA5 soil temperature shows improved annual ranges toward high latitudes and high altitudes. An ensemble application is likely helpful to highlight the consensus signals among the reanalyses at regional scales.

On the hemispheric scale, the averaged reanalyses reasonably depict the water–heat processes in relation to observed precipitation and air temperature in the growing seasons, which will facilitate the investigations of water–heat synergistic effects in the soil in such ecosystems.

All five products show strong skills for capturing seasonal variability in the soil water–heat states, but long-term trends are weaker than those in observations. Discrepancies in cold seasons over high-altitude and high-latitude regions require observation-specific evaluations because of the scarcity of the present observations. The developments in models, parameters, and input data related to water–heat processes in cold seasons require further research in the future.

ACKNOWLEDGEMENTS
This study was jointly sponsored by the National Key R&D Program of China (2018YFA0606002), the National Natural Science Foundation of China (41575087 and 41875082), the Jiangsu Collaborative Innovation Center for Climate Change, and the UK-China Research & Innovation Partnership Fund through the Met Office Climate Science for Service Partnership (CSSP) China as part of the Newton Fund.

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How to cite this article: Li M, Wu P, Ma Z. A comprehensive evaluation of soil moisture and soil temperature from third-generation atmospheric and land reanalysis data sets. *Int J Climatol.* 2020; 40:5744–5766. [https://doi.org/10.1002/joc.6549](https://doi.org/10.1002/joc.6549)