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Assessment of temporal and spatial changes of future climate in the Jhelum river basin, Pakistan and India

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ABSTRACT

The present study investigated future temporal and spatial changes in maximum temperature, minimum temperature, and precipitation in two sub-basins of the Jhelum River basin—the Two Peak Precipitation basin (TPPB) and the One Peak Precipitation basin (OPPB)—and in the Jhelum River basin on the whole, using the statistical downscaling model, SDSM. The Jhelum River is one of the biggest tributaries of the Indus River basin and the main source of water for Mangla reservoir, the second biggest reservoir in Pakistan.

An advanced interpolation method, kriging, was used to explore the spatial variations in the study area. Validation results showed a better relationship between simulated and observed monthly time series as well as between seasonal time series relative to daily time series, with an average R^2 of 0.92–0.97 for temperature and 0.22–0.62 for precipitation.

Mean annual temperature was projected to rise significantly in the entire basin under two emission scenarios of HadCM3 (A2 and B2). However, these changes in mean annual temperature were predicted to be higher in the TPPB than the OPPB. On the other hand, mean annual precipitation showed a distinct increase in the TPPB and a decrease in the OPPB under both scenarios.

In the case of seasonal changes, spring in the TPPB and autumn in the OPPB were projected to be the most affected seasons, with an average increase in temperature of 0.43–1.7 °C in both seasons relative to baseline period. Summer in the TPPB and autumn in the OPPB were projected to receive more precipitation, with an average increase of 4–9% in both seasons, and winter in the TPPB and spring in the OPPB were predicted to receive 2–11% less rainfall under both future scenarios, relative to the baseline period.

In the case of spatial changes, some patches of the basin showed a decrease in temperature but most areas of the basin showed an increase. During the 2020s (2011–2040), about half of the basin showed a decrease in precipitation. However, in the 2080s (2071–2099), most parts of the basin were projected to have decreased precipitation under both scenarios.

1. Introduction

The concentration of CO_2 and other greenhouse gases has been increasing dramatically since 1950, mostly because of industrialization (Gebremeskel et al., 2005). This increase has caused a global energy imbalance and has increased global warming. According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), global (land and ocean) mean surface temperature as calculated by a linear trend over the period 1880–2012, show a warming of 0.85 °C (0.65–1.06 °C). An alarming increase of 0.78 (0.72–0.85) °C has been observed for the period of 2003–2012 with respect to 1850–1900. Global mean surface temperatures is projected to increase by 0.3–1.7 °C, 1.1 to 2.6 °C, 1.4–3.1 °C, and 2.6–4.8 °C under RCP2.6, RCP4.5, RCP6.0 and RCP8.5, respectively, for 2081–2100 relative to 1986–2005 (IPCC, 2013).

This global warming can disturb the hydrological cycle of the world, and can pose problems for public health, industrial and municipal water demand, water energy exploitation, and the ecosystem (Chu et al., 2010; Zhang et al., 2011).

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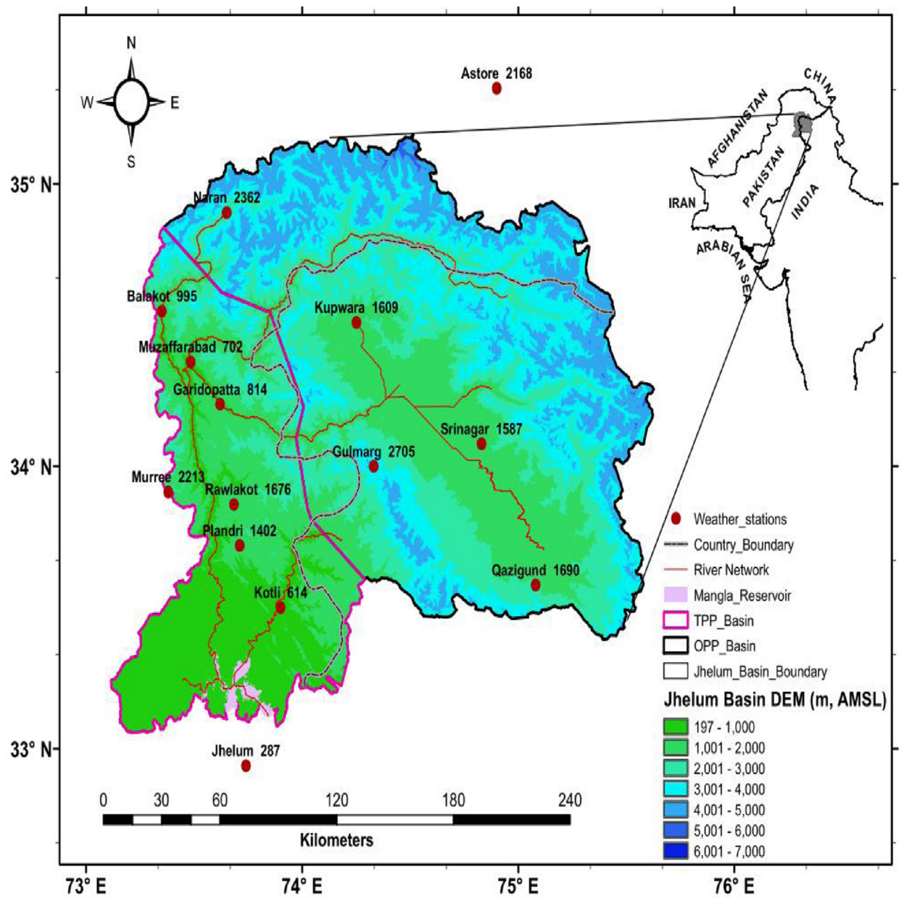

Fig. 1. Location map of the study area with the climate stations.

In the last few decades, Global Climate Models (GCMs)—the most advanced and numerical-based coupled models representing the global climate system—have been used to examine future changes in climate variables such as temperature, precipitation, and evaporation (Fowler et al., 2007). However, their outputs are temporally and spatially very coarse (Gebremeskel et al., 2005), which makes them useful only at continental and global levels. Their application at local/regional levels, such as at the basin and sub-basin scales, to assess the impacts of climate change on the environment and hydrological cycle, is problematic due to a clear resolution mismatch (Hay et al., 2000; Wilby et al., 2000). That is, GCMs cannot give a realistic presentation of local or regional scales due to parameterization limitations (Benestad et al., 2008). The local and regional scales are defined as 0–50 km and 50×50 km^2, respectively (Xu, 1999)

To overcome this problem, during the last two decades, many downscaling methods have been developed to make the large-scale outputs of GCMs useful at local/regional scales (Wetterhall et al., 2006). In the beginning, these methods were mostly implemented in Europe and in the USA but are now applied throughout the globe to examine changes in climate variables at the basin level (Mahmood and Babel, 2012).

Generally, downscaling techniques are divided into two main categories: Dynamical Downscaling (DD), and Statistical Downscaling (SD). In DD, a Regional Climate Model (RCM) of high resolution (5–50 km) (Chu et al., 2010), nested within a GCM, receives inputs from the GCM and then provides high resolution outputs on a local scale. Since the RCM is dependent on the boundary conditions of a GCM, there is a greater chance that systematic errors that belong to the driving fields of the GCM will be inherited by the RCM. In addition, simulations from RCMs are computationally intensive, and depend upon the domain size and resolution at which the RCMs are to run, which in turn limits the number of climate projections (Fowler et al., 2007).

In contrast, SD approaches, which establish a bridge among the large-scale variables (e.g., mean sea level pressure, temperature, zonal wind, and geopotential height) and local-scale variables (e.g., observed temperature and precipitation) by creating empirical/statistical relationships, are computationally inexpensive and much simpler than DD (Wetterhall et al., 2006). Moreover, SD approaches offer immediate solutions for downscaling climate variables and, accordingly, they have rapidly been adopted by a wider community of scientists (Wilby et al., 2000; Fowler et al., 2007). The limitation of SD is that historical meteorological station data over a long period of time is required to establish a suitable statistical or empirical relationship with large-scale variables (Chu et al., 2010). This relationship is considered to be temporally stationary, which is the main assumption of this method (Hay and Clark, 2003). In addition, SD is mainly dependent on the level of uncertainties of the parent GCM(s). DD, therefore, is a good alternative for SD in basins where no historical data is available (Benestad et al., 2008).

To date, many SD models have been developed for downscaling, and among them Statistical Downscaling Model (SDSM) was selected for this study. SDSM—a combination of multiple linear regression and a stochastic weather generator—is a well-known statistical model, and is frequently used for downscaling important climate variables (e.g., temperature, precipitation, and evaporation). The downscaled variables are used to assess hydrological responses under changing climatic conditions (Diaz-Nieto and Wilby, 2005; Gagnon et al., 2005; Gebremeskel et al., 2005; Wilby et al., 2006). SDSM has been widely used throughout the