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What is the importance of climate model bias when projecting the impacts of climate change on land surface processes?

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BGD

10, 17145–17192, 2013

Abstract

Regional climate change impact (CCI) studies have widely involved downscaling and bias-correcting (BC) Global Climate Model (GCM)-projected climate for driving land surface models. However, BC may cause uncertainties in projecting hydrologic and biogeochemical responses to future climate due to the impaired spatiotemporal covariance of climate variables and a breakdown of physical conservation principles. Here we quantify the impact of BC on simulated climate-driven changes in water variables (evapotranspiration, ET; runoff; snow water equivalent, SWE; and water demand for irrigation), crop yield, biogenic volatile organic compounds (BVOC), nitric oxide (NO) emissions, and dissolved inorganic nitrogen (DIN) export over the Pacific Northwest (PNW) Region. We also quantify the impacts on net primary production (NPP) over a small watershed in the region (HJ Andrews). Simulation results from the coupled ECHAM5/MPI-OM model with A1B emission scenario were firstly dynamically downscaled to 12 km resolutions with WRF model. Then a quantile mapping based statistical downscaling model was used to downscale them into 1/16th degree resolution daily climate data over historical and future periods. Two series climate data were generated according to the option of bias-correction (i.e. with bias-correction (BC) and without bias-correction, NBC). Impact models were then applied to estimate hydrologic and biogeochemical responses to both BC and NBC meteorological datasets. These impact models include a macro-scale hydrologic model (VIC), a coupled cropping system model (VIC-CropSyst), an ecohydrologic model (RHESSys), a biogenic emissions model (MEGAN), and a nutrient export model (Global-NEWS).

Results demonstrate that the BC and NBC climate data provide consistent estimates of the climate-driven changes in water fluxes (ET, runoff, and water demand), VOCs (isoprene and monoterpenes) and NO emissions, mean crop yield, and river DIN export over the PNW domain. However, significant differences rise from projected SWE, crop yield from dry lands, and HJ Andrews's ET between BC and NBC data. Even though BC post-processing has no significant impacts on most of the studied variables

when taking PNW as a whole, their effects have large spatial variations and some local areas are substantially influenced. In addition, there are months during which BC and NBC post-processing produces significant differences in projected changes, such as summer runoff. Factor-controlled simulations indicate that BC post-processing of precipitation and temperature both substantially contribute to these differences at region scales.

We conclude that there are trade-offs between using BC climate data for offline CCI studies vs. direct modeled climate data. These trade-offs should be considered when designing integrated modeling frameworks for specific applications; e.g., BC may be more important when considering impacts on reservoir operations in mountainous watersheds than when investigating impacts on biogenic emissions and air quality (where VOCs are a primary indicator).

1 Introduction

"To bias correct or not?" is debated in the scientific community (Ehret et al., 2012; Hagemann et al., 2011; Muerth et al., 2013). Bias correction (BC) discussed here is the process of adjusting Global Climate Model (GCM) or Regional Climate Model (RCM) output – mainly temperature (T) and precipitation (P) – depending on discrepancies between observed and modeled results over the period of observation. While BC is a post-processing step that is a widely applied for climate change impact (CCI) studies, there are several known issues. One concern is that most studies that use BC GCM/RCM data without adequate quantification of the effects of BC therefore introducing additional uncertainties (Ehret et al., 2012; Muerth et al., 2013; Teutschbein and Seibert, 2012).

Bias in climate models can be attributed to uncertainties in representations of atmospheric physics (Maraun, 2012), boundary conditions and initialization (Bromwich et al., 2012), inadequate reference datasets such as reanalysis data (Dee et al., 2010, 2011; Thorne and Vose, 2010), climate variability (Ehret et al., 2012), limitations in input

BGD
10, 17145–17192, 2013
Importance of climate model bias on land surface processes
M. Liu et al.

data resolution (Wood et al., 2011), and simplifications required due to limited computing capacity. BC of GCM/RCM output as a post-processing step has been used to address this deficiency (Wood et al., 2004). While GCMs/RCMs should continue to be developed to improve predictability, current deficiencies in GCMs/RCMs often necessitate correction of resulting climate biases to make the data useful as input for CCI studies.

Ehret (2012) reviewed the problems in using BC GCM/RCM data, including problematic assumptions of stationarity of the error statistics, independently adjusting climate variables, and lack of a physical basis. Several recent studies have questioned the validity of common assumptions for BC process (Berg et al., 2009; Christensen et al., 2008; Haerter et al., 2011; Hagemann et al., 2011; Johnson and Sharma, 2012; Maraun, 2012; Piani et al., 2010; Vannitsem, 2011). Recent advancement in BC methodology is attempting to address some of these shortcomings. There are methods that allow correction of biases in T and P while preserving the relationships between them (Hoffmann and Rath, 2012; Piani and Haerter, 2012) and attempts to allow non-stationary BC (Buser et al., 2009). Vannitsem et al. (2011) question the utility of BC particularly in the context of decadal forecasts of a transient climate, which is a time scale of importance in many impact studies – many state planning agencies operate on a 20 yr horizon, irrigation infrastructure and farm machinery often have 10 yr investment pay back periods, perennial crops have investment horizons of 10 to 30 yr.

Although the deficiencies of BC are known, the effects of BC on the climate change signal and hence the consequences of BC on hydrometeorology, biogeochemistry, ecological and agricultural estimates are still unclear. Recently, some studies have attempted to quantify the effects of bias correcting input climate data on model outcomes (Chen et al., 2011; Hagemann et al., 2011; Muerth et al., 2013). Results indicate that although BC better reproduces historical observations, it can also alter the climate change signal for certain locations (Hagemann et al., 2011), and/or for certain indicators (Muerth et al., 2013). However, these studies are currently limited to stand-alone hydrologic models. There is a need to characterize how bias correction of modeled cli-

BGD
10, 17145–17192, 2013

mate data affects projection of land surface processes, including water quality/quantity, ecosystem productivity, and emissions of reactive species that influence air quality.

As Earth System models (EaSM) currently stand, there are trade-offs associated with the decision to use offline (with BC) or online (without BC) simulations. While bias correction enhances model skill with respect to observations, it often violates laws for conservation of mass and energy that are fundamental to non bias-corrected models. Although NBC climate predictions are often inconsistent with observations on absolute magnitudes, CCI studies based on these data sets or online models have an assumption that models which get current processes wrong can still accurately characterize changes between current and future conditions. The central question this paper addresses is: to what extent do outputs from NBC models and BC post-processes differ, and when these outputs differ, what are the implications of these differences?

The objective of this work is to understand and quantify the sensitivity of multiple decision-relevant variables (related to hydrology, agriculture, ecosystems, air quality and nutrient export) to the bias-correction post-process on climate data. To achieve this objective, we use both BC and NBC meteorological variables as input to drive impact models which cover macro and watershed-scale hydrology, crop growth and phenology, river nutrient export, and biogenic emissions. This allows EaSM teams to make better informed decisions on the tradeoffs that exist when developing an integrated modeling application for a specific natural or agricultural management question.

2 Methods

2.1 Study domain description

The domain of this study is the US Pacific Northwest region (PNW), which includes the Columbia River Basin (CRB) and coastal watersheds in the states of Washington and Oregon (Fig. 1). The region supports a vast array of agricultural and natural resources. However, due to its winter-dominated precipitation therefore large seasonal storage of water as snowpack, this region is facing substantial risk from global warming (Adam et al., 2013; Liu et al., 2013; Mote, 2003). Farmland occupies 11 % of the CRB, with a highly diverse mix of crops, including alfalfa, hay, winter wheat, apples, sweet corn, potatoes, and sugar beets (National Research Council, 2004). Across the PNW region, 31 % of all farmland is irrigated and 70 % of this land area is irrigated from surface water (USDA National Agricultural Statistics Service, 2008).

For investigating impacts on forest ecosystem, we perform a watershed-scale simulation on the National Science Foundation (NSF) Long-Term Ecological Research (LTER) HJ Andrews site in central Oregon (see inset in Fig. 1). Located along the western slopes of the Cascade Mountain Range, the site encompasses 64 km^2 and extends to the Lookout Creek Watershed boundaries, which drains to the McKenzie River.

2.2 Land surface model descriptions

Impact models being used for this study are major components from a proposed regional earth system model (BioEarth) which aims to improve understanding of interactions among carbon, nitrogen, and water at the regional scale, in the context of global change, to inform decision makers' strategies regarding natural and agricultural resource management (Adam et al., 2013). These models include a macro-scale hydrologic model (VIC), a coupled cropping system model (VIC-CropSyst), an ecohydrologic model (RHESSys), a biogenic emissions model (MEGAN), and a nutrient export model (Global-NEWS). Each of these models is described briefly below.

The Variable Infiltration Capacity (Liang et al., 1994) model is a fully-distributed, physically-based macro-scale model which solves the water and energy budgets for every grid cell in the study domain. It was developed for large-scale applications (1/16th–2°), and sub-grid heterogeneities in land cover and topography is considered. VIC accounts for key moisture and energy fluxes between the land surface and the atmosphere and includes algorithms for shallow subsurface (frozen and unfrozen) moisture, snow, lake, and wetland dynamics (Andreadis et al., 2009; Bowling and Lettenmaier, 2010; Cherkauer and Lettenmaier, 2003). VIC has been applied over all continental land areas, and has been used extensively over the PNW (Adam et al., 2009; Elsner et al., 2010; Hamlet et al., 2007, 2012; Hamlet and Lettenmaier, 2005; Liu et al., 2013; Maurer et al., 2002). In this application, we use the implementation (version 4.0.7) described by Hamlet et al. (2012).

CropSyst (Stöckle et al., 1994, 2003) is a field scale, multi-year, multi-crop model developed to serve as an analytical tool to study the effect of climate, soils, and management on cropping systems productivity, nutrient cycling and fate, and the environment. Management options include crop rotation, cultivar selection, irrigation, nitrogen fertilization, tillage operations, and residue management. CropSyst has been evaluated and used in the PNW (e.g., Peralta and Stöckle, 2002) and around the world (e.g., Stöckle et al., 2003). A simplified version of CropSyst that focuses on water use and productivity was extracted for coupling with the VIC hydrology model (VIC-CropSyst v1.1; Rajagopalan et al., 2013). VIC passes meteorological and hydrological parameters to CropSyst and CropSyst handles crop growth and passes irrigation demand to VIC. The crop distribution and irrigation extension was generated from cropland data of the Washington State Department of Agriculture and the Cropland Data Layer from United States of Department of Agriculture (USDA) (USDA National Agricultural Statistics Service Cropland Data Layer, 2011). Irrigation extent outside Washington State is identified from survey data. All irrigated croplands are assumed to be managed with ideal irrigation practices, i.e. without drought-induced interruptions to water rights (Yorgey et al., 2011).

The Regional Hydrologic-Ecologic Simulation Systems (RHESSys v5.15; Tague and Band, 2004) is a physically-based watershed-scale eco-hydrological model designed to simulate climate and land use change impacts on ecosystem carbon and nutrient cycling and hydrology. It uses an adaptation of BIOME-BGC (White and Running, 1994) and a modified version of the Century-NGAS model (Parton et al., 1993) to simulate above and below ground carbon and nitrogen processes. RHESSys fully couples these biogeochemical processes with a spatially-distributed hydrologic model. RHESSys has

BGD
10, 17145–17192, 2013

been applied in a number of different environments, including watersheds in the PNW (e.g. Christensen et al., 2008; Meentemeyer and Moody, 2002; Tague and Grant, 2009; Tague et al., 2007, 2008a, b, 2009, 2013; Zierl and Bugmann, 2005).

The Model of Emissions of Gases and Aerosols from Nature (MEGAN v2.1; Guenther et al., 2012) incorporates recent advances in the understanding of the processes controlling biogenic emissions (e.g., solar radiation, temperature, soil moisture, carbon dioxide concentration, vegetation type, leaf age, and LAI) at a resolution suitable for regional modeling. While MEGANv2.1 can be run as an offline model or as an integrated component of land surface and atmospheric chemistry models, we used the offline version for this study. As we are most interested in examining the climate change impacts on biogenic emissions, the land cover used in all simulations were kept constant (i.e. 2008 conditions) based on MODIS LAI and plant functional types (PFTs) (Guenther et al., 2012; http://acd.ucar.edu/~guenther/MEGAN/MEGAN.htm).

The Global Nutrient Export from Water(S)heds (Global NEWS v2.0) model predicts annual average export of multiple forms of carbon and multiple nutrients as a function of climate, basin characteristics, and human activities within watersheds. NEWS submodels have been applied broadly to understand land-to-ocean transport of carbon and nutrients at regional and global scales (Dumont et al., 2005; Harrison et al., 2005a, b, 2010; Mayorga et al., 2010; Seitzinger et al., 2005, 2010). More recently, NEWS submodels have been successfully applied at regional and sub-basin spatial scales and at monthly time scales (Harrison et al., 2010; Thieu et al., 2010) and in hindcast and scenario modes to examine historic and potential future changes in coastal nutrient loading (Seitzinger et al., 2010). For this study, we apply the NEWS-DIN model to simulate the dissolved inorganic nitrogen (DIN) export from the CRB as a result of human activities, natural processes, and in-stream removal process (Dumont et al., 2005; Mayorga et al., 2010; Seitzinger et al., 2002). For this study, nutrient loading and reservoir information used to NEWS are derived from prior global-scale analyses (Bouwman et al., 2010; Van Drecht et al., 2009).

BGD
10, 17145–17192, 2013

2.3 Climate data

The climate data for this study are downscaled from a coupled global general circulation model consisting of ECHAM5 (the atmospheric component) (Roeckner et al., 1999, 2003) and the Max Planck Institute Ocean Model (MPI-OM; Marsland et al., 2003) (the ocean component). For historical period (1970–1999), the ECHAM5/MPI-OM simulations of the 20th century forced by historical greenhouse gas concentration, aerosol, and solar forcing were used; for the 21th Century, simulated results with the A1B emissions scenario of the Special Report on Emissions Scenarios (SRES) were used. The A1B is a medium-high greenhouse gas emission scenario that is for "business as usual" in the first half of the 21st century with greater mitigation in the second half, and a balanced energy system (Nakicenovic and Swart, 2000). Downscaling was performed by combining the Weather Research and Forecasting (WRF; Skamarock et al., 2008) regional-scale weather model with a post-processing Bias-Correction Spatial-Disaggregation (BCSD) approach (Salathe et al., 2010, 2013; Wood et al., 2002, 2004). First the WRF simulations of temperature (T), precipitation (P), and wind speed at 12 km × 12 km resolution and 6 h time step were aggregated to daily average T and wind speed and daily total P. The daily maximum and minimum T were identified from these 4 sub-daily records. These data were then downscaled to 1/16th degree with the Symap algorithm which uses a four nearest-neighbor inverse-distance weighting approach (Maurer et al., 2002; Shepard, 1984). Re-gridded T and P were then subjected to BC by using a quantile mapping approach applied at daily time step (Wood et al., 2002). Re-gridded wind speed from WRF was applied directly without BC. The observed training data for the quantile mapping were from gridded historical T and P (Elsner et al., 2010; Hamlet et al., 2012; which were also used in this study as baseline runs for the 1980s) and applied to WRF-simulated variables for both historical and future periods (Table 1). The wind-speed data in the observed historical climate were regridded from reanalysis data (Elsner et al., 2010). The assumption for this quantile-based BC approach is that historical biases in WRF simu-

BGD
10, 17145–17192, 2013

lations are comparable to those that would occur over future climates (Salathe et al., 2013). In the bias-correction and spatial-disaggregation processes, the downscaling largely preserved the spatial details of precipitation and temperature from the regional climate model while removing systematic biases when comparing with observations without losing the simulated spatial correlation between T and P (Salathe et al., 2013; Wood et al., 2002). Themessl et al. (2011) provided a detailed review on seven major statistical-downscaling and bias-correction approaches and concluded that quantile mapping has advantages in removing regional climate model deficiencies in the entire P distribution (including mean, day-to-day variability, and extremes). Recently, basing on the BCSD approach, a new archive of downscaled Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012) climate projections for the conterminous United States, called NASA Earth Exchange (NEX) Downscaled Climate Projections at 30 arcsec (NEX-DCP30), has been generated from NEX platform and distributed through the NASA Center for Climate Simulation (NCCS) (Thrasher et al., 2013). NEX-DCP30 contains more than 100 downscaled climate projections from 33 CMIP5 GCMs and 4 RCP scenarios (Thrasher et al., 2013). This case study on the hydrologic and biogeochemical consequences from the BCSD quantile mapping approach can provide valuable information to impact communities in using this data set and the typical statistical-downscaling method.

The VIC model uses daily T (including daily maximum and minimum T) and P to simulate other meteorological variables including short- and long-wave radiation, surface temperature, and relative humidity by solving surface energy budget equations and using algorithm from the Mountain Microclimate Simulation Model (MTCLIM; Bohn et al., 2013; Hungerford et al., 1989; Kimball et al., 1997; Thornton and Running, 1999; Thornton et al., 2000) (Liang et al., 1994; Maurer et al., 2002). RHESSys uses similar approach to estimate other meteorological variables relaying on T and P (Tague and Band, 2004). The meteorological driving forces for MEGAN were from VIC-modeled variables including surface temperature, short- and long-wave radiation, and humidity (Fig. 2).

BGD
10, 17145–17192, 2013

2.4 Simulation experiments

To quantify the effects of BC (individually on T and P, as well as the combined effects) on projected land surface response, different combinations of BC and NBC climate data are used to drive these models (Table 1). Figure 2 demonstrates the information and work flow between each model and data source. For the RHESSys simulations, we estimate forest net primary productivity (NPP) in response to climate variation, without accounting for disturbances and changes in nitrogen limitation. Global NEWS uses annual outputs of surface runoff and baseflow from VIC offline simulations as well as irrigation water demand from VIC-CropSyst.

The following terrestrial responses to climate change and bias-correction post-process are investigated: hydrological processes (evapotranspiration, ET; runoff; and snowpack water equivalent, SWE), agricultural processes (crop yields, CY; and irrigation water demand, WD), emissions of gases that contributes to ozone and aerosol formation in the atmosphere (isoprene; monoterpenes; and nitrogen monoxide, NO), river export of DIN, and forest NPP (Fig. 2). Except MEGAN, all model simulations are performed for three 30 yr periods: 1970–1999 (hereafter, 1980s), 2010–2039 (2020s), and 2040–2069 (2050s). For each 30 yr period, only the last 25 yr' simulated results are counted for analyses so that it provides a 5 yr model spin-up. MEGAN simulations are conducted with 25 yr averaged climate data for each period.

2.5 Attributing individual and combining effects of T&P bias-corrections

The projected impact of climate change on a given variable is quantified as a percent change (Eqs. 1 and 2).

$$\Delta \mathrm{BC}_{T\&P,t}(\%) = \frac{\mathrm{BC}_{T\&P,t} - \mathrm{BC}_{T\&P,1980s}}{\mathrm{BC}_{T\&P,1980s}} \times 100\,\% \tag{1}$$

$$\Delta \mathrm{NBC}_{T\&P,t}(\%) = \frac{\mathrm{NBC}_{T\&P,t} - \mathrm{NBC}_{T\&P,1980s}}{\mathrm{NBC}_{T\&P,1980s}} \times 100\,\% \tag{2}$$

BGD
10, 17145–17192, 2013

where t is time period in the future; i.e., 2020s or 2050s; ΔBC(%) is the estimated change in percentage based on BC climate data while ΔNBC(%) is the delta change from NBC data; $\mathrm{BC}_{T\&P,t}$ ($\mathrm{NBC}_{T\&P,t}$) is the simulated results during period t with BC(NBC) data; $T\&P$ represents both $T\&P$ are bias-corrected or both of them are non-bias-corrected. The total BC-derived discrepancy in the projected impact was calculated with Eq. (3).

$$\mathrm{eff}_{T\&P,t} = \Delta\mathrm{BC}_{T\&P,t}(\%) - \Delta\mathrm{NBC}_{T\&P,t}(\%) \tag{3}$$

The rationale for calculating this discrepancy is that, while there might be significant differences in simulated variables driven by BC and NBC climate data, the estimated relative change in percentage between the future and historical periods may possibly not be as dissimilar because the BC process is designed to conserve the deltas of $T\&P$ between future and historical periods. In this case, $\mathrm{eff}_{T\&P,t}$ from Eq. (3) would be small enough so that the BC process would not be necessary for this certain variable if its relative change is the major considerations in decision-making process.

We also consider the individual roles that BC of P and T have on these deltas and discrepancies. Eq. (6) is used to quantify the impact due to BC of T but not P, and Eq. (7) was used to quantify the impact due to BC of P but not T.

$$\Delta\mathrm{BC}_{\mathrm{T,t}}(\%) = \frac{\mathrm{BC}_{T,\wedge P,t} - \mathrm{BC}_{T,\wedge P,1980\mathrm{s}}}{\mathrm{BC}_{T,\wedge P,1980\mathrm{s}}} \times 100\,\% \tag{4}$$

$$\Delta\mathrm{BC}_{\mathrm{P,t}}(\%) = \frac{\mathrm{BC}_{\wedge T,P,t} - \mathrm{BC}_{\wedge T,P,1980\mathrm{s}}}{\mathrm{BC}_{\wedge T,P,1980\mathrm{s}}} \times 100\,\% \tag{5}$$

$$\mathrm{eff}_{T}^{t} = \frac{[\Delta\mathrm{BC}_{T\&P,t}(\%) - \Delta\mathrm{BC}_{P,t}(\%)] + [\Delta\mathrm{BC}_{T,t}(\%) - \Delta\mathrm{NBC}_{T\&P,t}(\%)]}{2} \tag{6}$$

$$\mathrm{eff}_{P}^{t} = \frac{[\Delta\mathrm{BC}_{T\&P,t}(\%) - \Delta\mathrm{BC}_{T,t}(\%)] + [\Delta\mathrm{BC}_{P,t}(\%) - \Delta\mathrm{NBC}_{T\&P,t}(\%)]}{2} \tag{7}$$

BGD
10, 17145–17192, 2013

where $\Delta BC_{T,t}$(%) and $\Delta BC_{P,t}$(%) are BC of T-only and BC of P-only caused percentage change; eff_T^t and eff_P^t are average effects of BC of T and BC of P, respectively, under the context of interactions between T&P; ^ represents without BC.

3 Results

We first discuss the changes to the climate signal (Sect. 3.1) and then discuss how this climate change signal translates into impacts on hydrologic and biogeochemical processes at both annual (Sect. 3.2) and seasonal (Sect. 3.3) time scales. Finally, we discuss the relative effectives of BC on T and P to the overall change signal (Sect. 3.4).

3.1 BC and NBC climate data over the historical and future periods

When spatially averaged over the study domain, there is a significant difference between non bias-correcting downscaled climate data of the 1980s (i.e., NBC climate) and observations. NBC has a mean annual T and P which is 2.7 °C lower and 156 mm yr^{-1} (or 17 %) higher than observations, respectively (Table 2). After BC, the modeled climate closely matches the observations (Table 2) as expected (i.e. Salathe et al., 2013; Wood et al., 2002). The absolute projected climate change signal in T (ΔT) in the 2020s and 2050s as compared to 1980s is preserved in the BC process (Table 2, Fig. 3). ΔT is approximately 1 °C for the period 1980s–2020s and 2.5 °C for the period 1980s–2050s for both BC and NBC cases. The projected climate change signal of P is a little higher under BC. P increases by 45 mm yr^{-1} (or 5.2 %) under BC and 37 mm yr^{-1} (or 3.5 %) under NBC for the period 1980s–2020s, and 97 mm yr^{-1} (or 11.1 %) under BC and 89 mm yr^{-1} (or 8.5 %) under NBC for the period 1980s–2050s. Overall, the average differences between BC and NBC in ΔT and percentage rate of change in P [ΔP (%)] over these two time periods (i.e., 1980s–2020s and 1980s–2050s) are insignificant; i.e., 0.03 °C (student's t test on anomaly in annual mean, $p = 0.89$) and 2.1 % (student's t test on anomaly in annual precipitation, $p = 0.72$) (Fig. 4).

BGD
10, 17145–17192, 2013

The downscaled ECHAM A1B simulation suggests that projected increases in T and P are greater in the southern PNW than in the western and central PNW in the next half century (Fig. 5a and b). Overall, BC post-processing of the downscaled climate has generally conserved the spatial patterns of ΔT and ΔP (%) over the study domain (as compared to the original NBC climate) (Figs. 3, 4, 5a and b). However, in certain regions, such as the central floodplain between the Cascade and Rocky Mountains, the BC climate change signal ΔP (%) is 5–10 % higher than the NBC climate signal over the period of 1980s–2050s (Fig. 5b).

3.2 Impacts of BC on annual-scale hydrological and biogeochemical processes

3.2.1 Impacts on large-scale hydrology (VIC simulations)

Evapotranspiration

ET, including soil evaporation, canopy evaporation, and plant transpiration, is the total water vapor leaving the land surface to the atmosphere and is controlled by the availability of energy and water. Climate change affects ET by altering both energy and moisture availability. VIC simulations indicate that both BC and NBC climate data result in 3 % and 12 % increases in ET during 1980s–2020s and 1980s–2050s, respectively (Table 2, Fig. 3). There are no significant differences in overall ET projections ($p = 0.52$ and 0.83 over ET anomalies in 2020s and 2050s, respectively) (Fig. 4). However, there is a large spatial variation in the ET climate change signal between BC and NBC climate inputs especially in the 2050s. Figure 5c shows that BC climate projects lower ΔET(%) in high-mountainous regions such as north Cascade Ranges and the Rocky Mountains, and higher ΔET(%) in plains such as the floodplain of the Snake River and the Harney Basin, than NBC climate inputs.

BGD
10, 17145–17192, 2013

Runoff

Runoff, including baseflow and surface runoff, is the total water that flows to rivers and reservoirs. Most of the runoff in the PNW is generated from the mountainous regions (Fig. 5d). Both BC and NBC climates predict increasing runoff in the future. BC climate data project increases by 6.7 % and 11.1 % in the periods of 1980s–2020s and 1980s–2050s, respectively; while NBC climate project lower increasing rates (by 3.7 % and 6.6 %, respectively) (Table 2, Figs. 3 and 4). The largest increase (up to 20 %) in runoff occurs near the confluence of the Yakima, Snake, and Columbia rivers in Washington, Harney Basin in Oregon, Salmon River Mountains in Idaho, and the mountainous areas in the northern PNW (Fig. 5d).

Snowpack water equivalent (SWE)

1 April SWE is a commonly-used indicator of water resources availability in the western US because melting of the snowpack generates spring-summer peak flows (Adam et al., 2009; Barnett et al., 2005; Hamlet et al., 2005). Model estimates show that the mountainous areas of the northern Cascade and Rocky Mountains have larger SWE storage than any other regions in the PNW (Fig. 5e). With the projected warming trend in the future, SWE will continuously decrease between the 1980s and 2050s. The BC climate change signal of 1 April SWE is significantly weaker than the NBC signal. BC climate projects SWE decreases of 4.8 % and 21.6 % in the periods 1980s–2020s and 1980s–2050s, respectively, which are much lower than the change signal projected by NBC climate (11.7 % and 44.3 %, respectively) (Table 2, Figs. 3 and 4). The differences between BC- and NBC-derived ΔSWE(%) are significant in both time periods ($p = 0.03$ for anomalies in 2020s and $p < 0.001$ for anomalies in 2050s) (Fig. 4). There are also significant spatial differences in the climate change signal of SWE between BC and NBC climate inputs. For the Northern Rocky Mountains, the NBC climate change signal is negative, whereas the BC climate change signal is positive (Fig. 5e).

3.2.2 Impacts on croplands (VIC-CropSyst simulations)

Crop yield and irrigation water demand are important factors in a farmer's decision making processes. In this domain, over 40 types of crops, including tree fruits, grains, cereals, vegetables and crop for forage are simulated by VIC-CropSyst. The crop yield in each grid cell and the regional mean crop yield are calculated as area-weighted average yields in this analysis (Fig. 5f).

Crop yield

BC has a large effect on estimated crop yield by VIC-CropSyst. Over the historical period, the total crop yield from BC and observed climate data are similar (31.1 and 29.6 million t (MT), respectively) while the NBC climate data resulted in a much higher crop yield (46.1 MT) (Table 2, Fig. 3). The major difference in estimated yields among NBC, BC and observed climate data occurs over dryland (non-irrigated) crops (Fig. 5f). Both projected BC and NBC climate will cause large increases in total yield in the 2020s and 2050s (Table 2, Fig. 5f). Again, the crop yield change signal is significantly different in dryland crops, while they are similar for irrigated crops between BC and NBC climate (Table 2, Figs. 3, 4, 5f and g). Note, however, that we made an assumption of full irrigation requirements being met for the irrigated crops.

Water demand (WD) over the irrigated area

Water demand is defined as the irrigation water required by crops to reach their potential yield. Observed, BC, and NBC climate produce significantly different estimations on water demand during the 1980s, i.e. 21.31, 25.36, and 17.75 billion $m^3 yr^{-1}$, respectively (Table 2). While, taking the PNW as a whole, both BC and NBC climate data predict insignificant changes during periods of 1980s–2020s and 1980s–2050s (Table 2, Figs. 3 and 4). However, there are large spatial variations in projected WD changes (Fig. 5g). Generally, WD decreases in central Washington and southern Idaho during the 2020s.

BGD
10, 17145–17192, 2013

In the 2050s, the irrigated area near the mountainous area shows an increase in WD, particularly based on NBC climate data, with strong decreases elsewhere in the basin (Fig. 5g). Overall, BC does impact projected changes in WD for the whole domain, but there is significant spatial variability in both the sign and magnitude of this impact (Fig. 5g).

3.2.3 Impacts on biogenic VOC and NO emissions (MEGAN simulations)

One of several mechanisms by which climate change affects air quality is by changing emissions of ozone and aerosol precursors, such as isoprene, monoterpene, and nitrogen oxides ($NO_x = NO + NO_2$), from the terrestrial ecosystems. Under projected future warmer climate over the PNW, isoprene, monoterpenes, and NO emissions are expected to increase from current emission levels as they are highly dependent on T (Guenther et al., 2012). The observed climate resulted in annual and area averaged isoprene emissions of 67 $\mu g\,m^{-2}\,h^{-1}$ over the simulation domain (Table 2). The highest emissions (> 120 $\mu g\,m^{-2}\,h^{-1}$) occur in the conifer-dominated forests on the western side of the Cascade Mountains, where temperature is also the highest (Fig. 5h). The lowest emissions occur in high elevation areas where temperatures are lowest (Fig. 5h). The magnitude of annual monoterpene emissions is on the same order as isoprene emissions (59 $\mu g\,m^{-2}\,h^{-1}$ for the whole domain) (Table 2). The highest monoterpene emissions appear in the west side of the Cascades, while the lowest occur in central and southern part of the domain, which are dominated by crop, shrub, and grasslands (Fig. 5i). NO emissions are the highest over the agricultural areas, with an average rate of 0.3 $\mu g\,m^{-2}\,h^{-1}$ over the whole domain (Fig. 5j).

Driven by BC climate data, MEGAN estimates slightly lower isoprene, monoterpenes, and NO emission rates by 1.2 % than by observed meteorological data (Table 2). In contrast, NBC climate underestimate by 49 %, 31 %, and 36 % on isoprene, monoterpenes and NO emissions respectively, comparing with observed meteorological data.

BGD
10, 17145–17192, 2013

Both BC and NBC cases project increasing emission trends in future climate, but the projected emission rates vary significantly. For example, isoprene emission is projected to increase from 65 $\mu g\,m^{-2}\,h^{-1}$ in 1980s to 75 $\mu g\,m^{-2}\,h^{-1}$ in 2020s with BC climate vs. 33 $\mu g\,m^{-2}\,h^{-1}$ in 1980s to 38 $\mu g\,m^{-2}\,h^{-1}$ in 2020s with NBC climate. Even though the magnitude of the estimated emission rates differ by a factor of two, the projected percent increases are similar. Isoprene, monoterpene, and NO emissions are projected to increase by 14 %, 9 %, and 10 % during 1980s–2020s and increase by 43 %, 28 %, and 13 % during 1980s–2050s, respectively, under both BC and NBC climate. Hence, in comparison to other CCI variables, BC has a small effect on the climate change signal for the biogenic emissions considered in this study (Table 2).

3.2.4 Impacts on export of dissolved inorganic nitrogen from the land to the ocean (NEWS simulations)

The concentration of DIN in streams and reservoirs is an important indicator for water quality and health of terrestrial ecosystems. For this study, Global NEWS simulates the DIN export from the CRB, which covers 85 % of the study domain (Fig. 1). For the 1980s, NEWS estimates an average DIN yield (i.e., the average DIN leaching from the land that is eventually exported to the ocean) to be 153 $kg\,N\,km^{-2}\,yr^{-1}$ by using NBC climate, which is 61 % larger than estimations based on BC and observed climate data (Table 2, Fig. 3). For the future, both BC and NBC cases predict increases in the 2020s and the 2050s, which closely match changes in P (Table 2). However, using NBC climate data results in lower percentage increases than using BC data, although the differences are not statistically significant ($p = 0.83$ and 0.74 for periods of 1980s–2020s and 1980s–2050s, respectively) (Figs. 3 and 4).

BGD
10, 17145–17192, 2013

3.2.5 Impacts on water and carbon fluxes in a small forested watershed (RHESSys simulations)

Evapotranspiration

For this small watershed study site, HJ-Andrews, observed meteorological data and BC and NBC estimates give similar P for the 1980s baseline. NBC data, however, indicate substantially lower T (6.6 °C and 9 °C for observed and BC, respectively). By using observed, BC, and NBC climate data, RHESSys estimates the mean annual ET to be 831, 876, and 743 $\mathrm{mm\,yr^{-1}}$, respectively, for the 1980s period. The lower T in NBC climate data (6.6 °C) results in lower modeled ET (Table 2). For the projection of future ΔET(%), BC and NBC climate produce significant differences over the period of 2020s (Figs. 3 and 4; $p = 0.02$); i.e., using BC climate data leads to a decrease of 3.3 % while using NBC data leads to an increase of 1.6 % (Table 2, Fig. 5k). In comparing ET in the 2050s relative to the 1980s baseline, the BC case predicts a lower ET by 2.7 % while the NBC case shows no significant change in ET (Table 2, Fig. 5k).

Net primary production

NPP is commonly used to provide an estimate of the carbon gained by an ecosystem and develop a carbon balance between the terrestrial biosphere and the atmosphere (Chapin et al., 2002; Clark et al., 2001). In this watershed, NBC climate data (colder) produce higher NPP than BC (warmer) and observed climate data (warmer) during the 1980s (Table 2). Following the ΔET(%), using BC and NBC inputs result in large differences in modeled ΔNPP(%). With BC climate data, RHESSys predicts decreases in NPP by 6.5 % and 4.4 % during the periods of 1980s–2020s and 1980s–2050s, respectively (Table 2). In contrast, using NBC climate data, RHESSys predicts slight increases in NPP for both future periods (Table 2, Fig. 5l). Although the differences in modeled NPP as a function of differences between BC and NBC climate are not statistically significant ($p = 0.12$ and 0.46 for 2020s and 2050s, respectively), they show

BGD
10, 17145–17192, 2013

a clear spatial pattern. Figure 5l shows that large differences in estimated ΔNPP(%) between BC and NBC climate data are concentrated at higher elevations where the NBC case predicts increases while BC results in decreases.

3.3 Impact of BC in estimates of seasonal patterns

To investigate the seasonal shift of CCI on water resources, we analyze the monthly water fluxes and water demand by using VIC offline and VIC-CropSyst simulations (Fig. 2).

3.3.1 Differences in BC and NBC climate data

Figure 6 depicts the average monthly climate (P and T), simulated water fluxes (ET and runoff), SWE, and water demand (WD) with different climate data and periods. BC and NBC climate data exhibit large discrepancies in summer P while they have similar patterns in monthly T (Figs. 6a and b). BC data for ΔP(%) result in greater increases than for NBC data in almost every month, particular between May and October (Fig. 6g). However, the difference between BC and NBC ΔP (%) is not statistically significant ($p > 0.05$) due to large inter-annual variations in monthly P. BC and NBC cases show only small discrepancies in predictions of monthly ΔT over the periods of 1980s–2020s and 1980s–2050s (Fig. 6h).

3.3.2 Seasonal patterns of discrepancies between BC and NBC climate data-driven changes in water fluxes

Figure 6d demonstrates that using NBC climate data (in comparison to BC and observed data) result in a large overestimation of runoff from May to August due to the high SWE for this scenario. Lower T and higher P for the NBC case (relative to the BC case) result in a larger area of snow cover as well as larger snowpack volumes (Fig. 6e). Irrigation WD is greater for the BC case than for NBC, particularly from May to August (Fig. 6f).

BGD
10, 17145–17192, 2013

The differences in predicted percentage change in ET, runoff, SWE, and WD driven by BC and NBC climate data vary seasonally, as depicted in the right panel of Fig. 6. Generally, use of BC (vs. NBC) climate data leads to lower ΔET(%) for the months of June–August in the 2050s (Fig. 6i). However, the differences are not statistically significant except for 2050s July ($p = 0.04$) (Fig. 6i). Use of BC (vs. NBC) produces significant discrepancies in many months for long-term predictions of ΔRunoff(%) (Fig. 6j); e.g., using 2050s BC climate results in higher ΔRunoff (%) in August ($p < 0.001$) and September ($p < 0.001$) by more than 25 %, while this difference is negative for most of the other months. We report very large differences in monthly ΔSWE(%) projections, which are much larger for the 2050s period than for the 2020s (Fig. 6k). BC results in larger SWE increases (in comparison to NBC) throughout the cold season, particularly for the 2050s. For changes in irrigation water demand, ΔWD(%), BC climate results in much larger growing season increases than NBC for the 2020s, although this increase is significant only for September (Fig. 6l). While, the magnitude of these differences between BC and NBC are smaller for the 2050s and vary by month in the sign of this difference; they are generally statistically significant.

3.4 Relative contributions of T and P to the overall differences between BC and NBC climate change impacts

We separate out the individual roles of T&P to differences between climate change projections using BC vs. NBC input datasets (Table 1). These tests showed that BC post-processing of WRF simulated P plays a more important role than BC post-processing of T in impacting changes in runoff, SWE, and dryland crop yield; i.e., using NBC P for CCI analyses can lead to underestimation of the increases in runoff and dry land crop yield and overestimation of the decrease in SWE (Fig. 7). Figure 7 also demonstrates that BC of T is the dominant factor in causing the BC and NBC differences in the projected changes of irrigated crop yield (recall that over-irrigated cropland, we assume that all crop water requirements are met, reducing the potential role of P) in the 2020s and 2050s and long-term ET changes in the 2050s, indicating a primarily energy-limited ET regime (Liu et al., 2013).

Because of non-linear responses of terrestrial ecosystems to climate change, the same amount of absolute change in T&P may produce significant differences in the response of hydrologic and biogeochemical processes when they start from different baselines. Figure 8 demonstrates that in responding to anomalies of T&P in the future, BC and NBC climate inputs result in different sensitivities. Of all of the variables considered, ET and SWE over the PNW, and DIN from the CRB show the greatest sensitivities to the baseline climate condition. As expected, the T baseline plays a strong role in determining SWE changes (Fig. 8c), while DIN changes are most sensitive to gradients in the P baseline (Fig. 8h), and ET changes are equally sensitive to gradients in both T&P (Fig. 8a and b). Furthermore, BC vs. NBC differences in relative sensitivities along the climate gradients exist for most the variables being considered. For example, with increasing T, using NBC climate data produces a linearly-increasing trend in total ET, while using BC climate data results in a relative leveling-off of changes at high T anomalies over the PNW (Fig. 8a). In responding to changes in P along the gradient of annual P, this difference in functional form between NBC and BC is opposite that of T (Fig. 8b).

4 Discussion

Our analysis indicates that the choice of bias-correcting or not bias-correcting downscaled global GCM projected climate could affect estimations on climate change impacts in the future. Non-linear responses of terrestrial ecosystems to climate change in hydrologic and biogeochemical processes can partly explain this phenomenon in the modeling realm. The spatial variations in different quasi-equilibria among local biotic and abiotic environment such as climate, vegetation, geology, and topology, etc., introduce more complexities to these uncertainties in regional assessments. Therefore, when using projected results from GCM and regional climate models, uncertainty

BGD
10, 17145–17192, 2013

analysis should be conducted, particularly in situations where some post-processing procedures such as BC, which is based on contemporary observational data, are involved.

Biases from not performing BC of modeled climate prior driving impact models may be obvious in some cases. Failing to account for BC impacts on snow processes could produce misleading projections on future water availability, an issue of importance to both ecosystems and society. BC (vs. NBC) climate data, results in fewer perceived threats to society and ecosystems, less shrinkage of the snowpack, higher crop yields, and lower water demand. However, due to the complex interactions between land surface and atmospheric processes, there are potentially large consequences that may be neglected in designing the level of model integration needed for a specific application, including the decision of whether or not to perform BC. While our study suggested that BC may not be necessary for projecting the impacts of climate change on the magnitude of some biogenic emissions, there are important air quality implications to not performing BC. For example, underestimation of biogenic VOCs emissions may affect the prediction of secondary organic aerosol (SOA) and thus fine particulate matter ($PM_{2.5}$) concentrations, which are important for predicting air quality and aerosol-climate implications.

As stated in the introduction, a fundamental assumption in using models to project climate change impacts is that models can predict the relative change of a variable of interest in response to climate change reasonably well, even if model prediction of the actual value of the variable is biased. As noted in Sect. 3.2.3, this assumption holds true for biogenic VOC emissions in the PNW case studied here, i.e. despite the large differences in estimated biogenic VOC and NO emission rates using BC vs. NBC data, the projected percent increase from the 1980s to future climate conditions are very similar; however, this assumption has not been evaluated with respect to model predictions of ozone and $PM_{2.5}$ concentrations, the key decision-making variables for air quality management.

BGD

10, 17145–17192, 2013

While dynamic downscaling of GCM in combination with chemical transport models has been widely used to study the impact of climate change on regional air quality (Avise et al., 2009, 2012; Chen et al., 2009a, b; Dawson et al., 2009; Lam et al., 2011; Nolte et al., 2008), to our knowledge, no studies have applied bias correction to RCM output in air quality modeling studies. One reason for this is because chemical transformation and physical transport of atmospheric pollutants and their precursors depends on knowledge of several climate variables in three-dimensional space. In contrast to T&P at the surface, necessary observational data in three-dimensional needed to apply BC are sparse. To assess how bias in climate model results affect projections of ozone, SOA, and $PM_{2.5}$ changes requires detailed analysis with the use of chemical transport models, that not only accounts for the changing emission rates but also explicitly simulates the non-linear, meteorological-dependent processes of ozone and SOA chemistry and atmospheric transport.

There are other limitations in this study. For example, we only quantified the effects of BC of T and P on CCI of regional hydrology, agricultural activities, and biogenic VOC and NO emissions. All other related climate factors including wind speed, relative humidity, and radiations are either based on reanalysis data or modeled by VIC model (Hamlet et al., 2007; Maurer et al., 2002; Salathe et al., 2013). Even though the derived climate factors from T&P by using MT-CLIM model have been evaluated against field observations (Bohn et al., 2013; Thornton and Running, 1999), the spatiotemporal relationships within climate variables in contemporary periods may change over the long-term future. Therefore, the CCI studies by only use climate change information of T&P can produce large uncertainties. Each bias-correction and downscaling approach may have individual advantage and weakness in reconstructing the spatial and temporal patterns of T and P, and extreme events (Maurer and Hidalgo, 2008; Quintana Segui et al., 2010; Themessl et al., 2011). Estimating the sensitivities of different downscaling methods on the hydrologic and ecological impacts is meaningful and necessary for quantifying the uncertainties from certain downscaled climate data in regional applications. This effort could be an extension of current intercomparisons on global GCMs

BGD
10, 17145–17192, 2013

and activities on model-data intercomparisons over carbon, water, and crops at continental and global scales (Asseng et al., 2013; Huntzinger et al., 2012; Rosenzweig et al., 2013; Taylor et al., 2012).

5 Conclusions

Herein, we quantify the effects of bias correction (BC) of climate model output on climate change impact (CCI) projections of regional and watershed-scale hydrologic and biogeochemical processes. As expected (due to the BC methodology), using BC climate data produced almost the same simulated results as using gridded meteorological observations for the historical time period. Without BC, however, the direct use of modeled climate data by land surface models produced very different hydrologic and biogeochemical results over the historical period. While we anticipated that these differences would be large, an interesting question is the degree to which the *response* to a climate change signal is preserved, even if the baseline climate conditions are not. This is an important question because, in fully coupled land-atmosphere schemes, BC is generally not performed so that dynamical consistency in simulated variables is retained. In doing this, a fundamental assumption is that models can predict the relative change of a variable of interest in response to climate change reasonably well, even if model prediction of the actual value of the variable is biased. Herein, we test whether or not this assumption holds true and for which land surface variables.

Due to the conservation of absolute change of T and percentage rate of change in P during BC post-processing, projected BC and NBC climate data produce somewhat similar results in the percentage rate of change in many of our response variables, including ET, runoff, total crop yield, irrigated water demand, VOC emissions (isoprene and monoterpenes), NO emission, and DIN river export over the Pacific Northwest over the time periods of 1980s–2020s and 1980s–2050s. However, there a few important variables where BC does have a large impact in the response to climate change, notably SWE and dryland (non-irrigated) crop yield. Both of these variables are key decision variables for managing our natural and agricultural resources. Overall, not performing BC would result in an overestimation of the decrease of SWE and an underestimation of the increase in dryland crop yield due to climate change, thus painting a more dire portrait of future conditions than would be suggesting by using BC data. Furthermore, even with variables where we may demonstrate that BC is not important for projecting responses to climate change, there is the potential for a large range of effects when performing land surface simulations with biased climate inputs.

We conclude that there are trade-offs between using BC climate data for offline CCI studies vs. applying coupled regional earth system models that retain dynamical consistency between variables and capture feedback effects. These trade-offs should be considered when designing integrated modeling frameworks for specific applications; e.g., BC may be more important when considering impacts on reservoir operations in mountainous watersheds (where 1 April SWE is an important decision factor) than when investigating impacts on biogenic emissions and air quality (where VOCs are a primary indicator). However, even in these instances where BC may not be deemed important, there may be some important negative consequences to not correcting for bias, such as a host of air quality effects caused by projecting biased values of biogenic emissions.

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Importance of climate model bias on land surface processes

M. Liu et al.

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Table 1. List of climate scenarios for this study. All WRF simulations used as boundary conditions results from the coupled ECHAM5/MPI-OM model run with the IPCC SRES A1B scenario (Salathé et al., 2010, 2013).

Time period	Source	Bias corrected variable	Variable name
1970–1999	Gridded observed	–	OBS
	WRF	$T\&P$	$\mathrm{BC}_{T\&P,1980s}$
	WRF	T	$\mathrm{BC}_{T,1980s}$
	WRF	P	$\mathrm{BC}_{P,1980s}$
	WRF	None	$\mathrm{NBC}_{T\&P,1980s}$
2010–2039	WRF	$T\&P$	$\mathrm{BC}_{T\&P,2020s}$
	WRF	T	$\mathrm{BC}_{T,2020s}$
	WRF	P	$\mathrm{BC}_{P,2020s}$
	WRF	None	$\mathrm{NBC}_{T\&P,2020s}$
2040–2069	WRF	$T\&P$	$\mathrm{BC}_{T\&P,2050s}$
	WRF	T	$\mathrm{BC}_{T,2050s}$
	WRF	P	$\mathrm{BC}_{P,2050s}$
	WRF	None	$\mathrm{NBC}_{T\&P,2050s}$

BGD
10, 17145–17192, 2013

BGD
10, 17145–17192, 2013

Table 2. Changes in climate and simulated variables during the periods of 1980s–2020s and 1980s–2050s, and differences in the changes between results with bias-correction (BC) and without bias-correction (NBC) of climate data.

Period	Variable	T (°C)	P (mm yr^{-1})	VIC offline			VIC-CropSyst (cropland)			
				ET (mm yr^{-1})	Runoff (mm yr^{-1})	SWE (mm H_2O)	Irrigation demand (billion m^3 yr^{-1})	Irrigated cropland yield (MT yr^{-1})	Dryland yield (MT yr^{-1})	Total yield (MT yr^{-1})
1980s (1970–1999)	OBS	6.45	893	410	482	127	21.31	17.7	11.9	29.6
	BC	6.40	877	421	456	105	25.36	20.0	11.1	31.1
	NBC	3.68	1049	393	652	358	17.75	19.7	26.3	46.1
2020s (2010–2039)	BC	7.35	922	437	486	100	25.36	20.9	13.6	34.6
	$\Delta BC^{1}_{20s\text{–}80s}$	0.95	45	15	30	−5	0.00	0.9	2.6	3.5
	Eq. (1): $\Delta BC_{20s\text{–}80s}$(%)		5.2 %	3.6 %	6.7 %	−4.8 %	0.0 %	4.5 %	23.1 %	11.1 %
	NBC	4.60	1086	406	677	316	17.94	21.0	30.0	50.9
	$\Delta NBC^{2}_{20s\text{–}80s}$	0.92	37	13	24	−42	0.19	1.2	3.7	4.9
	Eq. (2): $\Delta NBC_{20s\text{–}80s}$(%)		3.5 %	3.3 %	3.7 %	−11.7 %	1.3 %	6.3 %	13.9 %	10.6 %
	Eq. (3): ΔBC(%) − ΔNBC(%)		**1.6 %**	**0.3 %**	**2.9 %**	**6.9 %**[66]	−1.3 %	−1.8 %	**9.2 %**[6]	**0.5 %**
2050s (2040–2069)	BC	8.92	974	469	506	82	24.91	22.3	17.7	40.1
	$\Delta BC^{1}_{50s\text{–}80s}$	2.52	97	47	51	−23	−0.45	2.3	6.7	8.9
	Eq. (1): $\Delta BC_{50s\text{–}80s}$(%)		11.1 %	11.2 %	11.1 %	−21.6 %	−2.2 %	11.4 %	60.0 %	28.7 %
	NBC	6.17	1138	444	695	199	17.55	22.3	36.5	58.8
	$\Delta NBC^{2}_{50s\text{–}80s}$	2.48	89	52	43	−159	−0.20	2.5	10.2	12.7
	Eq. (2): $\Delta NBC_{50s\text{–}80s}$(%)		8.5 %	13.1 %	6.6 %	−44.3 %	−1.4 %	12.9 %	38.6 %	27.6 %
	Eq. (3): ΔBC(%) − ΔNBC(%)		**2.6 %**	−1.9 %	**4.6 %**	**22.7 %**[6]	−0.8 %	−1.5 %	**21.5 %**[6]	**1.1 %**
Avg. $(\Delta BC - \Delta NBC)^{3}_{2020s,2050s}$		0.03	8.29	−1.04	6.99	86.30	−0.18	−0.22	−2.30	−2.60
Avg. $(\Delta BC(\%) - \Delta NBC(\%))^{4}_{2020s,2050s}$			2.1 %	−0.8 %	3.8 %	14.8 %	−0.8 %	−1.0 %	15.4 %	8.4 %
Avg. $(\mathbf{\Delta BC - \Delta NBC})_{\mathbf{2020s,2050s}}/\mathbf{Obs.}(\%)^{5}$			**0.9 %**	−0.3 %	**1.5 %**	**67.7 %**	−1.0 %	−1.3 %	−19.3 %	−8.8 %

Table 2. Continued.

Periods	Climate data/items	MEGAN			RHESSys (HJ-Andrews)				NEWS (Columbia River Basin Export)		
		Isoprene ($\mu g\,m^{-2}\,h^{-1}$)	Mono-terpenes ($\mu g\,m^{-2}\,h^{-1}$)	NO ($\mu g\,m^{-2}\,h^{-1}$)	T (°C)	P ($mm\,yr^{-1}$)	NPP ($g\,C\,m^{-2}\,yr^{-1}$)	ET ($mm\,yr^{-1}$)	T (°C)	P ($mm\,yr^{-1}$)	DIN ($kg\,N\,km^{-2}\,yr^{-1}$)
1980s (1970–1999)	OBS	66.06	59.28	0.31	9.06	2218	1181	831	6.01	785	100.9
	BC	65.27	58.60	0.30	9.01	2201	1068	876	5.96	768	91.6
	NBC	33.47	40.99	0.21	6.62	2253	1356	743	3.14	961	153.7
2020s (2010–2039)	BC	74.80	64.38	0.34	9.86	2229	998	847	6.93	807	98.3
	$\Delta BC^{1}_{20s-80s}$	9.53	5.78	0.04	0.85	28	−70	−29	0.97	39.17	6.7
	Eq. (1): $\Delta BC_{20s-80s}$(%)	14.6 %	9.9 %	14.6 %		1.3 %	−6.5 %	−3.3 %		5.1 %	7.3 %
	NBC	38.16	44.70	0.23	7.41	2248	1373	755	4.08	995	159.3
	$\Delta NBC^{2}_{20s-80s}$	4.69	3.71	0.03	0.79	−5	17	12	0.94	33	5.6
	Eq. (2): $\Delta NBC_{20s-80s}$(%)	14.0 %	9.1 %	14.2 %		−0.2 %	1.2 %	1.6 %		3.5 %	3.6 %
	Eq. (3): ΔBC(%) – ΔNBC(%)	**0.6 %**	**0.8 %**	**0.4 %**		**1.5 %**	**−7.8 %**	**−4.9 %**[6]		**1.6 %**	**3.6 %**
2050s (2040–2069)	BC	93.47	75.67	0.43	11.15	2316	1021	852	8.55	861	104.8
	$\Delta BC^{1}_{50s-80s}$	28.20	17.07	0.13	2.14	115	−47	−24	2.59	94	13.2
	Eq. (1): $\Delta BC_{50s-80s}$(%)	43.2 %	29.1 %	43.8 %		5.2 %	−4.4 %	−2.7 %		12.2 %	14.4 %
	NBC	47.91	52.31	0.30	8.69	2316	1365	741	5.70	1050	165.0
	$\Delta NBC^{2}_{50s-80s}$	14.44	11.32	0.09	2.07	63	9	−2	2.56	89	11.3
	Eq. (2): $\Delta NBC_{50s-80s}$(%)	43.1 %	27.6 %	43.6 %		2.8 %	0.7 %	−0.3 %		9.2 %	7.3 %
	Eq. (3): ΔBC(%) – ΔNBC(%)	**0.1 %**	**1.5 %**	**0.2 %**		**2.4 %**	**−5.1 %**	**−2.5 %**		**3.0 %**	**7.1 %**
Avg. $(\Delta BC - \Delta NBC)^{3}_{2020s,2050s}$		9.30	3.91	0.03	0.06	42	−71.24	−31.64		5.40	1.50
Avg. $(\Delta BC(\%) - \Delta NBC(\%))^{4}_{2020s,2050s}$		0.3 %	1.2 %	0.3 %		2.0 %	−6.4 %	−3.7 %	0.03	2.3 %	5.4 %
Avg. $(\Delta BC - \Delta NBC)_{2020s,2050s}$/Obs.(%)[5]		**14.1 %**	**6.6 %**	**9.3 %**		**1.9 %**	**−6.0 %**	**−3.8 %**		**0.7 %**	**1.5 %**

[1] ΔBC is the absolute change derived from BC climate between target periods, i.e., $\Delta BC_{20s-80s}$ represents the change between 1980s and 2020s and $\Delta BC_{50s-80s}$ represents the change between 1980s and 2050s.

[2] ΔNBC is the absolute change derived from NBC climate between target periods, i.e., $\Delta NBC_{20s-80s}$ represents the change between 1980s and 2020s and $\Delta NBC_{50s-80s}$ represents the change between 1980s and 2050s.

[3] The difference in absolute change between BC and NBC climate averaged over the changes between 1980s and 2020s and between 1980s and 2050s, i.e., $[(\Delta BC_{20s-80s} - \Delta NBC_{20s-80s}) + (\Delta BC_{50s-80s} - \Delta NBC_{50s-80s})]/2$.

[4] The difference in percentage change between BC and NBC climate averaged over the changes between 1980s and 2020s and between 1980ss and 2050s, i.e., $\{[\Delta BC_{20s-80s}(\%) - \Delta NBC_{20s-80s}(\%)] + [\Delta BC_{50s-80s}(\%) - \Delta NBC_{50s-80s}(\%)]\}/2$.

[5] The percentage difference between BC and NBC climate averaged over the changes between 1980s and 2020s and between 1980s and 2050s and relative to observed climate (or the simulated outputs driven by observed data), i.e., $[(\Delta BC_{20s-80s} - \Delta NBC_{20s-80s}) + (\Delta BC_{50s-80s} - \Delta NBC_{50s-80s})]/(2 \times Obs_{1980s}) \times 100\%$.

[6] This signifies a p value < 0.05 for the student's t test (not applicable for MEGAN results).

BGD
10, 17145–17192, 2013

Title Page
Abstract Introduction
Conclusions References
Tables Figures
◂◂ ▸▸
◂ ▸
Back Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

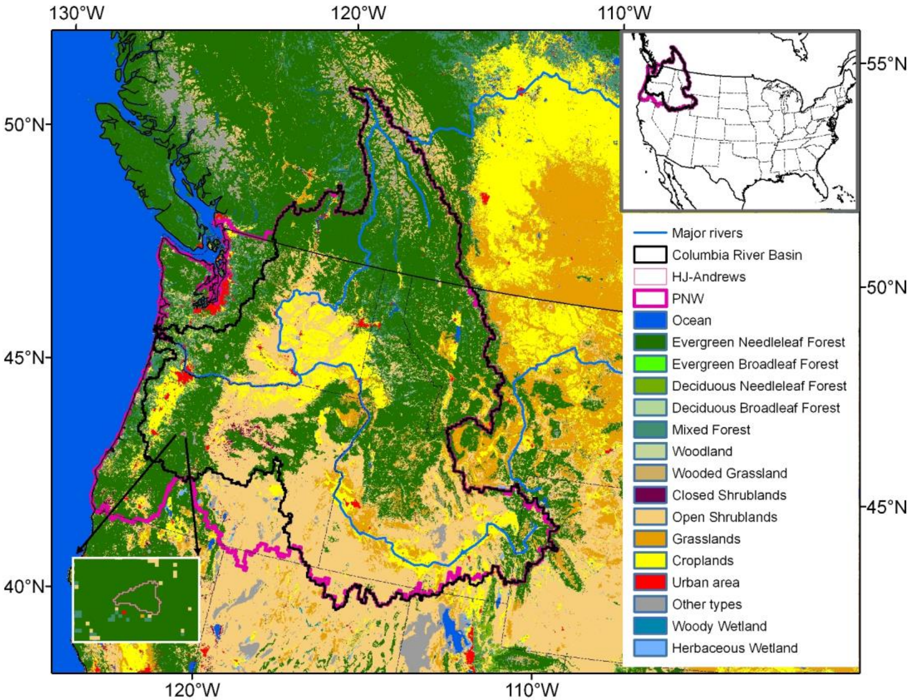

Fig. 1. Study area and simulation domain for this study. Pacific Northwest: VIC, VIC-CropSyst, and MEGAN domains; Columbia River Basin: NEWS-DIN domain; HJ-Andrews: RHESSys domain.

BGD
10, 17145–17192, 2013

Importance of climate model bias on land surface processes

M. Liu et al.

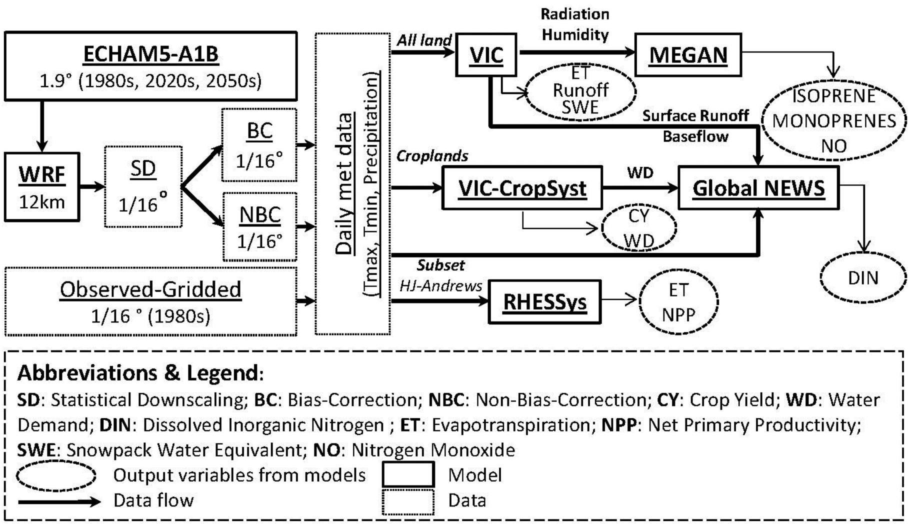

Fig. 2. Offline simulations and data flow for this study.

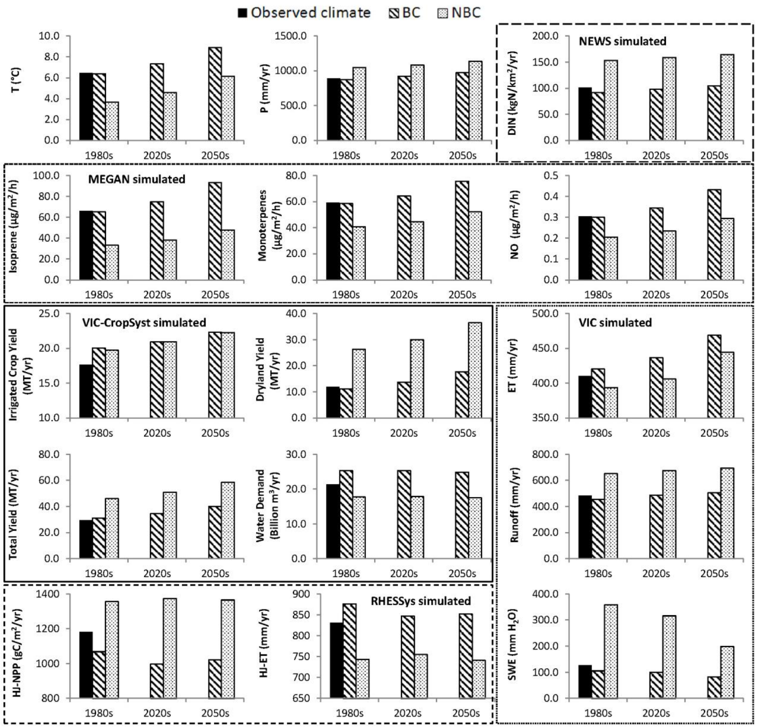

Fig. 3. Changes in climate and major variables driven by different climate scenarios. T: annual mean temperature, P: average annual precipitation, ET: average annual evapotranspiration, SWE: snowpack water equivalent on 1 April, Total Yield: total yield from all croplands; Irrigated Crop Yield: Yield from irrigated cropland; Dryland Yield: Yield from dryland; Water Demand: total irrigation water demand over irrigated cropland; HJ-ET: RHESSys modeled ET over HJ-Andrews watershed; HJ-NPP: RHESSys modeled Net Primary Production (NPP) over HJ-Andrews watershed; DIN: NEWS modeled Dissolved Inorganic Nitrogen yield over the Columbia River Basin.

BGD
10, 17145–17192, 2013

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M. Liu et al.

BGD
10, 17145–17192, 2013

Importance of climate model bias on land surface processes

M. Liu et al.

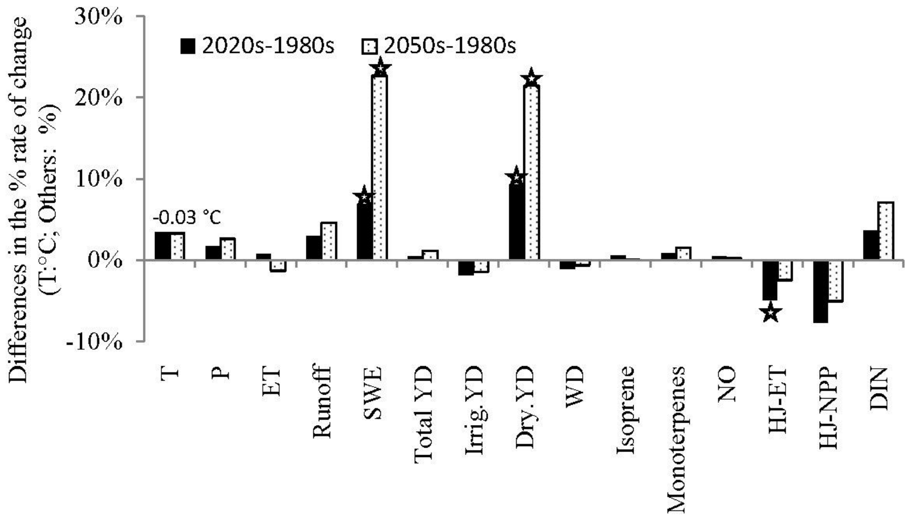

Fig. 4. Differences in the percentage change between BC and NBC climate data and the simulated outputs driven by bias-corrected (BC) and non-bias-corrected (NBC) climate. They are calculated as [$\Delta BC_{20s-80s}$(%) – $\Delta NBC_{20s-80s}$(%)] for the change between 1980s and 2020s and [$\Delta BC_{50s-80s}$(%) – $\Delta NBC_{50s-80s}$(%)] for the change between 1980s and 2050s. For *T*, it is total differences in degreeC, i.e. ($\Delta BC_{20s-80s}$ – $\Delta NBC_{20s-80s}$) for the change between 1980s and 2020s, and ($\Delta BC_{50s-80s}$ – $\Delta NBC_{50s-80s}$) for the change between 1980s and 2050s. *T*: annual mean temperature, *P*: average annual precipitation, ET: average annual evapotranspiration, Runoff: total runoff, SWE: Snowpack Water Equivalent on 1 April, Total YD: total yield from all croplands; Irrig.YD: Yield from irrigated cropland; D. YD: Yield from dryland (non-irrigated cropland); WD: total irrigation water demand over irrigated cropland, HJ-ET: RHESSys modeled ET over HJ-Andrews watershed; HJ-NPP: RHESSys modeled Net Primary Production (NPP) over HJ-Andrews watershed; DIN: NEWS modeled Dissolved Inorganic Nitrogen yield over the Columbia River Basin. The small stars under or above each column mean p value < 0.05 for the student's t test of differences between BC anomalies and NBC anomalies during period of 2020s and 2050s, respectively.

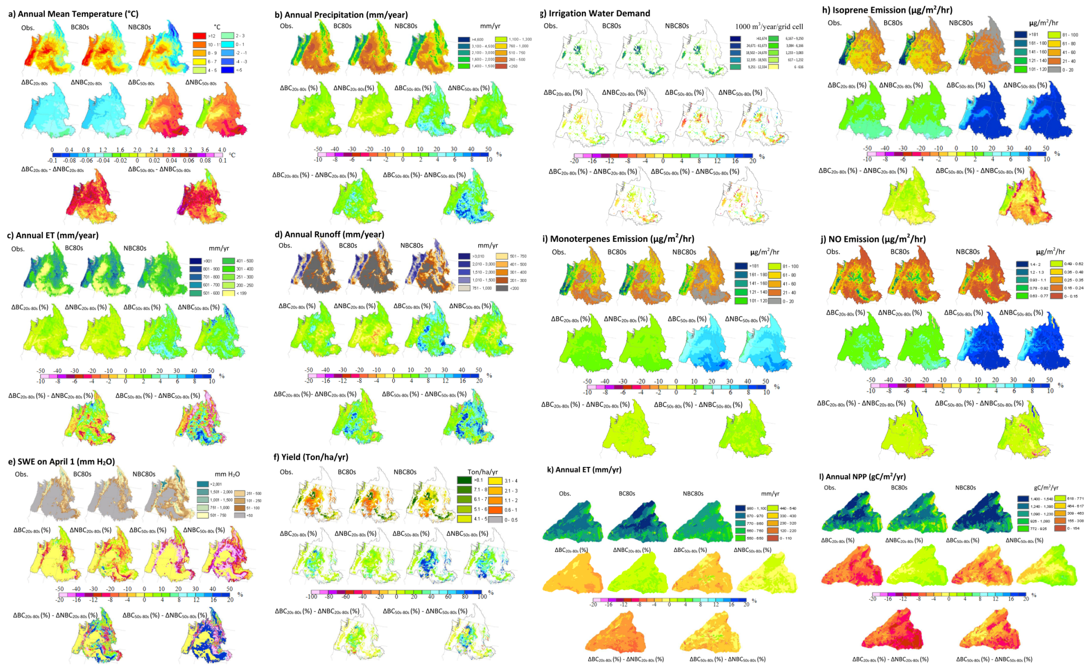

Fig. 5. Spatial patterns of differences in climate and modeled variables driven by observed data (Obs.), bias-corrected (BC), and non-bias-corrected (NBC) climate. $\Delta BC_{20s–80s}$ and $\Delta BC_{50s–80s}$ are total change between 1980s and 2020s and between 1980s and 2050s, respectively, under BC climate. $\Delta BC_{20s–80s}(\%)$ and $\Delta BC_{50s–80s}(\%)$ are the percentage change between 1980s and 2020s and between 1980s and 2050s, respectively, and they are calculated as $\Delta BC_{2020s}/BC_{1980s} \times 100\,\%$ and $\Delta BC_{2050s}/BC_{1980s} \times 100\,\%$, respectively. "$\Delta BC_{20s–80s}(\%) - \Delta NBC_{20s–80s}(\%)$" is the difference in the percentage change between 1980s and 2020s in simulated results driven by BC and NBC climate; similarly "$\Delta BC_{50s–80s}(\%) - \Delta NBC_{50s–80s}(\%)$" is the difference in the percentage change between 1980s and 2050s. "$\Delta BC_{20s–80s} - \Delta NBC_{20s–80s}$" is the difference in the total change between 1980s and 2020s in simulated results driven by BC and NBC. Legend: if the legend has two lines of label, the lower line of label is directing to the panel below, and vise versa.

BGD
10, 17145–17192, 2013

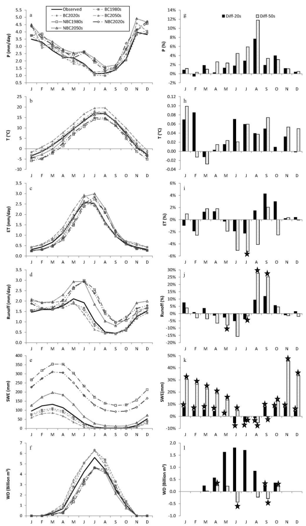

Fig. 6. Seasonal patterns of differences in climate and simulated hydrological variables driven by bias-corrected (BC) and without bias-corrected (NBC) data. Left column is monthly mean (from January to December) over different scenarios and time periods; right column is the differences between BC- and NBC climate and modeled variables in two periods, i.e., 2020s–1980s and 2050s–1980s. The unit of water demand (WD) is billion m^3. Note: plotted for precipitation, ET, runoff, and SWE are differences in percent changes, i.e., $(\Delta BC_{20s\text{–}80s}/BC_{1980s} \times 100\,\%) - (\Delta NBC_{20s\text{–}80s}/NBC_{1980s} \times 100\,\%)$ for changes between 1980s and 2020s and $(\Delta BC_{50s\text{–}80s}/BC_{1980s} \times 100\,\%) - (\Delta NBC_{50s\text{–}80s}/NBC_{1980s} \times 100\,\%)$ for changes between 1980s and 2050s; plotted for temperature and water demand are differences in absolute changes, i.e., $\Delta BC_{20s\text{–}80s} - \Delta NBC_{20s\text{–}80s}$ for changes between 1980s and 2020s and $\Delta BC_{50s\text{–}80s} - \Delta NBC_{50s\text{–}80s}$ for changes between 1980s and 2050s. The small stars under or above each column mean p value < 0.05 for the student's t test of differences between BC anomalies and NBC anomalies for each month; the big star in the diagram of SWE monthly differences means all months are significant ($p < 0.05$).

BGD

10, 17145–17192, 2013

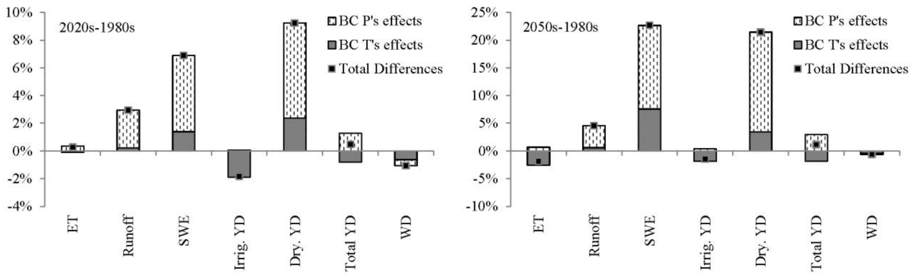

Fig. 7. Contributions of bias-corrections (BC) on temperature (T) (Eq. 5) and precipitation (P) (Eq. 7) to the total differences (Eq. 3) of modeled changes in major hydrologic variables and crop yield between BC and NBC climate driving forces. Left panel: changes between 1980s and 2020s; and right panel: changes between 1980s and 2050s. ET: average annual evapotranspiration, runoff: total runoff, SWE: snowpack water equivalent on 1 April, Total YD: total yield from all croplands; Irrig.YD: yield from irrigated cropland; Dry. YD: yield from dryland (non-irrigated cropland); WD: total irrigation water demand over irrigated cropland.

BGD
10, 17145–17192, 2013

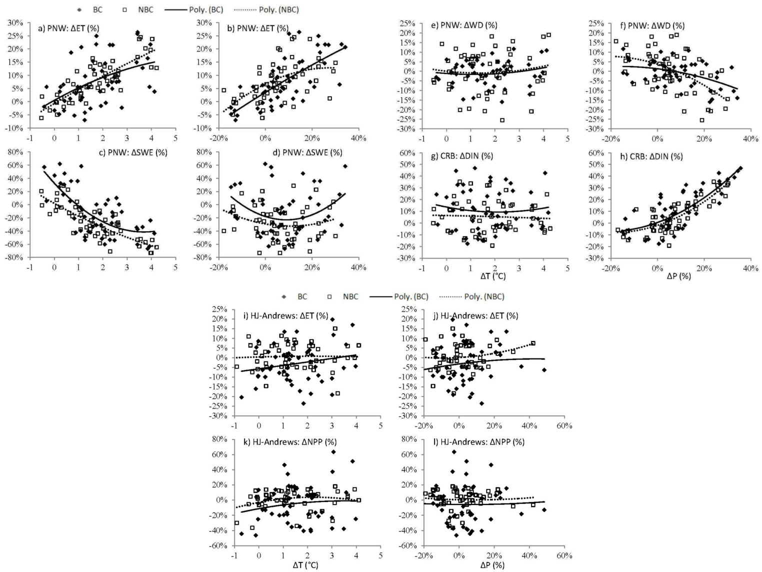

Fig. 8. Land surface response to climate change with bias-corrected (BC) and non-bias-corrected (NBC) data between 1980s and 2020s and between 1980s and 2050s. Horizontal axes indicate the anomaly of T (left column, °C) or the anomaly of P (right column, %). Vertical axes indicate anomalies of evapotranspiration (ET), snowpack water equivalent (SWE), irrigation water demand (WD), export of dissolved inorganic nitrogen (DIN), and net primary productivity (NPP) in responding to BC and NBC climate data. Diamond points represent anomalies according to BC climate and rectangles represent estimated anomalies driven by NBC climate in each future year comparing with the base period of 1980s. The black lines represent second order polynomial regression curves for responses and BC climate and dashed lines represent second order polynomial repression curves for responses and NBC climate. PNW (Pacific Northwest) represents the domain for ET, SWE, and WD estimations from VIC or VIC-CropSyst models; CRB represents the simulation domain of NEWS model; and HJ-Andrews represents the simulation domain of RHESSys on ET and NPP (Fig. 1).

BGD
10, 17145–17192, 2013