1 Assimilating urban heat island effects into climate projections

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10 Submitted to the Journal of Arid Environments, 7/28/2015

11 Revisions submitted on 12/3/2015

Abstract

An urban heat island (UHI) effect is identified in Reno, Nevada by analyzing regional temperature trends calculated from seven long-term observation stations for the summer and winter seasons between 1950-2014. The UHI is maximized during summer (June-August) and characterized by asymmetric increases in minimum ($\sim 1.1^{\circ}\text{C}/\text{decade}$, $p < 0.01$) versus maximum temperature ($\sim 0.1^{\circ}\text{C}/\text{decade}$, $p < 0.01$) trends in excess of trends from regional climate stations. Comparisons of historical Reno temperatures with an ensemble of 66 bias-corrected and downscaled global climate model (GCM) outputs spanning 1950-2014 demonstrates cold biases of $1.5\text{-}4.5^{\circ}\text{C}$ during summer with minimum temperature having the largest bias. We show that a secondary bias correction step utilizing the statistical downscaling method of quantile-quantile mapping (QQM) can reduce biases in future climate projections assuming no changes to the UHI. The QQM results in an additional total warming of ensemble mean temperatures by $\sim 3^{\circ}\text{C}$ for downscaled GCM output and $\sim 4^{\circ}\text{C}$ for re-gridded 1° grid resolution GCM output for 2030-2049 under the RCP8.5 emissions scenario. These temperature differences produce additional increases in summer potential evapotranspiration of 10% compared to non-QQM bias-corrected GCM output. It was shown that the QQM method represents a useful and computationally efficient method for bias correction of temperature projections for cities where UHI effects exist. Planning and impacts studies of urban water resources can benefit from these improved climate projections, particularly in regions where downscaled GCM output is unavailable.

Figure 1: a) Aridity map (P/PET) of the Western United States and the Great Basin. b) Aridity and elevation map of the western Great Basin with the study area of Reno, Nevada and the Cooperative Observational (COOP) weather stations used in the analysis. c) Aerial image and elevation contours of the Reno, Nevada urban area and location of major roads (black lines), the Truckee River (blue line), and the location of the urban weather station (white star). d-g) Time series of winter and summer maximum and minimum temperature for the mean of the seven regional weather stations (blue line) and the Reno station (black line) with the range of observations of the regional stations bounded by the grey fill and the Reno trend (red line) upon removal of the regional climate trend (RCT). Dashed lines show long-term linear trends.

The Great Basin of the western United States (Figure 1a) is North America's largest dryland region. It is characterized by low ratios of precipitation (P) to potential evapotranspiration (PET; $P/PET < 0.65$) and mountainous basin and range topography. This study focuses on the city of Reno, Nevada (39.5°N , 119°W , population 400,000 in 2010), which is located along the western edge of the Great Basin in the rainshadow of the 3000m high Sierra Nevada (Figure 1b-c). The population of Reno has increased fourfold since 1950 and the urban footprint spans the extent of the valley floor (Figure 1c). The development of a UHI in Reno has been previously assessed through a double-mass technique and attributed to urban expansion (e.g., Arndt and Redmond, 2004). Using U.S. National Weather Cooperative Observation Stations (COOPs; Figure 2b) with relatively complete (>90% complete records) and long-term (1950-2014) daily records of minimum and maximum temperature ($T_{\min}$ and $T_{\max}$), we confirm the existence of a UHI in Reno through an independent assessment. We then show the importance of assimilating UHI effects into climate projections through a bias correction step and discuss how this step impacts future potential evapotranspiration demand.

Daily values of $T_{\min}$ and $T_{\max}$ from seven COOP stations (Figure 1b) were acquired from the Western Regional Climate Center (<http://www.wrcc.dri.edu>) and aggregated to seasonal averages for winter (December-January-February; DJF) and summer (June-July-August; JJA). The Reno COOP station is the only first order weather station located within the urban area. Anomalies of $T_{\min}$ and $T_{\max}$ were calculated by removing the long-term means for each season. Seasonal values at the six regional COOP stations, selected to capture a range of Great Basin

environments (Figure 1b), were averaged together to produce a regional climate trend (RCT). Compared to the RCT, the Reno station shows greater positive trends of $T_{\min}$ during winter (Figure 1e) and $T_{\max}$ and $T_{\min}$ during summer (Figure 1f-g). Calculation and removal of long-term linear trends from the regional stations and Reno displayed residual and significant ($p < 0.01$) positive trends for both $T_{\max}$ and $T_{\min}$ using a Kolmogorov-Smirnoff test. The more rapid rate of Reno summer $T_{\min}$ warming ($1.1^{\circ}\text{C}/\text{decade}$, $p < 0.01$) relative to the RCT ($0.3^{\circ}\text{C}/\text{decade}$, $p < 0.01$) provides strong evidence for the UHI in agreement with the findings of Arndt and Redmond (2004). Similar findings for the UHI in Phoenix, Arizona have been reported (see Chow et al., 2012 and references therein). It is also consistent with UHI causality during summer, as solar energy input is maximized allowing nocturnal re-radiation of longwave energy into the boundary layer and warming $T_{\min}$.

To evaluate biases in GCM outputs and determine if they capture the UHI effect in Reno, we examined 66 monthly GCM projections of $T_{\max}$ and $T_{\min}$ from the Coupled Model Intercomparison Project 5 (CMIP5) archive (Maurer et al., 2007; available at: <http://gdcdcp.ucllnl.org/>). We selected the grid point nearest Reno and evaluated the historical period of 1950-2014. Because the native grid resolutions of GCM outputs are often too coarse for impact studies ($< 1^{\circ}$ or < 125 km; Wood et al., 2004), the CMIP5 projections available for the United States have been bias-corrected and spatially downscaled to 12.5 km resolution following the methods described in Maurer et al. (2007). We selected the Representative Concentration Pathway 8.5 (RCP8.5) experiment, a scenario representing the continuation of aggressive anthropogenic greenhouse gas emissions into the late 21st century. We selected the period spanning 2030-2049 to highlight temperature changes that could be immediately addressed by long-term (~20 years) city planning efforts aimed towards mitigation and adaptation. We

evaluated the suite of CMIP5 projections using all downscaled GCM products available to produce an ensemble of solutions.

Figure 2: Summer (JJA) temperature trends during the historical period (1950-2014) observed at Reno (thick black line) and produced by the ensemble mean of 66 CMIP5 GCMs (thin black line; range shown by grey fill) for a) maximum temperature and b) minimum temperature. Summer temperature differences between the GCM ensemble means and the Reno historical observations (the RCT has not been removed) are shown in c) with the percent biases calculated. The increasing cool bias in minimum temperature (dashed line) is consistent with the growing urban heat island that is not captured by the GCMs.

Because the UHI effect is maximized in summer (Figure 1g) and the impacts of temperature increases are also maximized in this season via water and energy demands for cooling (Chow et al., 2012) and negative health impacts (Zhao et al., 2014), we focus on summer GCM biases. On average, observed Reno T_{max} and T_{min} tend to be 1-3°C warmer than the historical GCM ensemble mean (Figure 2a-b) despite being coarsely (12.5 km) bias-corrected and downscaled (Maurer et al. 2007). While the Reno COOP station was included in this procedure, the 12.5 km resolution and lapse rate corrections may have minimized removal of the

cold bias. The GCMs also do not capture the long-term increase in $T_{\min}$ that is attributed to UHI development that produces a cold bias in excess of 5°C during the early 21st century (Figure 2b). The negative (cold) biases of the GCM ensemble mean relative to observed Reno temperatures are on the order of -7% and -27% for $T_{\max}$ and $T_{\min}$ (Figure 2c) between 1950 and 2014. The trend towards increasingly cold biases in the GCM ensemble averages for the period spanning 1985-2014 is consistent with the strengthening UHI (Figure 2g) shown by Arndt and Redmond (2004).

Biases of GCM outputs must be removed from future projections in order to develop robust and specifically tailored management and adaptation strategies. If the projections are biased cold, impacts may be underestimated. To reduce biases in GCM projections, we applied a quantile-quantile mapping (QQM) bias correction procedure similar to that of Wood et al. (2004). The QQM method preserves differences across quantiles and can be described as an equiprobability transformation by Panofsky and Brier (1958) or an equidistant-based cumulative distribution function approach (Li et al., 2010). The method can improve skill in GCM projections used for impact studies (Wood et al., 2004; Li et al., 2010; Bürger et al., 2012; Mejía et al., 2012). The method works as follows: Each temperature value of the i -th quantile of the GCM historical cumulative distribution function is mapped to the corresponding i -th quantile of the historical observed temperature. The temperature shift associated with the historical mapping is then applied to the future GCM quantiles. Bürger et al. (2012) provide a succinct formal description of the modeled series mapping as $f = F_M \circ F_O^{-1}: M \rightarrow M_{\text{qm}}$, where M , F_M , and F_O denote the modeled series and modeled and observed cumulative distribution functions, respectively. We let $\varphi: [0,1] \rightarrow [0,1]$ represent the identity map of the unit interval. The mapping is performed at increments of 0.01 between 0 and 100, and data percentiles from outside the

historical period are achieved using an extrapolated Gaussian fit. We used the period of time representing the maximum UHI development (1985-2014; Figure 1g) as the historical calibration period.

Figure 3: Cumulative distribution functions for observed and future June-August maximum (a) and minimum (b) temperatures demonstrating the cool biases of 66 historical and future GCM runs (light and medium grey lines) compared to the Reno observed data (thick black line) for temperatures. The quantile-quantile mapping (QQM) shifts the future projections to the right (dark grey lines). The QQM produces higher temperatures in 2030-2049 ensemble ranges (dark and light grey fill) and means (lines) of GCM output compared non-bias corrected GCM output for c) maximum and d) minimum future summer temperatures. The medium gray fill shows the overlap of the GCM output.

The cumulative distribution functions of GCM-estimated historical and future Reno temperatures demonstrate the cold biases of the GCM ensemble, as they are located to the left of the observed Reno values for 1985-2014 (Figures 3a-b). Applying the QQM method to the future GCM outputs removes the cold bias and produces a rightward shift towards higher temperatures for both T_{max} and T_{min} for the period 2030-2049. This shift produces an additional ensemble

average increase of $\sim 2^{\circ}\text{C}$ for T_{max} and $\sim 4^{\circ}\text{C}$ for T_{min} by the mid-2040s from the suite of CMIP5 GCMs (Figure 3c-d), consistent with removal of the cold bias identified during the calibration period. Repeating the procedure for GCM projections that were re-gridded from native GCM resolutions to 1° resolution, but had no bias correction or spatial downscaling applied (Maurer et al. 2007), results in an additional increase of 1°C (not shown).

The benefit of eliminating cold biases in GCM output using a method such as QQM will enhance the robustness of climate projections compared to ignoring these biases. However, by using monthly values of T_{min} and T_{max} and aggregating these to seasonal values, our approach neglects changes in the frequency and magnitude of daily maximum and minimum temperature extremes. Changes in these extremes have important societal and ecological impacts (Abatzoglou and Barbero, 2014) including heat stress and energy demand produced by extreme daily temperatures. This work should be extended to properly characterize how the distribution of daily extreme temperature values may change in the future. To do so, the use of daily GCM output can be used with QQM or more advanced techniques such as dynamical downscaling in conjunction with bias correction (Mejía et al., 2012) can be applied. Dynamical downscaling better resolves land surface physics feedbacks but is more computationally intensive and susceptible to inheritance of GCM biases (Wood et al., 2004).

Another limiting factor of the present study is the simplifying assumption of a stationary UHI effect over the historical period that is transferred to the future period through QQM. This assumption may not be completely valid in the future because of continued land use changes that alter the land surface and boundary layer characteristics. Similarly, the large-scale climate system fluctuates within a shifting range of variability (Milly et al., 2008) and may contribute to future nonstationarity of UHI effects. Assessments of how past land use change has influenced

on urban climate, perhaps through modeling and remote sensing studies, are necessary to best estimate how projected land use change may affect future UHI effects. Georgescu et al. (2014) found that regional warming rates from urban expansion is of the same order of magnitude as large-scale climate change. Under anticipated urban growth, our results can thus be interpreted as a minimum baseline increase. Urban canopy modeling represents a useful method to help cities prioritize proposed adaptation and mitigation strategies to reduce UHI effects, some of which may help offset large-scale climate warming (Georgescu et al. 2014). Nonetheless, by including even a stationary UHI effect compared to neglecting this effect shows promise for improving urban climate projections of regionally downscaled GCM output. The application of QQM for bias correction of native GCM resolution output is also possible with QQM. Cities that have available urban and rural weather stations can use these to identify UHI effects and for historical calibration. If these cities lack sufficient resources (e.g., high-resolution gridded climate data products) to perform intensive regional bias corrections, using these stations with QQM for bias correction is encouraged.

The elimination of the 2-4°C cold bias in the summer GCM ensemble averages has important consequences for urban water resources. Cities in dryland climates often rely upon water deliveries from remote, often mountainous regions that are also susceptible to climatic change (Beniston, 2003). In Reno, urban consumptive demands are met by runoff produced from snowmelt in the Sierra Nevada and delivered via the Truckee River (Figure 1b-c). The impacts of temperature changes on summer water demand for Reno can be illustrated using the Hamon equation for potential evapotranspiration (Allen et al., 1998) that has been calibrated for climate change studies in the western Great Basin (Hatchett et al., 2015). During 1995-2014, Reno summer mean temperatures were approximately 22°C (Figure 1f-g). Projections of summer mean

temperatures for 2030-2049 with the additional increase of 3°C (from QQM) is equivalent to an additional PET demand of ~10% beyond the original GCM-based projections. The original projected increases are ~1°C (Figure 3c-d). This discrepancy would place increased strain on existing water resources (Major et al., 2011). It would also exacerbate problems of water scarcity in cities reliant on water deliveries should distributions of water resources become altered by regional warming (Cayan et al., 2010) or by changes in runoff production in the regions providing water supplies (Hatchett et al., 2015). Such changes affecting the Sierra Nevada and juxtaposed with increased (particularly if underestimated) urban consumptive water demands would reduce future water availability in Reno. Quantification of heat stress and negative impacts on air quality are beyond the scope of this work, but would likely place increased strain on public health and healthcare infrastructure (Zhao et al., 2014).

Climate change adaptation strategies have been implemented in many major cities, yet there still exists a critical need to apply similar work in smaller, modern cities as well as rapidly growing megacities in the developing world to ensure sustainable urban communities (Rosenzweig et al., 2011). Although an analysis of observational measurements showed that a UHI exists in Reno, Nevada, the GCMs were not able to capture the magnitude of this phenomenon. As a result, their outputs indicate cold biases in $T_{\min}$ and $T_{\max}$ during the measurement period. Since these biases are transferred into climate change projections, a correction step is necessary to improve urban climate change impacts studies. The relatively simple to perform and computationally inexpensive bias-correction technique (QQM), in conjunction with a representative urban weather station, aids in reducing these biases. The method can be applied to readily available native resolution CMIP5 GCM output. The use of an ensemble approach provides policymakers with the multimodel mean and provides the range of

possible outcomes to plan for in light of uncertainties regarding future emissions resulting from inherent GCM differences. This method should improve the ability to evaluate climate change impacts and future resource demands in urban areas where water scarcity and human health will remain at the forefront of global policy challenges in the coming decades.

Acknowledgements

This material is based upon work supported by the National Science Foundation under grant number EPS-0814372. We thank John Abatzoglou for helpful comments on an early version of this manuscript and providing the QQM code and the World Climate Research Programme's Working Group on Coupled Modeling for providing CMIP5 output. MATLAB code and original data is available from the corresponding author upon request. We thank the anonymous reviewer for providing constructive and insightful comments.

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