The Increasing Role of Vegetation Transpiration in Soil Moisture Loss across China under Global Warming

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ABSTRACT: Changing pathways of soil moisture loss, either directly from soil (evaporation) or indirectly through vegetation (transpiration), are an indicator of ecosystem and land hydrological cycle responses to the changing climate. Based on the ratio of transpiration to evaporation, this paper investigates soil moisture loss pathway changes across China using five reanalysis-type datasets for the past and Coupled Model Intercomparison Project Phase 6 (CMIP6) climate projections for the future. The results show that across China, the ratio of vegetation transpiration to soil evaporation has generally increased across vegetated land areas, except in grasslands and croplands in north China. During 1981–2014, there was an increase by 51.4 percentage points (pps, $p < 0.01$) on average according to the reanalyses and by 42.7 pps according to 13 CMIP6 models. The CMIP6 projections suggest that the holistic increasing trend will continue into the twenty-first century at a rate of 40.8 pps for SSP585, 30.6 pps for SSP245, and -1.0 pps for SSP126 shared socioeconomic pathway scenarios for the period 2015–2100 relative to 1981–2014. Major contributions come from the increases in vegetation transpiration over the semiarid and subhumid grasslands, croplands, and forestlands under the influence of increasing temperatures and prolonged growing seasons (with twin peaks in May and October). The future increasing vegetation transpiration ratio in soil moisture loss implies the potential of regional greening across China under global warming and the risks of intensifying land surface dryness and altering the coupling between soil moisture and climate in regions with water-limited ecosystems.

KEYWORDS: Climate change; Ecosystem effects; Evapotranspiration; Soil moisture; Water budget/balance

1. Introduction

Soil moisture variability is a fundamental process linking Earth's energy, water, and carbon cycles and strongly regulates the regional climate (Seneviratne et al. 2010). Soil moisture can be transferred to the atmosphere from the soil by evaporation (a direct pathway) or through vegetation by transpiration (an indirect pathway). Changes in both the amount and the pathways of soil moisture loss reflect climate variability and can also trigger cascading actions in terrestrial environments (D'Odorico and Porporato 2004; Seneviratne et al. 2010). Under a changing climate, the anomaly of soil moisture loss is largely a signal of the effects of climate change and human activities on terrestrial environments (Diffenbaugh et al. 2015; Seneviratne et al. 2010). Therefore, understanding changes in soil moisture loss can help clarify the mechanisms of how the soil moisture balance varies with global warming and identify the potential effects of soil moisture loss on regional climate and terrestrial environments.

Soil moisture balance changes are significant to our climate and environment. On the one hand, soil moisture can

“memorize” atmospheric anomalies such as drought events. On the other hand, soil moisture anomalies play an important role in regulating the spatiotemporal regimes of precipitation and dry–wet variability in critical zones (Koster et al. 2004; Li et al. 2020b). Building on the understanding of soil moisture's role in transferring water and energy between land and the atmosphere, Philip (1966) first used the concept of the soil–plant–atmosphere continuum (SPAC) to highlight the effects of soil moisture on the whole simultaneous process. In this continuum, soil moisture plays a crucial role, regulating terrestrial water redistribution, solar radiation partitioning, and plant productivity. Observational evidence has demonstrated that soil moisture heterogeneity, which leads to convective initiation over drier soils, can create feedbacks that affect rainfall (Taylor et al. 2012); the state of heterogeneity is also the major control on runoff–precipitation responses (Robinson et al. 2008). For example, initial soil moisture conditions largely determine minor or severe flood damage in a storm event (Berthet et al. 2009). A typical exponential relation between soil moisture and surface albedo has also been corroborated in semiarid regions, and albedo decreases with an increase in soil moisture (Wang et al. 2005). The resulting variability in surface energy partitioning plays an important role in the monsoon climate system, which in turn affects the global energy and water cycles (Wu et al. 2012). Regarding soil moisture–climate interactions, Seneviratne et al. (2010) reviewed their coupling with precipitation, evapotranspiration and temperature and highlighted that soil moisture–climate

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feedbacks could increase but also dampen climate variability in various regions, and these feedbacks could be mediated by vegetation activities.

From the perspective of the biosphere, soil moisture can directly affect vegetation water and energy use efficiency in water-limited ecosystems. For example, soil moisture dominates dryness stress on more than 70% of vegetated land, especially in semiarid ecosystems (Liu et al. 2020). The terrestrial ecosystem capability of carbon sinks is also highly dependent on soil moisture conditions (Green et al. 2019). In addition, soil moisture directly affects surface solar radiation partitioning, namely, the Bowen ratio. With increasing soil moisture, the ratio decreases rapidly, resulting in an increase in the net surface radiation and thus promoting the primary productivity of terrestrial ecosystems (Jones and Brunsell 2009).

Given the coupled roles played by soil moisture and vegetation in land–atmosphere interactions and the large portion of the global land surface that is vegetated (Piao et al. 2020), the partitioning of soil moisture loss, namely, the ratio of transpiration to soil evaporation, can indicate the general ways in which soil moisture affects land–atmosphere interactions through biotic (transpiration) and abiotic (soil evaporation) processes. Extensive studies have found that approximately 60% of soil moisture loss occurs biotically despite the large spread among various estimation methods and ecosystems (Lian et al. 2018; Nelson et al. 2020; Zhang et al. 2016, 2012; Zhou et al. 2016). This large proportion of soil water loss by transpiration is regulated mainly by deeper soil moisture that can be taken up by plant roots; in contrast, soil evaporation is controlled by the surface and upper soil moisture contents and thus occurs more slowly and substantially contributes to the characteristics of regional soil moisture–climate feedbacks (Koster and Suarez 1996; Seneviratne et al. 2010). Since transpiration is the process by which soil moisture is lost through plant stomata, accompanied by the absorption of carbon dioxide, the ratio of transpiration to soil evaporation can demarcate soil water limitations on ecosystem water use efficiency, gross primary productivity, and other service functions (Bonan et al. 2011; Chang et al. 2018; Zhang et al. 2017). Furthermore, plant transpiration links the biotic and abiotic processes of soil moisture loss and further correlates the regional water and energy balances to carbon budgets between the land and the atmosphere via biogeochemical processes and modulates the influences of the soil moisture balance on environments and regional climate.

Because of its important role in the land–atmosphere system, changes in the partitioning and balance of soil moisture have attracted increasing attention with a changing climate. Currently, in situ measurements are still sparse on global and regional scales (Jung et al. 2019; Williams et al. 2004). However, on specific ecosystem scales, observational efforts have confirmed the dominant role of vegetation transpiration in soil moisture loss. Its ratio can be dominated only by soil evaporation in the case of sparse canopies (Perez-Priego et al. 2018; Williams et al. 2004). A data-driven estimate of evapotranspiration revealed that global annual evapotranspiration increased from 1982 to 1997, and then the increase ceased

until 2008 due to increased soil moisture limitations (Jung et al. 2010). Model simulations generally agree with the above estimate, showing an expansion of drying areas due to the globally widespread increases in potential evapotranspiration (Berg and Sheffield 2019a,b; Cook et al. 2014; Lian et al. 2018). In China, using a process-based model driven with remotely sensed vegetation data and meteorological observations, a study revealed an increasing trend in the ratio of transpiration to total evapotranspiration from 1982 to 2015 (Niu et al. 2019). During the same period, increasing evapotranspiration was observed over 104 catchments in humid south China, with 90% attributed to climate warming and 9% to vegetation greening (D. Zhang et al. 2020). In terms of soil moisture content, modeling studies suggest increases in northwest and southeast China but significant decreases across dry–wet transition zones (Li and Ma 2015).

In response to changes in the terrestrial water cycle and climate warming, large-scale vegetation greening during recent decades has been observed (Piao et al. 2020). An ensemble of remote sensing data has shown that over half of global vegetated lands have been experiencing an increasing leaf area index (LAI) in the growing season since the 1980s (Zhu et al. 2016). Across China, vegetation greening has been observed over the same period, mainly in forests and croplands (Chen et al. 2019). With increasing concentrations of carbon dioxide, its fertilization effect acts as an important driver of vegetation greening, and additional contributions are made from land use changes, such as increases in crops, grasslands, and forests. Moreover, global warming has eased climatic constraints on temperature-limited ecosystems. As a component of the land–atmosphere system, vegetation process changes reflect the variability of water and energy balances with intensifying global change.

These studies have shown credible evidence of changes in terrestrial water, energy, and ecological systems during recent decades and the pivotal role played by soil moisture in modulating these changes. Despite the considerable efforts that have been made to understand these changes, at the important node of land–atmosphere coupling, the response of the soil moisture balance to climate change remains somewhat unclear. This paper focuses on the changes in the pathways by which soil moisture is lost from the land surface, measured by the ratio of vegetation transpiration to soil evaporation. The goal is to quantify the impacts of climate change on soil moisture balance and terrestrial environments. Thus, five reanalysis-like datasets for present-day climate and 26 CMIP6 model simulations for three future emission scenarios were used, with details of these data and processing methods described in section 2. Their capability to depict soil moisture balance change was evaluated in terms of soil moisture, evapotranspiration, and transpiration using in situ observations and several benchmark datasets, as shown in section 3, and then the main results on the spatiotemporal features and changes from present-day climate to future scenarios follow. The possible mechanisms for the soil moisture balance's response to regional climate change, and implications for terrestrial environments in China, as well as the uncertainties in soil moisture balances and potential effects on the results, are

TABLE 1. Information on the five reanalysis-related model datasets of soil moisture, evapotranspiration, soil evaporation, and transpiration data used in this study.

Dataset	Institution	Spatial resolution (lat, lon)	Soil layer depths (cm)	Land model	Temporal coverage
GLDAS	NASA ^a , United States	$0.25^\circ \times 0.25^\circ$	10, 40, 100, 200	Noah-3.6	1948–2014
ERA5L	ECMWF ^b	$0.1^\circ \times 0.1^\circ$	7, 28, 100, 289	HTESSEL ^c	1981–2020
MERRA-2	NASA, United States	$0.5^\circ \times 0.625^\circ$	5, 100, to bedrock, nested depths	Catchment	1980–2020
20CRv3	NOAA ^d , CIRES ^e , DOE ^f , United States	$1^\circ \times 1^\circ$	10, 40, 100, 200	Noah	1936–2015
GLEAM	Ghent University, Belgium	$0.25^\circ \times 0.25^\circ$	Surface (5 cm) and root zone (5–100, 5–250 cm for short, tall vegetation)		1980–2020

^a National Aeronautics and Space Administration.

^b European Centre for Medium-Range Weather Forecasts.

^c Carbon Hydrology-Tiled ECMWF Scheme for Surface Exchanges over Land.

^d National Oceanic and Atmospheric Administration.

^e Cooperative Institute for Research in Environmental Sciences at the University of Colorado.

^f Department of Energy.

discussed in [section 4](#). The paper is summarized with conclusions in [section 5](#).

2. Data and methodology

a. Data

1) REANALYSIS DATASETS OF SOIL MOISTURE, EVAPOTRANSPIRATION, SOIL EVAPORATION, AND TRANSPIRATION

To assess the changes in the pathways of soil moisture loss in the present-day climate, we used soil moisture, evapotranspiration, soil evaporation, and transpiration data from five reanalysis-related model datasets (referred to as reanalysis data for brevity).

- 1) The Global Land Data Assimilation System (GLDAS), version 2. The GLDAS dataset is generated by land models (here, only Noah-3.6 outputs were used) forced with bias-corrected meteorological data ([Sheffield et al. 2006](#)), providing a temporally consistent description of land processes for the period 1948–2014 ([Rodell et al. 2004](#)).
- 2) The rerun land data of the European Center for Medium-Range Weather Forecasts climate reanalysis, fifth generation (ERA5L). This land dataset is reproduced with the ERA5's land model, H-TESSEL, forced by ERA5 atmospheric fields. High-resolution surface descriptions and thermodynamic orographic adjustments provide high-resolution land variables ([Dutra et al. 2020](#); [Muñoz-Sabater et al. 2021](#)).
- 3) The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2). Its land process dataset is generated with the coupled atmosphere–land system, in which precipitation is corrected by observations ([Gelaro et al. 2017](#)). Because only the energy fluxes (F) for the three components of evapotranspiration were available, the equivalent water thickness (W) in units of

millimeters was estimated using $W = F/2.501$, where the units are 10^6 W m^{-2} .

- 4) The Twentieth Century Reanalysis, version 3 (20CRv3). This dataset uses an upgraded data assimilation method relative to the previous version and assimilates a larger set of pressure observations ([Slivinski et al. 2019](#)).
- 5) The Global Land Evaporation Amsterdam Model, version 3.3a (GLEAM). GLEAM estimates evapotranspiration and root-zone soil moisture using vegetation optical depth, snow water equivalent, and reanalysis air temperature and radiation data, in addition to a multisource precipitation product. It also assimilates soil moisture data from passive and active microwave sensors (European Space Agency Climate Change Initiative, ESA CCI) and the Soil Moisture and Ocean Salinity (SMOS) satellite ([Martens et al. 2017](#)).

Details of the five datasets are listed in [Table 1](#). In this work, monthly mean data for the period 1981–2014 were used to examine soil moisture loss due to present-day climate change. The five datasets were bilinearly interpolated onto the GLDAS spatial resolution ($0.25^\circ \times 0.25^\circ$). However, the respective resolutions were used to evaluate their skill levels to describe the variability of soil moisture loss against observations across China. In addition, their surface downward solar radiation data were used to investigate the sensitivity of soil moisture loss changes to the surface energy balances.

2) OBSERVATIONAL AND BENCHMARK DATA USED TO EVALUATE THE REANALYSES

To justify the applicability of soil moisture-related variables in the five reanalysis datasets [[section 2a\(1\)](#)] in China, we collected observational soil moisture data from 40 sites, four evapotranspiration benchmark products, and vegetation transpiration datasets from 10 sites and a model estimation with meteorological observations. Soil moisture observations were taken from the International Soil Moisture Network (ISMN, <https://ismn.geo.tuwien.ac.at>) ([Dorigo et al. 2011](#)). For the

FIG. 1. (a) Geographical locations of observational sites for soil moisture, with mean soil moisture (SM) and month counts of observations [marker label indicates the site No. on the y axis in (b)–(d)]. (b)–(d) The statistics between observations and reanalysis datasets (CC denotes the correlation coefficient, RRMSE is the ratio of RMSE to observational mean SM, and DStd indicates the difference in standard deviations between observations and model-based datasets).

period 1981–99, at 11 depths from 5 to 100 cm, in situ observations were available at 10-day intervals, excluding rainy and frozen days. The geographical distribution of the 40 sites (Fig. 1a) covers the typical climate zones and vegetation ecosystems in China except for the Tibetan Plateau and deserts.

Given the lack of in situ observations at the regional scale in China, four benchmark products were used to jointly evaluate the five reanalysis evapotranspiration datasets. The four products included the following:

- 1) A synthesis product known as LandFlux-EVAL (Mueller et al. 2013), which was merged from 14 datasets from satellite and in situ observations and land model outputs (driven with observation-based or reanalysis forcings), covering the period 1989–2005. Its monthly dataset, with a spatial resolution of $1^\circ \times 1^\circ$ latitude and longitude, was used in this work.
- 2) The Climate Data Record (CDR) for the global terrestrial water budget during the period 1984–2010 (Zhang et al. 2018) combines multisource data on precipitation, evapotranspiration, runoff, and total water storage change to obtain the water budget closure by a constrained Kalman filter assimilation technique. The monthly CDR dataset at a spatial resolution of $0.5^\circ \times 0.5^\circ$ was used.
- 3) Remote sensing estimates were obtained with the Moderate Resolution Imaging Spectroradiometer (MOD16) by

Mu et al. (2011). MOD16 has a regular 1-km² resolution for global vegetated land areas, with 8-day, monthly, and annual data available during the period from 2000 onward.

- 4) Estimation by merging flux measurements from FLUXNET eddy covariance towers, remote sensing, and meteorological data with a machine learning method. The resulting dataset, known as FLUXCOM, is considered a benchmark to evaluate land process simulations (Jung et al. 2019). Its monthly dataset with $0.083^\circ \times 0.083^\circ$ resolution during 2001–14 was used in this research.

Vegetation transpiration measurements are publicly available for only 10 sites in China during 2003–10. These measurements were conducted by the Chinese Flux Observation and Research Network with the eddy covariance method (Yu et al. 2006). After data quality control and postprocessing, these measured values can be compared with the other records from the international FLUXNET sites (Yu et al. 2006). The details on the sites are listed in Table 2. Their monthly mean dataset during 2003–10 was used in this research.

Due to the scarcity of vegetation transpiration measurements available (Table 2), a model-based estimate was used to evaluate the spatial patterns and long-term trends of the five reanalyses on the regional scale. This dataset was generated with the Priestley–Taylor Jet Propulsion Laboratory model (PT-JPL) driven by observational meteorological data

TABLE 2. Information on vegetation transpiration observations in China (<http://chinaflux.org/enn/index.aspx>; <https://fluxnet.org>; <http://www.cnern.org.cn/index.jsp>).

No.	Site name	Abbr.	Location (lat, lon)	Vegetation type	Period
1	Changbaishan	CBS	42.40°N, 128.10°E	Forests	2003–10
2	Changling	ChL	44.59°N, 123.51°E	Grasslands	2007–10
3	Dangxiong	DnX	30.50°N, 91.10°E	Grasslands	2004–10
4	Dinghushan	DHS	23.17°N, 112.53°E	Forests	2003–10
5	Haibei (grasslands)	HBG	37.67°N, 101.33°E	Grasslands	2003–10
6	Haibai (wetlands)	HBW	37.61°N, 101.33°E	Wetlands	2004–09
7	Neimenggu	NMG	43.33°N, 116.40°E	Grasslands	2004–10
8	Qianyanzhou	QYZ	26.74°N, 115.06°E	Croplands	2003–10
9	Xishuangbanna	XSB	21.61°N, 101.58°E	Forests	2003–10
10	Yucheng	YuC	36.83°N, 116.57°E	Croplands	2003–10

and satellite-based LAI, with a $0.05^\circ \times 0.05^\circ$ resolution during 1981–2015 (Niu et al. 2020). It is referred to as PT-JPL simulations hereafter. To evaluate not only the reanalysis transpiration but also its ratio to soil evaporation, the evapotranspiration additionally estimated with the Penman–Monteith–Leuning (PML) model (Zhang et al. 2016) was used because of the availability of the two corresponding components. The PML model was driven by atmospheric forcing based on reanalysis products, LAI data from the Advanced Very High Resolution Radiometer NDVI product, and emissivity and albedo data from the Global Land Surface Satellite products. The monthly mean evapotranspiration and its component data were available (<http://doi.org/10.4225/08/5719A5C48DB85>) for 1981–2012, with a $0.5^\circ \times 0.5^\circ$ spatial resolution. For more details on the model representation and simulation validation, refer to Zhang et al. (2016) and the references therein.

In addition, to detect varying vegetation responses to climate change, the Terra and Aqua combined MODIS land cover product (version 6, MCD12C1) was used to classify vegetation types in China (from <https://lpdaac.usgs.gov/products/mcd12c1v006>). According to the consistent types during 2001–10 (unless otherwise noted), their respective domains of land cover types were determined under the International Geosphere–Biosphere Programme classification scheme.

3) CMIP6 SOIL MOISTURE, EVAPOTRANSPIRATION, EVAPORATION, AND TRANSPIRATION OUTPUTS

To investigate the trend of soil moisture loss changes under future climate scenarios, we examined all the CMIP6 outputs of soil moisture, evapotranspiration, and transpiration for three shared socioeconomic pathway (SSP) scenarios (SSP126, SSP245, and SSP585). The models with three variables available are shown in Table 3, and detailed model information can be found online (https://wcrp-cmip.github.io/CMIP6_CVs). After some consistency checks, outputs from 13 models were finally selected. The evaluation is presented in section 3a(4).

b. Methodology

1) STATISTICAL METRICS FOR EVALUATIONS OF REANALYSIS AND CMIP6 DATASETS

In the processes of data evaluation and analysis, the following statistics are used: Pearson correlation coefficient r ,

$$r = \frac{\sum_{i=1}^n (x_i - m_x)(y_i - m_y)}{\sqrt{\sum_{i=1}^n (x_i - m_x)^2 \sum_{i=1}^n (y_i - m_y)^2}}, \quad (1)$$

where x_i and y_i denote modeled and observed time series, respectively, with n samples and m_x and m_y indicate their corresponding mean values. Then, the probability p is estimated according to a t distribution with $n - 2$ degrees of freedom. If p is less than a significance level (e.g., 0.05), r is statistically significant.

The root-mean-square error (RMSE) is computed as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (x_{m,i} - x_{o,i})^2}{n}}, \quad (2)$$

where $x_{m,i}$ and $x_{o,i}$ are the modeled and observed variables, respectively, with sample size n .

The standard deviation (SD) was estimated using the following formula:

$$\text{SD} = \sqrt{\frac{\sum_{i=1}^n (x_i - m_x)^2}{n - 1}}. \quad (3)$$

In addition, the linear trend was estimated with least squares regression, and to validate the trend's significance, the two-sided p value was calculated using the Wald test with t distribution of the test statistic (Siniksaran 2005). For monthly variables, the Butterworth low-pass filter was applied prior to linear regression analyses (Winter et al. 1974). The pattern correlation coefficient was the Pearson product-moment coefficient of linear correlation for corresponding grid cells on two different maps of the same variable (IPCC 2001, appendix 12.3).

2) SEASONAL TREND DECOMPOSITION OF REGIONALLY INTEGRATED SOIL MOISTURE DATA

Given the limited in situ soil moisture observations, to test the periodicity and long-term trends of the five reanalysis soil moisture datasets in China, the integrated series were generated by averaging the soil moisture data over sites or

TABLE 3. The currently available CMIP6 models with soil moisture loss-related outputs. Refer to the online tables on acronyms of institutions and models, and detailed model information (https://wcrp-cmip.github.io/CMIP6_CVs). An asterisk (*) indicates total soil moisture not available. A pound sign (#) indicates soil moisture of soil layer not available at the time.

No.	Model	Source ID	Land surface model	Resolution (lat × lon)
1	BCC-CSM2-MR (Wu et al. 2019)	BCC, China	BCC-AVIM2 (Ji 1995)	~1.12° × 1.125°
2	CAMS-CSM1-0* (Rong et al. 2020)	CAMS, China	CoLM (Dai et al. 2003)	~1.12° × 1.125°
3	CanESM5 (Swart et al. 2019)	CCCma, Canada	CLASS3.6/CTEM1.2 (Verseghy et al. 1993)	~2.8° × 2.8°
4	CanESM5-CanOE# (Swart et al. 2019)	CCCma, Canada	CLASS3.6/CTEM1.2 (Verseghy et al. 1993)	~2.8° × 2.8°
5	CAS-ESM2-0* (H. Zhang et al. 2020)	CAS, China	CoLM (Dai et al. 2003)	~1.4° × 1.4°
6	CESM2 (Danabasoglu et al. 2020)	NCAR, United States	CLM5 (Lawrence et al. 2019)	~0.94° × 1.25°
7	CESM2-WACCM (Gettelman et al. 2019)	NCAR, United States	CLM5 (Lawrence et al. 2019)	~0.94° × 1.25°
8	CMCC-CM2-SR5 (Cherchi et al. 2019)	CMCC, Italy	CLM4.5 (Lawrence et al. 2011)	~0.94° × 1.25°
9	CMCC-ESM2 (Cherchi et al. 2019)	CMCC, Italy	CLM4.5 (Lawrence et al. 2011)	~0.94° × 1.25°
10	CNRM-CM6-1 (Voldoire et al. 2019)	CNRM-CERFACS, France	SURFEX (Voldoire et al. 2013)	~1.4° × 1.4°
11	CNRM-ESM2-1 (Séférian et al. 2019)	CNRM-CERFACS, France	SURFEXv8.0 (Decharme et al. 2019)	~1.4° × 1.4°
12	EC-Earth3-Veg (Döscher et al. 2021)	EC-Earth-Consortium, 12 European countries	HTESSEL and LPJ-GUESS (Balsamo et al. 2009; Smith et al. 2014)	~0.70° × 0.70°
13	FGOALS-g3# (L. J. Li et al. 2020)	CAS, China	CAS-LSM (Xie et al. 2018)	~2.00° × 2.00°
14	FIO-ESM-2-0*# (Bao et al. 2020)	FIO, China	CLM4.0 (Lawrence et al. 2011)	~0.94° × 1.25°
15	GFDL-ESM4# (Dunne et al. 2020)	NOAA-GFDL, United States	LM4.1 (Dunne et al. 2020)	~1.0° × 1.25°
16	GISS-E2-1-G (Kelley et al. 2020)	NASA, United States	GISS LSM (Schmidt et al. 2006)	~2.00° × 2.50°
17	HadGEM3-GC31-LL (Williams et al. 2018)	MOHC, United Kingdom	JULES (Best et al. 2011)	~1.25° × 1.875°
18	IPSL-CM6A-LR (Boucher et al. 2020)	IPSL, France	ORCHIDEE (Krinner et al. 2005)	~1.27° × 2.50°
19	KACE-1-0-G* (J. Lee et al. 2020)	NIMS-KMA, South Korea	JULES (Best et al. 2011)	~1.25° × 1.875°
20	MIROC6 (Tatebe et al. 2019)	MIROC, Japan	MATSIRO6.0 (Takata et al. 2003)	~1.4° × 1.4°
21	MPI-ESM1-2-HR (Müller et al. 2018)	MPI-M, Germany	JSBACH3.20 (Stevens et al. 2013)	~0.94° × 0.94°
22	MRI-ESM2-0 (Yukimoto et al. 2019)	MRI, Japan	HAL (Yukimoto et al. 2012)	~1.12° × 1.125°
23	NorESM2-LM (Seland et al. 2020)	NCC, Norway	CLM5 (Lawrence et al. 2019)	~1.9° × 2.5°
24	NorESM2-MM (Seland et al. 2020)	NCC, Norway	CLM5 (Lawrence et al. 2019)	~0.9° × 1.25°
25	TaiESM1 (W. L. Lee et al. 2020)	AS-RCEC, China Taipei	CLM4 (Lawrence et al. 2011)	~0.9° × 1.25°
26	UKESM1-0-LL (Sellar et al. 2019)	MOHC, United Kingdom	JULES (Best et al. 2011)	~1.25° × 1.875°

corresponding grid cells along the time axes for both observations and reanalysis. The resulting series were decomposed with the method of seasonal trend decomposition based on local regression (LOESS, STL) (Cleveland et al. 1990) in an additive model as follows:

$$Y_t = T_t + S_t + R_t, t = 1, 2, \dots, N, \quad (4)$$

where the regionally integrated soil moisture (Y_t) is decomposed into the long-term (T_t), seasonal (S_t), and remaining (R_t) components at time step t . Using least squares linear regression, the linear trend can be isolated from the long-term component, and the remaining nonlinear signal manifests repeated but nonperiodic long-term variability. The seasonal term indicates variations over a fixed period (e.g., annual), and the residual component consists of subseasonal signals (e.g., daily) and noise except for the seasonal and long-term components. With the method of seasonal trend decomposition, the periodic signals in soil moisture can be disentangled and validated on daily, seasonal, and secular scales. The core method in STL decomposition is LOESS smoothing through a weighting function. Rigorous mathematical deductions can

be found in the literature (Cleveland et al. 1990; Cleveland 1979).

3. Results

a. Evaluation of reanalyses and validation of CMIP6 simulations

1) SOIL MOISTURE

Regarding the five widely used reanalysis-like datasets (Table 1), several evaluations have been performed on soil moisture using upper-layer observations (Dorigo et al. 2021; Li et al. 2020a). Herein, we focused on root layer soil moisture and cross examination with evapotranspiration and transpiration. Figure 1 shows the locations of the 40 sites with available root layer observations as well as their sample numbers, mean soil moisture values, and statistics of comparisons with reanalysis datasets. Their correlation coefficients with the five reanalyses ranged from -0.63 to 0.85 , significant at the $\alpha = 0.05$ level at 87.0% of sites; the ratio of the RMSE to the observational mean soil moisture (RRMSE, Fig. 1c) ranged from

FIG. 2. Seasonal trend decomposition for integrated monthly soil moisture from all 40 sites and the corresponding five reanalysis datasets for the top 1-m soil layer, with statistics shown in Table 4.

9.7% to 151%; and the differences in standard deviations between observations and reanalyses (DStd, Fig. 1d) ranged from -0.06 to 0.02 ($\text{m}^3 \text{m}^{-3}$). These statistics show that the five reanalyses were in reasonable agreement with the observations in terms of the soil moisture in the top 1-m layer, and the consistency varied more across observational sites than across the reanalysis datasets. Their coarse grid resolutions constrained the reanalyses to capture the soil moisture heterogeneity observed at site points as well as the inadequacy of water and energy representations and land data in the reanalysis systems.

To reduce the local effects of sites, the concurrent observations were averaged across 40 sites, as were the reanalyses during 1981–99. Then, by means of seasonal trend decomposition, the skill levels of the reanalyses were evaluated on various temporal scales against the decomposed observations (Fig. 2). All five reanalyses, especially GLEAM and MERRA2, could regenerate the observed dynamics on a monthly scale in terms of the correlation coefficient ($p < 0.01$) (Fig. 2a, Table 4). Although seasonal cycles contribute to a

large portion of the consistency (Fig. 2c, Table 4), the variations at low and high frequencies (trend and residual terms, Figs. 2b,d) were also in high agreement (with significant correlations, $p < 0.01$, Table 3). According to the linear trends, while the reanalyses tended to underestimate the long-term trend, two reanalyses, GLEAM and MERRA2, reproduced the observed decreasing trend with remarkable accuracy (Table 4). However, the two reanalyses mostly over/underestimated the mean soil moisture of the top 1 m layer. The better performance of GLEAM largely benefits from the fine footprint of remote sensing retrievals (Martens et al. 2017); however, the coarse grid cells somewhat hampered the ability of the 20CRv3 to present the soil moisture dynamics observed at the point scale (Table 1).

2) EVAPOTRANSPIRATION

Evapotranspiration, a core component of soil moisture loss, was evaluated using four benchmark datasets [EVAL, CDR,

TABLE 4. Statistics of seasonal trend decomposition analysis for the five reanalysis and observational soil moisture datasets (Fig. 2). Two asterisks (**) denote significances at the $p < 0.01$ level; v/v is volume ratio.

Statistics		GLDAS	ERA5L	MERRA2	20CRv3	GLEAM
Correlation coefficients	Monthly SM	0.52**	0.56**	0.72**	0.52**	0.77**
	Trend	0.59**	0.43**	0.58**	0.49**	0.59**
	Seasonal	0.70**	0.59**	0.79**	0.49**	0.94**
	Residual	0.58**	0.64**	0.68**	0.52**	0.65**
Linear trends (v/v over 19 years) -0.018 for obs.		-0.002	-0.009^{**}	-0.017	-0.003	-0.018

MODIS, and FLUXCOM; for details, see section 2a(2)]. Their significant correlations ($p < 0.05$) with the five reanalyses indicated that the reanalyses could regenerate the month-to-month variability in the benchmark data in the various periods [section 2a(2)]. The long-term linear trends in the reanalyses showed the same increasing evapotranspiration as those in EVAL and CDR during their respective periods, despite considerable differences in the absolute magnitudes. With respect to MODIS and FLUXCOM, the spreads of linear trends among the reanalyses increased. Overall, ERA5L showed a closer trend to those of the benchmark data, followed by GLEAM. The regionally averaged annual cycles for their respective durations showed that, in China as a whole, the reanalysis means were larger than those of the model-based datasets (EVAL and CDR) but smaller than those of the observation-based products (MODIS and FLUXCOM) (Fig. 3). Nevertheless, the reanalyses encouragingly captured the annual cycles in the benchmark datasets, with an identical peak in July. The significant pattern correlations (all larger than 0.78, $p < 0.01$) for the mean evapotranspiration across China further indicated the adequacy of the spatial structures of the reanalyses (figures not shown). Overall, the variability of reanalysis evapotranspiration was comparable with the established benchmark data for China.

3) VEGETATION TRANSPIRATION AND ITS RATIO TO SOIL EVAPORATION

For vegetation transpiration, another key component of soil moisture loss, the reanalyses were evaluated first using 10-site observations for the period 2003–10 (Table 2). At the

monthly scale, the correlations were all significant ($p < 0.05$) as their annual cycles were retained. At the CBS, ChL, HBG, and QYZ sites, the much higher correlations across all the reanalyses largely resulted from the extensive spatial representativeness of in situ observations due to their homogenous surface conditions (Fig. 4a). Although the correlations declined considerably once their annual cycles were removed, GLEAM and ERA5L still had high levels of skill in presenting year-to-year variability (Fig. 4b). Likewise, in terms of errors (RMSE, Fig. 4c) and deviations (Fig. 4d), the spreads were larger across the sites than across the reanalysis datasets, and GLEAM was closest to the observations. From the perspective of linear trend, the five reanalyses all showed decreasing trends with the same sign as that of observations, and ERA5L displayed the closest decreasing trend to the observed trend.

Second, given the limited in situ observations, the PT-JPL and PML model simulations were used to examine the spatial structure and long-term variability of reanalysis transpiration in China as a whole. The spatially averaged time series in China (Fig. 5a) showed that four of the five reanalyses captured the significant interannual variations in the PT-JPL and PML estimates ($r > 0.55$ and 0.53, $p < 0.01$) except for the MERRA-2 data, even after the strong signals of annual cycles were filtered out by annual averages (Table 5). The increasing trends in the regionally averaged reanalyses were also in agreement with those in the two model estimates, although the reanalyses were considerably weaker. Their arithmetic mean was close to the PML-simulated values but much less than obtained with the PT-JPL model. These statistics highlight the overall comparability of the temporal and spatial variability between the

FIG. 3. Annual cycles of five reanalysis evapotranspiration vs four observation-based datasets. For each of the four panels, “Obs.” represents the EVAL, CDR, MODIS, and FLUXCOM datasets, respectively.

FIG. 4. Statistics for the comparisons among the five reanalysis vegetation transpiration datasets and in situ observations at 10 sites (Table 2) in China. Herein, STD denotes the standard deviation.

reanalysis transpiration datasets and the observation-driven estimates during the period 1981–2014.

The ratio of reanalysis transpiration to soil evaporation was further evaluated in comparison only with the PML simulations because components from both the observations and the PT-JPL data were unavailable (Fig. 5b). Among the reanalysis datasets, the spread of their annual mean ratios was broad (0.5–7.4 on average), which is attributed to the remarkably low ratio of MERRA-2 and the high ratio of GLEAM (Table 5). Nevertheless, their arithmetic mean ratio (2.6) substantially narrowed the spread with the PML simulations (1.6); the temporal dynamics were also in agreement to some degree, particularly the intensified fluctuations ($r = 0.24$, $P = 0.19$). The mean linear trend (0.003 per year) also captured the increasing trend of the PML simulations (0.013 per year) despite the lower strength.

These evaluations of soil moisture, evapotranspiration, and vegetation transpiration, along with previous validations (Dorigo et al. 2021), confirmed that the five reanalysis datasets could reasonably represent soil moisture evolution across China at various temporal scales. Accordingly, the use of reanalysis data to detect soil moisture loss changes in China was justified at the time. The uncertainties in the

data and their negative influence on the results are discussed in section 4.

4) CMIP6 VALIDATION AND SELECTION

Given that the reanalysis data could reasonably regenerate the observed soil moisture processes, the CMIP6 simulations were validated and selected by comparing the results with the reanalyses. Analogous to the notion of the Bowen ratio, the ratio of vegetation transpiration to soil evaporation (VT/SV) is sensitive to the pathway changes in soil moisture loss from the land surface. Conditional on the plausibility of soil moisture, evapotranspiration, and soil evaporation simulations (figures not shown), the VT/SV ratio, as an indicator, was used to select the CMIP6 simulations that were suitable to quantify soil moisture loss changes across China. Figure 6 shows the pattern correlation coefficients (PCCs) and linear trend ratios for the VT/SV ratio between the 26 CMIP6 simulations and the reanalysis mean. Most CMIP6 simulations could reasonably regenerate the spatial pattern of the reanalysis VT/SV ($PCC > 0.32$ at $\alpha = 0.01$). However, it was more challenging for them to reproduce the long-term trends on the regional scale. Ruling out the simulations with opposite

FIG. 5. Comparisons of (a) spatially averaged vegetation transpiration and (b) its ratio to soil evaporation in China for the five reanalysis datasets and the PML and PT-JPL simulations. Rea_mean denotes the arithmetic mean of the five reanalysis datasets.

linear trends over 1981–2014 and lower PCCs ($PCC < 0.32$) for the means of that period, 13 of 26 model simulations were selected (with blue labels in Fig. 6). Note that we focused on the spatial patterns and long-term trends of the ratios in the CMIP6 outputs, and thus, we did not seek to evaluate the skill levels of soil moisture–related simulations in the CMIP6 models. Rather, the ratio was introduced to test the pathway changes of soil moisture loss from the land surface.

b. Spatial structures of the soil moisture loss process in China over 1981–2014

Based on the five reanalysis datasets over 1981–2014, the spatial structures of the core components related to soil moisture loss (Fig. 7) showed that soil moisture increased

gradually from arid northwest China (less than 50 mm in the 0–1-m soil layer) to humid northeast and southeast China (approximately 400 mm), generally following the pattern of precipitation; however, there were regional discrepancies due to the forcing from land processes such as the radiation balance, topography, vegetation, and soil properties (Ma et al. 2015). Evapotranspiration, which ranged from approximately 0–100 mm, showed a similar spatial gradient to that of soil moisture but decreased faster in northeastern China and the Tibetan Plateau under the constraint of radiation. Vegetation transpiration and soil evaporation broadly had equal shares of the evapotranspiration total (ranging from 0 to 50 mm). Soil evaporation tended to be concentrated in humid regions while contributing to higher moisture loss across semiarid areas with lower vegetation cover (Fig. 7d).

TABLE 5. Statistics of the regional mean transpiration for the five reanalysis and observation-driven PT-JPL and PML estimation datasets (Fig. 5). CC_{PT-JPL} and CC_{PML} denote the correlation coefficients between the reanalyses and PT-JPL and PML model simulations, respectively. The superscripts ** and * represent significance at the $p < 0.01$ and 0.05 level, respectively; the subscripts a and b denote the statistics for Figs. 5a and 5b, respectively.

	GLEAM	20CR	MERRA	ERA5L	GLDAS	Rea_mean
CC_{PT-JPL}	0.55**	0.66**	0.01	0.68**	0.58**	0.57**
CC_{PML}	0.53**	0.64**	0.04	0.54**	0.82**	0.66**
CC = 0.64 between PT-JPL and PML						
$Trend_a$ (mm month ⁻¹ a ⁻¹)	0.031**	0.021**	0.011	0.021**	0.034**	0.024**
PT-JPL = 0.038**, PML = 0.072**						
$Mean_b$	7.37	0.79	0.49	2.96	1.13	2.55
$mean_{PML} = 1.62$						
$Trend_b$ (unitless)	0.018**	−0.0002	−0.0001	−0.002	0.001	0.003**
$Trend_{PML} = 0.013**$

FIG. 6. Comparisons of the ratios of vegetation transpiration to soil evaporation (VT/SE) among 26 CMIP6 simulations and the reanalysis mean. (a) Pattern correlation coefficients (PCCs) of the mean VT/SE ratios over 1981–2014; (b) the relative slope (Rslp), the slope of the regional mean VT/SE ratio time series over 1981–2014 from CMIP6 divided by that from the reanalyses. The negative Rslp indicates that the slope in CMIP6 is opposite to that in the reanalyses. A value close to one indicates the trend is closer to that of the reanalyses. The blue color of the labels indicates the simulations selected for detecting soil moisture loss changes (section 3c).

Figure 8 shows the ratio of vegetation transpiration to soil evaporation (VT/SE), which depicts the partitioning of soil moisture loss between the two quantities. This ratio gradually increased from arid regions to humid regions, following the increase in vegetation cover. In arid regions, the ratio was less than 0.1, so most soil moisture loss, if there was any, was due to the pathway of soil evaporation. With the increase in soil moisture and vegetation cover, the VT/SE increased from 0.5 to 1 and reached 1.5 in northeast and north China, which are mainly covered by croplands and forests. The ratio values were approximately 0.77, 1.20, 1.55, 1.56, and 1.91 in the areas dominated by grasslands, evergreen forests, deciduous forests, savanna, and croplands, respectively. The climatological dry–wet gradient (e.g., soil moisture) and vegetation cover types largely formed the pattern of the partitioning of soil moisture loss in China.

Figure 9 shows the seasonality of the VT/SE ratio. The ratios increased and expanded in spring with vegetation growth, especially in the croplands in north China. In summer, vegetation transpiration played a dominant role (VT/SE > 1.0) in both proportion and area, especially in northeast China, with temperature constraints on the physiological processes of vegetation. From summer to autumn, cropland transpiration in north China played a major role in soil moisture loss because of the long period of agricultural production. In winter, larger VT/SE ratios emerged in subtropical southwest China. In these regions, the LAI of vegetation still retains 80% of its peak value during dry winter seasons (Song et al. 2017). With the decrease in topsoil moisture, the increased surface radiation partitioning contributed to the increase in the ratio. This variation was consistent with the observed higher transpiration and albedo in the dry season for the evergreen broadleaf forests in Cambodia, and this result was similar to the higher winter latent heat flux measured in an evergreen forest of north Thailand and the higher dry-season transpiration in northern

Australia (Nobuhiro et al. 2007; O’Grady et al. 1999; Tanaka et al. 2003).

c. Pathway variability of soil moisture loss for the present-day climate

During 1981–2014, there was an overall positive trend of soil moisture across China except in arid northwest China, semiarid northeast China, and humid southwest China (Fig. 10a). Evapotranspiration changes showed a similar spatial pattern but had stronger trends (Fig. 10b). Additionally, the pathway of soil moisture loss presented significant changes across China (Fig. 10c). The VT/SE ratio significantly increased in most areas covered by vegetation, from semiarid to humid areas. Larger increases appeared [>10 percentage points (pps)] over 1981–2014] in northeastern croplands and forestlands and southern forestlands, with the maximum value (approximately 20 pps) in the southwestern forestlands. Slight increases appeared in parts of arid areas and the western Tibetan Plateau. Significant decreases (<-10 pps) prevailed in north China, which is predominantly covered by grasslands and croplands.

Regarding the seasonality of VT/SE changes, the differences between the means over 2010–14 and 1981–85 (Fig. 11) showed that over north China, the persistent decrease from March to June totaled 36 pps with a trough value of 17 pps in May, despite an increase of 11 pps in August (Fig. 11a). In contrast, across the regions with increasing trends, the VT/SE ratio increased year-round with a total increase of up to 91 pps, except for a decrease of 4.2 pps that emerged in May and June (Fig. 11b). In addition, the increases reached 15, 14, and 17 pps in February, August, and October, respectively. The decreases in north China around spring might have been a result of water stress affecting the growth of vegetation due to the aridification of soil moisture from winter to spring (Li and Ma 2015; Li et al. 2020b). The increased ratio was largely associated with variations in soil moisture (Fig. 10a) and warming climate (Cao et al. 2016). The

FIG. 7. Spatial distributions of (a) mean soil moisture (SM), (b) evapotranspiration (ET), (c) vegetation transpiration (VT), and (d) soil evaporation (SE) for the period 1981–2014 calculated from the reanalysis datasets.

potential mechanisms for the changes in the ratio are discussed in [section 4](#).

d. Pathway changes in soil moisture loss under future climate scenarios

Given that the pathway of soil moisture loss has been changing considerably across China with present-day climate change, the future tendencies of these changes are important because of their immediate relevance to our terrestrial environments. [Figure 12](#) shows a comparison of the trends of the VT/SE ratios among the means of the 13 CMIP6 model historical simulations and five reanalysis datasets for the period 1981–2014. The selected CMIP6 models, based on their patterns of the mean VT/SE ratio and long-term dynamics ([Fig. 6](#)), considerably regenerated the spatial characteristics of

the increasing VT/SE ratio in China; however, they failed to capture the decreasing trends in north China. The likely cause and potential implications of the results are further discussed in [section 4](#). Given the discrepancy in trends in north China, the dynamics of the ratio, excluding north China with decreasing reanalysis trends, showed ([Fig. 13](#)) that the overall increase ratio in China was as high as 42.7 pps ($p < 0.01$) during 1981–2014 according to the 13 CMIP6 model simulation mean, and this value was comparable to that obtained by the reanalyses (51.4 pps, $p < 0.01$). In the future from 2015 to 2100, the CMIP6 models project that the significant increasing trend is held consistently, reaching 30.6 pps under the SSP245 scenario (Mann–Kendall test, $\alpha = 0.05$). The increase is as high as 40.8 pps under the SSP585 scenario. Under the SSP126 scenario, the dynamics show more periodic changes of

FIG. 8. Temporal mean spatial patterns of the VT/SE ratio distribution for the period 1981–2014 and land cover types in China in 2010.

decrease–increase–decrease with changepoints in 2031 and 2067, and the overall linear trend is -1.0 pps for the 85-yr period.

In terms of the seasonality of the ratio changes (Fig. 14), the differences of the 2030s, 2060s, and 2090s means to the historical (1980–2014) mean show that, from the SSP26 to

SSP245 and SSP585 scenarios, the annual changes enhanced remarkably based on both means and variances. The means of the differences between the 2030s and the historical scenarios spanned from 2.1 to 3.7 pps, those between the 2060s and the historical scenarios spanned from 3.2 to 5.1 pps, and

FIG. 9. Averaged seasonal patterns of the VT/SE ratio for the period 1981–2014.

FIG. 10. Patterns of linear trends for soil moisture (SM), evapotranspiration (ET), and the ratio of VT to SE during 1981–2014. Dots indicate the significance of the slope by linear least squares regression at the $p < 0.05$ level.

those between the 2090s and the historical scenarios spanned 2.5–4.9 pps. Additionally, the corresponding standard deviations were 1.6–1.9, 2.7–4.2, and 2.7–5.5 pps, respectively. In comparison with the historical scenario, the increases under the three scenarios were mainly produced in the spring and winter seasons, with peak increases in May (4.7–10.0 pps) and October (2.0–9.8 pps); additionally, peaks occurred in November for the 2060s and 2090s under SSP585 (10.4 and 11.2 pps, respectively). In contrast, the increases in summer substantially declined and even changed to negative values, especially in July, with decreases of -1.7 , -1.1 , and -7.9 pps in the 2090s under the three scenarios, respectively.

From the perspective of spatial construction, the VT/SE ratio changes (Fig. 15) were generally characterized by significant increases ($p < 0.05$) during the 2030s, 2060s, and 2090s compared with the historical baseline ratios (means over 1980–2014).

Under SSP245, an intermediate level of greenhouse gas emissions, the ratios increased across areas covered by vegetation throughout the 2030s, 2060s, and 2090s; additionally, larger increases (>10 pps) appeared in the areas of grasslands and south China forestlands, and until the 2090s, the ratios tended to decline in southeast China forestlands. Under a low level of greenhouse gas emissions, SSP126, the increasing pattern was the same as that under SSP245 but with declining intensity in the 2030s and 2090s, especially the decreases (<-5 pps) that appeared in southeast China. Under a high level of greenhouse gas emissions, SSP585, increases in the ratios were similarly held throughout the twenty-first century, with a maximum (>20 pps) in the 2060s and decreases (from -5 to -20 pps) in east China in the 2090s. Under the three scenarios, grasslands, croplands, and evergreen forestlands contributed to the main increases in soil moisture loss by the vegetation pathway in China.

FIG. 11. Annual cycle comparisons of the mean VT/SE ratio between 1981–85 and 2010–14 in the areas with decreasing and increasing trends, respectively (shown in Fig. 10c).

4. Discussion

a. Possible mechanisms of pathway changes of soil moisture loss

In the present-day climate, the increasing VT/SE ratios of soil moisture loss are consistent with credible greening trends based on the long-term remote sensing LAI data of terrestrial ecosystems (Piao et al. 2020). A prominent greening pattern was observed in China during 2000–17, mainly from forests (42%) and croplands (32%) (Chen et al. 2019), and these results largely agreed with the trends from the CMIP6 models, especially regarding the greening of croplands in north China (Fig. 12b). In addition, an increasing seasonal LAI amplitude was observed in the remote sensing data (Cortés et al. 2021), which was analogous to the intensified annual cycle of the VT/SE ratio (Fig. 11b) and future projections (Fig. 14). Piao et al. (2020) reviewed the drivers of greening trends of terrestrial ecosystems: human activities (afforestation and agricultural intensification) and global change (warming and carbon dioxide fertilization) are two dominant category drivers in China. Given that CMIP6 models do not explicitly represent the processes of

human activities, it can be expected that the increase in the VT/SE ratio based on CMIP6 modeling is smaller than that in the reanalyses (which partly incorporate remote sensing data, e.g., GLEAM, Fig. 13a). Such a vegetation greening trend indicates increases in leaf size, leaf number, and plant density due to eased temperature constraints and carbon dioxide fertilization with a warming climate and intensified emissions (Lucht et al. 2002; Piao et al. 2020), thereby enhancing vegetation water competitiveness and use efficiency (Keenan et al. 2013). The increases in growing season length and water use efficiency dominantly underlie the increase in the ratio of vegetation transpiration in soil moisture loss relative to soil evaporation. In semiarid and subhumid regions, the enhancement of evaporation resistance due to drying in the upper soil layer (Li and Ma 2015; Meng et al. 2021) contributes to an increase in the VT/SE ratio.

The projected VT/SE ratio increases in the future climate projections (SSP126, SSP245, and SSP585 scenarios), can largely be attributed to the same mechanisms as those in the present-day climate. The main reason is that the representations of biogeochemical processes in the Earth system models used for the CMIP6 projections have been incorporated in those used for the reanalysis simulations (Table 3 and references therein). Moreover, the 13-model mean LAI projection differences between the 2090s and 2020s under SSP585 showed significant increases in response to the warming climate in China (0.52 on average, figure not shown). Accordingly, with the warming climate and eased ambient conditions in part of growing season, enhanced vegetation water competitiveness and use efficiency are expected to contribute to the projected increases in the VT/SE ratio in the future climate scenarios.

Furthermore, due to the heterogeneity of climates and vegetation properties, the interactions between vegetation and climatic factors varied widely. From the perspectives of water (e.g., soil moisture) and energy (e.g., surface downward solar radiation) (Fig. 16), in grasslands, which are drier areas, the soil moisture loss pathway is primarily regulated by the water

FIG. 12. Ensemble mean linear trends of the VT/SE ratio for the period 1981–2014 from (a) the five reanalysis datasets (Reana.) and (b) the 13 CMIP6 models.

FIG. 13. Time series of average VT/SE ratio anomalies excluding north China where decreasing trends are shown in Fig. 12a. Thick blue lines are the ensemble mean of the 13 CMIP6 models, vertical bars are the ensemble spread, and dashed orange lines are the nonlinear regression. The solid orange line shows the mean of the five reanalysis datasets.

availability in soil (i.e., the area is water limited). Therefore, the decreased VT/SE ratio in north China grasslands (Figs. 10 and 12) over 1981–2014 is a result of concurrent long-term soil drying in the context of decreasing precipitation regulated by the interdecadal Pacific oscillation (Yang et al. 2019); the failure to regenerate the trend by CMIP6 models also results from the wetter bias in soil moisture simulations. In south China savanna and evergreen forestlands, which have wetter soil, the available radiation energy controls the pathway of soil moisture loss (i.e., the area is energy limited). For the tight coupling between soil moisture and radiation changes, in subtropical areas, increasing radiation (increasing temperature) enhances vegetation transpiration and water use, causing soil

moisture drying. The increased correlations of the ratio with soil moisture (from 0.48 to -0.78 , $p < 0.01$, Fig. 16) and radiation (0.16–0.53) anomalies reveal the tighter link throughout vegetation, water, and radiation processes over these regions. For this reason, changes in soil moisture loss pathways feature regionality and seasonality under a changing climate.

b. Limitations and uncertainty

Based on the five reanalysis-like datasets, the ensemble mean showed decreasing trends in north China grasslands and croplands (Fig. 10). In the north China grasslands, the decreasing trends were aligned with that of remote sensing LAI changes (Piao et al. 2020); however, the 13-CMIP6-

FIG. 14. Projected area-averaged changes in the annual cycle of the VT/SE ratio relative to the period of 1981–2014 for the three climate scenarios (SSP126, 245, and 585). The area with decreasing trends (north China, as shown in Fig. 12a) is excluded.

FIG. 15. Projected VT/SE ratio changes relative to the historical period (1981–2014) for the three climate scenarios, where dots indicate statistical significance at the $\alpha = 0.05$ level from a paired t test.

model ensemble yielded the opposite trends during the same period. As a result, the increases in the vegetation pathway of soil moisture loss in this region face uncertainties under the three future scenarios. For the croplands, the decreasing trends of the VT/SE ratio were jointly produced by 20CRv3, GLDAS, and ERA5L. In contrast, MERRA2 and GLEAM exhibited increasing trends that were qualitatively consistent with greening trends and the increasing trends from the CMIP6 model mean.

This study summarized the performance of CMIP6 models in terms of soil moisture balance using a metric-based approach; however, it should be noted that Earth system models are complex in nature, and the selection of CMIP6 from the perspective of soil moisture balance is quite

challenging and may be inadequate using only two metrics, the VT/SE mean and its long-term trend; thus, different model sets may contribute to differences in the magnitudes of soil moisture loss changes, as noted in (Srivastava et al. 2020). Despite this caveat, the increasing role played by vegetation in the water cycle under a changing climate deserves attention in model development and climate impact studies.

The large spreads of the VT and VT/SE magnitudes among the reanalyses, and relative to the observations and observation-driven estimates (Figs. 4 and 5) were caused mainly by differences in the forcing data. For example, the GLEAM estimates were preferentially forced with satellite observation retrievals. In contrast, the other four reanalyses assimilated

FIG. 16. Joint distributions of the VT/SE ratio with anomalies of soil moisture (SM) and surface downward solar radiation (Rd) for five dominant vegetation types during 1981–2014. The linear relationships (solid lines) between the VT/SE ratio and SM or Rd were derived from ordinary least squares regressions. The R denotes the Pearson correlation coefficient with statistical significance at the $p < 0.01$ (**) or 0.05 (*) level.

few satellite observations, especially precipitation data. In particular, the larger VT/SE ratios in the GLEAM data, similar to those during 2005–07 [Fig. 11 in Miralles et al. (2016)], resulted from the far lower partitioning of soil evaporation. Separately calculating the components of evapotranspiration, i.e., transpiration and soil evaporation, together with the data assimilation algorithm, may account for the large ratios in GLEAM (Martens et al. 2017). In the case of ERA5L, the negative VT/SE trend is attributed to the strong vegetation response to the soil moisture decline in north China (e.g., Fig. 12). In the other reanalysis products, the lower VT/SE ratio is associated with the inadequate representation of water vapor diffusion in the soil within Earth system models (Chang et al. 2018). LAI is another important driver of the modeled VT/SE variability, and thus, inaccuracies in its values may directly lead to lower VT/SE ratios in the models (Lian et al. 2018). In addition, the reanalysis and CMIP6 model systems

have yet to adequately represent the processes of the terrestrial water cycle (e.g., groundwater), vegetation processes (succession, extension, plant root dynamics), and human activities (agricultural management, afforestation) (Best et al. 2011; Dai et al. 2003; Dunne et al. 2020; Lawrence et al. 2019), thereby contributing uncertainties to the simulations of the partitioning of evapotranspiration. As a result, the lower VT/SE ratio in the present study relative to observation-based estimates may underestimate the changes in the soil moisture loss in historical and future climates.

Note that the in situ observations and observation-based benchmark data are influenced to various degrees by human activities, such as land use and land cover changes and irrigation, which have yet to be explicitly considered in Earth system models. Moreover, mismatches in the spatial scale between point-scale in situ observations and model grid means may undermine the effectiveness of model validations using in situ observations (Entekhabi et al. 2010). On the other hand, measuring vegetation transpiration is still a challenging task, and discrepancies among benchmark data are still considerable (Miralles et al. 2016; Zhang et al. 2016).

Accordingly, accurately quantifying the historical and future changes in the VT/SE ratio on regional scales using Earth system models remains a challenging task given the inadequate representations of surface water, energy, and carbon interactions. Nevertheless, the credibility of ensemble means in predicting the overall relative changes or trends in surface processes provides reasonable confidence in the simulated and projected response of VT/SE to the warming climate and thus in the first-order knowledge of the VT/SE response to climate change.

c. Implications of pathway changes for terrestrial environments

Increases in the VT/SE ratio clarify the process of increasing soil water loss by vegetation transpiration instead of by the soil evaporation pathway. Such a change in water balance can increase water loss in the root soil layer (Shellito et al. 2018), resulting in the variability of the terrestrial water cycle on various temporal scales. In past decades, changes in soil moisture persistence have been observed across China (Li et al. 2020b). This observation coupled with the changes in land surface properties such as roughness and albedo and the radiation energy balance trigger feedback changes in land–atmosphere systems, especially over semiarid and subhumid regions that have strong land–atmosphere coupling (Koster et al. 2004). Therefore, future studies can shed light on climate change and terrestrial environments in these regions in terms of the feedbacks between the land and atmosphere.

Increases in the VT/SE ratio are highly associated with the physiological processes of vegetation. The historical trends and projections for the future promise positive trends related to the carbon budget and sequestration as the vegetation function is enhanced across China. To fulfill such a potential, particularly over semiarid and subhumid regions, ecological efforts should be made consistently.

Additionally, the enhancement of the vegetation pathway of soil moisture loss increases both the risk of soil aridification, especially in deep soil, due to root uptake (Schenk and Jackson 2002) and the decrease in runoff due to vertical water cycle changes and alteration of precipitation patterns through land-atmosphere feedbacks (Zhou et al. 2021).

5. Summary and conclusions

Global warming drives changes not only in the atmospheric climate but also in the feedbacks of surface processes, leading to surface water balance variations and environmental changes. This paper aimed to investigate the responses of soil moisture to the changing climate while focusing on the pathway changes in soil moisture loss, namely, the VT/SE ratio. The investigation was based on combining reanalysis datasets and CMIP6 climate model projections. Five reanalysis datasets were first evaluated using in situ observations of soil moisture and vegetation transpiration as well as benchmark data for evapotranspiration. Thirteen CMIP6 projections under three emission scenarios (SSP126, SSP245, and SSP585) were selected after some cross validation of their historical simulations with the reanalysis datasets. The reanalysis datasets were used to analyze historical changes, while CMIP6 projections were used to analyze the future. Because of limited in situ observations, this study is confined to China only. The main findings are as follows:

- For the present-day climate, there has been a significant change in the balance of soil moisture loss across China, except in the northern arid regions. The VT/SE ratio increased by 51.4 pps according to the reanalysis datasets and by 42.7 pps based on the CMIP6 simulations during the period 1981–2014.
- The CMIP6 projections suggest the historical trends will continue into the twenty-first century. From 2015 to 2100, the increasing loss ratio held with increases of 30.6 and 40.8 pps in comparison with that of historical simulations under SSP245 and SSP58, respectively. The increase featured double peaks in May and October in response to the extension of the growing season under a warming climate.
- The reanalyses and CMIP6 models used herein could generally regenerate changes in soil moisture balance and vegetation processes driven by the warming climate in China during the present period. The increase in the loss ratio, VT/SE, was directly caused by the increasing loss through the vegetation transpiration pathway, while a local decrease occurred in north China due to the decreasing soil moisture.
- The changing soil moisture loss balance may alter and be altered by land-atmosphere feedbacks in terms of the water balance and carbon budget, thus giving rise to effects on the local climate and terrestrial environments. However, the predicted enhancement of vegetation water use efficiency will help counterbalance carbon dioxide emissions in the future.

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