Projections of aridity and its regional variability over China in the mid-21st century

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ABSTRACT: The effects of aridity on ecosystems and water cycles are pronounced and have received considerable attention. However, aridity changes due to future warming and its regional variability over China remain uncertain. This paper aims to identify the spatiotemporal variations in aridity and its key influencing factors over China in the mid-21st century based on five general circulation models (GCMs) and four representative concentration pathway (RCP) scenarios. An aridity index (*AI*), defined as the ratio of reference evapotranspiration (ET_0) to precipitation (P), was calculated. We show that the GCM ensemble means are able to reproduce the variation of aridity during the baseline period. Generally, ET_0 anomalies are consistently positive. Other than for the RCP2.6 low-emission scenario, precipitation and aridity are both projected to increase. There are pronounced regional differences in aridity changes; i.e. wetter across most of western China and drier across most of eastern China in the mid-21st century. Negative *AI* anomalies in western China can be attributed mainly to the projected increase in precipitation. In eastern China, the *AI* was higher despite positive precipitation anomalies, due mainly to the greater effect of climate change on increasing atmospheric moisture demand. This suggests that evapotranspiration demand should be incorporated into aridity changes under future warming.

KEY WORDS aridity; China; regional variability; climate models; evapotranspiration

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1. Introduction

Greenhouse gas and aerosol emissions have a pronounced effect on global climate. Climate scenarios project an increase in the global mean surface temperature of 0.3 °C to 4.8 °C for the period 2081–2100 relative to 1986–2005 (IPCC, 2013), and regional and global changes in moisture conditions related to climate change have received considerable attention. Drier or wetter conditions caused by global warming can be identified by capturing the changes in the background aridity rather than temporary anomalies such as droughts (Sherwood and Fu, 2014). Increased aridity is linked to changing biogeochemical cycles, and could negatively affect key ecosystem functions and services (Delgado-Baquerizo *et al.*, 2013). For example, if aridity continues to increase in the future, trees will experience substantially reduced growth (Williams *et al.*, 2010). Moreover, changing aridity may affect the global water balance; have a significant influence on runoff (Arora, 2002); and cause anomalies in the intensity, spatial extent, and frequency of droughts (Nastos *et al.*, 2013). However, the impact of climate change on aridity over the land surface is complex. To address this complexity, it is necessary

to recognize projected changes in aridity over different spatial-temporal scales.

Studies of the impact of climate change on aridity during the 21st century have predicted increased aridity over most tropical and mid-latitude land regions (Feng and Fu, 2013), specifically over most of Africa, the Americas, Australia, Southeast Asia, and the Mediterranean region (Gao and Giorgi, 2008; Dai, 2011). Changes in aridity are influenced by many complex factors. Surface aridity is sensitive to rising temperatures, and the effects of increased temperatures on aridity will be exacerbated if precipitation decreases (McCabe and Wolock, 2002). Overall, surface aridity is controlled by the balance between precipitation, P (atmospheric supply), and reference evapotranspiration, ET_0 (atmospheric demand) (Budyko, 1974; Middleton and Thomas, 1992; Wu *et al.*, 2006; Sherwood and Fu, 2014). ET_0 is an expression of the evaporative power of the atmosphere at a specific location and time of year (Allen *et al.*, 1998), and it is an important indicator of aridity besides precipitation. Generally, aridity will increase in a specific region as P decreases and ET_0 increases.

Widespread and significant decreasing trends in ET_0 have been observed during the past half-century at regional to continental scales (Peterson *et al.*, 1995; Golubev *et al.*, 2001; Roderick and Farquhar, 2002; Liu *et al.*, 2004; Xu *et al.*, 2006; Dolman and de Jeu, 2010; Yin *et al.*, 2010), and analysis of global aridity trends shows that severe and widespread droughts are likely to occur in the next

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30–90 years over many land areas due to either decreased precipitation and/or increased evaporation (Dai, 2013). Future projections in ET_0 are therefore important in terms of reducing uncertainty in aridity assessments. Moreover, as ET_0 is not routinely calculated by climate models, its uncertainties have been largely ignored in climate change impact assessments (Prudhomme and Williamson, 2013). Therefore, improving our understanding of changes in ET_0 is an important step towards improving confidence in future climate change assessments (Kingston *et al.*, 2009).

Recently in China, there have been several studies to identify future changes in precipitation and evapotranspiration with climate models (e.g. Shi *et al.*, 2007; Gu *et al.*, 2012; Wang *et al.*, 2013; Chen and Frauenfeld, 2014; Wang and Chen, 2014; Xing *et al.*, 2014; Xu *et al.*, 2014). However, most studies on future ET_0 have been conducted at local area or basin, thus the regional differences and pattern of future changes in evapotranspiration have been poorly understood over China. Undertaking regional variability assessments is important to reveal detailed impacts of climate change, particularly on agriculture crop production (Izaurrealde *et al.*, 2003; Eitzinger *et al.*, 2013) and hydrological cycle (Held and Soden, 2006; Roderick *et al.*, 2014). This highlights the need to investigate the regional variability of projected evapotranspiration and aridity changes over China, as it is characterized by various climate zones from cold temperate in the north to tropical in the south, and from humid in the east to arid in the west.

Furthermore, seldom studies have colligated ET_0 to evaluate aridity which is much more complex responding to climate change over China. Wang and Chen (2014) explored the climatological droughts in the future in China using the Palmer Drought Severity Index. However, it was based on Thornthwaite method ET_0 , which may be overestimated by excluding cloud cover and vapour pressure deficit in the parameterization (Wang and Chen, 2014). In the present study, we propose the Penman–Monteith model to estimate ET_0 .

In addition, aridity changes under the representative concentration pathways (RCPs) (Moss *et al.*, 2010) have been poorly quantified. RCPs were used in the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (IPCC, 2013) to investigate the impact of greenhouse gases on climate change. In consequence, here we use the four RCP projections to evaluate the regional variability of future aridity changes by incorporating both atmospheric water demand and supply dynamics. The present study has importance and significance for understanding water cycles and planning optimized adaptation schemes for ecosystem and agriculture management response to climate change.

In this study, regional variability of projected changes in aridity over China in the mid-21st century are analyzed using various RCP projections. The major objectives of this study are: (1) to evaluate the performance of climate models in reproducing the spatial and temporal variability of aridity over China during the recent historical period; (2) to access temporal changes in aridity under various RCPs relative to 1981–2010; and (3) to identify regional differences in aridity and the key climatic factors that influence these differences.

2. Materials and methods

2.1. Future climate projections

Simulated climate projections from 1950 to 2099 were acquired from five GCMs (HadGEM2-ES, IPSL-CM5A-LR, GFDL-ESM2M, MIROC-ESM-CHEM, and NorESM1-M) (Table 1), participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5) experiment (Taylor *et al.*, 2012). The outputs of the GCMs were downscaled to 0.5° and bias-corrected by the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) (Hempel *et al.*, 2013; Warszawski *et al.*, 2014). Time-evolving land cover was included for the first time in the suite of CMIP5 long-term experiments (Taylor *et al.*,

Table 1. General circulation models used in this study.

Model name	Modelling centre	Original resolution (latitude $\times$ longitude)	Main references
GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory, USA	$2.0^\circ \times 2.5^\circ$	Dunne <i>et al.</i> (2012)
HadGEM2-ES	Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais), UK	$1.25^\circ \times 1.875^\circ$	Collins <i>et al.</i> (2011)
IPSL-CM5A-LR	Institut Pierre-Simon Laplace, France	$1.875^\circ \times 3.75^\circ$	Dufresne <i>et al.</i> (2013)
MIROC-ESM-CHEM	Model for Interdisciplinary Research On Climate, Atmosphere and Ocean Research Institute of The University of Tokyo, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	$2.8^\circ \times 2.8^\circ$	Watanabe <i>et al.</i> (2011)
NorESM1-M	Norwegian Climate Centre, Norway	$1.875^\circ \times 2.5^\circ$	Bentsen <i>et al.</i> (2013)

2012). A statistical bias correction approach was applied to the ISI-MIP dataset to preserve the absolute or relative trends in simulated daily climate data. This approach uses a constant offset or multiplicative correction factor that corrects for long-term differences between simulated and observed monthly mean data in the historical period (Hempel *et al.*, 2013). These five GCMs have driven global hydrological and land-surface models to assess water resources (Davie *et al.*, 2013; Schewe *et al.*, 2014), and meet the data requirement to estimate ET_0 using Penman–Monteith model in the present study.

The bias-corrected daily variables from the GCMs, including the average, maximum, and minimum temperatures (K); precipitation ($\text{kg m}^{-2} \text{s}^{-1}$); shortwave downwelling radiation (W m^{-1}); near-surface wind speed (m s^{-1}); and relative humidity (%) on a horizontal grid with a $0.5^\circ \times 0.5^\circ$ resolution are used to simulate ET_0 and aridity. Wind speed measured 2 m above the surface is required for evapotranspiration calculations, so wind speed data from a height of 10 m was adjusted to the standard height of 2 m using a logarithmic wind-profile relationship (Allen *et al.*, 1998).

This study analyzes changes in aridity under the RCP2.6, RCP 4.5, RCP 6.0, and RCP 8.5 climate projections. Four pathways were produced that led to radiative forcing levels of 2.6, 4.5, 6.0, and 8.5 W m^{-2} by 2100 (Moss *et al.*, 2010). RCP8.5 is the highest pathway with a radiative forcing of around 8.5 W m^{-2} in 2100, equivalent to an atmospheric CO_2 concentration of approximately 1370 ppm (Moss *et al.*, 2010). By 2100, projected global mean surface temperature increases range from 1.5 $^\circ\text{C}$ for the lowest-emission RCP to 4.5 $^\circ\text{C}$ for the highest-emission RCP relative to pre-industrial levels (Meinshausen *et al.*, 2011).

To estimate future aridity, five GCM runs for ET_0 and the aridity index (AI), where AI is defined as a ratio of ET_0 to P , were produced for each of the four emission scenarios. For RCP2.6, RCP 4.5, RCP 6.0, and RCP 8.5, projected changes were assessed for a 30-year period in the mid-21st century covering 2041–2070, relative to the baseline period of 1981–2010. AI anomalies, as the differences between the period of 2041–2070 and 1981–2010 averaged for the five future GCM-simulated climates, were computed for each grid. Models were assumed to be independent and given the same weight. The multi-model ensemble can be used to provide both a consensus representation of the climate system and some measure of how much confidence might be placed in that consensus (Taylor *et al.*, 2012). P , ET_0 , and AI anomalies for China as a whole (ΔM) for each RCP were computed as follows:

$$\Delta M_s = \frac{\sum_{i=1}^n ((M_{s,if} - M_{s,ibs}) / M_{s,ibs} \times 100 \times A_i)}{\sum_{i=1}^n A_i} \quad (1)$$

where s denotes the climate scenario, i is the number of the grid (between 1 and 3997 for the study boundaries),

f denotes the period from 2014 to 2070, bs denotes the baseline period from 1981 to 2010, and A_i is area of the i th grid.

2.2. Meteorological data and model performance matrix

To evaluate the behaviour of the five GCMs in simulating aridity over China, simulated present temperature (T), P , ET_0 , and AI were compared with gauge-based observations and estimates. Observations of daily mean, maximum, and minimum air temperatures; mean relative humidity; sunshine duration; and mean wind speed at multiple sites over China were obtained from the National Meteorological Center of the China Meteorological Administration (CMA). Quality-controlled observations from 603 meteorological stations with less than 5% missing data for the period 1981–2010 were compiled. Missing data were estimated by averaging values obtained from the same station during other years. To facilitate GCM validation, the annual gauge-based observations and estimates were interpolated onto a $0.5^\circ \times 0.5^\circ$ grid, identical to that of the ISI-MIP resolution, using the thin-spline plate approach.

We present an analysis of the model outputs in terms of the root-mean-square error (RMSE), correlation (r), and standard deviation (SD). Values are presented in a Taylor diagram (Taylor, 2001), which summarizes these three values using a single point. Smaller RMSE values indicate more accurate model estimates. Correlation coefficients are used to describe the temporal and spatial similarity between the observation and the simulation. RMSE is given by:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n [(y_i - \bar{y}) - (x_i - \bar{x})]^2}{n}} \quad (2)$$

where x_i represents the i th sample of a variable, y_i is the corresponding climatology in the GCM simulation, and n is the number of samples. To facilitate evaluations for different fields with different units, the RMSE and SD for each variable were normalized against the standard deviation of the corresponding observed field (Taylor, 2001).

2.3. Reference evapotranspiration and aridity index

Direct measurements of ET_0 using methods such as eddy covariance, lysimeters, and the Bowen ratio method are generally localized and expensive, making estimates from meteorological variables desirable. Here ET_0 is simulated by the Penman–Monteith model recommended by the Food and Agricultural Organization (hereafter the FAO56-PM model). The FAO56 reference crop evapotranspiration method (Allen *et al.*, 1998) is recognized as the most effective and reliable method for estimating evapotranspiration, and is a simplified parameterization of the classical PM model for ET_0 (van der Schrier *et al.*, 2013). The FAO56-PM model is the most effective method for humid and arid conditions (Jensen *et al.*, 1990), and has been found to provide a good reproduction of the spatial and seasonal variability of ET_0 across Great Britain

(Prudhomme and Williamson, 2013). In addition, McVicar *et al.* (2012) advocate that assessing evaporative demand trends requires consideration of all four primary meteorological variables; i.e. wind speed, atmospheric humidity, radiation, and air temperature. Thus, the physically based FAO56-PM method was used in this study to evaluate ET_o . The model defines a hypothetical reference crop, 0.12 m high, without water stress, and integrates the mass transfer and energy balance by considering vegetation physiological functions (Allen *et al.*, 1998). Daily ET_o is calculated as:

$$ET_o = \frac{0.408\Delta (R_n - G) + \gamma \frac{900}{T+273} U_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34U_2)} \quad (3)$$

where R_n is net radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$), G is the soil heat flux ($\text{MJ m}^{-2} \text{ day}^{-1}$), γ is the psychrometric constant ($\text{kPa } ^\circ\text{C}^{-1}$), Δ is the slope of the saturation vapour pressure curve ($\text{kPa } ^\circ\text{C}^{-1}$), T is air temperature ($^\circ\text{C}$), U_2 is wind speed at a height of 2 m (m s^{-1}), e_s is the mean saturation vapour pressure (kPa) and e_a is the actual vapour pressure (kPa), respectively. As the magnitude of the daytime soil-heat flux beneath the grass reference surface is relatively small, it can be ignored (Allen *et al.*, 1998). Gauge-based ET_o is estimated based on the radiation-calibrated FAO56 Penman–Monteith model, which uses the calibrated Ångström solar radiation formula (Yin *et al.*, 2008).

The AI , as the ratio between ET_o and P (Budyko, 1974; Middleton and Thomas, 1992), is a widely used indicator of regional moisture conditions, and high values of the index indicate higher aridity.

3. Results

3.1. Model evaluation

The performance of the models in capturing the observed T , P , ET_o , and AI was estimated before investigating

changes in aridity over China. Figure 1 shows the time series of regionally averaged surface T , P , ET_o , and AI anomalies relative to baseline (1981–2010) conditions. These results were compared with observations over China between 1981 and 2010, and both series were smoothed using the 10-year running mean. Generally, observations over the historical period tend to be within the ensemble's one standard-deviation spread. For regionally averaged temporal changes, the models compare well with observed climate variables, except for ET_o and AI in the 1990s when there is a positive bias. The bias is probably related to the observed decline of wind speed which has not been captured by the GCMs.

Changes in the four fields show considerable variation between models and scenarios. The fields have similar trends, but the magnitude of the changes varies between RCPs, particularly after 2030. Annual surface T and ET_o increase consistently in all models. Relative to the baseline period, annual T rises by 1.81°C and 2.84°C by 2050, and by 1.58°C and 6.50°C at the end of the 21st century, for RCP2.6 and RCP8.5, respectively. Annual ET_o increases substantially, particularly for RCP 8.5, which shows an increase of 10.35% by 2050, and 24.22% at the end of the 21st century. P anomalies are projected to be negative between 2010 and 2020, after which they become positive for the remainder of the study period. The lowest increase in P was for RCP6.0, which resulted in increases of 2.07% and 4.85% by 2050 and 2099, respectively. At the end of the 21st century, P in China as a whole is likely to increase by about 10% (except for RCP6.0).

AI anomalies are more heterogeneous than other variables with a low variance between models. After 2010, there are slight upward trends in AI anomalies in RCP6.0 and RCP8.5. However, for RCP2.6 and RCP4.5, although positive anomalies do occur after 2010, there are no obvious trends in AI (Figure 1). AI increases for RCP 8.5 are the most significant, with increases of 8.18% and 13.08% in 2050 and 2099, respectively (Table 2).

Figure 1. Modelled and observed regional spatial averages of (a) temperature change, (b) precipitation, (c) reference evapotranspiration, and (d) aridity index over China displayed as anomalies relative to 1981–2010. Solid lines indicate the five-GCM ensemble means under representative concentration pathway scenarios, and the shading indicates one standard deviation of the ensemble mean spread. The time series were smoothed using the 10-year running mean.

Table 2. Changes in temperature, precipitation, reference evapotranspiration, and aridity index relative to the baseline period for four RCPs over China by 2050 and 2099.

Variable	Year	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
T (°C)	2050	1.81	2.18	1.52	2.84
	2099	1.58	2.94	3.78	6.50
P (%)	2050	5.73	3.50	2.07	2.15
	2099	9.00	10.33	4.85	10.17
ET_0 (%)	2050	6.60	9.27	4.05	10.35
	2099	6.36	10.53	15.89	24.22
AI (%)	2050	0.58	5.45	1.57	8.18
	2099	−2.56	−0.11	11.06	13.08

Statistics are presented on a Taylor diagram in Figure 2, which shows the total spatial and temporal variability of the four evaluated fields. For surface air temperature, all five GCMs have a correlation with observations of $r > 0.96$, for P the correlation is approximately 0.80, and for ET_0 it is between 0.68 and 0.76. The correlation is lower for AI than for the other variables, with $r \approx 0.60$. The normalized standard deviation of space–time variations in T is near 1, and for the other modelled variables, it is between 0.75 and 1.25. Nevertheless, all GCMs are generally capable of simulating the regional variability in

aridity over China, but multi-model means have a higher correlation and lower RMSE than any individual GCM. Thus, the multi-model mean was used in the climate projections to reduce the errors and uncertainties associated with using an individual model.

The spatial distribution of observed and multi-model mean ET_0 and AI over China averaged for the three decades between 1981 and 2010 are presented in Figure 3. The results show lower ET_0 primarily in northeast China and east of the Tibetan Plateau, and higher ET_0 mainly in northwest China and southeast China. The model does show the spatial variability in ET_0 , but the magnitudes tend to be higher than observations, especially in northwest and central China. Nevertheless, the simulated spatial distribution of ET_0 is generally consistent with the observations, and has a spatial correlation coefficient of 0.77.

For AI , there is a spatial transition from low AI (humid) in southeast China to high AI (arid) in northwest China. As shown in Figure 3(c) and (d), the simulations capture the southeast–northwest contrast and compare favourably with observations, with a spatial correlation coefficient of 0.76. However, there is both a positive and negative bias in the simulated AI , with larger modelled magnitudes over southeast China, but smaller magnitudes mainly in northwest China, when compared with the observations.

Figure 2. Taylor diagrams for projected (a) temperature change, (b) precipitation, (c) reference evapotranspiration, and (d) aridity index over China evaluated against observed fields for the 30-year period 1981–2010. The Taylor diagrams compare actual observations with GCM simulations, and summarize three metrics of the correlation (curved axis), the ratio of the standard deviations (x and y axes), and the RMSE (dashed line). The closer a point is to the observed data, the better the fit between observed and simulated data.

Figure 3. Observed (a, c) and simulated multi-model mean (b, d) reference evapotranspiration (a, b) and aridity index (c, d) over China from 1981 to 2010. Dark dots indicate the 603 meteorological stations used in the analysis (spatial correlations of ET_0 and AI are 0.77 and 0.76, respectively).

3.2. Future changes in aridity over China

Figure 4 shows the projected ensemble-mean changes in P for each RCP over China from the mid-21st century (2041–2070) to the present-day (1981–2010). Precipitation is projected to increase in the future over large areas of China relative to the baseline period. Spatial patterns shown in Figure 4 indicate that total annual P will increase substantially, especially in parts of western China, which show increases of more than 20%. This larger-scale pattern is very similar for RCP2.6, RCP4.5, and RCP8.5, with the largest positive anomalies for RCP8.5. The main negative P anomalies are found over southeast China in RCP6.0. The mean P anomalies over China in the mid-21st century are 7.94%, 8.09%, 4.62%, and 10.15% for RCP2.6, RCP4.5, RCP6.0, and RCP8.5, respectively (Figure 5).

Figure 6 shows the spatial distribution of changes in simulated ET_0 in the mid-21st century relative to the baseline period. Results show positive changes in annual ET_0 for all four RCPs. Changes in ET_0 for RCP8.5, with the highest greenhouse gas increase, have a larger magnitude than for other RCPs. For RCP8.5, annual ET_0 has a clear increase of more than 10% in northeast and southeast China, but a smaller increase of no more than 10% in regions west of 100°E. The magnitude of modelled ET_0 is similar for RCP2.6 and RCP6.0, with positive anomalies of no more than 6% in western China, and between 6% and 10% for the majority of eastern China. As shown in Figure 5, the mean ET_0 anomalies over China in the mid-21st century are similar for RCP2.6 and RCP6.0, with means of around 7%, but a little higher for RCP8.5 with a mean of 11.24%. It is also of note that the range of ET_0 anomalies is not

much higher than that of P and AI, and that all the values are positive.

Generally, negative AI anomalies indicate increased humidity, while positive anomalies indicate severe aridity. Figure 7 shows the spatial patterns of percentage changes in annual AI for the period 2041–2070 relative to 1981–2010. The large-scale patterns of annual AI are generally similar among the four RCPs. Anomalies in annual AI are positive over the majority of China, with increases of 63.57%, 74.26%, and 61.37% in RCP4.5, RCP6.0, and RCP8.5, respectively. The positive changes in AI indicate a drying trend over most of China for all RCPs, except for RCP2.6, in which the negative and positive changes in AI are nearly balanced. The increase in P is likely to outweigh the increase in ET_0 in most of western China, leading to negative changes in AI and thus lessening the effects of increased aridity. The exception to this trend is northwest China, which is expected to have an increased AI. In contrast, for the majority of eastern China, AI is projected to increase by approximately 10%. Here, the positive changes in AI are mainly due to a larger increase in ET_0 compared with P . Generally, the mean AI change anomalies over China in the mid-21st century are relatively small (<3%) except for RCP2.6, which has a slightly negative mean anomaly (Figure 5).

4. Discussion

To evaluate climate model performance in the baseline period, spatial and temporal variations from historical simulations were compared with observations. Validation of simulated aridity for 1981–2010 showed that the patterns

Figure 4. Percentage deviations in precipitation over China for the period 2041–2070 relative to 1981–2010 under (a) RCP2.6, (b) RCP4.5, (c) RCP6.0, and (d) RCP8.5, respectively.

Figure 5. Predicted percentage changes in precipitation, reference evapotranspiration, and aridity index over China in the mid-21st century for each RCP. The median and mean values of the predicted changes are shown as solid and dashed lines inside the boxes; the box shows the 25th–75th percentile range; whiskers extend to the 5th and 95th percentiles; and stars represent the 1st and 99th percentiles.

of ET_0 and the AI were generally similar between models and observations over China. However, a number of uncertainties still remain. Higher uncertainties occur, especially in the Tibetan Plateau, where there is a sparse distribution of weather stations and complex topography (Figure 3). There may be a systematic bias over the Tibetan Plateau in the CMIP5 models (Su *et al.*, 2012). Moreover, Inter-GCM variation in projected P change is much larger than that of evapotranspiration change (Thompson *et al.*, 2014). As indicated by Endo *et al.* (2012), uncertainties in future P simulations in South and Southeast Asia are derived mainly from differences in cumulus schemes.

Projected evapotranspiration is a crucial challenge facing the assessment of climate change impact since uncertainty exists in estimated ET_0 (Prudhomme and Williamson, 2013). Uncertainty in ET_0 mainly arises from GCMs and various ET_0 methods. For certain regions and GCMs, ET_0 method can determine the direction of projections of future water resources, and further adds substantial uncertainty to the existing uncertainty associated with the climate change signal between GCMs (Kingston *et al.*, 2009). McAfee (2013) suggested to use data-intensive methods to estimate changes in evaporative demand because the source(s) of uncertainty can be identified (McAfee, 2013). Even so, the ET_0 method-related uncertainty is much less than the GCM-related uncertainty as for runoff projection (Kay and Davies, 2008; Thompson *et al.*, 2014).

To reduce uncertainty in GCMs performance, an ensemble average of GCMs was used in this study. However, this does not provide a systematic assessment of true GCM structural uncertainty, an alternative is to apply GCM perturbed physics ensembles (Gosling *et al.*, 2012),

Figure 6. Percentage deviations in reference evapotranspiration over China during the period 2041–2070 relative to 1981–2010 under (a) RCP2.6, (b) RCP4.5, (c) RCP6.0, and (d) RCP8.5, respectively.

or a Bayesian model averaging method to reduce the GCM-ensemble uncertainty (Tebaldi and Knutti, 2007; Wang and Chen, 2014). For example, the multi-model ensemble bias in future ET_0 prediction of in the Haihe River Basin of China (Xing *et al.*, 2014) and future precipitation prediction at regional scales (Tebaldi *et al.*, 2004) has been reduced based on the Bayesian approach. Moreover, uncertainty in GCMs to simulate variability and trend in P and ET_0 can be reduced by exclusion of the poorer GCMs according to their skill score and a certain threshold (Kirono and Kent, 2011). Generally, although climate models in CMIP5 capture most of the climatic processes, uncertainties in climate change are unlikely to decrease quickly, and the impact-relevant predictions may be even harder to improve (Knutti and Sedlacek, 2013). Further efforts should be made to deal with uncertainties in the impact of climate change, for example to constrain the sea surface temperature (SST) response pattern and the soil-moisture feedback in global climate scenarios (Joetzer *et al.*, 2013).

For temporal variations in the baseline period, simulated ET_0 and AI have a positive bias in the 1990s, which results in a lower correlation and higher RMSE compared with T and P . The discrepancy is probably related to wind speed simulations. As indicated by Chen *et al.* (2012), a positive bias exists in mean near-surface wind speeds over China, and hence none of the models reproduce the recent decline in wind speed that is manifest in near-surface observations. During the last several decades, annual ET_0 has decreased in most regions worldwide, and this has been

mainly attributed to declining wind speeds (Yin *et al.*, 2010; McVicar *et al.*, 2012). Decreased wind speed is usually associated with changes in the strength of large-scale changes in atmospheric circulation (Chen *et al.*, 2006; Rayner, 2007). Despite the bias, GCM ensemble means are able to reproduce the general temporal and spatial variations of aridity over China between 1981 and 2010.

The projected increment of P in China based on the latest GCMs from CMIP5 generally confirms the findings from previous studies. For example, Gu *et al.* (2012) applied a regional climate model (RegCM4) and found positive changes in annual precipitation over most of China north of 30°N and negative or little change in the rest of China in 2070–2099. Recently, based on CMIP5 climate models, precipitation was generally projected to increase in China by the end of the 21st century (Wang and Chen, 2014). Moreover, the most significant increases were projected to occur over the Tibetan Plateau and East China in summer, indicating the change in monsoonal circulation in the future (Chen and Frauenfeld, 2014). Precipitation is the main source of increased moisture, and ET_0 , as a main source of atmospheric water demand, also plays an important role in the hydrologic budget. Therefore, although future annual mean total P is projected to increase over most of China, it is likely to become drier over most of eastern China due to enhanced atmospheric water demand as greenhouse gas concentrations increase.

The positive changes in annual ET_0 projected in this study in response to future warming are comparable with previous results at both global scale (Kingston *et al.*, 2009;

Figure 7. Percentage deviations in aridity index over China for the period 2041–2070 relative to 1981–2010 under (a) RCP2.6, (b) RCP4.5, (c) RCP6.0, and (d) RCP8.5, respectively.

Scheff and Frierson, 2013) and regions in China, such as the Tibetan Plateau (Wang *et al.*, 2013), the Haihe River Basin (Xing *et al.*, 2014), and the Zhejiang Province (Xu *et al.*, 2014). The main reason for the projected increase in global ET_0 is increased temperature, which increases the vapour pressure deficit and increases the Clausius–Clapeyron slope (Scheff and Frierson, 2013).

Projected changes in evapotranspiration demand and aridity provides profound implications that may be useful for future water resource management, agriculture and ecosystem structure and function. Our simulation of future aridity changes indicates that most of semiarid and arid regions in western China will experience less aridity, which may induce more available water and benefit to local ecosystem. However, there will not be possible to devoid water scarcity situation in the 21st century because higher water demand than supply typically occurs. Meanwhile, increased evapotranspiration and aridity were projected across most of eastern China in the mid-21st century. Enhancement ET_0 may have negative implications on ecosystem and agriculture, like crop growth in the Haihe River Basin which is an important grain production base in eastern China (Wang *et al.*, 2011). Moreover, increased aridity has the potential impact on grassland composition and productivity (Clark *et al.*, 2002), and the forest growth would decline and mortality rates may increase substantially response to rising aridity (Williams *et al.*, 2010). Therefore, ecosystem across the eastern China would be affected adversely by future warming and increasing aridity.

At global or regional scales, *AI* is conventionally used to classify the land surface into different moisture regimes such as arid, semi-arid, sub-humid, and humid zones, corresponding to the following types of natural potential vegetation: forest, forest steppe including meadow, steppe, and desert, respectively (Zheng, 1999; Zheng *et al.*, 2013). The spatial differences in *AI* changes may result in the migration of arid or humid regimes, and transfer ecosystem patterns as well. For example, the substantially decreased projected *AI* in western China would probably lead to a reduction in the arid zone, and increased *AI* in eastern China would lead to a reduction in the humid zone. Further analysis will be necessary if we are to evaluate the potential impacts of future aridity changes and the migration of moisture regimes.

5. Summary and conclusions

This paper aims to provide an overview of aridity changes projected for the mid-21st century relative to the 1981–2010 baseline conditions. Future projections of changing aridity using five GCMs that participated in the ISI-MIP over China were analyzed for four RCPs, after evaluating the performances of the GCMs against observations from 603 meteorological stations. The FAO56 Penman–Monteith model was used to simulate ET_0 and the corresponding aridity over China.

GCM ensemble-means reproduced the general temporal and spatial variations of aridity during the baseline period over China. A positive ET_0 bias was found mainly in

northwest and central China. Simulated annual AI had a positive bias over southeast China and a negative bias mainly in northwest China.

In the mid-21st century, modelled ET_0 anomalies are consistently positive for all four RCPs over China, especially in the southeast and northeast, which show positive changes of more than 10%. In contrast to the ET_0 trends, which are spatially homogeneous, annual P anomalies show little spatial consistency. Precipitation is generally projected to increase over China in the mid-21st century relative to the baseline period. Regions with significantly increased P are mainly concentrated in western China. RCP8.5, which has the highest greenhouse gas increase, results in higher-magnitude anomalies than the three other RCPs for both P and ET_0 . There are also large differences between modelled anomalies in each RCP, particularly after 2030. For most areas in eastern China, AI is projected to increase, while for most of western China AI is projected to decrease between 1981–2010 and 2041–2070.

In general, future aridity changes are projected to show strong contrasts from west (decreased aridity) to east (increased aridity). Wide areas of eastern China are likely to face an increased risk of drought, despite positive P anomalies, due to the much more substantial effects of climate change on atmospheric moisture demand (ET_0). However, the projected increase in P generally outweighs that in atmospheric moisture demand, and this should lead to higher humidity across the majority of western China in the 21st century.

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