Soil moisture controlled the variability of air temperature and oasis effect in a large inland basin in arid region

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Abstract: Soil moisture plays a significant role in land-atmosphere interactions. Changing fractions of latent and sensible heat fluxes caused by soil moisture variations can affect near-surface air temperature, thus influencing the cooling effect of the oasis in arid regions. In this study, the framework for the evaporative fraction (EF) dependence on soil moisture is used to analyze the impacts of soil moisture variation on near-surface air temperature and the oasis effect. The results showed that the contribution rate of soil moisture to EF was significantly higher than that of EF to temperature. Under the interaction of temperature sensitivity to EF and EF to soil moisture, the $\partial T/\partial \Theta$ presented a similar tempo-spatial variation with both of the above. It was most significant in oasis areas during summer (−1.676), while it was weaker in plain desert areas during the autumn (−0.071). In the study region, the effect of soil moisture variation on air temperature can reach 0.018–0.242 K for different land-cover types in summer. The maximum variation of soil moisture in summer can alter air temperature by up to 0.386 K. The difference in temperature variability between the oasis and desert areas promoted the formation of the oasis effect. For different oasis, the multi-year average oasis cold effect index (OCI) ranged from −1.36 K to −0.26 K, while average summer OCI ranged from −1.38 K to −0.29 K. The lower bound of the cooling effect of oasis ranged from −4.97 to −1.69 K. The analysis framework and results of this study will provide a new perspective for further research on the evolution process of the oasis effect and water-heat balance in arid areas.

Keywords: Evaporative fraction, near-surface air temperature, coupling relation, oasis and desert, arid region

1. Introduction

Soil moisture plays a crucial role in the exchanges of water and energy on the land surface (Koster *et al.*, 2004; Feldman *et al.*, 2019). The spatiotemporal variations of soil moisture closely correlate with the variability of precipitation, evapotranspiration, and runoff (Wang *et al.*, 2012; Sazib *et al.*, 2020). Generally, there is a strong coupling between soil moisture and precipitation (Koster et al., 2004). Precipitation events triggered by wet advantage conditions have larger accumulations than the similar events triggered under the dry advantage conditions during all seasons (Huggannavar and Indu, 2020). In addition, soil moisture also controlled evapotranspiration (*ET*), especially in the water-limited regions. Therefore, in Priestley Taylor Jet Propulsion Laboratory (PT-JPL) ET algorithm, soil moisture can be used as an important input variable to estimate actual evaporation (Purdy et al., 2018; Walker et al., 2019). Meanwhile, soil moisture is commonly used to estimate *ET* based on the water balance equation (Gribovszki and Zoltan, 2018). In some cases, the complex correlation between soil moisture and evapotranspiration affected the moisture-precipitation feedback in dry and wet regions (Yang et al., 2018). In the quantitative analysis of the coupling relationship between soil and evaporation, researchers proposed a simple schematic of *ET*/ soil moisture parameterizations, in which soil moisture and *ET* of forest presented a linear relationship (Brandes and Wilcox, 2000). A deterministic continuous simulation model of soil moisture was established using actual evapotranspiration as a function of potential evapotranspiration and soil moisture (a piecewise function of *ET* and soil moisture considering various soil moisture thresholds). The model was successfully verified by climate and field data from the Guelph lawn Research Institute and environmental research center in Ontario, Canada (Nishat et al., 2007). Recently, researchers have proposed a conceptual framework for the dependence of evaporative fraction (EF) on soil moisture, in which using the EF ruled out the influence of variations in net radiation, so it is suitable to analyze the control of soil moisture on energy partitioning (Seneviratne *et al.*, 2010; Schwingshackl *et al.*, 2017). Soil moisture can affect surface air temperature by controlling the latent heat flux. Research has indicated that soil moisture feedback over North China contributes 6% of the total air temperature variation from 1961–2012 and reaches 36% after the regional warming from 1994–2012 (Xu et al., 2019). While in the subtropical southwest of China, soil moisture contributed 10–50% of the total air temperature variance (Zhao et al., 2020). Over the monsoon-dominated region of India, the long-term decrease of soil moisture increased the incidence of temperature extremes (Ganeshi et al., 2020).

Generally, the strength of soil moisture control on the energy partitioning at the land surface depends on the geographical location and can over the year. Only in regions where soil moisture is the limiting factor for this partitioning can the dependence of water and energy fluxes on soil moisture be expected (Schwingshackl et al., 2017). Thus, for the arid region of Xinjiang, located in Central Asia's inland region, with an annual temperature of 10–13°C and precipitation of 150 mm, soil moisture may have stronger control on the surface air temperature. Several studies have shown that, during the past 60 years, the temperature rise of the Xinjiang region was 0.32–0.35°C/10a (Jiang et al., 2013; Xu et al., 2014), higher than the temperature rise in China and across the world. However, little is known about the role of soil moisture in the warming process and the seasonal variation of the coupling strength between soil moisture and temperature in arid regions of Central Asia Also, there is a typical mountain-oasis-desert ecosystem in arid Central Asia. An oasis is a medium-sized or small-scale non-zonal landscape that occurs in an arid climate and is supported by natural or artificial rivers in the desert (Li et al., 2013; Yi et al., 2015). Oases are characterized by comparatively high primary productivity and evapotranspiration (Bruelheide et al., 2003; Zhao et al., 2010). The oasis cooling effect caused by strong evapotranspiration in the oasis area compared to the surrounding desert area exists in arid regions such as Northwest China and southern Israel (Taha *et al.*, 1991; Saaroni *et al.*, 2004; Chu *et al.*, 2005; Liu *et al.*, 2011; Li *et al.*, 2013; Wen, 2014). Although the oasis effect was studied using a numerical model and MODIS land surface temperature (LST) data (Su and Hu, 1987; Hao *et al.*, 2016), there is still a lack of research on the control mechanism of the oasis effect, primarily concerning how soil moisture controls evapotranspiration, which mutually affects the surface air temperature.

Here, we focus our analysis on a typical arid region of Central Asia and address three questions through integrated site observation, simulated data and the conceptual framework for the coupling relation between evaporative fraction and soil moisture. (i) How does surface air temperature respond to the soil moistue variation in the arid region? (ii) Which landscape units have the greatest change in surface air temperature due to soil moisture variation? (iii) How does the negative feedback of soil moisture to air temperature promote the formation of the oasis effect and its seasonal variation?

2 Materials and Methods

2.1 Study area

In this study, the coupling relationship between soil moisture and evapotranspiration in the Xinjiang region, a provincial-level autonomous region of Northwest China, were analyzed. The Xinjiang region covered approximately 1.6 million km^2 and bordered Mongolia, Russia, Kazakhstan, Kyrgyzstan, Tajikistan, Afghanistan, Pakistan, and India. The study region is bounded by the Altai and Kunlun (Karakorum) Mountains on the northern and southern borders, respectively (Fig. 1). The Tianshan Mountains are located in the middle of Xinjiang and divide Xinjiang into two major basins, the Junggar basin and the Tarim Basin, the two largest inland basins of China. The study area has a typical landscape pattern of the mountain-oasis-desert. Among them, the mountainous area is the formation area of water resources. Rivers in this region, similar to other rivers in Central Asia, all originate in mountainous areas and flow into or disappear in the basin. Natural and artificial oases are often formed in plain alluvial areas where rivers flow surrounded by a vast desert area. The climate of Xinjiang is a typical continental arid climate. The annual temperature is 10–13°C, and precipitation is 20–100 mm and 100–500 mm in the southern and northern parts of the study area, respectively. The land-cover types of the study areas were predominantly desert, including sand (21.16%), Gobi desert (17.48%), and bare land (18.83%). The forest, grassland, and farming land accounted for 2.26%, 28.61%, and 4.72% of the total study area, respectively (Fig. 1).

Fig. 1 Sketch map of topography and primary land-use types in the study area.

2.2 Data

The surface energy balance algorithms for the land (SEBAL) model based on MODIS data estimated the ET data. In this study, MODIS LST, normalized difference vegetation index (NDVI), surface albedo, and land-use/cover (LUCC) data were used. These data were first processed by mosaic, band match, and re-projection methods and then resampled (using the nearest neighbor method) to 1 km resolution. We adopted the global vegetation classification system of the International Geosphere–Biosphere Program (IGBP) for the LUCC data. The primary land-use types (vegetation types) were reclassified into six categories: forest (FT), shrub (SH), grassland (GS), wetland (WL), cultivated land (CL), and desert (DS). In addition, the DEM data were downloaded from U.S. Geological Survey.

The classification data set of the soil texture (sand, silt, and clay content in 0–100 cm soil depth) was provided by the "National Tibetan Plateau Data Center" of China (http://data.tpdc.ac.cn). This data was developed based on the 1:1000000 scale soil map and 8595 soil profiles from the second national soil survey, and the USDA regional land and climate simulation standard in China. The dataset of soil hydraulic parameters in China using pedotransfer functions for Land Surface Modeling (CDSHP) is also used in this study, which provided by "National Cryosphere Desert Data Center of China."

Soil moisture data based on observed and microwave remote sensing were used in this study. The observed relative soil moisture data (0–100 cm) was obtained in 49 sites from 2000 to 2013, provided by the China Meteorological Data Service Center (CMDC). The soil moisture data of microwave sensing were provided by the National Tibetan Plateau Data Center of China, which used a high spatial and temporal resolution surface meteorological dataset and the improved land surface assimilation system. These parameters were used to drive the land surface process model SiB2 and assimilate the brightness temperature observed by the AMSR-E satellite to obtain soil moisture data for China (Yang *et al.*, 2007; Yang *et al.*, 2020). The detailed information of these above datasets are shown in Table1.

Table 1 Overview of the data information used in this study

	Dataset	Spatial resolution	Temporal resolution	Data sources
MODIS	LST,MOD11A2	1 km	8 days, 2000–2018	National Aeronautics and Space Administration (http://modis.gsfc.nasa.gov/)
	NDVI,MOD13A1	500 m	16 days, 2000–2018	
	Surface albedo, MCD43B3	1 km	8 days, 2000–2018	
	LUCC,MOD12Q1	1 km	yearly, 2001–2018	

Observed, simulated or assimilated	DEM data, USGS	30 m	/	U.S. Geological Survey (USGS; http://tahoe.usgs.gov/DEM.html, data
	Soil texture (0–100 cm)	1 Km	/	National Tibetan Plateau Data Center” of China (http://data.tpdc.ac.cn)
	soil hydraulic parameters (0–100 cm)	30″	/	National Cryosphere Desert Data Center of China” (http://www.crensed.ac.cn/portal/)
	observed relative soil moisture (0–100 cm)	49 sites	monthly, 2002–2013	China Meteorological Data Service Center (CMDC) website (http://data.cma.cn/data/cdcdetail/dataCode/AGME_AB2_CHN_TEN.html)
	soil moisture based on microwave sensing (0–100 cm)	0.25°	monthly, 2002–2011	National Tibetan Plateau Data Center” of China (http://data.tpdc.ac.cn)
	near-surface air temperature (2 m)	1 km	monthly, 2000–2018	Meteorological stations

The daily mean air temperature data were obtained from 68 national meteorological stations from 2000–2018. The gridded 1 km × 1 km monthly air temperature dataset was produced by Anusplin software (V4.3) using latitude, longitude, and elevation as independent variables. The Anusplin software is a professional interpolation software for meteorology data, which uses the thin-plate smoothing spline algorithm for interpolation (Qian, 2010).

2.3 Methods

a. Theoretical background

A conceptual framework for the EF dependence on soil moisture was already assumed and applied well (Seneviratne *et al.*, 2010; Schwingshackl *et al.*, 2017). In this framework, the dependence of evaporative fraction (*EF*) on soil moisture (θ) expressed as:

$$EF(\theta)\begin{cases} 0, if\, \theta < \theta_r \\ EF_{max}\dfrac{\theta-\theta_r}{\theta_c-\theta_r}, if\, \theta_r \leq \theta \leq \theta_s \\ EF_{max}, if\, \theta > \theta_s \end{cases} \quad (1)$$

where EF is the evaporative fraction, and θ_c is the soil moisture at *the critical point. When* $\theta > \theta_c$, soil moisture no longer is the limiting factor for evapotranspiration, dominated by the energy. θ_r is the saturated and residual soil moisture. The parameter EF can be calculated as follows:

$$EF = \frac{¿}{Rn} \quad (2)$$

where LE is the latent heat flux, and R_n is the surface net radiation. The ET (LE) and R_n data were estimated using the SEBAL model based on the MODIS dataset. The detailed calculation process of the SEBAL model can be found in (Allen et al., 2011).

However, when $\theta<\theta_r$, the EF is not always 0 because hygroscopic soil moisture can still maintain a soil evaporation level (Nishat et al., 2007). In addition, there is certain background noise in both NDVI and ET data in extremely arid desert areas. Thus, this study defined the EF_{min} as the EF value corresponding to the percentage of *EF's* cumulative frequency, which is 5% in each land-cover type of the study area. Similarly, the EF value corresponding to the cumulative frequency percentage of 95% is EF_{max}. Therefore, in formula (1), the *EF is approximately equal to* EF_{min} when $\theta < \theta$r.

b. Downscaling and estimation of soil moisture data

This study estimated the soil moisture mainly in the area of $EF_{min} \leq EF \leq EF_{max}$. Based on the deformation of equation 1, the following equation can be obtained:

$$\theta = \frac{EF}{EF_{max}}(\theta_c - \theta_r) + \theta_r \quad (3)$$

where θ_r is the wilting moisture. The gridded θ_r was estimated based on the China dataset of soil hydraulic parameters (CDSHP) and soil texture classification data (Wang et al., 2015). Generally, the critical soil moisture (θ_c) is larger than θ_r and smaller than the saturated soil moisture (θ_s) and has great spatial variation. This study obtained the gridded monthly θ_c by inverse operation of equation (3) based on the assimilated monthly soil moisture dataset of the AMSR-E satellite data. Then, the lower spatial resolution (0.25°) θ_c is interpolated by the IDW method to obtain the high-resolution (1 km) θ_c. After obtaining the above parameters (θ_c, θ_r, EF, and EF_{max}), the high-resolution (1 km) monthly soil moisture data for the Xinjiang region from 2001 to 2018 were obtained using formula (3). Thus, the spatial downscaling application of the assimilated soil moisture dataset in Xinjiang was realized, and the data series was extended from 2002–2011 to 2001–2018.

c. The impacts of soil moisture variation on near-surface air temperature

The sensitivity of surface air temperature to soil moisture can be divided into two contributions:

$$\frac{\partial T}{\partial \theta}=\frac{\partial T}{\partial EF}\frac{\partial EF}{\partial \theta} \qquad (3)$$

where the first term on the right-hand side is the sensitivity $\partial T/\partial EF$, describes to what extent changes in energy portioning influence air temperature. Here, temperature anomalies were used for calculating this sensitivity through a statistical sensitivity analysis method (Hao et al., 2019). The second term on the right-hand side, the slope $\partial EF/\partial \theta$, represents the coupling between soil moisture and the EF and is directly obtained from the fitted equation (3).

Eventually, it is possible to estimate how strongly soil moisture variations influence the near-surface air temperature:

$$\Delta T = \left| \frac{\partial T}{\partial \theta} \right| \Delta \theta \qquad (4)$$

where $\Delta \theta$ is the linear slope of soil moisture in the respective seasons (March to May, MAM; June to August, JJA, and September to November, SON) from 2001 to 2018. ΔT is a measure of the average effect of soil moisture variations on the near-surface temperature.

Similarly, the maximum impact of soil moisture on temperature is estimated as follows:

$$\Delta T_{max} = \left| \frac{\partial T}{\partial \theta} \right| \Delta \theta_{max} \qquad (5)$$

where $\Delta \theta_{max}$ is the maximum change rate of soil moisture in the respective seasons from 2001 to 2018, calculated by the maximum and minimum soil moisture values.ΔT_{max} is the upper bound of the impact that soil moisture can have on temperature.

d. Analysis framework of oasis cold effect index

In winter, the surface soil freezes, and the dependence of EF on soil moisture no longer exists. Without the influence of the evapotranspiration process, there should be no significant difference in temperature between the oasis and the surrounding desert area under the same external radiation conditions. Until the beginning of spring, the soil thaws, and the evapotranspiration process is gradually strengthened. At this time, soil moisture began to have a strong impact on temperature, and the oasis effect began to be highlighted. Based on this assumption, this study defined the oasis cold effect index (*OCI*) as follows:

$$T_{oasis} = T_0 + \Delta T_{oasis}$$

$$T_{desert} = T_0 + \Delta T_{desert}$$

$$OCI = \Delta T_{oasis} - \Delta T_{desert}$$

where *OCI* is the index of the oasis cold effect, which usually has a negative value and the smaller the value, the stronger the cold effect of the oasis. T_{oasis} and T_{desert} are the air temperatures in the oasis and desert zones, respectively. T_0 is the external temperature forcing, which changes with the time driven by net radiation. ΔToasis and ΔT_{desert} are the temperature variations caused by the change in soil moisture in the respective seasons (MAM, JJA, and SON) compared with winter (December to next February, DJF). Here, ΔT_{oasis} and ΔT_{desert} were no longer absolute values but their original positive or negative values, which are often negative values.

3 Results

3.1 The sensitivity of temperature to soil moisture

The sensitivity of near-surface air temperature to the variation of soil moisture can be split into two components: sensitivity of temperature to *EF* and *EF* sensitivity to soil moisture. The results showed that the $\partial T/\partial EF$ generally ranged from −10 to 10 and have apparent tempo-spatial variations in the region (Fig2a-d). The average values of $\partial T/\partial EF$ were −0.053, −0.152, −0.047, and −0.028 in MAM, JJA, SON, and the entire warm season, respectively. The $\partial T/\partial EF$ in the whole region has a standard deviation of 0.17 in the warm season, while it was 0.36, 1.26, and 0.35 in MAM, JJA, and SON, respectively. In the mountainous, plain desert, and plain oasis areas, the average values of $\partial T/\partial EF$ were −0.043, −0.008, and −0.083 during the entire warm season, while it was −0.101, −0.043, and −1.141 in the summer season, respectively. Thus, the sensitivity of temperature to *EF* has the highest spatial variation in summer, followed by spring and autumn.

Fig. 2 The sensitivity of near-surface air temperature to evaporative fraction (EF) ($\partial T/\partial EF$), EF to soil moisture ($\partial EF/\partial \Theta$) and the near-surface air temperature to soil moisture ($\partial T/\partial \Theta$). (a)-(d) was the $\partial T/\partial EF$ in MAM (March to May, spring), JJA (June to August, summer), SON (September to November, autumn) and entire warm season (from

March to November), respectively. Similarly, (e)–(h) and (i)–(l) was the $\partial EF/\partial\Theta$ and $\partial T/\partial\Theta$ in the MAM, JJA, SON and entire warm season, respectively.

The sensitivity of *EF* to soil moisture also has obvious seasonal and spatial variations (Fig2e-h). In the MAM, JJA, SON, and the entire warm season, the average value of $\partial EF/\partial\Theta$ was 5.286, 5.061, 5.676, and 4.937, respectively. For the mountainous, plain desert and plain oasis areas, the average value of $\partial EF/\partial\Theta$ was 4.860, 5.017, and 5.584 during entire warm season, while it was 5.208, 4.891, and 6.141 in the summer season, respectively. Similar to the changing trend of $\partial T/\partial EF$, the sensitivity of *EF* to soil moisture also has the highest spatial variation in summer, followed by autumn and spring.

Under the interaction of temperature sensitivity to *EF* and *EF* to soil moisture, the $\partial T/\partial\Theta$ presented a similar tempo-spatial variation with both of the above. The negative coupling between temperature and soil moisture was obvious, and the average value of $\partial T/\partial\Theta$ was −0.281, −0.338, −0.241, and −0.130 in MAM, JJA, SON, and entire warm season, respectively. The standard deviation of $\partial T/\partial\Theta$ was highest in JJA, with a value of 1.35, while it was lowest in MAM and with a value of 0.56. The $\partial T/\partial\Theta$ showed a higher spatial variation than $\partial T/\partial EF$ and $\partial EF/\partial\Theta$. Specifically, in the mountainous, plain desert and plain oasis areas, the average value of $\partial T/\partial\Theta$ was −0.184, −0.040, and −0.431 during the entire warm season, while it was −0.385, −0.094, and −1.676 in the summer season. The sensitivity of temperature to soil moisture was highest in oasis areas during summer, while it was lowest in plain desert areas during autumn.

3.2 Temperature variability caused by soil moisture

Although the average temperature variability (ΔT) caused by soil moisture was slightly lower (0.013 K) throughout the warm season (Fig. 3a4), the ΔT in summer (JJA) can reach a high level, with variability of 0.242 K in the CL type. Among the other land-use types, the ΔT values for wetlands, grasslands, shrubs, desert, and forest were 0.205 K, 0.096 K, 0.039 K, 0.025, and 0.018 K, respectively. The trend of ΔT for different land-use types in spring (MAM) and autumn (SON) is similar to summer. The largest ΔT in spring and autumn also appeared in the CL, with values of 0.067 K and 0.056 K. During the same period, the smallest ΔT appeared in the desert with values of 0.013 K and 0.009 K, respectively (Fig. 3a1-a3). The ΔT_{max} caused by soil moisture variation have the same tempo-spatial changing trend with the ΔT. The largest value also appeared in CL with values of 0.386 K, 0.133 K, and 0.098 K in summer, spring, and autumn, respectively, which is almost two times of that for ΔT (Fig. 3b1-b4).

The temperature variability caused by the change in soil moisture was measured by the absolute value of ΔT and ΔT_{max}. However, soil moisture variation usually leads to negative temperature variability. For different land-use types, there were 43%–79%, 51%–77%, and 41%–81% of the areas in spring, summer, and autumn, showing a negative ΔT. The largest negative ΔT was −0.294 K, −0.076 K, and −0.066 K in summer, spring, and autumn, respectively, all of which appeared in CL. The negative ΔT_{max} appeared in areas larger than ΔT, and the largest negative ΔT_{max} (in CL) was −0.426 K, −0.143 K, and −0.107 K in summer, spring, and autumn, respectively. In summary, the ΔT and ΔT_{max} were highest in CL during summer, and negative temperature variability occurred in most areas of the study region due to increased soil moisture.

Fig. 3 The average (ΔT) and maximum (ΔT_{max}) effects of soil moisture change on near-surface temperature. The ΔT and ΔT_{max} were the absolute value of temperature variability, thus the study also analyzed the positive and negative effects, including the ΔT and ΔT_{max}, of soil moisture change on temperature. (a1)–(a4) was the ΔT in different land-use types during MAM, JJA, SON and entire warm season, respectively. While the (b1)–(b4), (c1)–

(c4), (d1)–(d4), (e1)–(e4) and (f1)–(f4) were the ΔT_{max}, $+\Delta T$, $+\Delta T_{max}$, $-\Delta T$ and $-\Delta T_{max}$ during the same period, respectively. The abscissa numbers in (c1) to (f4) indicated the proportion (percentage) of areas with positive or negative effects of soil moisture variation on air temperature in each land-use type.

3.3 Evaluation of oasis cold-island effect

Based on the coupling relationship between soil moisture and temperature, the oasis effects of eight typical oases, including the Hotan oasis (a), Yarkant oasis (b), Kashgar oasis (c), Akesu oasis (d), Kucha oasis (e), Korla oasis (f), oasis in the north of the Tianshan Mountains (g), and an oasis in the east Tianshan Mountains (h), were identified and evaluated (Fig. 4a). The results indicated that, for a single oasis, the minimum value of the multi-year average *OCI* was −1.36 K, occurring in the Kucha oasis. The maximum *OCI* was −0.26 K, which occurred in the oasis north of the Tianshan Mountains. In other oases, the multi-year average *OCI* ranged from −1.17 to −0.34 K (Fig. 4b). From 2001 to 2018, the oasis effects were strengthened in all oases, especially in the Kucha (e), Korla (f), and Akesu (d) oases.

Fig. 4 The spatial variation of multi-year average oasis cold index (a), and the changing trend of annual average cold index of eight typical oases (b) from 2001 to 2018. The annual average value was calculated from the average value of spring, summer and autumn. The letters a - h in the figure represent the Hotan oasis (a), Yarkant oasis (b), Kashgar oasis (c), Akesu oasis (d), Kucha oasis (e), Korla oasis (f), oasis in north of Tianshan Mountains (g) and oasis in east Tianshan Mountains (h), respectively.

Fig. 5 The monthly oasis cold index in the Hotan oasis (a), Yarkant oasis (b), Kashgar oasis (c), Akesu oasis (d), Kucha oasis (e), Korla oasis (f), oasis in north of Tianshan Mountains (g) and oasis in east Tianshan Mountains (h), respectively.

Oasis effects have significant seasonal variation. The change in *OCI* showed a unimodal trend from March to November, which usually has the largest value in March or November while having the lowest value in July or August (Fig. 5). During summer (JJA), the oasis cooling effect was most significant in the Kucha oasis (*OCI* = −1.38), followed by the Korla (*OCI* = −1.15) and Akesu (*OCI* was −0.96) oasis. The oasis effects were relatively lower for the other oases, and the *OCI* ranged from −0.49 to −0.29. In addition, the highest intra-annual variability of the oasis effect was detected in the Kucha oasis, and the *OCI* difference was 1.56 K between the month with the lowest (August) and the highest (March) *OCI*. The higher intra-annual variability of OCI also appeared in the Korla and Akesu oasis, and the *OCI* difference between July and March was 1.29 K and 1.00 K, respectively. For the other oases, the intra-annual variability of *OCI* ranged from 0.36. to 0.50 K. These results indicated that the oasis effect was generally highest in summer and the oasis area with the most significant oasis effect also has a larger intra-annual variability of *OCI*.

4. Discussion

4.1 Assessment of model fit

Generally, there are three approaches to obtain the SM data: (1) in situ observations; (2) remote sensing (Han et al., 2018; Senanayake et al., 2019); and (3) modeled data (Shrivastava *et al.*, 2018; Schmidt-Walter *et al.*, 2020; Shao *et al.*, 2020). However, retrieving soil moisture through a remote sensing approach often faces great challenges in arid areas with sparse vegetation because of the adverse effects of surface roughness and vegetation cover (Kong et al., 2018). In addition, the simulation model of soil moisture usually requires a lot of input data and parameters, limiting the application of the model. While considering the difference in simulation methods, the final simulation results typically have a certain degree of uncertainty (Lannoy et al., 2006; Maroufpoor et al., 2019). Thus, it has always been a hot issue to construct a simple, easy-to-use, and accurate method to obtain regional soil moisture. This study attempted to establish a simple algorithm based on the coupling relationship between soil moisture and evapotranspiration to estimate monthly soil moisture in arid areas with sparse vegetation. The estimated monthly soil moisture data were converted to relative soil moisture (RWC) and verified by the measured relative soil moisture data of 49 stations in the study area (Fig. 6). The overall changing trend of the estimated relative soil moisture was close to the observed value, and the coefficient of determination R^2 was 0.85. Meanwhile, the root mean square error (RMSE), mean absolute percent error (MAPE), and the Nash–Sutcliffe efficiency coefficient (NSE) of this simulation was 5.17, 6.94, and 0.26, respectively. Such results indicate that the error between the estimated and observed value was approximately 7% RWC, while the relative soil moisture difference is about 5% RWC. The fitting error mainly comes from the overestimation of soil moisture, especially when the actual soil moisture is lower. In other words, the estimation model used in this study may overestimate the actual soil moisture in some dry areas or during the dry season of soil. Although there were still some simulation errors, the estimated soil moisture overall was reliable. The changing trend of the estimated value is consistent with the observed value, so the relationship between them and *EF* is also consistent. Therefore, the estimated value can be a useful substitute index for actual soil moisture, which often lacks long-term and regional scale observations to analyze soil moisture and *EF's* coupling relationship.

The method can also be applied to the downscaling of the soil moisture dataset assimilated based on the microwave remote sensing data. This study used the assimilated soil moisture dataset with 0.25° spatial resolution, which was obtained based on microwave remote sensing data. Although the dataset's accuracy is higher, and the RMSE of soil moisture is 5% VWC, the resolution is still low for regional research. Thus, it cannot effectively reflect the spatial heterogeneity of soil moisture, which is the main reason for the cold effect of the oasis. In our study, the soil moisture dataset with 1 km resolution was obtained based on the coupling relationship between soil moisture and evaporation fraction. The downscaling data also had good fitting accuracy and could fully meet the spatial heterogeneity analysis of soil moisture. More importantly, this method can also extend the data series. In this case, the soil moisture data series was extended from 2002–2011 to 2001–2018. Thus, the analysis framework used in the study may be an effective and simple method for downscaling soil moisture data from microwave remote sensing.

Fig. 6 Estimated and observed relative soil moisture in 0–100 cm soil layers of the study area. The relative soil moisture data were observed in March to November during 2000 to 2013 in 49 sites.

4.2 Effect of soil moisture on temperature variation

Many studies have proved that soil moisture has a profound impact on near-surface temperature. Over North China, soil moisture feedback contributes 36% of the temperature variation during 1994–2012 (Xu et al., 2019). In subtropical southwest China, soil moisture contributed 10%–50% of the total air temperature variance (Zhao et al., 2020). Over the monsoon-dominated region of India, the decrease in soil moisture increased the incidence of temperature extremes (Ganeshi et al., 2020). Correspondingly, our study also showed that the average maximum temperature variation caused by soil moisture change could reach 0.386 K in the whole study region during the summer from 2001 to 2018, explaining 18.52% of the total air temperature variance. In mountainous areas, plain oasis areas, and plain desert areas, the soil moisture contributed 24.6%, 60%, and 4.9% of the air temperature variance. Thus, two issues need to be reconsidered from a new perspective: 1) the temperature rise was highest in mountainous areas of the region (Tang et al., 2013; Tang et al., 2014), which was partly attributed to the changes in upper-air temperature trends (Chen et al., 2015). However, studies have shown that the land water storage of mountainous areas has decreased significantly in this region (Yang and Chen, 2015; Deng *et al.*, 2019). Therefore, the decreasing trend of land water storage may lead to the drying of soil, which contributes to the temperature rise in mountainous areas. At present, the understanding and evaluation of the feedback relationship between soil moisture and surface temperature in mountainous areas are still relatively weak, which should be further interpreted. 2) The representativeness of meteorological station observation data in arid areas requires further evaluation. In arid regions, most meteorological stations located in the oasis area (town or city, only account for 5% of the total area). During the last century, artificial oasis rapidly expanded, and artificial vegetation replaced natural vegetation (Fan et al., 2002; Yang et al., 2006). In the oasis areas, artificial irrigation often leads to significant seasonal differences in soil moisture, and the soil maintains a higher moisture level during the growing season. The negative feedback between soil moisture and air temperature would strongly impact on the observed air temperature, especially in summer. Because the observed temperature is strongly affected by the local oasis microclimate, it is necessary to reevaluate the representativeness of meteorological stations in the entire region.

4.3 Evolutional of Oasis effect and its plausible impacts

The oasis effect resulted from higher water consumption in the oasis areas (Zhao et al., 2010) and the evapotranspiration from the oasis surface, which cools the oasis (Chu *et al.* 2005; Qiu *et al.* 2013). Higher evapotranspiration usually leads to a higher oasis cold effect in summer (Hao and Li, 2016). Our study showed that for a single oasis, the minimum *OCI* was −1.36 K in summer. Some factors can affect the oasis effect, such as the mesoscale and secondary circulation (Chu *et al.*, 2005; Liu *et al.*, 2007; Li *et al.*, 2011), background winds (Su and Hu, 1987), surface conditions (Wan and Li, 1997; Schwarz *et al.*, 2011) and the land-use and land-cover change (LUCC) (Hao and Li, 2016). The difference in evapotranspiration between the oasis and the desert should be a crucial factor affecting the oasis effect. Soil moisture determines the partition of surface energy (Purdy *et al.*, 2018; Feldman *et al.*, 2019; Lin *et al.*, 2020). Soil moisture variations between oasis and desert controlled the difference in evapotranspiration between them. Thus, soil moisture should be a determining factor for the oasis effect in arid regions. Here, this study outlined the basic process of the formation of the oasis effect as three phases: I) the quiet period (without oasis effect), which spans from December of the previous year to February of the current year (winter time). During this time, almost all vegetation stops growth, and the shallow soil is often frozen. Therefore, the evapotranspiration of the land surface declined to the lowest, with it also having no spatial variation between oasis and desert. II) Development and stable period, from March to August (spring to summer). Crops and natural vegetation began to enter the growth period, and evapotranspiration increased gradually under irrigation conditions in the oasis. The evapotranspiration of oasis is higher than that of the desert, and the difference increases with time. Such change brings the obvious oasis effect, and it usually reaches a peak from July to August. In contrast, during September to November, the oasis effect enters the III) period, that is, the fallback period. During this period, the decreased difference in soil moisture and evapotranspiration between oasis and desert led to the weakening of the oasis effect until it disappeared.

Since the strong evaporation of oasis causes an oasis cold effect, the cooling effect limit is questioned. The existing observational data are difficult to give a satisfactory answer to the limit of the oasis effect. Here, we attempt to answer this question based on the feedback between soil moisture and air temperature. We assumed that the limit of the oasis effect is the upper bound of soil moisture variation. Therefore, the theoretical lower bound of the oasis effect is determined by the difference between the field capacity of soil and annual average minimum soil moisture. It is assumed that the soil moisture in the desert area maintains the average multi-year level in the same period. In this study, the calculated theoretical *OCI* value corresponding to the 10% cumulative frequency percentage is defined as the lower bound of the oasis effect. Thus, the lower bound of the cooling effect in the oasis of Hotan, Yarkant, Kashgar, Akesu, Kucha, and Korla, north of the Tianshan Mountains and east of the Tianshan Mountains was −2.09, −2.47, −2.19, −3.47, −4.49, −4.97, −1.69, and −2.29 K, respectively, which was 3.2 to 5.9 times the summer mean *OCI* (Fig. 5). Soil texture, which determines the available soil water capacity, is a precondition for the maximum cooling effect of the oasis. In addition, the irrigation intensity or irrigation quota, which determines the actual water recharge of soil, is another important factor that affects the cooling effect.

The question of if the oasification process exacerbates this cooling effect is also considered. The oasification is usually dominated by expanding the oasis area (Cheng *et al.*, 2006; Wang *et al.*, 2019). With the oasification, the water-saving irrigation measures have been gradually popularized in the oasis area. Thus, the oasification itself can only expand the cooling area, but not strengthen the cooling effect. However, due to the expansion of artificial oasis, the total irrigation water demand increased sharply (Wang *et al.*, 2019), which often leads to the draught-off of the lower reaches of the river, and soil drying in the desert areas around the oasis (Hao et al., 2008). In addition, the afforestation activities for soil conservation in desert areas may lead to a decrease in soil moisture (Jia et al., 2017). Therefore, oasification may cause serious desertification, and the drying of desert soil further highlights the cooling effect on the oasis. Thus, the process of desertification may enhance the cooling effect of the oasis.

4 Conclusions

The sensitivity coefficients of $\partial T/\partial EF$ and $\partial EF/\partial \Theta$ all have obvious tempo-spatial variation. They usually have the highest absolute values in summer and the highest in plain oasis areas, followed by mountainous and plain desert areas. Compared with the contribution rate of *EF* to air temperature, the contribution rate of soil moisture to *EF* was significantly higher. Under the interaction of temperature sensitivity to *EF* and *EF* to soil moisture, the $\partial T/\partial \Theta$ presented a similar tempo-spatial variation with both of the above. $\partial T/\partial \Theta$ was highest in oasis areas during summer (−1.676), while it was lowest in plain desert areas during autumn (−0.071).

During summer, the ΔT values for CL, wetland, grassland, shrubs, desert, and forest were 0.242 K, 0.205 K, 0.096 K, 0.039 K, 0.025, and 0.018 K, respectively. The ΔT_{max} has the same tempo-spatial changing trend as ΔT, and the largest value also appeared in CL with a value of 0.386 K. In the study region, soil moisture often leads to negative effects on air temperature, and the negatively affected area accounts for 41%–82% of the total area.

The difference in temperature variability between the oasis and desert areas promoted the formation of the oasis effect. The oasis effect was generally highest in summer, and the oasis area with the strong oasis effect also has a larger intra-annual variability of *OCI*. For different oasis, the multi-year average *OCI* ranged from −1.36 K to −0.26 K, while average summer *OCI* ranged from −1.38 K to −0.29 K.

This study reveals the process and mechanism of soil moisture variation on surface air temperature in extremely arid areas. Based on the negative feedback between soil moisture and air temperature, the study analyzed the dynamics and the upper bound of the oasis cooling effect.

The analysis framework and results will provide a new perspective for further research of water and heat balance in arid areas.

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Data availability

The MODIS data was downloaded from website of "National Aeronautics and Space Administration" (http://modis.gsfc.nasa.gov/). The soil texture data and the soil moisture data based on microwave sensing were provided by the "National Tibetan Plateau Data Center" of China (http://data.tpdc.ac.cn). The dataset of soil hydraulic parameters in China was provided by "National Cryosphere Desert Data Center of China" (http://www.crensed.ac.cn/portal/). The observed relative soil moisture data was downloaded from the China Meteorological Data Service Center (CMDC) website (http://data.cma.cn/data/cdcdetail/dataCode/AGME_AB2_CHN_TEN.html).

Additional Information

I declare that the authors have no competing interests as defined by 'Hydrological Processes', or other interests that might be perceived to influence the results and/or discussion reported in this paper.

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