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Future aridity under conditions of global climate change

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ABSTRACT

Global climate change is anticipated to cause some major changes in hydroclimatic conditions around the world. As aridity is a reliable indicator of potential available water, assessment of its changes under future climatic conditions is important for proper management of water. This study employs the UNESCO aridity/humidity index, which is a derivative of precipitation (P) and potential evapotranspiration (PET), for assessment of aridity. Historical (1901–2005) simulations and future (2006–2100) projections of 22 global climate models (GCMs) from the fifth phase of the Coupled Model Intercomparison Project (CMIP5) are studied. The Nested Bias Correction (NBC) approach is used to correct possible biases of precipitation (simulated directly by the GCMs) and PET (estimated by applying FAO56-Penman-Monteith model on simulated parameters of the GCMs). To detect future aridity changes, the areal extents of the aridity zones in the past and future periods as well as through four sub-periods (2006–2025, 2026–2050, 2051–2075, and 2076–2100) of the future are compared. The results indicate that changes in climate will alter the areal extents of aridity zones in the future. In general, from the first sub-period towards the last one, the area covered by hyper-arid, arid, semi-arid, and sub-humid zones will increase (by 7.46%, 7.01%, 5.80%, and 2.78%, respectively), while the area of the humid regions will decrease (by 4.76%), suggesting that there will be less water over the global land area in the future. To understand the cause of these changes, precipitation and PET are also separately assumed to be stationary throughout the four future sub-periods and the resulting aridity changes are then analyzed. The results reveal that the aridity changes are mostly caused by the positive PET trends, even though the slight precipitation increase lessens the magnitude of the changes.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) reports that recent decades have witnessed a continued increase in the emissions of carbon dioxide (e.g. IPCC, 2013). The global mean atmospheric carbon dioxide concentration increased by 40% from a pre-industrial value of 278 ppm to 390.5 ppm in 2011. There is convincing evidence that increases in global atmospheric carbon dioxide and other greenhouse gas concentration levels have resulted in rising global average surface air temperature. The rise in global mean temperature over the period 1880–2012 has been estimated to be 0.85 °C. Projections based on Global Climate Models (GCMs), notwithstanding their uncertainties, generally indicate that by the end of the 21st century, global temperature will likely increase between 1.5 and 2 °C relative to 1850–1900 (IPCC, 2013).

Since, on one hand, changes in the water cycle, and subsequently water resources availability, are projected to occur in a warming climate (IPCC, 2013) and, on the other hand, changes in the availability of water resources will affect the planning and management of water resources systems (Burn and Simonovic, 1996), modeling future climate change and its associated impacts on water availability is crucial for future water planning and management strategies; see also, for example, Sivakumar (2011), Chen et al. (2011), Yang and Yang (2012), Singh et al. (2014), and Vu et al. (2015) for some recent studies on the impacts of climate change and associated challenges. In this regard, aridity classes, determined based on aridity/humidity indexes, are reliable representations of potential water availability, especially at large scales; see, for example, Yang et al. (2006), Han et al. (2011), Xu et al. (2014), and Asadi Zarch et al. (2015) for some recent aridity-related studies. To this end, projection of future aridity levels can provide a reliable means for detecting possible water availability shifts that may happen in the future. There exist several aridity indexes, such as the Budyko's aridity index (Budyko, 1974), UNEP

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aridity index (UNEP, 1992), Aridity intensity index (Costa and Soares, 2009), de Martonne aridity index (de Martonne, 1926), Thornthwaite aridity index (Thornthwaite, 1948), Pinna combinative index (Zambakas, 1992; Baltas, 2007), and UNESCO aridity index (UNESCO, 1979). However, the UNESCO aridity index, which is based on the ratio of annual precipitation (P) to potential evapotranspiration (PET), is the most widely used one.

Many studies have attempted to project future aridity levels around the world. However, a majority of such studies have focused on the assessment of future aridity levels at specific locations. For instance, Nastos et al. (2013) used Regional Climate Models (RCMs) to study the spatio-temporal variability of aridity in Greece during 2021–2050 and 2071–2100. García-Garizábal et al. (2014) projected aridity for the future (2011–2099), using MPI-ECHAM5 model, for a region in the Middle Ebro Valley, Spain. Marengo and Bernasconi (2014) used downscaled HadCM3 data to estimate extension of areas covered by semi-arid and arid conditions in the future in northeast Brazil. Among other studies, more recently, Chen et al. (2017) projected the future aridity (and also discharge) trends for China for the period 2001–2050. They used CMIP5 data from five models under RCP2.6, RCP4.5, and RCP8.5 scenarios.

In recent years, there has certainly been an increasing interest in projecting future aridity levels at the global scale. For instance, Girvetz and Zganjar (2014) projected aridity index and three more moisture metrics for the period 2081–2100 using simulations of nine CMIP3 (Phase 3 of the Coupled Model Intercomparison Project) models. Feng and Fu (2013) used raw CMIP5 (Phase 5 of the Coupled Model Intercomparison Project) (Liu et al., 2014) simulations for 1948–2100 to project drylands in the future. In a follow-up study, Fu and Feng (2014) investigated how precipitation, PET, and the ratio of annual precipitation to PET (as a terrestrial climate dryness indicator) respond to 1 °C rise in mean surface air temperature by analyzing raw CMIP5 data. Greve and Seneviratne (2015) used P–E to estimate aridity during the 21st century. Scheff and Frierson (2015) employed 16 CMIP5 models to project changes in P, PET, and P/PET between 1981–1999 and 2081–2099. Lin et al. (2015) used the Community Earth System Model Large Ensemble (CESM-LE) and 19 CMIP5 models to project aridity changes during the period 1980–2080. Huang et al. (2016) analyzed future area of drylands using 20 GCMs under moderate and high-end scenarios (RCP4.5 and RCP8.5, respectively).

As is evident from the above literature review, studies projecting future aridity levels under conditions of climate change have adopted different models and methods. While the usefulness of such projections is unquestionable, regardless of CMIP3 or CMIP5 projections, for example, it is important to recognize that GCM simulations have inherent uncertainties. The uncertainties in GCM projections result due to, among others, errors in the model structure, scenarios, and initial conditions (Woldemeskel et al., 2014). These uncertainties in GCM projections, including for temperature and precipitation, cause uncertainties in aridity assessment, which is often a function of one or more of these variables. To address and reduce these uncertainties in GCM projections, bias-correction approaches are commonly employed, using real (or "proxy") observations as reference data, as has been done in many of the studies projecting future aridity levels mentioned above.

Several bias-correction approaches exist in the literature. They are often statistical in nature, and are mean-based or distribution-based. The approaches include: linear scaling (LS), local intensity scaling (LOCI), and quantile mapping (e.g. Wood et al., 2004; Hashino et al., 2007). Each of these methods has its own advantages and limitations, details of which are available elsewhere (e.g. Chen et al., 2013). In addressing such limitations, Johnson and Sharma (2012) proposed a nesting bias correction (NBC) methodology for rainfall, which was then further refined by Mehrotra and Sharma (2012). The NBC method assumes that biases in the future projections will be the same as the observed biases in the current climate simulations. Therefore, the statistics of the observed climatic data and the corresponding statistics of the past GCM outputs are used in the correction of the GCM outputs pertaining to future (Sachindra et al., 2014). The NBC approach has been shown to be very effective, especially for temperature and rainfall projections (e.g. Johnson and Sharma, 2012; Mehrotra and Sharma, 2012; Woldemeskel et al., 2014).

With these observations, the present study attempts to assess the future global aridity levels using CMIP5 projections with due consideration to their uncertainties. In particular, the study addresses if, how, and why the boundaries of aridity classes will be influenced by global warming in the future. To this end, the UNESCO aridity index is applied to the precipitation and PET projections from CMIP5 models with application of the NBC method for bias correction to reduce the uncertainties. The precipitation and PET projections are obtained from a total of 22 GCMs, with the PET estimated based on the Penman–Monteith approach (Allen et al., 1998). The raw and NBC bias-corrected historical simulations of precipitation, PET, and aridity are evaluated using real observations. Pre- and post-NBC GCM projections for the period 2006–2100 are then compared across different aridity zones. Aridity classes in both past and future periods (including four future sub-periods: 2006–2025, 2026–2050, 2051–2075, and 2076–2100) are analyzed to detect probable changes across the world. The causes of possible future aridity changes are also revealed, including through an examination of the future aridity levels for stationary precipitation or PET conditions.

2. Methods

The UNESCO aridity index (AI) (UNESCO, 1979) is based on the ratio of annual precipitation (P) to potential evapotranspiration (PET). Based on the classification system of this index (see Asadi Zarch et al., 2015), there are five climatic zones: hyper-arid, arid, semi-arid, sub-humid, and humid. Larger aridity index values refer to more humid climates. The precipitation data for this study are gathered from real observations (historical) as well as from CMIP5 models (historical and future). The PET data are obtained using the Penman-Monteith method (Allen et al., 1998). The UNESCO aridity index is ascertained using the NBC bias-corrected precipitation and PET.

As the bias-correction procedure and the PET assessment procedure remain the same for any GCM projection (and real data, in the latter case), such procedures are explained here first. The data used in this study are described in Section 3.

2.1. Nested bias correction (NBC) approach

Johnson and Sharma (2012) developed the Nested Bias Correction (NBC) approach based on the idea of nesting time series at multiple timescales addressed by stochastic models generating rainfall. However, the NBC uses 'current climate' GCM simulations and modifies them by nesting in the observed monthly and annual time series. The GCM simulations for the future can then be corrected by applying the defined nested model. While the bias-correction approaches mostly focus on either monthly or daily statistics (Ojha et al., 2012), biases in GCM simulations at multiple timescales (daily, monthly, and annual) can be corrected by the NBC approach (Woldemeskel et al., 2014).

The nesting bias correction procedure described here is the overall approach for correcting GCM data, with GCM precipitation outputs as an example at monthly and annual timescales,