Spatial and decadal variations in satellite-based terrestrial evapotranspiration and drought over Inner Mongolia Autonomous Region of China during 1982–2009

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Evapotranspiration (*ET*) plays an important role in exchange of water budget and carbon cycles over the Inner Mongolia autonomous region of China (IMARC). However, the spatial and decadal variations in terrestrial *ET* and drought over the IMARC in the past was calculated by only using sparse meteorological point-based data which remain quite uncertain. In this study, by combining satellite and meteorology datasets, a satellite-based semi-empirical Penman *ET* (SEMI-PM) algorithm is used to estimate regional *ET* and evaporative wet index (EWI) calculated by the ratio of *ET* and potential *ET* (*PET*) over the IMARC. Validation result shows that the square of the correlation coefficients (R^2) for the four sites varies from 0.45 to 0.84 and the root-mean-square error (RMSE) is <0.78 mm. We found that the *ET* has decreased on an average of 4.8 mm per decade ($p = 0.10$) over the entire IMARC during 1982–2009 and the EWI has decreased on an average of 1.1% per decade ($p = 0.08$) during the study period. Importantly, the patterns of monthly EWI anomalies have a good spatial and temporal correlation with the Palmer Drought Severity Index (PDSI) anomalies from 1982 to 2009, indicating EWI can be used to monitor regional surface drought with high spatial resolution. In high-latitude ecosystems of northeast region of the IMARC, both air temperature (T_a) and incident solar radiation (R_s) are the most important parameters in determining *ET*. However, in semiarid and arid areas of the central and southwest regions of the IMARC, both relative humidity (RH) and normalized difference vegetation index (NDVI) are the most important factors controlling annual variation of *ET*.

Keywords. Terrestrial evapotranspiration; evaporative wet index; inner Mongolia autonomous region; surface drought.

1. Introduction

Evapotranspiration (ET) is an important process in an ecosystem water budget, energy balance, and carbon cycles, and strongly affects global or regional surface dry conditions and climate change (Priestley and Taylor 1972; Wang and Dickinson 2012; Yao *et al.* 2014, 2016; Zhang *et al.* 2016). Over the last three decades, substantial changes in ET associated with precipitation (P), river discharge (Q) and soil moisture (SM), occurred in the Inner Mongolia autonomous region of China (IMARC) (Shi *et al.* 2007; Yang and Zhou 2011; Xia *et al.* 2014; Cao *et al.* 2015). Numerous evidences reveal that the variations in water budget are influencing ecosystem processes and surface drought in the IMARC (Xiao *et al.* 2009; Xia *et al.* 2014). However, there are still large errors to estimate ET for detection of the variations in water budget and surface drought in the IMARC. Therefore, it is crucial to improve ET estimation to understand the long-term variations in water budget and drought as well as their dominant climate factors.

Remote sensing has provided many land surface biophysical parameters, such as leaf area index (LAI), normalized difference vegetation index (NDVI), albedo and land surface temperature (LST), which characterize terrestrial ET and drought in the IMARC. Previous numerous studies showed satellite-based ET algorithms improved ET estimation and drought monitoring in the IMARC since 1980's (Yang and Zhou 2011; Yao *et al.* 2013; Li *et al.* 2014; Xia *et al.* 2014). For example, Xia *et al.* (2014) used the regression tree method and satellite-derived NDVI data to estimate regional ET in the grassland ecosystems of dryland East Asia, and found that the algorithm explained 76% of the variations of ET observations to characterize a decreasing trend over 61% of the dryland East Asia region. However, the data-based ET algorithms require a lot of ground-observations data to train the model and there are limited training data available (Yang *et al.* 2006; Jung *et al.* 2010, 2011). In contrast, the process-based ET algorithms require fewer training data but they have low performance in the grassland ecosystems in this region due to their complex parameterization schemes (Yao *et al.* 2013, 2015a; Ershadi *et al.* 2014).

Several satellite-based hybrid ET algorithms by combining empirical and physical algorithms (e.g., semi-empirical Penman algorithm, hybrid

Priestley–Taylor algorithm, semi-empirical exponential algorithm) have been widely used to estimate regional and global ET and drought using eddy covariance (EC), meteorological, and satellite observations (Wang *et al.* 2010; Yao *et al.* 2015b). Among these hybrid algorithms, semi-empirical Penman algorithm proposed by Wang *et al.* (2010) can detect global and regional ET variations on a scale of several decades because it considers the impact of incident solar radiation (R_s), air temperature (T_a), vapour pressure deficit (VPD), relative humidity (RH), NDVI, and wind speed (WS) (Skidmore *et al.* 1969; Wang *et al.* 2010; McVicar *et al.* 2012). Previous comparison of measured and estimated daily ET at 64 globally distributed flux tower sites indicated that 16 day average daily ET can be reasonably estimated with a squared correlation coefficient (R^2) of 0.88 and average root mean square error (RMSE) of 0.6 mm (Wang *et al.* 2010). Currently, selection of this algorithm for the regions covered with mainly grassland, such as IMARC, is still not documented in current contributions. Moreover, the spatiotemporal variations in terrestrial ET and drought over the IMARC in the past were calculated by only using sparse meteorological point-based data that remain quite uncertain (Yang *et al.* 2012a).

In this study, we used the semi-empirical Penman algorithm driven by long-term satellite and meteorology datasets to estimate ET in the IMARC. We then used an evaporative wet index (EWI) derived from ET and potential ET (PET) to assess the terrestrial drought and the variations in ET and EWI across the IMARC. Our study has three major objectives. First, we evaluate the capacity of the semi-empirical Penman algorithm to estimate ET and EWI at a regional scale. Second, we analyze the spatial and decadal variation in ET , EWI, PET and climate factors during 1982–2009. Finally, we detect the correlations between ET and meteorological variables.

2. Study area and data

2.1 Study area

The study area is Inner Mongolia autonomous region of China (IMARC), which is located in the north China, containing most of China's border with Mongolia and a small section of the border with Russia situated between 37.40°–53.38°N and 97.20°–126.07°E (Guo *et al.* 2014). The total area

of the study is approximately 1.18 million km² (figure 1). Except for the relatively humid Da Hinggan Ling Mountain area, most part of Inner Mongolia is arid, semi-arid or semi-humid from west to east (Liu *et al.* 2016). The region is dominated by monsoon climate pattern, where high temperatures and variable rainfall occur in the summer and cold northwesterly winds occur in winter (Brogaard *et al.* 2005; Yang *et al.* 2012b). There is an increase in precipitation and a decrease in temperature from southwest to northeast of the IMARC. The annual temperature in the IMARC ranges from -5° to 10°C and the mean annual precipitation rate is 30–500 mm. The cold temperate humid and medium temperate sub-humid region in the northeast is dominated by the forest. The medium temperate semiarid region in the central area is dominated by grass and cropland. The land cover type of the medium temperate arid region in the southwest is a desert (Wu *et al.* 2003). Figure 1 shows the International Geosphere-Biosphere Programme (IGBP) land cover types from MOD12 product that characterizes the study region.

2.2 Data

Here we used the ground-measured daily R_s , T_a , vapour pressure (e), RH and P during 1982–2009 from China Administration of Meteorology

(CMA), which includes 51 stations. The MOD16 ET product (2001–2009) (Mu *et al.* 2011) with temporal resolution of 8 days and spatial resolution of 1 km was acquired from the University of Montana's Numerical Terradynamic Simulation group to evaluate estimated ET . All meteorological variables and MOD16 ET product were interpolated into 0.1 degree gridded datasets using bilinear interpolation method. Land cover data of 2008 was derived from the MODIS Land Cover product (MOD12Q1) with 0.05 degree. We also used the bimonthly normalized difference vegetation index (NDVI) products derived from the Global Inventory Modelling and Mapping Studies (GIMMS) group (Tucker *et al.* 2005) with a spatial resolution of 8 km to estimate actual ET and EWI. To better correspond with the gridded meteorological data, the land cover data and the GIMMS-NDVI data were converted to a resolution of $0.1^{\circ} \times 0.1^{\circ}$ using bilinear interpolation. The daily NDVI values were temporally interpolated from the bimonthly averages using linear interpolation. We also used the monthly Palmer Drought Severity Index (PDSI) product (Dai *et al.* 2004) derived from the NCAR CGD's Climate Analysis Section dataset with a 2.5 degree spatial resolution, for the period 1982–2009. We also interpolated the PDSI products into 0.1 degree from a 2.5-degree spatial resolution.

Figure 1. The map of the study area. IGBP land cover types are shown: 0: water body; 1: evergreen needleleaf forest; 2: evergreen broadleaf forest; 3: deciduous needleleaf forest; 4: deciduous broadleaf forest; 5: mixed forest; 6: closed shrubland; 7: open shrubland; 8: woody savanna; 9: savanna; 10: grassland; 11: permanent wetland; 12: crop land; 13: urban/build up; 14: crop land/natural vegetation mosaic; 15: snow/ice; and 16: barren lands.

Table 1. Site name, location, land cover, elevation, time period, network and reference of the EC data used in this study.

Site name	Latitude, longitude	Land cover	Elevation (m)	Time period	Network	Reference
Xilinhot Inner Mongolia fenced typical steppe site (XFS)	44.13°N, 116.33°E	Grassland	1187	2004–2006	LathuileFlux	Wang <i>et al.</i> (2008)
Xilinhot Inner Mongolia grassland site (XLG)	43.55°N, 116.67°E	Grassland	1250	2006(January– December)	LathuileFlux	Chen <i>et al.</i> (2009)
Dongsu Inner Mongolia grassland site (DSG)	44.09°N, 113.57°E	Grassland	970	2008(January– December)	CEOP	Zeng <i>et al.</i> (2011)
Duolun Inner Mongolia grassland site (DLG)	42.05°N, 116.28°E	Grassland	1350	2006(January– December)	LathuileFlux	Chen <i>et al.</i> (2009)

To validate the actual ET , we used the ground-measured ET , sensible heat flux (H), ground heat flux (G), T_a , RH, WS, e , R_s and net radiation (R_n) derived from four flux tower sites (table 1). The data are provided by LathuileFlux and the Coordinated Enhanced Observation Network of China (CEOP). The data cover 2004–2008 and the land-cover type at four sites is grassland. The turbulent flux data are measured according to the eddy covariance (EC) method. These flux datasets include half-hourly ground-measured data. The site descriptions for all 22 sites including name, location, vegetation type, years of data available, and references are provided in table 1. Because the EC method suffers from an energy imbalance problem, where the measured available energy ($R_n - G$) is greater than the sum of the measured ET and H (Jung *et al.* 2010), the method proposed by Twine *et al.* (2000) has been chosen to correct the ET values at four sites and the corrected method is as follows:

$$LE = \frac{(R_n - G)}{(LE_{ori} + H_{ori})} \times LE_{ori}. \quad (1)$$

Here LE is the corrected latent heat flux. H_{ori} and LE_{ori} are the uncorrected sensible heat flux and latent heat flux, respectively.

3. Methods

3.1 Satellite-based semi-empirical Penman ET algorithm

Because a semi-empirical Penman ET (SEMI-PM) algorithm proposed by Wang *et al.* (2010) can be used for monitoring regional ET on decadal scales, we have selected this algorithm to estimate terrestrial ET in the IMARC for analyzing spatiotemporal variation in ET . This algorithm can

be expressed as:

$$ET = a_1(ET_E + ET_A) + a_2(ET_E + ET_A)^2 \quad (2)$$

$$ET_E = \frac{\Delta}{\Delta + \gamma} R_s [a_3 + a_4 NDVI + RHD(a_5 + a_6 NDVI)] \quad (3)$$

$$ET_A = \frac{\gamma}{\Delta + \gamma} WS [a_7 + RHD(a_8 + a_9 NDVI)] VPD \quad (4)$$

where $a_1 = 0.819$, $a_2 = 0.0017$, $a_3 = 0.476$, $a_4 = 0.284$, $a_5 = -0.654$, $a_6 = 0.264$, $a_7 = 3.06$, $a_8 = -3.86$, $a_9 = 3.64$, Δ is the slope of the saturated vapour pressure curve ($K P_a/^\circ C$), γ is the psychrometric constant ($K P_a/^\circ C$) and RHD equals to 1 minus RH. VPD is calculated using the saturated water vapour pressure (e_s) minus actual water vapour pressure (e). To calculate Δ simply, we use the below equation proposed by Richards (1971):

$$\Delta = \frac{373.15e_s}{(T_a + 273.15)^2} (13.3185 - 3.952T_r - 1.9335T_r^2 - 0.5196T_r^3) \quad (5)$$

$$e_s = 1013.15 \exp(13.3185T_r - 1.976T_r^2 - 0.6645T_r^3 - 0.1299T_r^4) \quad (6)$$

$$T_r = 1 - 373.15/(T_a + 273.15). \quad (7)$$

Psychrometric constant γ can be calculated from:

$$\gamma = \frac{C_p P_s}{0.622 \lambda}, \quad (8)$$

$$P_s = 1013.15 \times 10^{(\frac{-z}{18400} \times \frac{T_a + 273.15}{273})}, \quad (9)$$

$$\lambda = 4200 \times [597 - 0.6(T_a + 0.15)], \quad (10)$$

where z is the height above sea level (m), C_p is the isobaric specific heat for dry air and is equal

to $1012 \text{ J kg}^{-1} \text{ K}^{-1}$, λ is the latent heat of vapourization. Considering that estimated ET using LAI will be overestimated when LAI is higher than 3 or 4, using NDVI to replace LAI can effectively correct this issue though NDVI will saturate under dense forests (Wang and Dickinson 2012). In this study, we use the SEMI-PM algorithm driven by daily gridded meteorological datasets to estimate regional ET in the IMARC during 1982–2010.

3.2 Evaporative wet index

Following the evaporative drought index (EDI) (Yao et al. 2010), a simple evaporative wet index (EWI) is developed by Zhang et al. (2016) based on the ratio of actual ET and PET , to monitor the terrestrial drought conditions. EWI can be expressed as:

$$\text{EWI} = 1 - \text{EDI} = \frac{ET}{PET}. \quad (11)$$

In the above equation, higher EWI indicates ample surface soil moisture, lower EWI indicates more severe water stress. The value of EWI varies from 0 to 1 and reflects the changes of surface moisture and P , which indicates the surface drought status.

3.3 Potential ET estimation

PET refers to the ideal evaporation rate for capturing the response to meteorological variables when soil moisture is unlimited. In this study, the FAO Penman–Monteith (PM) method was used to estimate PET of the IMARC because it is considered as a standard reference method (Allen et al. 1998) and it can be written as:

$$PET = \frac{0.408\Delta(R_n - G) + \gamma(900/(T_a + 273))WS(e_s - e)}{\Delta + \gamma(1 + 0.34WS)}, \quad (12)$$

where e_s is the saturated vapour pressure (KPa). G can be calculated using a simple empirical R_n -based algorithm based on vegetation fractional cover (f_c) with a fixed empirical coefficient ($a_g = 0.35$) (Yao et al. 2013):

$$G = a_g(1 - f_c)R_n \quad (13)$$

$$f_c = \frac{\text{NDVI} - \text{NDVI}_{\min}}{\text{NDVI}_{\max} - \text{NDVI}_{\min}} \quad (14)$$

where $\text{NDVI}_{\min}$ and $\text{NDVI}_{\max}$ are the minimum and maximum normalized difference vegetation

index (NDVI) during the study period, which are set as invariant constants: 0.05 and 0.95, respectively (Yao et al. 2013).

3.4 Trends analysis

A simple linear regression equation was used to calculate the annual values and trends in variable y (including ET , EWI, PET , PDSI, NDVI and climate factors) against time x .

$$y = ax + b \quad (15)$$

where a is the linear trend in variables and b is the constant. Student's t test distribution was also used to test the confidence levels (p values) of the tendencies (Pinker et al. 2005; Zhang et al. 2016).

4. Results and discussion

4.1 Decadal variations in climate factors over the inner Mongolia region

During 1982–2009, T_a in the IMARC from meteorological stations data after removal of the mean annual cycle (T_a anomaly) increased on an average by 0.6°C per decade ($p < 0.05$) with global warming (figure 2). Overall, T_a in more than 95% of areas over the IMARC increased from 1982 to 2009 (figure 3). Numerous studies have reported substantial increase in T_a in this region (Zhang et al. 2009; Liu et al. 2016). According to the report by the IPCC, the increasing trend in global average T_a is 0.074°C per decade (IPCC 2007). However, our result is much higher than this value, which indicates that the IMARC has experienced a significant and severe climate change. Similarly, R_s in the IMARC from meteorological stations data after removal of the mean annual cycle has a slightly positive trend of 0.2 W/m^2 per decade ($p > 0.05$) (figure 2). Southwest and northeast of IMARC experienced a strong positive trend of R_s from 1982 to 2009, while central regions of IMARC experienced a strong negative trend during this period (figure 3).

RH had a strong negative trend of -1.4% per decade ($p < 0.01$) based on meteorology observations. In contrast, VPD had a strong positive trend of 26.3 Pa per decade ($p < 0.01$) because the opposite relations between RH and VPD (figure 2). Almost all regions experienced a strong

Figure 2. Interannual variability of meteorological variables (Ta, Rs, RH, VPD, WS and P) over the Inner Mongolia of China during 1982–2009.

negative (positive) trend of RH (VPD) during 1982–2009 (figure 3), which is consistent with previous studies (Guo *et al.* 2014; Xia *et al.* 2014). WS had a strong negative trend of -0.15 m/s per decade ($p < 0.01$) based on meteorology observations (figure 2). More than 93% regions of the IMARC experienced a negative trend of WS during 1982–2009 (figure 3). Similarly, P also had a negative trend of -18.8 mm per decade ($p = 0.1$) based on meteorology observations (figure 2). Northeast regions of the IMARC experienced a strong negative trend of P from 1982 to 2009, while southwest regions experienced a weak positive trend of P during this period (figure 3), which is similar to the previously documented increasing trend in P over the desert and barren land over western region of the Dryland East Asia, as reported by Xia *et al.* (2014).

4.2 Spatial and decadal variation in ET and EWI

4.2.1 Evaluation of the ET algorithm

Figure 4 shows the biases, the root-mean-square error (RMSE), and the square of the correlation coefficients (R^2) for comparison between the

ground-measured and estimated daily ET using daily gridded meteorological data and GIMMIS NDVI product at the four sites (XFS, XLG, DSG and DLG). We can notice that the bias for XFS, XLG, DSG and DLG are 0.27, 0.14, 0.54 and 0.19 mm, respectively. The R^2 for XFS, XLG, DSG and DLG are 0.61, 0.55, 0.45 and 0.84, respectively. The RMSE for the four sites are < 0.78 mm. The positive bias may be partially due to the unclosed energy balance problem in the eddy covariance datasets and the limitations of the SEMI-PM algorithm (Wang *et al.* 2010; Yao *et al.* 2014). However, at the DLG site, the algorithm overestimates ET . Perhaps complex terrain and instrument calibration contribute to the large bias at the DLG site. Jiang *et al.* (2004) documented that a reasonable upper limit for the accuracy of estimating ET using satellite data is about 20%. Seguin *et al.* (1999) suggested that the required ET retrieval accuracy varies according to the application, but is typically 15–30%. The accuracy of our validation meets this requirement.

Although the ground-based eddy covariance data for 2–3 years prohibits the validation of long-term ET estimates, Wang *et al.* (2010) verified that the

Figure 3. Maps of the linear trend in meteorological variables (Ta, Rs, RH, VPD, WS and P) over the Inner Mongolia region of China from 1982 to 2009. The black solid dots refer to grids with 95% confidence.

SEMI-PM algorithm is satisfactory for reproducing inter-annual variability at sites with 5 years of global FLUXNET eddy covariance data. However, *ET* has still existed with large uncertainty and the possible sources of uncertainty in *ET* estimation may be attributed to: (1) the errors in gridded data inputs (e.g., errors of $\pm 20 \text{ W/m}^2$ in R_s); (2) the biases of the ground-measured *ET*, where the typical error of is about 20% (Babamajji and Lee 2014; Hollinger and Richardson 2005); (3) the energy imbalance issue of the eddy covariance method (Twine *et al.* 2000); (4) simulation errors in the SEMI-PM algorithm (Wang *et al.* 2010); and (5) the spatial scale mismatch between the footprint and gridded datasets (including meteorological datasets and GIMMIS-NDVI dataset). The observed *ET* footprint only represents the vapour evaporation over about a few hundred meters in the vertical and horizontal directions (Twine *et al.* 2000). However, the gridded

datasets with coarse spatial resolution (10 km) may not capture the *ET* information measured at the scale of footprints (Yao *et al.* 2014). Therefore, a series of errors may be introduced in the *ET* estimates.

We also compared the average annual estimated *ET* during 2001–2009 with the corresponding MOD16 *ET* product. Figure 5(a and b) shows similar spatial distribution patterns in both maps, though the *ET* over the central eastern areas of the IMARC exhibits small differences and the MOD16 *ET* product has no *ET* value over the western barren land areas. One can see that the bias of the average annual estimated *ET* during 2001–2009 that deviates from the MOD16 *ET* is -2.71 mm , the RMSE is 37.25 mm and the R^2 is 0.50 (figure 5c). This small discrepancy may be caused by the errors of input data and different structures of the algorithms. The input data for MODIS *ET* product is the

Figure 4. Validation of the estimated daily evapotranspiration (ET) using the semi-empirical Penman ET algorithm for four sites.

Modern Era Retrospective Analysis for Research and Applications (MERRA) meteorological data. Previous studies found that substantial errors for MERRA data when compared to ground measurements (Zhao *et al.* 2006). MODIS ET product is generated based on the satellite-based Penman–Monteith (PM) method. Recent studies reveal that although PM method can be widely used across a range of land cover and climate conditions, there is a significant underestimation of evaporation in croplands or in deciduous forests (Ershadi *et al.* 2014). Fortunately, there is a relatively good agreement between the two independent datasets in this study, which indicates that the SEMI-PM algorithm provides reliable information for ET estimation in this region.

4.2.2 Mapping terrestrial ET and drought

Figure 6 shows the spatial patterns of multi-year (1982–2009) mean annual ET , PET , EWI and $PDSI$ over the IMARC from all gridded datasets. They show the strong regional variations corresponding to the climate patterns. ET , EWI and $PDSI$ have increased from the southwest to the northeast. In contrast, PET has the opposite spatial patterns with high values

in southwest and low values in northeast. Generally, $PDSI$ characterizes surface drought by combining P and soil moisture (SM) while EWI reflects surface drought by combining R_n , T_a , WS , RH and $NDVI$, without requiring information regarding antecedent P . IMARC belongs to arid and semiarid region, in which water supply is mainly determined by the variation in both P and SM. Therefore, grass and other vegetation are affected by P to sustain long term ET because vegetative roots can extract moisture from deeper soil layers (Anderson *et al.* 2007). These spatial distribution maps supply an important background and physical interpretation for energy, water and climate change in arid and semiarid regions of China.

Figure 7(a) shows the seasonal cycle of the spatially averaged and integrated monthly ET for four land cover types from January 1982 to December 2009. Forest has the largest seasonal variability in spatial averaged ET , followed by crop and grass, and bare land has the least variability. The seasonal cycle of the spatially averaged and integrated monthly PET also showed clear dependence on biome (figure 7b). Taken separately, bare land has the highest seasonal variability in monthly PET , followed by grass and crop and forest has the least variability. Both spatially averaged ET and PET

Figure 5. (a) The spatial distribution of the estimated mean annual ET from 2001 to 2009 in this study; (b) spatial distribution of the corresponding MOD16 ET ; and (c) scatter plots of the estimated mean annual ET from 2001 to 2009 and the corresponding MOD16 ET .

Figure 6. Maps of multi-year (1982–2009) mean annual ET , PET , EWI and $PDSI$ over the Inner Mongolia region of China.

Figure 7. Seasonal cycle of the spatially averaged and integrated monthly ET and PET for four land cover types from January 1982 to December 2009.

show seasonal and inter-annual variability for each land cover type.

Although some uncertainties are present, the ET magnitudes and spatial pattern of ET in the IMARC is generally consistent with previous reports (Yang and Zhou 2011; Xia *et al.* 2014). Xia *et al.* (2014) found the increasing patterns from the southwest to the northeast using the Modern-Era Retrospective Analysis for Research and Applications (MERRA) data. Yang and Zhou (2011) reported that seasonal variation in ET followed closely the variation in soil water content (SWC) and is consistent with the variation in PDSI. Although different algorithm parameterizations and inputs have an impact on their simulation by partitioning the surface energy flux in a different manner (Robock *et al.* 2003), the spatial patterns of the estimated ET and EWI is acceptable for assessing the surface water budget and drought conditions at regional scales.

To analyze the spatial pattern in both anomalies of EWI (ΔEWI) and PDSI ($\Delta PDSI$) during 1982–2009, we mapped the annual EWI deviations (ΔEWI) and PDSI deviations ($\Delta PDSI$) for 1998 (wet year) and 2000 (dry year). In dry year of 1998, both ΔEWI and $\Delta PDSI$ show that the western and central regions were wetter (figure 8), a result which is consistent with those of previous studies (Dai *et al.* 2004; Zhao and Running 2010). El Niño event occurred in 1998 and heavy P in north regions of China lead to wet surface. The ΔEWI map reveals that during this year, there was an extreme drought stretching across Northeast regions of the IMARC, but the $\Delta PDSI$ map shows an opposite trend. These discrepancies between the ΔEWI and $\Delta PDSI$ map may be caused by the interpolation errors of the coarse spatial resolution of PDSI product and the errors of input data

of the EWI. In contrast to 1998, both indices for 2000 show the western and central eastern regions became dryer. El Niño event extends to 2000 and sparse precipitation led to large drought of mainland China (Brogaard *et al.* 2005). However, for both indices, there are opposite trends in northeast regions of the IMARC. Perhaps the errors of the interpolation of the sparse meteorological variables observed points across the IMARC led to their differences.

4.2.3 Spatial and decadal variation from 1982 to 2009

The estimated ET , PET , EWI, PDSI and NDVI in the IMARC from the gridded reanalysis meteorological datasets and GIMMIS-NDVI product after removal of the mean annual cycle show that NDVI has decreased on an average by 0.15% per decade ($p < 0.05$) during the study period. In contrast, PET has increased on an average by 16.1 mm per decade ($p = 0.09$) (figure 9). On the whole, ET , EWI and PDSI have decreased on an average by 4.8 mm/decade ($p = 0.10$), 1.1%/decade ($p = 0.08$) and 0.8%/decade ($p = 0.10$), respectively over the entire IMARC during 1982–2009 (figure 9). However, these values (ET , EWI and PDSI) increased by approximately 0.7 mm/decade, 0.2%/decade and 0.1%/decade, respectively, with no significant change from 1982 to 1998 due to a large El Niño event. After that, they decline by approximately 10.2 mm/decade, 2.8%/decade and 1.9%/decade (significant at the 99% level), respectively. Figure 9 also shows the strong coherence between 1982 and 2009 EWI trends derived from satellite data, and trends in the independent gridded PDSI over the IMARC in which surface moisture is expected to affect

Figure 8. An example of annual composites of anomalies of EWI (ΔEWI) compared with anomalies in the PDSI (ΔPDSI) for 1998 (wet year) and 2000 (dry year).

Figure 9. Interannual variability of ET , PET , $NDVI$, EWI and $PDSI$ over the Inner Mongolia of China during 1982–2009.

terrestrial ET . The result is similar to the previously documented data that the annual terrestrial ET in the IMARC has also declined since 1992 and may be attributed to the limitation of severe drought (Yao *et al.* 2013; Xia *et al.* 2014).

Figure 10 shows the spatial pattern of the trends in the terrestrial ET , PET , EWI , $PDSI$ and $NDVI$ over the IMARC during 1982–2009. We notice that a widely significant decreasing trend in ET appears from 1982 to 2009 in central regions of the IMARC. However, a widely increasing trend in PET appears

for the study period in both central and northeast regions of the IMARC due to the high atmospheric evaporative demand (Zhang *et al.* 2016). Similarly, Yao *et al.* (2014) reported that the PET substantially increased in arid areas while the few changes in the Qinghai–Tibet region may be caused by increased precipitation in the area during the study period. The largest decreasing EWI , $PDSI$ and $NDVI$ trends appear in both central and northeast regions of the IMARC. The similar trends of both indices reflect the widely severe drought in this region, which is consistent with the findings

Figure 10. Maps of the linear trend in *ET*, *PET*, *EWI*, *PDSI* and *NDVI* over the Inner Mongolia region of China from 1982 to 2009. The black solid dots refer to grids with 95% confidence.

of Yao *et al.* (2013). In theory, *EWI* trends are more consistent with *PDSI* trends because *EWI* is a better indicator of surface SM supply of *ET* and *PDSI* contains the *P* and SM information.

According to the definition of *EWI*, the change of *ET* contributes to the long-term variation of *EWI*. The variations of *EWI* over most regions of XUARC (Xinjiang Uighur Autonomous Region of China) are almost consistent with *ET* variations. *EWI* characterizes the surface dryness conditions and is also consistent with the variations in *NDVI*. This may be explained by the fact that the drying trend occurring over the IMARC can exert profound impacts on a variety of terrestrial ecosystem structures and functions including the carbon and water cycle, plant distribution and vegetation growth (John *et al.* 2009). Zhang *et al.* (2009) reported drought-induced reductions in vegetation net primary productivity (NPP) over northern

Mongolia. Xia *et al.* (2014) also documented that the changes in *ET* and water balance over the Dryland East Asia are spatially complex. These will facilitate drought monitoring at field, regional and global scales, which will be valuable for drought assessment induced crop yield loss.

4.3 Correlations between *ET* and meteorological variables

Both T_a and R_s showed strong positive correlations with *ET* over the northeast region of the IMARC, while they showed strong negative correlations with *ET* over the central region of the IMARC because the contributions of the temperature and energy to *ET* differ greatly in different regions (figure 11). Additionally, the coefficients between *ET* and *RH* are positive over the southwest and central regions of the IMARC and are negative

Figure 11. Maps of the correlation coefficient between annual ET and T_a , R_s , RH , VPD , WS and $NDVI$, respectively.

over the northeast region of the IMARC. This can be explained that RH , as an indicator of the surface moisture, controls ET of arid and semi-arid regions. In contrast, there are opposite spatial patterns of the correlations between ET and VPD due to the negative correlations between RH and VPD (figure 11). Both $NDVI$ and WS also showed strong positive correlations with ET over majority of the central and northeast Inner Mongolia except the region near the Gobi desert (figure 11) due to the effects of supply water of vegetation and vapour transferring by air motion.

Regional climate change has produced substantial effects on terrestrial ET and surface drought by altering environmental controlling factors. However, there are different controlling factors for ET in different climate zones (Wang and Dickinson 2012). In high-latitude ecosystems of northeast region of the IMARC, both T_a and R_s are the

most important parameters in determining ET in these ecosystems (Nemani *et al.* 2003). ET in this region is also related to VPD (Kelliher *et al.* 1997). Forests in this region is little affected by surface drought because near-surface soil water was depleted and the water table remained in the root zone (Krishnan *et al.* 2006). However, in semi-arid and arid areas of the central and southwest regions of the IMARC, Both RH and $NDVI$ are the most important factors controlling annual variation of ET because they are the primary surface moisture factors, which determine the ET (Wang and Dickinson 2012). Recent studies found that soil moisture in north-central and northeastern China had significant downward trends, implying that northern China has become slightly drier in terms of soil moisture to influence the variation in ET (Cong *et al.* 2009; Yao *et al.* 2016). Our study also illustrated the contributions of WS to ET ,

which is consistent with the previous studies that reported WS as an aerodynamic controlling variable for atmospheric evaporative demand during the *ET* process and contributes to long-term *ET* variations (McVicar *et al.* 2012).

5. Conclusion

The goal of the study was to present a strategy for estimating terrestrial *ET* and assessing surface drought using a semi-empirical Penman *ET* (SEMI-PM) algorithm proposed by Wang *et al.* (2010) over Inner Mongolia Autonomous Region of China (IMARC). We also used meteorological data and satellite data to analyze the spatiotemporal variation in *ET* and EWI during 1982–2009. The results demonstrated that SEMI-PM algorithm has a good performance in estimating *ET* and assessing regional drought monitoring over the IMARC.

In this paper, we produced the daily and annual *ET* and EWI from 1982 to 2009 using the SEMI-PM algorithm driven by daily gridded meteorological data and GIMMIS-NDVI product. Using the *ET* measurements of the four eddy covariance sites, our validation showed the SEMI-PM algorithm provided the reliable *ET* estimations which were useful to detect regional *ET* and surface drought conditions. Over the entire study area, both *ET* and EWI have decreased during 1982–2009. Especially, a widely significant decreasing trend in *ET* appears from 1982 to 2009 in central regions of the IMARC. Importantly, the patterns of monthly EWI anomalies have a good spatial and temporal correlation with the Palmer Drought Severity Index (PDSI) anomalies from 1982 to 2009. In high-latitude ecosystems of northeast region of the IMARC, both T_a and R_s are the most important parameters in determining *ET* in these ecosystems. However, in semiarid and arid areas of the central and southwest regions of the IMARC, Both RH and NDVI are the most important factors controlling annual variation of *ET*.

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