East–West Reverse Coupling Between Spring Soil Moisture and Summer Precipitation and Its Possible Responsibility for Wet Bias in GCMs Over Tibetan Plateau

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Key Points:
- Spring soil moisture and summer precipitation coupling (SSM-SP-C) shows an east–west reversal, with positive coupling in eastern and central Tibetan Plateau (TP) and negative coupling in the western TP.
- The SSM-SP-C has elevation-dependent variations, the maximum coupling strength appears over regions with 3–4 km elevation.
- Wet bias of summer precipitation is significantly associated with the model’s failure in capturing SSM-SP-C.

Abstract
The impact of soil moisture (SM) and precipitation coupling (SM-P-C) on the subsequent climate at daily to seasonal scales over the Tibetan Plateau (TP) is a critical issue. In this study, the spring SM and summer precipitation coupling (SSM-SP-C) were investigated using multi-reanalysis and validated with 13 global climate models (GCMs) in Coupled Model Intercomparison Project Phase 5, and its relationship with the wet bias in GCMs was explored. The results reveal that SSM-SP-C shows an east–west reversal, with positive coupling in eastern and central TP and negative coupling in the western TP. The spring surface sensible heat has significantly negative effects on the strength of SSM-SP-C in eastern and central TP, while significantly positive effects in western TP; whereas, the SM shows the reverse effects in eastern and western TP. The concurrent SM-P-C over TP shows a positive trend from spring to summer, but coupling strength has significant spatial differences. The 13 GCMs ensemble mean underestimates the positive SSM-SP-C in eastern TP and can’t reproduce the negative SSM-SP-C in western TP. The wet bias of summer precipitation is significantly associated with the model’s failure in capturing SSM-SP-C. This study highlights the impacts of SM-P-C on subsequent climate in the alpine cold region and provides a potential way for reducing precipitation biases by improving SM-P-C parameterizations in GCMs.

1. Introduction
The land-atmosphere interaction (LA-I) over the Tibetan Plateau (TP) has been a topic of study (e.g., Ma et al., 2009; Meng et al., 2017; Talib et al., 2021; Xu et al., 2002; Yang et al., 2004; Zhu et al., 2018). In situ observations (e.g., GAME/Tibet) show that characteristics of the land surface heat fluxes, soil variables, and atmospheric processes (i.e., the structure of the atmospheric boundary layer, the turbulent and convection characteristics) vary significantly over different land surfaces and during the dry and wet seasons over TP (e.g., Ma et al., 2009; Sun et al., 2007; Yang et al., 2004, 2009). The thermal forcing of TP, which can be influenced by the land surface process, has a significant impact on the surrounding and downstream climate (Wu et al., 2013). Studies have shown that anomalies in the soil freeze-thaw process have a significant impact on the East Asian atmospheric circulation and summer precipitation in eastern China (e.g., Shang & Wang, 2006; Wang et al., 2003, 2020; Yang & Wang, 2019a). The decrease in TP surface diabatic heating can weaken water-heat exchanges between the TP and South Asian Monsoon regions, resulting in less precipitation in the eastern and southern TP (Yang et al., 2014). Recent studies (Zhang et al., 2016, 2019) show that the south-north reverse changes in annual mean precipitation over TP are caused by water vapor transport anomalies. Water vapor transport from upstream and external regions is modulated by the atmospheric circulation, which should be influenced by surface diabatic heating anomalies (Feng & Zhou, 2012). Soil moisture plays an important role in land surface processes, and its anomalies can persist for several weeks or months, influencing the partitioning of incoming energy in latent and sensible heat fluxes (Seneviratne et al., 2010). How soil moisture anomalies affect the local subsequent precipitation is important for understanding the LA-I over the TP process.

Soil moisture and precipitation coupling (SM-P-C) is a complex process, and the relationship between the two is still inconclusive (e.g., Koster et al., 2004; Seneviratne et al., 2010; Wei & Dirmeyer, 2012). The results have indicated that soil moisture anomalies can affect subsequent precipitation over TP (Zhou et al., 2018), but the feedback of precipitation anomalies on soil moisture is not significant and depends on the magnitude of precipitation (Meng et al., 2017). Snow melting and frozen soil thawing in the spring which is the period for transitions from dry to wet season over TP, causes rapid changes in soil water and heat transport, as well as enhancing the
water and energy exchange between land and atmosphere (Wang et al., 2008; Yang et al., 2007). The increase in soil moisture caused by the frozen soil thawing in spring has been suggested to play a significant role in the occurrence of early summer precipitation over TP (Wang & Shang, 2007). However, because of the larger spatial heterogeneity, the land surface processes over TP have large variances (Yang et al., 2014). Further study needs determine whether the SM-P-C over the entire TP is uniform and the physical process.

The GCMs' performance over TP have been aware of having biases. For example, there is a systematically cold bias of surface temperature and wet bias of precipitation in models over TP (e.g., Li et al., 2013; Lin et al., 2018; Y. Wang, et al., 2020; Yu et al., 2015). The land surface process simulation in GCMs has a distinct bias (e.g., Gao et al., 2015; Lin et al., 2017; Meng et al., 2018), which can affect surface diabatic heating estimation in models and reanalysis datasets over TP (e.g., Cui & Wang, 2009; Shi & Liang, 2014; Yang et al., 2009), and further influence the LA-I in aspects of water-heat exchanges, boundary layer process, convection, and resultant precipitation (Fu et al., 2006; Ma et al., 2009; Yang et al., 2014). This implies that the ability of GCMs to capture the SM-P-C may be related to their performance in precipitation simulation over TP. How GCMs perform in capturing SM-P-C should be evaluated.

This study aims to answer the following questions: what are the SSM-SP-C across the entire TP? Can GCM capture SSM-SP-C, and what influence can SSM-SP-C have on precipitation simulation in GCMs? The structures of this study are organized as follows. Section 2 introduces data and methodology. Section 3 analyzes the SSM-SP-C over TP, and the spatial pattern is extracted. In Section 4, the evolution of SM-P-C from spring to summer is analyzed. In Section 5, the performances of modes in capturing SSM-SP-C over TP are evaluated, and its possible relationship to model precipitation bias is explored. The discussions on the physical processes associated with SSM-SP-C are contained in Section 6. Section 7 contains the conclusion.

2. Data and Methodology

2.1. Precipitation Dataset and Multi-Reanalysis Dataset of Soil Moisture

In this study, the monthly precipitation data is obtained from the Global Precipitation Climatology Center (GPCC) with a horizontal resolution of 0.5° × 0.5° (Schneider et al., 2013), GPCC dataset synthesizes station-based data, which has been validated and widely used over TP (Hamm et al., 2020; Sun et al., 2019; Wang & Wang, 2017).

Performances of different soil moisture products have large discrepancies, to reduce the uncertainties of soil moisture over TP, four sets of reanalysis datasets of soil moisture are used as follows:

1. The ERA-Interim monthly soil moisture data with a horizontal resolution 1° × 1° (Dee et al., 2011). The ERA-Interim soil moisture dataset includes four depth layers: 0–0.07 m, 0.07–0.28 m, 0.28–1.0 m, and 1.0–2.89 m. The ERA-Interim uses advanced nudging techniques to correct soil moisture drift caused by imperfect precipitation and insolation, which makes the variability in soil moisture more realistic (Li et al., 2005)

2. The NCEP-DOE reanalysis 2 (NCEP-II) monthly soil moisture data with a horizontal resolution of 2.5° × 2.5° (Kanamitsu et al., 2002). The NCEP-II uses a simple land surface model (Mahrt & Pan, 1984), with two soil layers 0–0.1 m and 0.1–2.0 m

3. The Global Land Data Assimilation System (GLDAS) monthly soil moisture dataset (Rodell et al., 2004), Version 2 with a horizontal resolution of 1° × 1° and four depth layers 0–0.1 m, 0.1–0.4 m, 0.4–1.0 m, and 1.0–2.0 m generated by the Noah land surface model. The GLDAS generates satellite- and ground-based observational data using advanced land surface modeling and a data assimilation technique. GLDAS soil moisture data have been verified and widely used over the TP (Bao et al., 2017; Bi et al., 2016; Chen et al., 2013)

4. NASA's Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) monthly soil moisture data on the surface (0–0.05 m) and root-zone layers (0–1.0 m) with a horizontal resolution of 0.5° latitude × 0.625° longitude is used (Gelaro et al., 2017). MERRA-2 has significantly better surface moisture dynamics than MERRA (Bosilovich et al., 2015) because of an increase in precipitation forcing

All the datasets are interpolated to a 1° × 1° latitude-longitude grid for the analysis, the interpolation of soil moisture dataset uses the bilinear interpolation method, while the interpolation of precipitation dataset uses the nearest-neighbor average method (Accadia et al., 2003); the period covers 1980–2005. The soil moisture is analyzed at a soil layer of 0–1.0 m.
2.2. Reanalysis Dataset for Other Variables

The ERA-Interim monthly surface sensible heat flux data with a horizontal resolution of $1° \times 1°$ during 1980–2005 was used to analyze the relationship between SSM-SP-C and surface diabatic heating.

The ERA-Interim monthly specific humidity ($q$) and horizontal wind field ($\mathbf{V}$) at the land surface with a horizontal resolution of $1° \times 1°$ during 1980–2005 were used to calculate the water vapor flux ($q \mathbf{V}$, g/[s • hPa • cm]).

The Global Land Evaporation Amsterdam Model (GLEAM) monthly actual Evaporation ($E$) data (Martens et al., 2017) with a horizontal resolution of $0.25° \times 0.25°$ during 1980–2005 was obtained to calculate the surface water budget (precipitation [$P$] minus $E$). The data are interpolated to a $1° \times 1°$ latitude-longitude grid for analysis through the bilinear interpolation method.

2.3. CMIP5 Dataset

To investigate the GCMs’ capability in capturing SSM-SP-C over TP, 13 CMIP5 models with monthly soil moisture in the upper portion of the soil column and precipitation for the historical simulations from 1980 to 2005 were obtained. The selection of these models was based on the evaluation results over TP in previous study (Shi & Wang, 2015; Zhu & Yang, 2020). Detailed information about CMIP5 models (i.e., BCC-CSM1-1, BCC-CSM1-1-M, BNU-ESM, CanESM2, CCSM4, CNRM-CM5, GFDL-CM3, GISS-E2-R, HadGEM2-ES, MIROC-ESM-CHEM, MIROC-ESM, NorESM1-ME, and NorESM1-M) is shown in Table 1.

To facilitate the comparison with the reanalysis dataset, models' outputs are interpolated to a $1° \times 1°$ latitude-longitude grid, which is same as the procedure of reanalysis dataset. The data covered period is 1980–2005, which is the same as that of the reanalysis dataset.

2.4. Coupling Index

To investigate the SSM-SP-C over TP, the coupling index is adapted (Zhang et al., 2008, 2011),

$$k = \frac{\text{Cor}(S(t - \tau), P(t))}{\text{Cor}(S(t - \tau), S(t))}$$

(1)
where \( \text{Cov}(S(t - \tau), P(t)) \) refers to the lagged covariance between soil moisture at the time \( t - \tau \) and precipitation at a time \( t \), same as to \( \text{Cov}(S(t - \tau), S(t)) \); \( \tau \) is the time interval (3 months in this study). Thus, \( S(t - \tau) \) is the spring (March–April–May) soil moisture, \( P(t) \) is the summer (June–July–August) precipitation.

The coupling index \( k \) represents the fraction of subsequent precipitation changes attributed to the variations in soil moisture. The feedback between soil moisture and precipitation is assumed to be local (Zhang et al., 2008).

### 2.5. Analysis Method

To reduce uncertainties from reanalysis dataset and CMIP5 models, the selected mean is made for results of multi-reanalysis dataset and CMIP5 models based on the criteria that, more than half of the reanalysis results (i.e., at least 3 of 4 sets of reanalysis dataset) or CMIP5 models (i.e., at least 7 of 13 models) agree on the sign of the SSM-SP-C on a grid; otherwise, the SSM-SP-C of this grid is identified as doubtful and value is set to the Missing.

To analyze the spatial variations of soil moisture and surface sensible heat flux, spatial anomalies of soil moisture and surface sensible heating are calculated as follow:

\[
\text{Anomaly}_{\text{spatial},i} = \frac{X_i - \overline{X}}{\overline{X}} \tag{2}
\]

where \( X_i \) is the soil moisture or surface sensible heating at \( i \) grid, \( \overline{X} \) is the spatial mean of the entire grids.

The model performance in simulating precipitation is evaluated by the root-mean-square error (RMSE):

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left( X_i^{\text{sim}} - X_i^{\text{obs}} \right)^2} \tag{3}
\]

where \( X_i^{\text{sim}} \) is model-simulated precipitation, \( X_i^{\text{obs}} \) is the corresponding observation. The GPCC precipitation dataset is the precipitation observation.

The selected mean of coupling index \( k \) from four sets of reanalysis datasets is regarded as the observation of \( k \), when the biases of \( k \) for CMIP5 models are calculated.

### 3. Spring Soil Moisture and Summer Precipitation Coupling (SSM-SP-C) Over TP

Figure 1 shows the spatial distribution of the coupling index \( k \) between spring soil moisture and summer precipitation over TP to analyze the SSM-SP-C over the entire TP. The coupling index \( k \) calculated from GPCC precipitation data and GLDAS2.0 Noah soil moisture data shows, the SSM-SP-C in eastern TP mainly appears positive, whereas SSM-SP-C shows negative in most regions of the western TP (Figure 1a), the coupling index \( k \) ranges from −0.4–0.6, which means that the soil moisture anomalies in spring contribute 20%–60% to the summer precipitation in eastern TP and −20% to −40% in most regions of the western TP. The \( k \) calculated from ERA-Interim data shows positive in eastern and central TP, whereas the SSM-SP-C in western TP shows negative (Figure 1b); the \( k \) ranges from −0.7 to 0.8, which is greater than that calculated from GLDAS2.0 Noah soil moisture data. The calculation of \( k \) from NCEP-II data shows that, the SSM-SP-C over southeastern and southwestern TP is positive, while the SSM-SP-C show weakly negative in the northwestern and northeastern TP (Figure 1c). The \( k \) calculated from MERRA-2 data shows positive SSM-SP-C over the entire TP, despite the sporadic appearance of negative SSM-SP-C in southern TP (Figure 1d). The mean of coupling index \( k \) shows that the positive SSM-SP-C is dominant in central and eastern TP, whereas the SSM-SP-C is negative in northwestern and southern edges of TP (Figure 1e).

Compared with the spatial distribution of SSM-SP-C among results from different datasets, although some inconsistencies exist over the southern margin and sporadic regions in central and eastern TP, the east–west reverse SSM-SP-C can be reflected in more than half of the reanalysis results (i.e., at least 3 of 4 sets of reanalysis dataset), shown in the selected mean of coupling index \( k \) (Figure 1f). Specifically, in most regions of the TP, the SSM-SP-C is positive, especially in the central and eastern TP, with a \( k \) value of 0.2–0.5, indicating that wet
spring soil moisture anomalies will lead to more precipitation in summer over these regions. In most regions of western TP (approximately 75°–89°E), except for southwestern margin, the SSM-SP-C is negative, with \( k \) of approximately \(-0.4\) to \(-0.2\), which means that wet spring soil moisture anomalies will not favor summer precipitation in most regions of western TP.

The SM-P-C is related to the soil water storage and surface energy budget in the local feedback. The SM-P-C hotspot areas are mainly located in the transition zones between wet and dry climates (e.g., Guo et al., 2006; Koster et al., 2004). This is mainly because, in wet climates, although the soil water storage is abundant, the surface evaporation is mainly influenced by the surface net radiative energy and is not sensitive to variations of 

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**Figure 1.** The distribution of coupling index \( k \) between spring (March–April–May) soil moisture (SM) and summer (June–July–August) precipitation over TP, calculated based on Global Precipitation Climatology Center precipitation and different SM dataset from (a) GLDAS2.0 Noah, (b) ERA-Interim data, (c) NCEP-II data, (d) Modern-Era Retrospective analysis for Research and Applications, Version 2 data (e) mean of above four results, and (f) selected mean made at each grid where at least three results are consistent (all are positive or all are negative coupling). The white shadings mean the Missing.
Figure 2. The spatial variation of SSM-SP-C and its relation with variations of soil moisture (SM) and surface sensible heat (SH). (a) Zonal evaluation of coupling index $k$, spatial anomalies of SM and SH in spring over Tibetan Plateau (TP), meridional mean is made over 25°–40°N and regions with elevation larger than 2500 m, the shading is indicated with ±mean 1 standard deviation. Scatters between $k$ and SM, SH for (b) whole TP (75°–105°E), (c) western TP (75°–85°E), (d) central TP (85°–95°E) and (d) eastern TP (95°–105°E), the blue and red lines are the linear fitting lines, and * represents the linear fitting significant at $p < 0.1$ or a higher level by student's t-test. The SSM-SP-C was produced from the selected mean of four sets of reanalysis, SM and SH were obtained from GLDAS2.0 Noah and ERA-Interim, respectively.
To quantify the relation between SSM-SP-C and soil water storage, surface energy budget, Figure 2b shows the scatters between \( k \) and SM, SH for the entire TP, the linear relations between \( k \) and SM or SH show insignificantly positive. The characteristics of SSM-SP-C in different regions are further analyzed. In western TP, the linear relation between \( k \) and SH is significantly positive (\( R^2 = 0.43; p < 0.05 \)), whereas it is negative between \( k \) and SM (\( R^2 = 0.70; p < 0.05 \)) (Figure 2c), which is due to the net surface energy in western TP is insufficient and the surface evaporation is weak in spring. In the central TP, the linear relationship between \( k \) and SH is significantly negative (\( R^2 = 0.35; p < 0.05 \)), which means the larger SH in spring will lead to the weaker SSM-SP-C (Figure 2d); and the relation with SM shows insignificantly negative. In eastern TP, the linear relationships between \( k \) and SM or SH are reverse with that in western TP (Figure 2e), the significantly positive relation (\( R^2 = 0.31; p < 0.1 \)) between SSM-SP-C and SM in eastern TP is due to the net surface energy satisfy the atmospheric conditions for precipitation (e.g., the convective trigger), increase of SM can provide more water vapor to the atmosphere and promote the subsequent precipitation; while the SH has significantly negative effects (\( R^2 = 0.50; p < 0.05 \)) on SSM-SP-C. Above results indicate the east–west reverse of SSM-SP-C over TP is closely related to the zonal variation of SM and SH in spring, although the coupling index \( k \) is calculated at assumption of local effects, the effect of SH on precipitation includes the non-local processes, for example, large-scale circulation patterns affects the remote water vapor transport (Douville, 2002; Shukla & Mintz, 1982), especially over the eastern TP (Luan et al., 2018).

4. Evolution of SM-P-C From Spring to Summer

The land surface processes impact the SM-P-C. The SM-P-C should change along with the remarkable changes in land surface processes from spring to summer (i.e., snow melting, frozen soil thawing). SM anomalies in the spring can last for months and affect subsequent precipitation (Dirmeyer et al., 2008; Koster & Suarez, 2001). A question arises; how does the SM-P-C vary from spring to summer?
Figure 3 shows the distribution of the coupling index $k$ between soil moisture and simultaneous or subsequently from 1–2-month lagged precipitation from spring to summer over TP to analyze the evolution of SM-P-C from spring to summer. The concurrent SM-P-C in spring (e.g., April SM and April precipitation coupling) generally show positive over most regions of TP (Figures 3a, 3c and 3f), despite sporadic negative coupling over the interior TP, where the soil is still frozen or starts thawing in spring, the low soil liquid water and weak surface diabatic heating is not conducive to the precipitation occurring. The concurrent SM-P-C in summer (e.g., June SM and June precipitation coupling) shows positive over the entire TP (Figures 3b and 3h), indicating that the wetter SM anomalies result in more precipitation in summer, and the strength of SM-P-C (values of $k$) in summer is larger than that in spring. The coupling between soil moisture in April and 1–2-month lagged precipitation show the positive SM-P-C over edges of TP, negative SM-P-C appears interior and eastern TP (Figures 3d, 3e, 3g).

The concurrent SM-P-C from the spring to summer is positive; whereas coupling between soil moisture in spring (i.e., April and May) and 1–2-month lagged precipitation (May and June) is positive over the edges of TP, whereas negative SM-P-C appears in the interior and eastern TP; from April to June, the strength of SM-P-C enhances, the areas with negative SM-P-C in eastern TP reduce. The evolution of SM-P-C from spring to summer is related to the remarkable changes in land surface processes, that is, along with the increase of net solar energy absorbed by land surface, the frozen soil thaws and snow melts gradually from the spring to summer, the increases of surface sensible heat and latent heat are conducive to precipitation occurrence.

5. Performance in Capturing SSM-SP-C and Precipitation Bias of CMIP5 Models

Many studies have shown that the GCMs have large biases (e.g., cold and wet bias in CMIP5 models) in simulation climate over TP, some improvements (e.g., surface albedo, topography drag effects) reducing biases have been tried (e.g., Meng et al., 2018; Y. Wang, et al., 2020). How do CMIP5 models perform in capturing SSM-SP-C?

To evaluate the performance of CMIP5 models in capturing SSM-SP-C over TP, distributions of coupling index $k$ between spring SM and summer precipitation over TP calculated from 13 CMIP5 models are shown in Figure 4. Large disagreements exist in different members of CMIP5 GCMs in the description of SSM-SP-C, with only several models (i.e., BCC-CSM1-1-M, BCC-CSM1-1, CanESM2, MIROC-ESM-CHEM, MIROC-ESM) generally capture the east–west reverse SSM-SP-C over TP (Figures 4a, 4b, 4d, 4j, and 4k), whereas most models show widespread failure in capturing spatial characteristics of SSM-SP-C. The ensemble mean of coupling index $k$ shows positive SSM-SP-C over TP (Figure 4n). The CMIP5 models selected mean of coupling index $k$ shows, the SSM-SP-C in the central and eastern TP and western margin show positive, only sporadic negative existing (Figure 4o), comparing to the selected mean of four reanalysis results (Figure 1f), the CMIP5 models selected mean underestimates the positive SSM-SP-C in eastern TP, doesn't reproduce the negative SSM-SP-C coupling in western TP.

To validate the SSM-SP-C simulated in CMIP5 models, Figures 5a and 5b show the scatter of coupling index $k$ between reanalysis data and 13 CMIP5 models, the consistency between them is poor. SSM-SP-C in some regions is inverse between reanalysis data and CMIP5 models mean, specifically, the negative SSM-SP-C reflected in reanalysis data in some grids inversely become positive described in CMIP5 models(Figure 5a), which further illustrates the failure in reproducing negative SSM-SP-C in western TP. After eliminating inconsistent data, the CMIP5 models still overestimates the strength of positive SSM-SP-C with values of $k$ 0–0.2 (Figure 5b), while
underestimates coupling strength with values of $k$ larger than 0.2. The merged mean of coupling index $k$, which is made at each grid where CMIP5 models selected mean is consistent with the reanalysis data selected mean, indicates that the SSM-SP-C in central and central TP is positive, whereas the SSM-SP-C is negative in the western TP. Nevertheless, the SSM-SP-C in most regions of eastern and western TP are inconsistent between them (Figure 5c).

The TP warming and variations of surface SH have elevation-dependent characteristics (e.g., Gao et al., 2018; Zhu et al., 2018). Whether the SSM-SP-C has elevation-dependent variations? Selected mean coupling index $k$ from multi-reanalysis shows that in the region with elevation less than 4 km, the coupling index $k$ gradually increases with the higher elevation, the coupling index $k$ reaches the maximum value at 3–4 km elevation; in regions with an elevation higher than 4 km, the coupling index $k$ gradually decreases (Figure 5d), this means that the effects of SM anomalies in spring on subsequent precipitation are smaller in the higher elevation regions. In regions with elevation lower than 4 km, the variation of SSM-SP-C along with elevation from CMIP5 model ensemble selected mean and merged mean of coupling index $k$ are generally consistent with that of reanalysis data mean.

The weather and climate over TP are significantly influenced by the LA-I. Whether wet bias of precipitation link with the failure in capturing SSM-SP-C in CMIP5 models? The distributions of $k$ biases relative to the selected mean of reanalysis data are shown in Figure 6, and the corresponding biases and RMSE of summer (JJA) precipitation for 13 CMIP5 models are shown in Figure 7. Most CMIP5 models have a negative bias of coupling

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**Figure 5.** Comparison of SSM-SP-C between reanalysis data and Coupled Model Intercomparison Project Phase 5 (CMIP5) models. (a) Scatter of coupling index $k$ between reanalysis data and CMIP5 ensemble mean. (b) Same as (a), but only reanalysis data values and CMIP5 mean are consistent (all are positive or all are negative coupling). (c) Distribution of merged mean of coupling index $k$ made at each grid where two results are consistent. The white shadings mean the Missing. (d) Coupling index $k$ versus. elevation bands with 1 km width, the shading is indicated with ±mean 0.5 standard deviations.
index $k$ in eastern TP and positive bias in western TP, this is due to the underestimation of SSM-SP-C strength in eastern TP and failure in capturing negative SSM-SP-C in western TP for CMIP5 models. Except for CCSM4, all other models have wet biases of summer precipitation (Figure 7). The RMSE of summer precipitation mainly appears over the eastern and southwestern TP where the SSP-SP-C in CMIP5 models are inconsistent with that of reanalysis data mean (Figure 6), this implies there a possible relationship between precipitation bias and failure in capturing SSM-SP-C in CMIP5 models.

To quantify this relationship, Figure 8 shows the scatter of regional mean RMSE of summer (JJA) precipitation corresponding to the spatial mean bias of coupling index $k$. There is a significantly positive relationship between precipitation RMSE and bias of $k$ in CMIP5 models ($R^2 = 0.30; p < 0.05$), indicating that if the model captures the SSM-SP-C worse, the bias of summer precipitation over TP will be larger (Figure 8a). The relationship between RMSE of summer precipitation and bias of $k$ in different regions of TP are also examined, positive relationships between RMSE of precipitation and positive biases of $k$ exist over western and central (Figures 8b and 8c), which means the worse performances in describing SSM-SP-C will lead to larger precipitation bias through local coupling; whereas, positive relationships between RMSE of precipitation and negative biases of $k$ over eastern TP (Figure 8d) means that, if the model underestimates the strength of positive SSM-SP-C, the bias of summer precipitation over eastern TP will be small, this unexpected relationship is due to the negative bias of coupling in CMIP5 models restraining the summer precipitation accidently offset the wet bias. In addition, the regional relationships between RMSE of precipitation and negative biases of $k$ become not significant, which implies the coupling between soil moisture and precipitation is not only local or regional, but also includes the non-local or large-scale effects.

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**Figure 6.** The distribution of coupling index $k$ biases relative to the selected mean of reanalysis data for 13 Coupled Model Intercomparison Project Phase 5 models. The white shadings mean the Missing.
6. Discussions

The water vapor from either local evaporation or remote transport is the determining factor influencing precipitation over TP (e.g., Zhang et al., 2016). Figure 9 shows the differences \((P-E)\) between the actual surface evaporation \((E)\) and precipitation \((P)\) over TP in spring and summer to discuss the possible physical processes associated with SM-P-C in the context of surface water storage. In the spring, \(E-P\) is positive in most regions of TP, except for the southeastern region and western edges (Figure 9a), indicating that the land surface provides water vapor to the atmosphere through evaporation, which is closely related to the increase of SM (Figure 9c). External water vapor can be transported to the southeastern TP, where the elevation is relatively low (<3 km), whereas the external water vapor is difficult to transport to the high elevation region of TP in spring. The rainy season in TP begins in May–June (Wei et al., 2003), the onset of the South Asian Summer Monsoon (SASM) begins in early June (Wu et al., 2013), Shang and Wang (2006) suggested that SM leads precipitation in TP about 20 days, implying that the SM-P-C in spring (i.e., April, May) is adjusted and controlled by the local feedback process, which should be related to the land surface processes (i.e., snow melting, frozen soil thawing).

In the summer, the \(E-P\) is negative in TP, except for the northern edges of TP, indicating that precipitation is greater than surface evaporation. With the onset of SASM in early June (Wu et al., 2013), southerly winds transport abundant water vapor from the south side (i.e., Bay of Bengal and the Indian Ocean) to the TP (Figure 9b). The atmospheric circulation decides remote water vapor transport (nonlocal process). The spring SM anomalies persist into the summer and cause surface diabatic heating anomalies, which can affect the atmospheric circulation and thus water vapor transport in the south region of TP. Therefore, rather than local feedback, the effects of nonlocal process SSM-SP-C cannot be neglected.

Figure 7. The distribution of biases (color) and RMSE (contour) of summer (JJA) precipitation (P; mm/day) relative to the Global Precipitation Climatology Center dataset for 13 Coupled Model Intercomparison Project Phase 5 models.
The possible causes of precipitation bias in CMIP5/CMIP6 models have been extensively discussed in terms of parameterizations (e.g., imperfect orographic drag parameterization; Y. Wang, et al., 2020), physical processes of precipitation (e.g., failure in capturing strong rainfall events; Lin et al., 2017), land-atmosphere interaction (e.g., feedbacks with the SM bias; Knutti & Sedlácek, 2012), and other processes, such as the cloud. Cheruy et al. (2014) proposed a strong warm bias in mid-latitudes because of the role of land-atmosphere coupling through solar incoming radiation-soil moisture-evaporation process. This means that the wet bias of summer precipitation over TP in CMIP5 models, such as the bias of SM, should be related to the SSM-SP-C. The precipitation is a direct source of SM, a wet bias of precipitation may result in a wet bias of SM in spring. The performances of CMIP5 models over TP suggested that all models overestimate annual precipitation by more than 0.5 mm/day, and wet bias in eastern TP can be greater than 1.8 mm/day, especially in spring and summer (e.g., Hu et al., 2014; Su et al., 2013; Xu & Xu, 2012); our results (Figure 7) agree with previous studies. Recently, evaluations of precipitation simulation by CMIP6 models over TP show some improvements and still display similarly wet biases pattern by comparing with CMIP5 models (Zhu & Yang, 2020). SM evaluations in CMIP6 models (Qiao et al., 2021) show that a significant wet bias exists in the mid-latitudes of the Northern Hemisphere (e.g., TP). Similarly, except for BCC-CSM1-1-M, BCC-CSM1-1, BNU-ESM, and CCSM4, most of the models (9 of 13 CMIP5 models) have wet biases of SM over eastern TP (Figure 10). Therefore, the basic elements soil moisture and precipitation in SM-P-C in the CMIP6 models should be similar with the CMIP5 models, although this need be further verified and more studies, even the accuracy of precipitation or SM have improved, the SM-P-C pattern in CMIP6 should be consistent with that of CMIP5 models. The differences in SM biases among these models

Figure 8. (a) Scatter of regional mean RMSE of summer (JJA) precipitation (mm/day) and spatial mean bias of coupling index k. (b), (c) and (d) same as (a), but for the western Tibetan Plateau (TP) (75°–85°E), (d) the central TP (85°–95°E) and (d) eastern TP (95°–105°), black lines represent the linear fit among models, * represents the linear fit significant at p < 0.05 level by student’s t-test.
are attributed to different hydrology parameterizations (e.g., surface runoff, infiltration) in their land surface models. For models that better capture the SSM-SP-C, the wet bias of SM should result in excessive precipitation because of their positive coupling, thus, the wet bias of precipitation is larger; however, for models that perform poorly in the SSM-SP-C simulation, the negative biases of coupling index $k$ restrain the feedback of wet SM biases to summer precipitation, thus, the bias of precipitation is smaller in eastern TP. It implies that, SSM-SP-C can amplify the precipitation bias caused by the simulation bias of SM. Frozen soil and snow are distributed over TP, and soil water-heat transport has a significant impact on SM variation (Hansson et al., 2004; Swenson et al., 2012; Yang & Wang, 2019b). The poor simulation of SM performance reflects the incomplete parameterization of frozen soil and snow in models, implying the importance of improving the land surface process in parameterization in GCMs in climate simulation and future projection. In other words, if we can well simulate soil moisture or thawing of frozen soil and snow melting, that is, the coupling pattern can be captured, the precipitation simulation should be improved in GCMs.

### 7. Conclusions

In this study, the SSM-SP-C over the TP were revealed from multi-reanalysis datasets and validated by CMIP5 models, and the relationship between SSM-SP-C and summer precipitation bias was explored. The results show that SSM-SP-C is positive in central and eastern TP, indicating that wet SM anomalies in spring will result in more precipitation in summer, and vice versa; negative SSM-SP-C dominates in western TP, indicating that wet SM anomalies in spring do not favor the precipitation occurring in summer. The SSM-SP-C has significantly negative relation with the spring SH in central and eastern TP, the SSM-SP-C has significantly positive relation with spring SM in eastern TP; while, the SSM-SP-C in western TP is positively related with SH and negatively related with SM. The concurrent SM-P-C in spring and summer are generally positive; the coupling between soil moisture in April or May and subsequent precipitation lagged 1–2 months are generally consistent, with positive coupling in the edges of TP and negative coupling in the interior and eastern TP. The spatial variation of SM-P-C depends on the hydrothermal process of land surface (i.e., frozen soil thawing and snow melting) in different regions of TP.

The SSM-SP-C has elevation-dependent variations, the maximum strength of SSM-SP-C appears over regions with 3–4 km elevation. The ensemble mean of 13 CMIP5 models underestimate the strength of positive SSM-SP-C in eastern TP and can’t reproduce the negative SSM-SP-C in western TP. More than half of CMIP5 models fail to capture the east–west reverse pattern of SSM-SP-C, and there are large inconsistencies of SSM-SP-C patterns among models, which might be the reason for precipitation biases in GCM over TP. Most of CMIP5 models have negative biases of coupling index $k$ in eastern TP, and positive biases of coupling index $k$ in center and western TP.

A significant linear relation between coupling index $k$ bias and summer bias from CMIP5 models was revealed, implying that SSM-SP-C has considerable responsibility for model bias over TP. Due to the poor performance of CMIP5 models in capturing SSM-SP-C, there is a positive contribution of SM bias in spring on subsequent precipitation bias in western and central TP; while, underestimation of SSM-SP-C in eastern TP leads to a negative contribution of SM bias in spring on subsequent precipitation, in other words, the precipitation attributed to SM bias will be deficient, which only offsets the positive bias of precipitation due to other physical processes in models. The above results imply that the performance of GCMs over TP is closely related to the land surface processes and SSM-SP-C simulation.
Data Availability Statement

The ERA-Interim reanalysis dataset is downloaded from https://apps.ecmwf.int/datasets/data/interim-full-moda/levtype=sfc/. NCEP-II reanalysis dataset is obtained from https://psl.noaa.gov/data/gridded/data.ncep.reanalysis2.html. Global Land Data Assimilation System soil moisture dataset is available from https://disc.gsfc.nasa.gov/datasets?keywords=GLDAS. GPCC monthly precipitation is obtained from https://climatedataguide.ucar.edu/climate-data/gpcc-global-precipitation-climatology-centre. MERRA2 dataset can download from https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/. CMIP5 dataset is provided from the Intergovernmental Panel on Climate Change (http://www.ipcc-data.org/sim/gcm_monthly/AR5/Reference-Archive.html). Global Land Evaporation Amsterdam Model dataset can be obtained from https://www.gleam.eu/#downloads.

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References

Accadia, C., Mariani, S., Casaioli, M., Lavagnini, A., & Speranza, A. (2003). Sensitivity of precipitation forecast skill scores to bilinear interpolation and a simple nearest-neighbor average method on high-resolution verification grids. Weather and Forecasting, 18(5), 918–932. https://doi.org/10.1175/1520-0434(2003)018<0918:sopfss>2.0.co;2

Bao, H., Yang, K., & Wang, C. (2017). Characteristics of GLDAS soil-moisture data on the Tibetan plateau. Sciences in Cold and Arid Regions, 9, 127–141.

Bi, H., Ma, J., Zheng, W., & Zeng, J. (2016). Comparison of soil moisture in GLDAS model simulations and in situ observations over the Tibetan Plateau. Journal of Geophysical Research: Atmospheres, 121, 2658–2678. https://doi.org/10.1002/2015jd024131

Bosilovich, M. (2015). MERRA-2: Initial evaluation of the climate. NASA Technical report series on global modeling and data assimilation. NASA/TM-2015-196484, 9, 136.

Chen, Y., Yang, K., Qin, J., Zhao, L., Tang, W., & Han, M. (2013). Evaluation of AMSR-E retrievals and GLDAS simulations against observations of a soil moisture network on the central Tibetan Plateau. Journal of Geophysical Research: Atmospheres, 118, 4466–4475. https://doi.org/10.1002/2012jd017989
Shi, Q., & Liang, S. (2014). Surface-sensible and latent heat fluxes over the Tibetan Plateau from ground measurements, reanalysis, and satellite data. Atmospheric Chemistry and Physics, 14(11), 5659–5677. https://doi.org/10.5194/acp-14-5659-2014

Shukla, J., & Mintz, Y. (1982). The influence of land-surface evapotranspiration on the Earth’s climate. Science, 215(4539), 1498–1501. https://doi.org/10.1126/science.215.4539.1498

Su, F., Duan, X., Chen, D., Hao, Z., & Cuo, L. (2013). Evaluation of the global climate models in the CMIP5 over the Tibetan Plateau. Journal of Climate, 26, 3187–3208. https://doi.org/10.1175/jcli-d-12-00321.1

Sud, Y. C., Chao, W. C., & Walker, G. K. (1993). Dependence of rainfall on vegetation: Theoretical considerations, simulation experiments, observations, and inferences from simulated atmospheric soundings. Journal of Arid Environments, 25(1), 5–18. https://doi.org/10.1016/j.jaridenv.1993.1038

Sun, C., Wang, Z., & Yang, S. (2019). Interannual variability of winter precipitation over the western side of Tibetan Plateau and its impact factors (in Chinese). Chinese Journal of Atmospheric Sciences, 43(2), 350–360.

Sun, F., Ma, Y., Li, M., Ma, W., Tian, H., & Metzge, S. (2007). Boundary layer effects above a Himalayan valley near Mount Everest. Geophysical Research Letters, 34, L08808. https://doi.org/10.1029/2007GL029484

Swenson, S. C., Lawrence, D. M., & Lee, H. (2012). Improved simulation of the terrestrial hydrological cycle in permafrost regions by the Community Land Model. Journal of Advances in Modeling Earth Systems, 4, M08002. https://doi.org/10.1029/2012ms001615

Talib, J., Taylor, C. M., Duan, A., & Turner, A. G. (2021). Intraseasonal soil moisture-atmosphere feedbacks on the Tibetan Plateau circulation. Journal of Climate, 34(5), 1789–1807. https://doi.org/10.1175/jcli-d-20-0377.1

Wang, C., Cheng, G., Deng, A., & Dong, W. (2008). Numerical simulation on climate effects of freezing-thawing processes using CCM3. Science in Cold and Arid Regions, 1, 68–79.

Wang, C., Dong, W., & Wei, Z. (2003). A study on relationship between freezing-thawing processes of the Qinghai-Xizang Plateau and the atmospheric circulation over East Asia. Chinese Journal of Geophysics, 46, 438–448. https://doi.org/10.1002/cjg2.3361

Wang, C., & Shang, D. (2007). Effect of the variation of the soil temperature and moisture in the transition from dry-season to wet-season over northern Tibetan Plateau. Plateau Meteorology, 26(4), 678–685.

Wang, C., Yang, K., & Zhang, F. (2020). Impacts of soil freeze-thaw process and snow melting over Tibetan Plateau on Asian Summer Monsoon system: A review and perspective. Frontiers in Earth Science, 8, 133. https://doi.org/10.3389/feart.2020.00133

Wang, D., & Wang, A. (2017). Applicability assessment of GPCC and CRU precipitation products in China during 1901 to 2013 (in Chinese). Chinese Journal of Geophysics.

Wang, Y., Yang, K., Zhou, X., Chen, D., Lu, H., Ouyang, L., et al. (2020). Synergy of orographic drag parameterization and high resolution greatly reduces biases of WRF-simulated precipitation in central Himalaya. Climate Dynamics, 54, 1729–1740. https://doi.org/10.1007/s00382-019-05080-w

Wei, J., & Dirmeyer, P. A. (2012). Dissecting soil moisture-precipitation coupling. Geophysical Research Letters, 39, L19711. https://doi.org/10.1029/2012GL053038

Wei, Z., Huang, R., & Dong, W. (2003). Interannual and Interdecadal variations of air temperature and precipitation over the Tibetan Plateau (in Chinese). Chinese Journal of Atmospheric Sciences, 27, 157–170.

Wu, G., Duan, A., & Liu, Y. (2013). Recent advances in the study on the dynamics of the Asian Summer Monsoon onset. Chinese Journal of Atmospheric Sciences, 37(2), 211–228.

Xu, L., & Dirmeyer, P. (2011). Snow-atmosphere coupling strength in a global atmospheric model. Geophysical Research Letters, 38, L13401. https://doi.org/10.1029/2010GL048049

Xu, X., Tao, S., Wang, J., Zhou, L. L., & Wang, X. (2002). The relationship between water vapor transport features of Tibetan Plateau-Monsoon “large triangle” affecting region and drought-flood abnormality of China. Acta Meteorologica Sinica, 60(3), 257–266.

Xu, Y., & Xu, C. (2012). Preliminary assessment of simulations of climate changes over China by CMIP5 multi-models. Atmospheric and Oceanic Science Letters, 5, 489–494.

Yang, K., Koike, T., Fuji, H., Tamura, T., Xu, X., Bian, L., & Zhou, M. (2004). The daytime evolution of the atmospheric boundary layer and convection over the Tibetan Plateau: Observations and Simulations. Journal of the Meteorological Society of Japan, 82, 1777–1792. https://doi.org/10.2155/jmsj.82.1777

Yang, K., Qin, J., Guo, X., Zhou, D., & Ma, Y. (2009). Method development for estimating sensible heat flux over the Tibetan Plateau from CMA data. Journal of Applied Meteorology and Climatology, 48, 2474–2486. https://doi.org/10.1175/2009jamc2167.1

Yang, K., & Wang, C. (2019a). Seasonal persistence of soil moisture anomalies related to freeze–thaw over the Tibetan Plateau and prediction signal of Summer precipitation in eastern China. Climate Dynamics, 53, 2411–2424. https://doi.org/10.1007/s00382-019-04867-1

Yang, K., & Wang, C. (2019b). Water storage effect of soil freeze-thaw process and its impacts on soil hydro-thermal regime variations. Agricultural and Forest Meteorology, 265, 280–294. https://doi.org/10.1016/j.agrformet.2018.11.011

Yang, K., Xu, Y., Chen, L., Lin, C., Tang, W., & Chen, Y. (2014). Recent climate changes over the Tibetan Plateau and their impacts on energy and water cycle: A review. Global and Planetary Change, 112, 79–91. https://doi.org/10.1016/j.gloplacha.2013.12.001

Yang, M., Yao, T., Gou, X., Wang, H., & Hao, L. (2007). Comparison analysis of the Summer Monsoon precipitation between northern and southern slopes of Tanggula Mountains, Qinghai–Xizang (Tibetan Plateau): A case study in Summer 1998. Hydrological Processes, 21(14), 1841–1847. https://doi.org/10.1002/hyp.6319

Yu, R., Li, J., Zhang, Y., & Chen, H. (2015). Improvement of rainfall simulation on the steep edge of the Tibetan Plateau by using a finite-difference transport scheme in CAM5. Climate Dynamics, 45, 2937–2948. https://doi.org/10.1007/s00382-015-2515-3

Zhang, C., Tang, Q., & Chen, D. (2016). Recent changes in the moisture source of precipitation over the Tibetan Plateau. Journal of Climate, 30(5), 1807–1819.

Zhang, C., Tang, Q., Chen, D., van der Ent, R. J., Liu, X., Li, W., & Haile, G. G. (2019). Moisture source changes contributed to different precipitation changes over the northern and southern Tibetan Plateau. Journal of Hydrometeorology, 20(2), 217–229. https://doi.org/10.1175/jhm-d-18-0094.1

Zhang, D., Wang, W., & Wei, J. (2008). Assessing land-atmosphere coupling using soil moisture from the Global Land Data Assimilation System and observational precipitation. Journal of Geophysical Research, 113, D17119. https://doi.org/10.1029/2007jd009807

Zhang, J., Wu, L., & Dong, W. (2011). Land-atmosphere coupling and Summer climate variability over East Asia. Journal of Geophysical Research, 116, D05117. https://doi.org/10.1029/2010JD014714

Zhou, J., Wen, J., Liu, R., Wang, X., & Xie, Y. (2018). Late spring soil moisture variation over the Tibetan Plateau and its influences on the plateau Summer Monsoon. International Journal of Climatology, 38, 4597–4609. https://doi.org/10.1002/joc.5723

Zhu, L., Huang, G., Fan, G., Qi, X., Wang, Z., & Hua, W. (2018). Elevation-dependent sensible heat flux trend over the Tibetan Plateau and its possible causes. Climate Dynamics, 52, 3997–4009. https://doi.org/10.1007/s00382-018-4360-7

Zhu, Y., & Yang, S. (2020). Evaluation of CMIP5 for historical temperature and precipitation over the Tibetan Plateau and its comparison with CMIP5. Advances in Climate Change Research, 11(3), 239–251. https://doi.org/10.1016/j.accre.2020.08.001