Climatic Change (2023) 176:169
https://doi.org/10.1007/s10584-023-03623-z

Examining current bias and future projection consistency of globally downscaled climate projections commonly used in climate impact studies

Lucas Berio Fortini[1] · Lauren R. Kaiser[2] · Abby G. Frazier[3] · Thomas W. Giambelluca[4]

Received: 7 April 2022 / Accepted: 1 October 2023 / Published online: 1 December 2023

Abstract
The associated uncertainties of future climate projections are one of the biggest obstacles to overcome in studies exploring the potential regional impacts of future climate shifts. In remote and climatically complex regions, the limited number of available downscaled projections may not provide an accurate representation of the underlying uncertainty in future climate or the possible range of potential scenarios. Consequently, global downscaled projections are now some of the most widely used climate datasets in the world. However, they are rarely examined for representativeness of local climate or the plausibility of their projected changes. Here we explore the utility of two such global datasets (CHELSA and WorldClim2) in providing plausible future climate scenarios for regional climate change impact studies. Our analysis was based on three steps: (1) standardizing a baseline period to compare available global downscaled projections with regional observation-based datasets and regional downscaled datasets; (2) bias correcting projections using a single observation-based baseline; and (3) having controlled differences in baselines between datasets, exploring the patterns and magnitude of projected climate shifts from these datasets to determine their plausibility as future climate scenarios, using Hawai‘i as an example region. Focusing on mean annual temperature and precipitation, we show projected climate shifts from these commonly used global datasets not only may vary significantly from one another but may also fall well outside the range of future scenarios derived from regional downscaling efforts. As species distribution models are commonly created from these datasets, we further illustrate how a substantial portion of variability in future species distribution shifts can arise from the choice of global dataset used. Hence, projected shifts between baseline and future scenarios from these global downscaled projections warrant careful evaluation before use in climate impact studies, something rarely done in the existing literature.

Keywords Climate shifts · Downscaling · GCMs · Regional projections · Future scenarios · Bioclimatic variables

Extended author information available on the last page of the article

1 Introduction

Adequate climate change projections are needed for regional climate impact studies and the resource managers that ultimately use the results. These products are essential to understand current climate as well as any potential future climatic changes. A single future climate projection is only one of many plausible future outcomes. Hence, when considering potential future climate impacts, best practices include using multiple future climate scenarios to account for the range of possible future climatic conditions (Hawkins et al. 2016). Past syntheses indicate that a range of projected climate outcomes based on multiple scenarios when examined better consider both short- and long-term risks and opportunities, while reducing the possibility of negative outcomes that were not intended in planning processes (Terando et al. 2020).

A paucity of fine-scale regional climate projections has left managers with limited resources to inform climate adaptation and long-term planning in remote and climatically complex regions. Although climate projections are available on a global scale, many outputs do not capture the smaller scale processes of places that may fit into only a handful of General Circulation Model (GCM) grid cells. Furthermore, variability and uncertainty between individual models can differ as well. For small or isolated regions such as Hawai‘i, the development of multiple regionally tailored downscaled climate projections is limited by available resources. As a result, in Hawai‘i, until recently there were only three efforts to regionally downscale global models (Elison Timm et al. 2015; Elison Timm 2017; Zhang et al. 2016a, b; Xue et al. 2020) representing a small sample of the available GCMs, and few future emissions scenarios. Thus, these currently available climate projections for Hawai‘i do not reflect a wider range of possible climate futures and only provide limited options for regional research, management, and planning efforts.

Global spatially downscaled datasets such as WorldClim2 (Hijmans et al. 2005; Fick and Hijmans 2017) and CHELSA (Karger et al. 2017a) are especially used in ecological studies, such as those exploring potential species distribution shifts under alternative climate scenarios (Rodder 2009; Rovzar et al. 2013; Kodis et al. 2018; Mausio et al. 2020). These convenient and readily accessible datasets are nearly ubiquitous, with over 32,000 Google Scholar citations for WorldClim2 alone by March 2023. However, past research has cautioned against the unexamined use of such global spatial climate datasets (Daly 2006; Bedia et al. 2013; Poggio et al. 2018), with an increasing number of studies examining how these datasets replicate local climatic patterns (Wango et al. 2018; Marchi et al. 2019) and how climate dataset choice may impact modeled distribution under current conditions (Bobrowski and Schickhoff 2017; Lembrechts et al. 2019; Morales-Barbero and Vega-Álvarez 2019).

Our research aims to further explore differences in these common global datasets to better inform the choices of climate impact studies for data-poor regions like Hawai‘i. In data-poor regions, climate data may be difficult to obtain or lacking due to limited historical records and/or sparse or unreliable station coverage, making it challenging to accurately characterize local climate patterns. We assess mean annual temperature and precipitation from the two global datasets CHELSA (climatologies at high resolution for the earth's land surface areas, Karger et al. 2017a) and WorldClim2 (Fick and Hijmans 2017) to determine their skill in representing current climate in Hawai‘i. After applying a bias correction based on regional baseline observational data, we explore the consistency and plausibility of these commonly used future climate projections. We do this by first comparing the projected climate shifts from the bias corrected global datasets with those from a limited set of regional downscaled projections (Elison Timm et al. 2015; Zhang et al. 2016a, b; Elison Timm 2017; Xue et al. 2020). Then, we assess their resulting influence on projected species range to illustrate how differences in future projections between these global datasets can affect species distributions shifts, which is a very common use of these global datasets.

2 Data

2.1 Global datasets

Downscaled global climate datasets have not been prominently used previously in Hawai ‘i because their ability to represent the fine scale and spatially complex climatic patterns of the islands has not been fully examined. We considered two widely used global datasets in our analysis: WorldClim2 (Fick and Hijmans 2017) and CHELSA (Karger et al. 2017a). The WorldClim2 and CHELSA global datasets include multiple mid- (2041–2060) and late-century (2061–2080) projections. These global datasets calculate future projections and anomalies by using a combination of climate model simulations, statistical downscaling, and interpolation techniques that simulate the future climate under different greenhouse gas emission scenarios. These downscaled projections are available for multiple individual GCMs for the Coupled Model Intercomparison Project 5 (CMIP5) simulations under four representative concentration pathways (RCPs; 2.6, 4.5, 6.0, and 8.5) (IPCC 2000). However, not all GCMs had available CMIP5 simulations across all mid- and late-century periods and RCPs. Hence, of the nearly 60 GCM-specific CMIP5 simulations, we focused only on GCM and RCP combinations common in both CHELSA and WorldClim2 datasets (e.g., 16 GCMs for RCP8.5 2061–2080). To assess the adequacy of these global datasets in representing local climate patterns, we compared the historical simulations from these new global downscaled datasets with a regional observation-based baseline climatology and with a set of widely used regionally downscaled projections described in Section 2.2 below.

2.1.1 WorldClim2

WorldClim2’s high spatial resolution global weather and climate data have been available since 2005 (version 1.4, Hijmans et al. 2005) and has been improved upon over time (version 2.1, Fick and Hijmans 2017). The WorldClim2 datasets have been used in numerous species distribution models and many other climate impact studies (Escalera-Vazquez et al. 2018; Brandl et al. 2020; Çoban and Örücü 2020; Sydenham et al. 2020). The data consist of spatially interpolated monthly climate data, with downscaled temperature and rainfall being the most widely used variables. The WorldClim2 baseline climate data were created by thin-plate splines interpolation using covariates such as elevation, distance to the coast, and MODIS-derived (Moderate Resolution Imaging Spectroradiometer) covariates including maximum and minimum land surface temperature and cloud cover. The interpolation was done for 23 separate regions delineated by considering station density. The baseline period for WorldClim2 is 1970–2000, and the finest spatial resolution available is 30 arc seconds (approximately 1 km). Future WorldClim2 data include projections of monthly values from multiple GCMs for the four RCPs that are downscaled and calibrated using the WorldClim2 baseline dataset. There is minimal information on the downscaling of WorldClim2 future climate projections, as these are simply described as the relative and absolute deltas between baseline and future GCM runs that are spatially interpolated to 1 km resolution (https://www.worldclim.org/data/downscaling.html).

2.1.2 CHELSA

As a newer global downscaling effort that partially accounts for orographic effects in its precipitation downscaling, CHELSA has been shown to yield better rainfall projections than using a single GCM projection alone or other downscaled products that do not account for orographic effects (Raju and Kumar 2020). CHELSA provides high resolution climatologies for the earth's land surfaces based on a downscaled global reanalysis of multiple GCMs (Karger et al. 2017a, b). CHELSA is essentially a statistical downscaling of the ERA-Interim Reanalysis data (European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis Interim; Berrisford et al. 2011), with the downscaled temperature based on mean lapse rates and elevation and a precipitation algorithm that incorporates orographic predictors including wind fields, valley exposition, and boundary layer height. The baseline period for CHELSA data is 1979–2013, and the finest spatial resolution available is 30 arc seconds (approximately 1 km). CHELSA uses a delta change method to project future climate. This method involves interpolating anomalies (deltas) of the respective CMIP5 GCM dataset using B-spline interpolation. The anomalies are then added (for temperature variables) or multiplied (in the case of precipitation) to high resolution climate data from CHELSA V1.2. Future CHELSA data include projected mean monthly values for the four RCPs.

2.2 Regional projections

The Hawai‘i regional climate model (HRCM) is a Weather Research and Forecasting (WRF) dynamic downscaling model configured for the Hawaiian Islands (Zhang et al. 2012). In general, the dynamical downscaling approach of the HRCM realistically simulates the magnitude and geographical distribution of mean rainfall in Hawai‘i and reasonably reproduces heavy rainfall events as well. As the HRCM projections are commonly used for climate impact studies in Hawai‘i (Fortini et al. 2017; Camp et al. 2018; Brewington et al. 2019; Pau et al. 2019; Westerband et al. 2020), we included it as a benchmark in our baseline comparisons to see how newer globally downscaled products compare with it. The HRCM baseline period is 1990–2009, and the data are available at 3 km resolution for all the major Hawaiian Islands, except for Maui, for which data are available at a resolution of 1 km. Future projections are available for end-of-century (2080–2099) conditions under the CMIP3 A1B scenario of the Special Report on Emissions Scenarios (SRES; IPCC 2000). Although the HRCM has since been further improved upon and updated, we used the latest published HRCM configurations (Zhang et al. 2016c) as those outputs are the only ones available for all the major Hawaiian islands.

The projected climate shifts from the bias-corrected global datasets were compared with a wider set of regional downscaling climate projections. This includes a more recent effort by the National Center for Atmospheric Research (NCAR) that produced an additional dynamically downscaled dataset for projected future climate (2090–2100) using the Pseudo Global Warming (PGW) method to implement change to historical conditions based on climate signals from GCM averages under RCP8.5 emissions (Xue et al. 2020). We also used a statistical downscaling (SD) effort for comparison that produced end-of-century climate projections for Hawai‘i (2070–2099; Elison Timm et al. 2015; Elison Timm 2017) by developing a statistical relationship between regional-scale spatial patterns of atmospheric circulation, moisture transport, and stability and point-scale observations.

3 Methods

3.1 Comparing model-based baseline projections with regional observations

We considered mean annual temperature (MAT) and mean annual precipitation (MAP) as our primary variables for comparison because they are widely used datasets in climate impact studies. In Hawai‘i, the most accurate observation-based estimates of MAT and MAP patterns across the archipelago are the 250-m resolution MAP datasets from the Rainfall Atlas of Hawai‘i (Giambelluca et al. 2013) and the MAT dataset from the Climate of Hawai‘i data portals (Giambelluca et al. 2014). These two datasets also have differing baseline periods, with the MAP and MAT data representing 1978–2007 and 1957–1980, respectively. Once all observation and model-based MAP and MAT baselines were standardized (described below), we compared the CHELSA, WorldClim2, and the HRCM baseline climatologies to these observation-based datasets. Absolute and percent deviations were calculated for MAT and MAP, respectively. To avoid localized but extremely large MAP percent deviation values, pixels with absolute rainfall deviations < 200 mm/year were excluded (approximately 1% of the landscape), as deviations can vary widely when comparing relative deltas for precipitation. These calculated deviations were used to make comparisons between the newer global datasets and the widely used HRCM regionally downscaled projections.

Because the historical baseline periods for each of the three downscaled and the two observational reference datasets all differ, exact comparisons are impossible without standardization. Hence, for our comparisons we used a standard base period of 1983–2012 as a recent 30-year period with available MAP and MAT data for the state. To standardize modeled and observational MAP datasets, we used monthly gridded precipitation datasets available from 1920–2012 (Frazier et al. 2016). From these monthly datasets, we created grids matching the differing base periods for each of the observational (Rainfall Atlas of Hawai‘i), global (WorldClim 2 and CHELSA) and regional (HRCM) datasets. We then calculated the percent change between data from the original base period and the standard base period (1983–2012) for each dataset at each pixel. Ultimately, we applied this percent change as a standardization for each grid cell in the dataset used in this analysis:

$$\begin{aligned} CHELSA\ MAP_{1983-2012} = & CHELSA\ MAP_{1979-2013} \\ & \times \left(1 + \frac{Monthly\ ObsMAP_{1983-2012} - Monthly\ Obs\ MAP_{1979-2013}}{Monthly\ Obs\ MAP_{1979-2013}}\right) \end{aligned}$$

To standardize the MAT datasets, we used absolute deviation instead of percent deviation to make comparisons between datasets. However, because we did not have equivalent gridded monthly temperature data from prior to 1990, we used statewide annual temperature records from station points (McKenzie et al. 2019; Kagawa-Viviani and Giambelluca 2020) to calculate the absolute temperature deviation between the original dataset period and the standardized 1983–2012 baseline period. We standardized observational (Climate of Hawai‘i), global (WorldClim 2 and CHELSA), and regional (HRCM) datasets using the differences in mean anomalies between baseline periods based on the mean yearly temperature anomalies from these datasets to create a landscape level gridded product. We applied this absolute change value to standardize each of the datasets:

$$CHELSA\ MAT_{1983-2012} = CHELSA\ MAT_{1979-2013} + \left(Yearly\ Obs\ MAT_{1983-2012} - Yearly\ Obs\ MAT_{1979-2013}\right)$$

3.2 Regionally adapting projections by bias correction

After the baseline standardization, we relied on the delta method for bias correction (Teutschbein and Seibert 2012) to reduce the effects of deviations in the spatial patterns of baseline MAT and MAP across the different modeling approaches. The delta method is widely used, including in the development of the future projections for both global datasets we considered, but does not take into account future changes in variability. To apply it, we calculated the percent change in precipitation and the absolute change of temperature (in degrees) between the standardized baseline and future time periods of each global dataset, and applied those deltas to the observation-based baseline data:

$$Bias\ corrected\ CHELSA\ MAP_{2061-2080} = Obs\ MAP_{1983-2012} \times \left(1 + \frac{CHELSA\ MAP_{2061-2080} - CHELSA\ MAP_{1983-2012}}{CHELSA\ MAP_{1983-2012}}\right)$$

$$Bias\ corrected\ CHELSA\ MAT_{2061-2080} = Obs\ MAT_{1983-2012} + \left(CHELSA\ MAT_{2061-2080} - CHELSA\ MAT_{1983-2012}\right)$$

3.3 Comparing projected MAT and MAP shifts across bias-corrected global datasets and regional downscaling efforts

Beyond comparing baseline models with observation-based MAT and MAP, as has been done in previous studies examining global climate datasets (Wango et al. 2018; Marchi et al. 2019), we contextualized the projected shifts from the bias-corrected global datasets with projected shifts for a limited set of regional downscaled projections available for Hawai‘i (Elison Timm et al. 2015; Zhang et al. 2016c; Elison Timm 2017; Xue et al. 2020). To do this, we first calculated the change between future and baseline projections (i.e., deltas) for MAT and MAP across the 16 GCMs considered for the bias-corrected CHELSA and WorldClim2. In these delta comparisons, we used only late century RCP8.5 projections as those are the ones common across all global and regional downscaled efforts. However, because the future simulation periods differ across downscaled efforts (see 2.1 and 2.2), we calculated MAT and MAP shifts in terms of decadal rates (e.g., precipitation change in mm/decade; temperature change in °C/decade).

3.4 Demonstrating the impacts of global dataset choice on future species distribution projections

After standardizing these two global datasets to a common baseline for Hawai‘i, we assess their resulting differences on projected species range shifts, a key application of these global downscaled datasets (Liao et al. 2020; Mundis 2021; Panja et al. 2021; Li et al.

2022; Zarate et al. 2023), to illustrate the potential implications of the differences in future projections between the two global datasets on climate impact studies. Species distribution modeling (SDM) is a widely used approach to investigate the relationships between species occurrences and environmental variables, and thus to evaluate the potential impacts of climate change on species' distributions. Previous studies have examined the effects of dataset choice on the projected current distributions of species (Bedia et al. 2013; Bobrowski and Schickhoff 2017; Lembrechts et al. 2019; Morales-Barbero and Vega-Álvarez 2019). However, the consistency of future SDM projections across different global datasets remains largely unexplored. We take advantage of our temporally standardized and bias corrected WorldClim2 and CHELSA datasets to systematically compare the differences in future projected range shifts between them. By comparing the projected range shifts between the two datasets, we aimed to identify the magnitude of effects arising from the choice of global dataset and to evaluate the potential implications of these discrepancies on species distribution modeling and climate impact studies.

3.4.1 Virtual species and SDM data generation

We utilized the R package "virtualspecies" (R Core Team 2020) to create SDM models for 200 virtual species. This virtual species approach allowed us to ensure our results were not dependent on a limited number of real species distributions. The "virtualspecies" package generates random virtual species distributions based on predefined relationships between species and our environmental predictors, mean annual temperature (MAT) and mean annual precipitation (MAP). Four potential relationships were used in virtual species generation: Gaussian, linear, logistic, and quadratic. By using these diverse relationships in generating 200 virtual species, we were able to create a diverse set of species distribution models that mimic the variety of responses real species exhibit to local environmental gradients (e.g., high elevation dry adapted species, low elevation wet adapted species, broadly distributed species, etc.). Once a virtual species distribution was generated, we "collected" 600 sample presence and absence points across the landscape to serve as data for the SDMs. The MAT and MAP values from our standardized baseline rasters were then extracted and used as predictors in fitted and projected SDMs. SDM model fitting and evaluation details are included in Online Resource 1.

3.4.2 SDM model comparisons

To compare SDMs based on the different global datasets, we performed a series of analyses to assess the differences in baseline and future species distributions and associated range shifts. First, to understand the impact of dataset difference on baseline SDM projections, we fitted and projected baseline distributions using the bias corrected (observation-based baseline climate data) and the original non-bias corrected WorldClim2 and CHELSA baseline datasets, all standardized to the same 1983–2012 period for each virtual species. We then compared the overlap between modeled presence and the underlying (typically unknown) actual presence for each virtual species as a measure of model accuracy.

Second, to evaluate the impact of future projection differences across the two globally downscaled datasets, using models fitted to the bias corrected baseline, we projected and compared the future species distributions for both bias corrected WorldClim2 and CHELSA datasets for each of the 16 GCM-based climate projections common across the two datasets under the RCP8.5 scenario for the period of 2060 to 2079. The purpose of

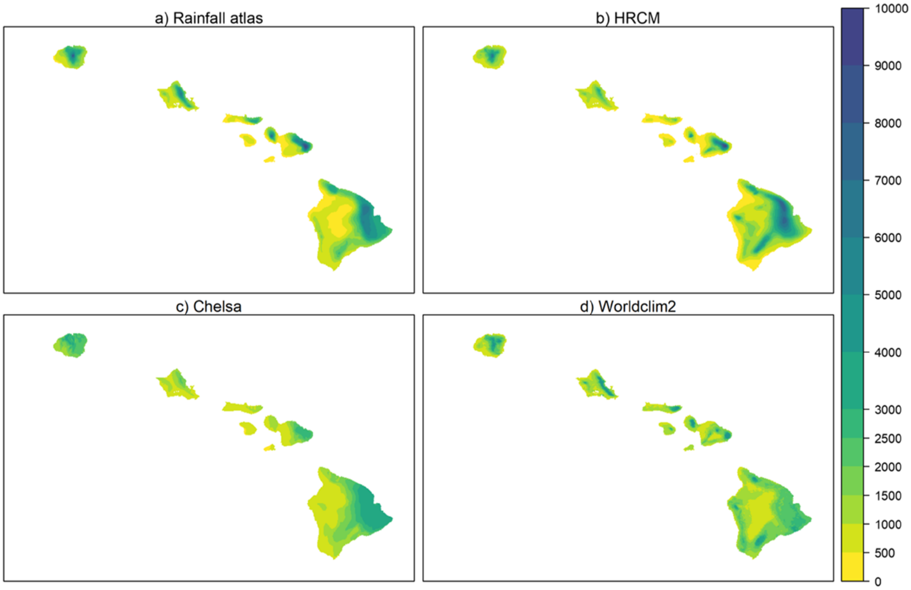

Fig. 1 Mean annual rainfall (mm) for the period 1983–2012 from (a) observations (the Rainfall Atlas of Hawai ‘i), (b) regional HRCM projections, (c) CHELSA, and (d) WorldClim2

these SDM analyses was not to explore the specific spatial patterns resulting from modeling virtual species, but to determine whether differences in baseline and future projections between these datasets result in consistent biases to be considered by potential global dataset users.

All data processing, analyses, and resulting maps were performed using R version 4.0.2 (R Core Team 2020), and when possible, we utilized the Viridis color scale designed to be perceived by viewers with common forms of color blindness and interpretable under color and black-and-white visualization (Garnier et al. 2021).

4 Results

4.1 Historical baseline comparisons

We compared downscaled projections for historical baseline MAP and MAT from the HRCM, CHELSA, and WorldClim2 datasets to observed rainfall and temperature data from the Rainfall Atlas of Hawai‘i (Giambelluca et al. 2013) and the Climate of Hawai‘i (Giambelluca et al. 2014), respectively.

4.1.1 Rainfall

When assessing the global datasets on the same standard baseline period as the observations (1983–2012), the HRCM data represent the observed MAP patterns reasonably well in magnitude and spatial pattern (Fig. 1). The spatial pattern of baseline MAP from WorldClim2 largely deviates from the clear windward and leeward rainfall patterns known

Table 1 Absolute deviations in MAT (°C) and MAP (mm) between observations and bias-corrected global datasets (CHELSA, WorldClim2) and the widely used regionally downscaled dataset (HRCM). Values are based on quantiles of pixel-level differences between each downscaled dataset and the observation-based dataset

Variable	Dataset	25% Quantile	Median	75% Quantile	Range (Q75–Q25)
MAP	WorldClim2	-428	198	598	1030
MAP	CHELSA	-255	159	392	648
MAP	HRCM	-598	-20.6	435	1030
MAT	WorldClim2	0.172	0.524	0.915	0.742
MAT	CHELSA	0.58	0.945	1.38	0.799
MAT	HRCM	-1.04	-0.565	-0.0863	0.955

to occur on the islands (Fig. 1a). The CHELSA and baseline MAP comparison shows a coarse windward and leeward rainfall pattern but deviates in the extent of this pattern and underestimates the overall magnitude of the orographic effect. The CHELSA data show higher precipitation in windward areas in comparison to the outputs from the WorldClim2 data, although the values for both CHELSA and WorldClim2 are much lower than the observed values. HRCM had the lowest median absolute and relative deviations in MAP (Table 1; Online Resource 2). Additionally, the histogram of deviations between each of

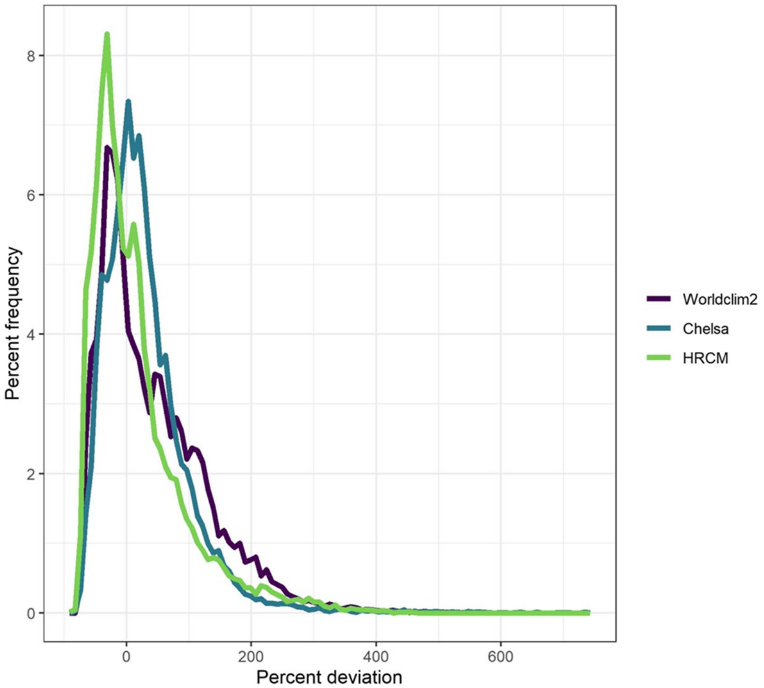

Fig. 2 Histograms of percent deviation of mean annual precipitation (MAP) for the baseline period of 1983–2012. Deviations were calculated based on a comparison of each model (WorldClim2, CHELSA, and HRCM) versus the observation-based MAP baseline from the Rainfall Atlas of Hawai‘i

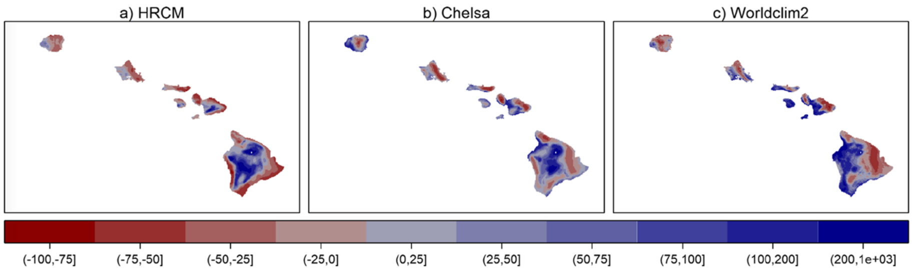

Fig. 3 Maps of percent deviation of mean annual precipitation (MAP) between baseline Rainfall Atlas of Hawaiʻi observed data and (a) HRCM, (b) CHELSA, and (c) WorldClim2 downscaled data

the three different model outputs and the observation-based rainfall patterns show a generally wider distribution of deviations for the WorldClim2 downscaled data compared to both the HRCM and CHELSA datasets (Fig. 2; Online Resource 2). However, in absolute terms, 50% of absolute deviations between modeled and observed MAP (i.e., the 25–75% quantile of deviations) for the CHELSA dataset span a range of 648 mm, an interval smaller than the corresponding intervals for the WorldClim2 and HRCM datasets (Table 1). Beyond the deviations in magnitude from observed MAP, there are notable differences in spatial patterns of modeled rainfall compared to the observed rainfall patterns (Fig. 3). All WorldClim2, CHELSA, and HRCM datasets underestimate windward rainfall values across the islands. Additionally, WorldClim2 largely overestimates rainfall in leeward areas. Both CHELSA and HRCM struggle to represent lower precipitation at higher elevations, which is due to the effects of an atmospheric inversion layer called the trade wind inversion (TWI; Longman et al. 2015). The discontinuity in the vertical temperature gradient produced by the local TWI prevents the moist trade winds from rising and producing clouds and precipitation. The inability of these global models to capture this local pattern of rainfall leads to some of the highest positive percent deviations (i.e., rainfall overestimates) in these high elevation areas above the TWI due to their larger scale projections.

4.1.2 Temperature

All downscaled products show a spatial pattern of historical mean annual temperature across the landscape very similar to the observed pattern (Online Resource 3). All downscaled MAT modeled datasets show small overall bias in baseline temperatures in relation to the observational data, with WorldClim2 having the smallest median deviation in comparison to the observed data (0.52 °C) and CHELSA having the largest deviation (0.95 °C) (Table 1). In absolute terms, the WorldClim2 dataset also had a narrower range of deviations between modeled and observed MAT (Fig. 4). Although all downscaled results reproduce the elevation dependency of temperature reasonably well, the spatial pattern of deviations from the observed temperature are complex (Fig. 5). Both the CHELSA and WorldClim2 datasets show subtle deviations in their mapped patterns that reflect the topographic complexity in Hawaiʻi on a fine spatial scale. Although CHELSA may show the smoothest patterns of deviation, it again struggles to perform above the TWI and showed higher biases in windward areas. In contrast, the HRCM deviations do not tend to follow any clear geographic pattern.

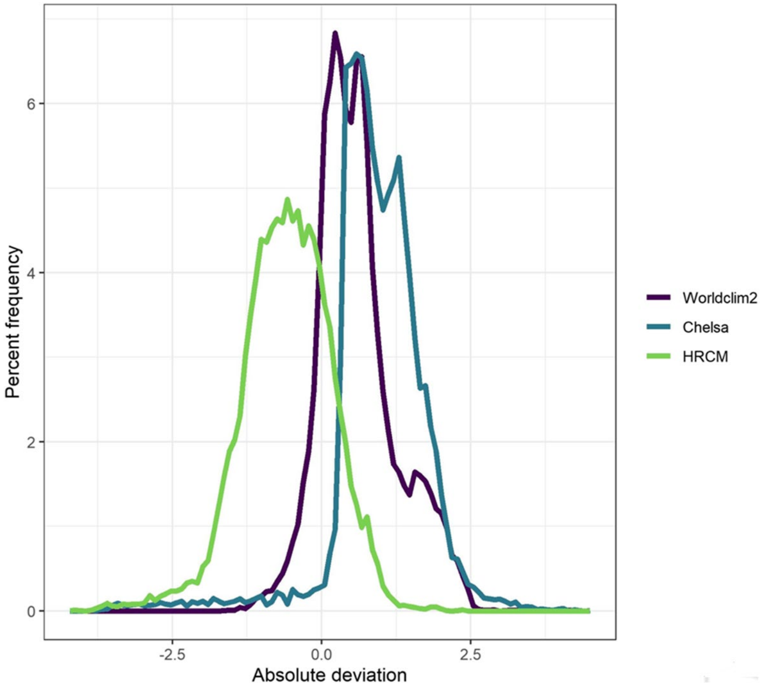

Fig. 4 Histograms of absolute deviation between model and observation-based mean annual temperature (MAT) for the baseline period of 1983–2012. Deviations were calculated based on a comparison of each model (WorldClim2, CHELSA, and HRCM) versus the observation-based MAT baseline from the Climate of Hawai‘i

4.2 Standardized deltas and bias correction of future downscaled projections

We calculated standardized deltas and bias corrected future projections for CHELSA and WorldClim2 for Hawai‘i under all 16 common GCMs, emission scenarios, and future time periods. Close examination of the standardized deltas between current and the late century RCP8.5 scenario for CHELSA and WorldClim2 showed highly contrasting patterns and magnitude of change between the two datasets (Online Resource 4). The median MAT deltas across the 16 considered GCMs for CHELSA showed a noisy but stronger warming for the islands in the southeast and modest warming for islands in the northwestern portion of the archipelago. In contrast, the median MAT deltas for WorldClim2 showed a much wider range of projected temperature shifts with abrupt spatial patterns, where sites with similar elevation and topography varied by > 1°C in projected MAT shifts. In terms of MAP median deltas for the same future climate scenario and GCMs, CHELSA projected a small magnitude of shifts across most of the archipelago (MAP deltas mostly < 5% change). In contrast, WorldClim2 projected large drying and wetting trends across the archipelago (MAP deltas > 50% change) that were very abrupt, as areas with > 50% projected drying were nearly adjacent to areas with > 50% projected wetter conditions.

To further examine the plausibility of these projections, we compared the deltas for MAT and MAP across the global datasets with the three regionally downscaled MAP and MAT climate projections available for Hawai‘i for end-of-century climate under RCP8.5. Both bias-corrected

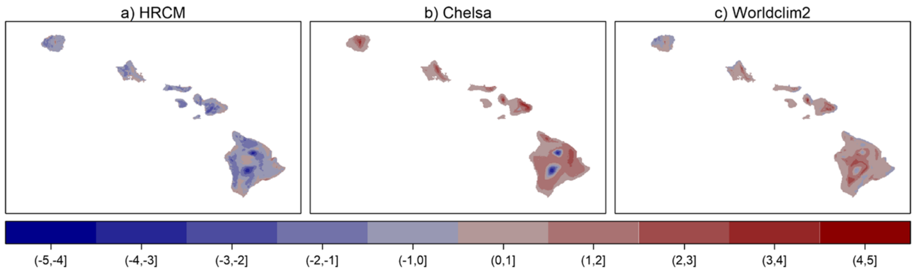

Fig. 5 Maps of absolute deviation (in °C) of mean annual temperature (MAT) between baseline Climate of Hawai‘i observed data and (a) HRCM, (b) CHELSA, and (c) WorldClim2 downscaled data

CHELSA and WorldClim2 datasets project a smaller median MAT and MAP rate of change across Hawai‘i compared to the regional datasets (Fig. 6). However, the lower (10%) and upper (90%) quantiles for these rates of change showed WorldClim2 projections often had rates of change for MAT and MAP that were more than twice of those from regional climate

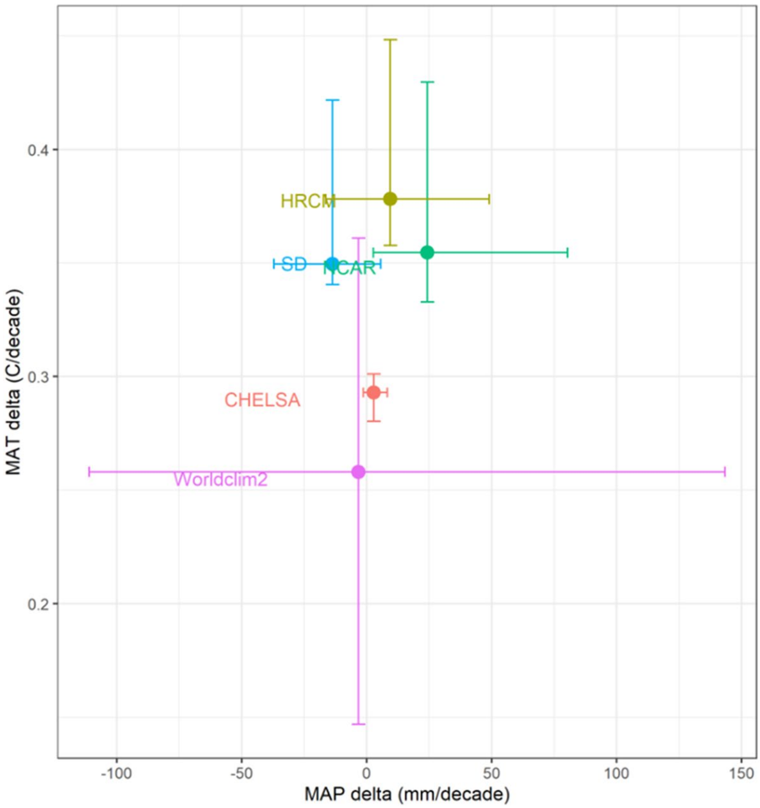

Fig. 6 Median projected rates of change in mean annual temperature (MAT) and mean annual precipitation (MAP) (with 10% and 90% quantile bars) across bias-corrected global datasets (CHELSA, WorldClim2), and Hawai‘i regionally downscaled datasets (HRCM, NCAR, SD). Median, 10% and 90% quantile values did not visibly change for the non-bias-corrected Worldclim2 and CHELSA global datasets

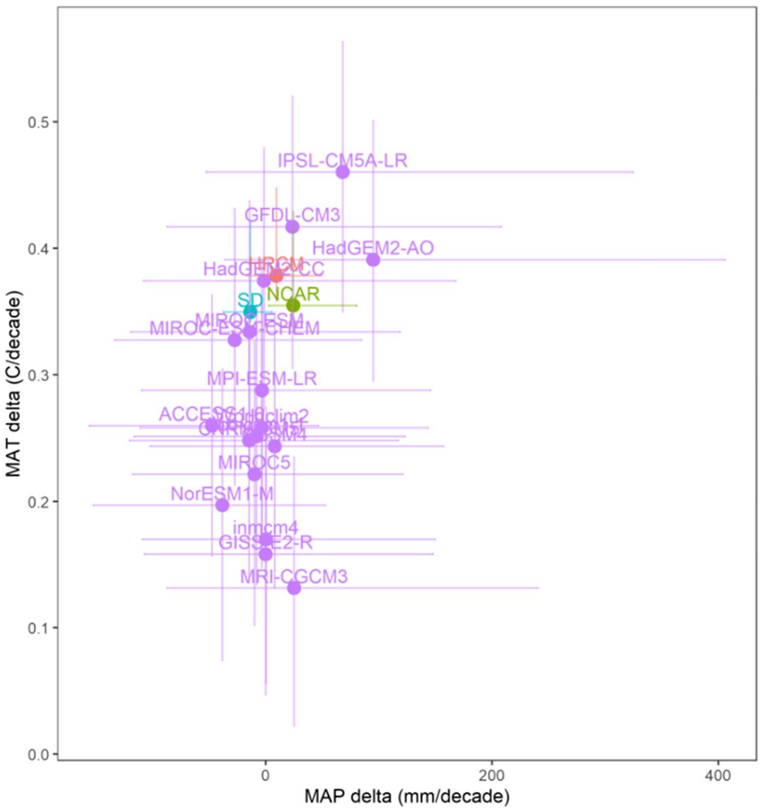

Fig. 7 Median projected rates of change in mean annual temperature (MAT) and mean annual precipitation (MAP) (with 10% and 90% quantile bars) across GCM-specific bias-corrected global WorldClim2 projections and Hawai‘i regionally downscaled datasets (HRCM, NCAR, SD) under late century RCP8.5. Similar figures for CHELSA projections are shown in Online Resource 5

projections. CHELSA projections, on the other hand, exhibited a narrow range of delta values, not only compared to WorldClim2 deltas but also to regionally downscaled deltas. Exploring GCM-specific bias-corrected datasets showed an even greater range of values for WorldClim2 in comparison to the regionally downscaled datasets and show that variability among GCMs is greater than the differences between regional or bias-corrected datasets (Fig. 7).

Lastly, using the bias-corrected datasets, we described patterns of projected future shifts in MAP and MAT in Hawai‘i (Online Resources 7–10). We explored the variability of future projections based on 16 available GCMs for late century (2061–2080) under RCP8.5 as these outputs were comparable to regional climate projections from the HRCM and the other two regional models. We also produced a similar dataset available in our online data release that offers mid-century results and a wider range of RCPs (Berio Fortini and Kaiser 2022).

4.3 Impact of global dataset choice on projected future species range shifts

The use of the globally downscaled datasets for species distribution model fitting resulted in a statistically significant decrease in accuracy (6% and 7% relative accuracy decrease for

CHELSA and WorldClim2, respectively) in comparison to models fitted using the observation-based bias corrected baseline data (Online Resource 6). Beyond the impact of different baselines on model accuracy, we isolated the effect of differences in future projections between the two globally downscaled datasets by fitting and projecting present range using a common bias corrected baseline climate dataset, and projecting future distributions using both bias corrected CHELSA and WorldClim2 datasets.

The effect of dataset choice on species modeled range shifts, independent of baseline differences, varied widely across species (Online Resource 6). The median percent range change differences between CHELSA and WorldClim2 projections was 5.7% the size of a given species current range. While apparently small, the median range change due to projected climate shifts between the baseline and the 2061–2080 RCP8.5 future scenarios considered for both datasets was also relatively small (19.7%). Hence, across all species, the relative effect of dataset choice could be consequentially large, as the median effect of dataset choice was 30.1% as large as the percent range change due to projected climate shifts between the baseline and the 2061–2080 RCP8.5 future scenarios considered. This relative effect of dataset choice could also be extremely high, with the 95% quantile across all species being 665% as large as the projected climate change driven range change (i.e., some species had little to no climate-driven range change but differed widely between CHELSA and WorldClim2 future projections). In general, CHELSA based future projections resulted in larger range overlaps between baseline and future projections when compared to WorldClim2 projections, even when using a common bias corrected baseline (71.6% versus 66.4% mean range overlap, CHELSA and WorldClim2 respectively). This agrees with the noticeably smaller range of MAT and MAP deltas across GCMs for CHELSA future projections in comparison to WorldClim2 (Fig. 6).

5 Discussion and conclusions

Downscaled climate projections are being increasingly used for biogeographical, hydrologic, and climate change impact modeling purposes (Rodder 2009; Rovzar et al. 2013; Kodis et al. 2018; Mausio et al. 2020). Consequently, globally downscaled climate datasets such as WorldClim2 and CHELSA are some of the most widely used climate datasets in the world (Lima-Ribeiro et al. 2015; Fick and Hijmans 2017; Karger et al. 2017a; Vega et al. 2017). In this study, we expand on previous work that recommended bias correction of such datasets (Poggio et al. 2018) by exploring the future projections from these datasets to characterize their utility as plausible future climate scenarios.

From our comparison of WorldClim2 with local observational data, it is apparent that for Hawai‘i, this downscaled dataset does not adequately represent MAP as it does not capture the well-known windward-leeward rainfall pattern. Rainfall in Hawai‘i is mainly driven by the steep orography and prevailing trade winds (Schroeder et al. 1984; Garza et al. 2012), where the windward sides of the mountains are major contributors to statewide rainfall totals (Lyons 1982), with some areas receiving mean annual rainfall of over 10,000 mm per year (Giambelluca et al. 2013). These steep rainfall gradients are difficult to capture at a larger scale and require more refined projections to capture local rainfall patterns on small islands like Hawai‘i. In fact, both global datasets encountered some difficulty in projecting orographic rainfall and also had problems with temperature projections in areas above the TWI that resulted in some of the highest positive percent deviations. The CHELSA dataset offers better results for MAP but exhibits consistent temperature bias across the islands, especially in areas above the TWI. The interaction of the TWI (typically located at 2,150 m elevation and above), which determines the cloud top height (Cao et al. 2007; Longman et al. 2015) and subsequently the precipitation in conjunction with the complex terrain, creates a unique response to climate change. The TWI creates sharp discontinuities in climate patterns as high elevation areas are some of the driest areas in Hawai‘i (Giambelluca et al. 2013). Because the TWI base height is usually lower than the tallest mountains that extend above 4,000 m, the summits on Maui and Hawai‘i Island can be dry and clear despite clouds on the lower slopes. However, the TWI can vary in base height, thickness, strength, and frequency across the island chain (Cao et al. 2007). Consequently, bias-corrected projections for areas above the TWI are to be used with caution. Nevertheless, given that a large portion of areas of conservation, water management, and other areas of concern are located below this elevation, this clear TWI limitation does not undermine the utility of these datasets to a broader portion of the Hawaiian landscape. Other researchers working in areas with similar topographically defined climate patterns may benefit from evaluating the capacity of such global datasets to properly represent similarly important regional climatic patterns.

In terms of exploring the ability of these global datasets in replicating fine scale MAT and MAP patterns of current climate, our work expands on past efforts (Wango et al. 2018) by including HRCM, a widely used regionally downscaled set of baseline projections, as a reference point for comparisons. In that respect, despite similar deviations between the regional downscaled model and the global datasets in representing local climate, the HRCM better represented the strong windward and leeward orographic MAP gradients in general but did not fully capture the TWI effect on high elevation temperatures, resulting in a small cold bias at high elevations. Overall, although the proposed regional adaptation of global climate datasets we describe in our work provide some additional resources to be incorporated into impact studies and resource management decisions, these are not a replacement for tailored regional downscaling efforts (Zhang et al. 2016c; Elison Timm 2017; Xue et al. 2020).

The examination of projected future rates of MAT and MAP change is a step not previously performed in studies examining global downscaled datasets but could improve the understanding of the differences seen in global models and datasets. The differences in MAT and MAP shifts from GCM-specific future projections from WorldClim2, and CHELSA were larger than the differences between median global downscaled projections and their regionally downscaled counterparts (Figs. 6 and 7). The spatial patterns and magnitudes of shifts for WorldClim2 late century MAT and MAP shifts under RCP8.5 were substantially larger than CHELSA and regionally downscaled projections (Online Resource 4). On the other hand, CHELSA equivalent projections had smaller shifts both in terms of median and range of change. These patterns were present irrespective of the application of baseline bias-correction. Given the differences in projected change between the bias-corrected GCM-specific projections, when available, regional downscaled projections can be useful to identify individual GCMs that yield projections more in line with regional downscaling values, such as Model for Interdisciplinary Research on Climate (MIROC) atmospheric chemistry coupled model (MIROC-CHEM) and earth system model (MIROC-ESM) for CHELSA (Online Resource 5). Using this subset of best performing bias-corrected GCMs, multiple bias-corrected future climate scenarios can be developed based on the wide availability of WorldClim2 and CHELSA projections for mid- and late-century under multiple RCPs (Fick and Hijmans 2017; Karger et al. 2017a, b).

Although Morales-Barbero and Vega-Álvarez (2019) recommended considering congruency among global datasets as a measure of certainty in climate change impact studies, the different ways in which future projections are created between CHELSA and WorldClim2 signify that additional discrepancies are possible when comparing future climate impact projections based on these two datasets. In fact, by isolating the differences in future projections by standardizing these global datasets to a common baseline showed that the implications of future projection differences alone could be quite large. Past work has already shown that differences in baseline climate data used to fit models can have a large effect on climate projections (Bedia et al. 2013; Poggio et al. 2018), and this work expands those cautionary notes by showing that differences in global downscaled dataset future projections alone can also have large effects on projections such as species distribution shifts and likely other uses. These differences were not only a matter of accuracy, magnitude and bias in projected range shifts, but often changes in overall spatial patterns of resulting projected distributions (Online Resource 6). Nevertheless, it is still important to note that our findings are based on a single study region, and that the specific patterns of deviations in baseline and future projections between WorldClim2, CHELSA, and local datasets are likely region-specific. Lastly, the generally limited descriptions of methods used to generate future projections for both datasets hinders their use and if improved would ensure that future research efforts could more easily understand potential sources of error and uncertainties in these products and derived climate impact analyses. In fact, both primary publications for WorldClim2 (Fick and Hijmans 2017) and CHELSA (Karger et al. 2017a) focus on the methods associated with current climatologies, and do not describe future GCM downscaling methods, with only limited information available in their respective websites (https://www.worldclim.org/data/downscaling.html and https://chelsa-climate.org/wp-admin/download-page/CHELSA_tech_specification.pdf (Section 3.4), respectively). Without more detailed description of the future GCM downscaling approaches, understanding the causes of our observed differences between the two approaches is challenging.

Although these high-resolution global datasets were developed to provide regional climatology for the terrestrial world and have been widely valued and used, past research has already cautioned against the unexamined use of global datasets in topographically complex regions (Bobrowski and Schickhoff 2017). Our analyses also highlight the need to examine the patterns of climatic change projected by these datasets. At a minimum, bias correction using locally available baseline datasets is one important step previously identified (Poggio et al. 2018) that warrants consideration by users of these global datasets. However, for our analysis, this step alone was not enough to address issues identified in comparisons with observational baseline data and fine-tuned regionally developed projections for complex, mountainous, small-scale areas. Although we did have the benefit of being able to compare the bias-corrected global projections with regionally downscaled projections, we expect in other similar regions without regional downscaling efforts for comparisons that averaging across datasets would still help reduce outlier values in bias-corrected global datasets. Lastly, the inspection of projected shifts from these global datasets was useful, especially when comparing to similar projections from regionally downscaled efforts. Even without regional projections for comparisons, the inspection of projected shifts in MAT and MAP provide a much clearer picture of the relative strengths and weaknesses of these datasets for studies that aim to project future climate change impacts at global and regional scales.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10584-023-03623-z.

Acknowledgements This work was made posssible with funding by the US Geological Survey Pacific Island Climate Adaptation Science Center (PICASC) and Alaska CASC, project awards #COA.16DIR.USGS.LFO.01 and #G21AC10110; Hawaiʻi Established Program to Stimulate Competitive Research (EPSCoR); and a National Science Foundation Research Infrastructure Improvement (RII) Track-1: 'Ike Wai: Securing Hawaii's Water Future Award # OIA-1557349. The authors have no relevant financial or non-financial interests to disclose. All authors contributed to the study conception and design. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the US Government.

Author contribution Material preparation, data collection and analysis were performed by Lucas Berio Fortini and Lauren Kaiser. The first draft of the manuscript was written by Lucas Berio Fortini and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data availability The datasets generated during and/or analyzed during the current study are available at https://doi.org/10.5066/P94IHW4X.

References

Bedia J, Herrera S, Gutiérrez JM (2013) Dangers of using global bioclimatic datasets for ecological niche modeling. Limitations for future climate projections. Global Planet Change 107:1–12. https://doi.org/10.1016/j.gloplacha.2013.04.005

Berio Fortini L, Kaiser LR (2022) Hawaiian Islands downscaled climate projections for baseline (1983–2012), mid- (2040–2059), and late-century (2060–2079) scenarios: U.S. Geological Survey data release. https://doi.org/10.5066/P94IHW4X

Berrisford P, Dee DP, Poli P et al (2011) The ERA-Interim archive Version 2.0. ERA Report Series 1. European Centre for Medium Range Weather Forecasts, Reading, UK. https://www.ecmwf.int/en/elibrary/8174-era-interim-archive-version-20

Bobrowski M, Schickhoff U (2017) Why input matters: Selection of climate data sets for modelling the potential distribution of a treeline species in the Himalayan region. Ecol Model 359:92–102. https://doi.org/10.1016/j.ecolmodel.2017.05.021

Brandl S, Paul C, Knoke T, Falk W (2020) The influence of climate and management on survival probability for Germany's most important tree species. For Ecol Manag 458:117652. https://doi.org/10.1016/j.foreco.2019.117652

Brewington L, Keener V, Mair A (2019) Simulating Land Cover Change Impacts on Groundwater Recharge under Selected Climate Projections, Maui. Hawaii. Remote Sens 11:3048. https://doi.org/10.3390/rs11243048

Camp RJ, Berkowitz SP, Brink KW et al (2018) Potential impacts of projected climate change on vegetation-management strategies in Hawaiʻi Volcanoes National Park. Reston. VA. Park Science 34:22–31

Cantor SB, Sun CC, Tortolero-Luna G et al (1999) A Comparison of C/B Ratios from Studies Using Receiver Operating Characteristic Curve Analysis. J Clin Epidemiol 52:885–892. https://doi.org/10.1016/S0895-4356(99)00075-X

Cao G, Giambelluca TW, Stevens DE, Schroeder TA (2007) Inversion Variability in the Hawaiian Trade Wind Regime. J Clim 20:1145–1160. https://doi.org/10.1175/JCLI4033.1

Çoban H, Örücü Ö (2020) MaxEnt Modeling for Predicting the Current and Future Potential Geographical Distribution of Quercus libani Olivier. Sustainability 12:2671. https://doi.org/10.3390/su12072671

Daly C (2006) Guidelines for assessing the suitability of spatial climate data sets. Int J Climatol 26:707–721. https://doi.org/10.1002/joc.1322

ElisonTimm O (2017) Future warming rates over the Hawaiian Islands based on elevation-dependent scaling factors. Int J Climatol 37:1093–1104. https://doi.org/10.1002/joc.5065

Elison Timm O, Giambelluca TW, Diaz HF (2015) Statistical downscaling of rainfall changes in Hawai‘i based on the CMIP5 global model projections. J Geophys Res: Atmos 120:92–112. https://doi.org/10.1002/2014JD022059
Elith J, Leathwick JR, Hastie T (2008) Working guide to boosted regression trees. J Anim Ecol 77:802–813. https://doi.org/10.1111/j.1365-2656.2008.01390.x
Escalera-Vazquez LH, Hernandez-Guzman R, Soto-Rojas C, Suazo-Ortuno I (2018) Predicting Ambystoma ordinarium Habitat in Central Mexico Using Species Distribution Models.(Report). Herpetologica 74:117. https://doi.org/10.1655/Herpetologica-D-16-00078.1
Fick SE, Hijmans RJ (2017) WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. Int J Climatol 37:4302–4315. https://doi.org/10.1002/joc.5086
Fortini LB, Kaiser LR, Vorsino AE et al (2017) Assessing the potential of translocating vulnerable forest birds by searching for novel and enduring climatic ranges. Ecol Evol 7:9119–9130. https://doi.org/10.1002/ece3.3451
Frazier AG, Giambelluca TW, Diaz HF, Needham HL (2016) Comparison of geostatistical approaches to spatially interpolate month-year rainfall for the Hawaiian Islands. Int J Climatol 36:1459–1470. https://doi.org/10.1002/joc.4437
Garnier S, Ross N, Rudis R et al (2021) viridis - Colorblind-Friendly Color Maps for R
Garza J, Chu P-S, Norton C, Schroeder T (2012) Changes of the prevailing trade winds over the islands of Hawaii and the North Pacific. J Geophys Res Atmos 117:D11109. https://doi.org/10.1029/2011JD016888
Giambelluca TW, Chen Q, Frazier AG et al (2013) Online rainfall atlas of Hawai‘i. Bull Am Meteor Soc 94:313–316. https://doi.org/10.1175/BAMS-D-11-00228.1
Giambelluca TW, Shuai X, Barnes ML et al (2014) Evapotranspiration of Hawai‘i. Final report submitted to the U.S. Army Corps of Engineers—Honolulu District, and the Commission on Water Resource Management, State of Hawai‘i
Hawkins E, Smith RS, Gregory JM, Stainforth DA (2016) Irreducible uncertainty in near-term climate projections. Clim Dyn 46:3807–3819. https://doi.org/10.1007/s00382-015-2806-8
Hijmans RJ, Cameron SE, Parra JL et al (2005) Very high resolution interpolated climate surfaces for global land areas. Int J Climatol 25:1965–1978. https://doi.org/10.1002/joc.1276
Hijmans RJ, Phillips S, Leatherwick J, Elith J (2017) dismo: Species Distribution Modeling
IPCC (2000) Emissions scenarios. Nebojsa Nakicenovic and Rob Swart (eds.) Cambridge University Press, UK. pp 570.Cambridge, England
Kagawa-Viviani AK, Giambelluca TW (2020) Spatial patterns and trends in surface air temperatures and implied changes in atmospheric moisture across the Hawaiian Islands, 1905–2017. J Geophys Res: Atmos 125:e2019JD031571. https://doi.org/10.1029/2019JD031571
Karger DN, Conrad O, Böhner J et al (2017a) Climatologies at high resolution for the earth's land surface areas. Sci Data 4(1):1–20. https://doi.org/10.1038/sdata.2017.122
Karger DN, Conrad O, Böhner J et al (2017b) Data from: Climatologies at high resolution for the earth's land surface areas. EnviDat. https://doi.org/10.16904/envidat.228.v2.1
Kodis M, Galante P, Sterling EJ, Blair ME (2018) Ecological niche modeling for a cultivated plant species: a case study on taro (*Colocasia esculenta*) in Hawaii. Ecol Appl 28:967–977. https://doi.org/10.1002/eap.1702
Lembrechts JJ, Lenoir J, Roth N et al (2019) Comparing temperature data sources for use in species distribution models: From in-situ logging to remote sensing. Glob Ecol Biogeogr 28:1578–1596. https://doi.org/10.1111/geb.12974
Li X, Ma L, Hu D et al (2022) Potential Range Shift of Snow Leopard in Future Climate Change Scenarios. Sustainability (Basel, Switzerland) 14:1115. https://doi.org/10.3390/su14031115
Liao Z, Zhang L, Nobis MP et al (2020) Climate change jointly with migration ability affect future range shifts of dominant fir species in Southwest China. Divers Distrib 26:352–367. https://doi.org/10.1111/ddi.13018
Lima-Ribeiro MS, Varela S, González-Hernández J et al (2015) ecoClimate: a database of climate data from multiple models for past, present, and future for Macroecologists and Biogeographers. Biodivers Inform 10:1–21. https://doi.org/10.17161/bi.v10i0.4955
Longman R, Diaz H, Giambelluca T (2015) Sustained Increases in Lower-Tropospheric Subsidence over the Central Tropical North Pacific Drive a Decline in High-Elevation Rainfall in Hawaii. J Clim 28:8743–8759. https://doi.org/10.1175/JCLI-D-15-0006.1
Lyons SW (1982) Empirical Orthogonal Function Analysis of Hawaiian Rainfall. J Appl Meteorol 1962–1982(21):1713–1729. https://doi.org/10.1175/1520-0450(1982)0212.0.CO;2
Marchi M, Sinjur I, Bozzano M, Westergren M (2019) Evaluating WorldClim Version 1 (1961–1990) as the Baseline for Sustainable Use of Forest and Environmental Resources in a Changing Climate. Sustainability (2071-1050) 11:3043. https://doi.org/10.3390/su11113043

Mausio K, Miura T, Lincoln NK (2020) Cultivation potential projections of breadfruit (Artocarpus altilis) under climate change scenarios using an empirically validated suitability model calibrated in Hawai'i. PLOS ONE 15:e0228552. https://doi.org/10.1371/journal.pone.0228552

McKenzie MM, Giambelluca TW, Diaz HF (2019) Temperature trends in Hawai'i: A century of change, 1917–2016. Int J Climatol 39:3987–4001. https://doi.org/10.1002/joc.6053

Morales-Barbero J, Vega-Álvarez J (2019) Input matters matter: Bioclimatic consistency to map more reliable species distribution models. Methods Ecol Evol 10:212–224. https://doi.org/10.1111/2041-210X.13124

Mundis SJ (2021) Spatial Patterns in Mosquito Populations that Mediate Vector Control Effectiveness and Disease Risk at the Local, State, and National Level in the United States. Doctoral Dissertation, University of Florida. ProQuest Dissertations Publishing

Panja S, Podder A, Homechaudhuri S (2021) Modeling the climate change impact on the habitat suitability and potential distribution of an economically important hill stream fish, *Neolissochilus hexagonolepis*, in the Ganges-Brahmaputra basin of Eastern Himalayas. Aquat Sci 83:66. https://doi.org/10.1007/s00027-021-00820-9

Pau S, Cordell S, Ostertag R et al (2019) Climatic sensitivity of species' vegetative and reproductive phenology in a Hawaiian montane wet forest. BioRxiv. https://doi.org/10.1101/749614

Poggio L, Simonetti E, Gimona A (2018) Enhancing the WorldClim data set for national and regional applications. Sci Total Environ 625:1628–1643. https://doi.org/10.1016/j.scitotenv.2017.12.258

R Core Team (2020) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Raju KS, Kumar DN (2020) Review of approaches for selection and ensembling of GCMs. J Water Clim Chang 11:577–599. https://doi.org/10.2166/wcc.2020.128

Rodder D (2009) "Sleepless in Hawaii" - does anthropogenic climate change enhance ecological and sociaoeconomic impacts of the alien invasive Eleutherodactylus coqui Thomas 1966 (Anura: Eleutherodactylidae)? North-Western J Zool 5:16–25

Rovzar C, Gillespie TW, Kawelo K et al (2013) Modelling the potential distribution of endangered, endemic Hibiscus brackenridgei on Oahu to assess the impacts of climate change and prioritize conservation efforts. Pac Conserv Biol 19:156–168. https://doi.org/10.1071/pc130156

Schroeder T, Kilonsky B, Ramage C (1984) Diurnal Rainfall Variability over the Hawaiian Islands. Collected Reprints Volume V: 1978–1981, June 1984 Water Resources Research Center, Honolulu, Hawaii p 12–17, 5 Fig, 1 Tab, 12 Ref, 1984

Sydenham MAK, Moe SR, Eldegard K (2020) When context matters: Spatial prediction models of environmental conditions can identify target areas for wild bee habitat management interventions. Landsc Urban Plan 193:103673. https://doi.org/10.1016/j.landurbplan.2019.103673

Terando A, Reidmiller D, Hostetler SW et al (2020) Using information from global climate models to inform policymaking—The role of the U.S. Geological Survey: U.S. Geological Survey Open-File Report 2020–1058. 25 p. Reston, VA. https://doi.org/10.3133/ofr20201058

Teutschbein C, Seibert J (2012) Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. J Hydrol 456:12–29

Vega GC, Pertierra LR, Olalla-Tárraga MÁ (2017) MERRAclim, a high-resolution global dataset of remotely sensed bioclimatic variables for ecological modelling. Sci Data 4:170078. https://doi.org/10.1038/sdata.2017.78

Wango TJL, Musiega D, Mundia CN (2018) Assessing the Suitability of the WorldClim Dataset for Ecological Studies in Southern Kenya. J Geogr Inf Syst 10:643–658. https://doi.org/10.4236/jgis.2018.106033

Westerband AC, Bialic-Murphy L, Weisenberger LA, Barton KE (2020) Intraspecific variation in seedling drought tolerance and associated traits in a critically endangered, endemic Hawaiian shrub. Plant Ecolog Divers 13:159–174. https://doi.org/10.1080/17550874.2020.1730459

Xue L, Wang Y, Newman AJ et al (2020) How will rainfall change over Hawai'i in the future? High-resolution regional climate simulation of the Hawaiian Islands. Bull of Atmos Sci Technol 1:459–490. https://doi.org/10.1007/s42865-020-00022-5

Zarate MA, Shanee S, Charpentier E et al (2023) Expanded distribution and predicted suitable habitat for the critically endangered yellow-tailed woolly monkey (Lagothrix flavicauda) in Perú. Am J Primatol 85:e23464. https://doi.org/10.1002/ajp.23464

Zhang C, Wang Y, Lauer A, Hamilton K (2012) Configuration and Evaluation of the WRF Model for the Study of Hawaiian Regional Climate. Mon Weather Rev 140:3259–3277. https://doi.org/10.1175/MWR-D-11-00260.1

Zhang C, Wang Y, Hamilton K, Lauer A (2016a) Dynamical Downscaling of the Climate for the Hawaiian Islands. Part I: Present Day. J Clim 29:3027–3048. https://doi.org/10.1175/JCLI-D-15-0432.1

Zhang C, Wang Y, Hamilton K, Lauer A (2016b) Dynamical Downscaling of the Climate for the Hawaiian Islands. Part II: Projection for the Late Twenty-First Century. J Clim 29:8333–8354. https://doi.org/10.1175/JCLI-D-16-0038.1

Zhang C, Wang Y, Hamilton K, Lauer A (2016c) Dynamical Downscaling of the Climate for the Hawaiian Islands. Part I Present Day. J Clim 29:3027–3048. https://doi.org/10.1175/JCLI-D-15-0432.1

Authors and Affiliations

Lucas Berio Fortini[1] · **Lauren R. Kaiser**[2] · **Abby G. Frazier**[3] · **Thomas W. Giambelluca**[4]

✉ Lucas Berio Fortini
lfortini@usgs.gov

1 US Geological Survey, Pacific Island Ecosystems Research Center, Honolulu, HI, USA

2 Hawai‘i Cooperative Studies Unit, Honolulu, HI, USA

3 Graduate School of Geography, Clark University, Worcester, MA 01610, USA

4 Water Resources Research Center, University of Hawai‘i at Mānoa, Honolulu, HI 96822, USA