Designing Sustainable Landscapes: Climate data

A project of the University of Massachusetts Landscape Ecology Lab

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1 Problem Statement

To evaluate the effects of climate change on ecological settings space, ecological integrity, and wildlife habitat in the northeast region over the next 70 years, it is necessary to develop climate projections under multiple emissions scenarios at a fine spatial resolution throughout the entire Northeast.

Global coupled Atmospheric-Ocean General Circulation Models (AOGCMs) are complex models used to produce long-term climate projections by integrating both oceanic and atmospheric processes and the interactions between them. As part of the Coupled Model Intercomparison Project, each AOGCM was standardized using standard historic data - the 20^{th} Century in Coupled Models scenario (20C3M)(Covey et al. 2003) and forced with standard Representative Concentration Pathways (RCPs)(Moss et al. 2010). These simulations produced results comparable across models for each of the RCPs. Output from these models is produced in large grid cells, up to 300km on a side. These cells are too coarse to incorporate the local variation (e.g., climate differences due to local topographic effects) that is an important driver of ecological processes. Consequently, it is necessary to downscale the AOGCM output to a finer cell size for use in the Landscape Change, Assessment and Design (LCAD) model of the Designing Sustainable Landscapes (DSL) project (McGarigal et al 2017).

2 Solution Statement

We used AOGCM data downscaled using the Bias Corrected Spatial Disaggregation (BCSD) approach (Wood et al. 2002, 2004) spatially to 1/8 degree (approximately 12km) and temporally to daily values provided by Eleonora Demaria of the Northeast Climate Science Center-UMass, Amherst and derived from datasets publicly available through World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 5 (CMIP5).

We averaged the results of 14 AOGCMs to create an ensemble average projection for each of 2 RCPs, subtracted a baseline to create projected anomalies, and resampled these data at 800m cells. We then combined these data with 800m resolution, 30-year normal temperature and precipitation data (PRISM Climate Group, Oregon State University) using the “delta method”. Finally, these data were further resampled and projected to 600m cells which aligned with 30m cells used in the LCAD model. The complete process is outlined in figure 1 and described in detail below.

3 Key Features

In order to downscale the AOGCM climate projections, we utilized two major data sources: 1) World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 5 (CMIP5) multi-model dataset, which had been downscaled to 12km, and 2) the 800m resolution Parameter-elevation Relationships on Independent Slopes Model (PRISM) dataset developed by Oregon State University.

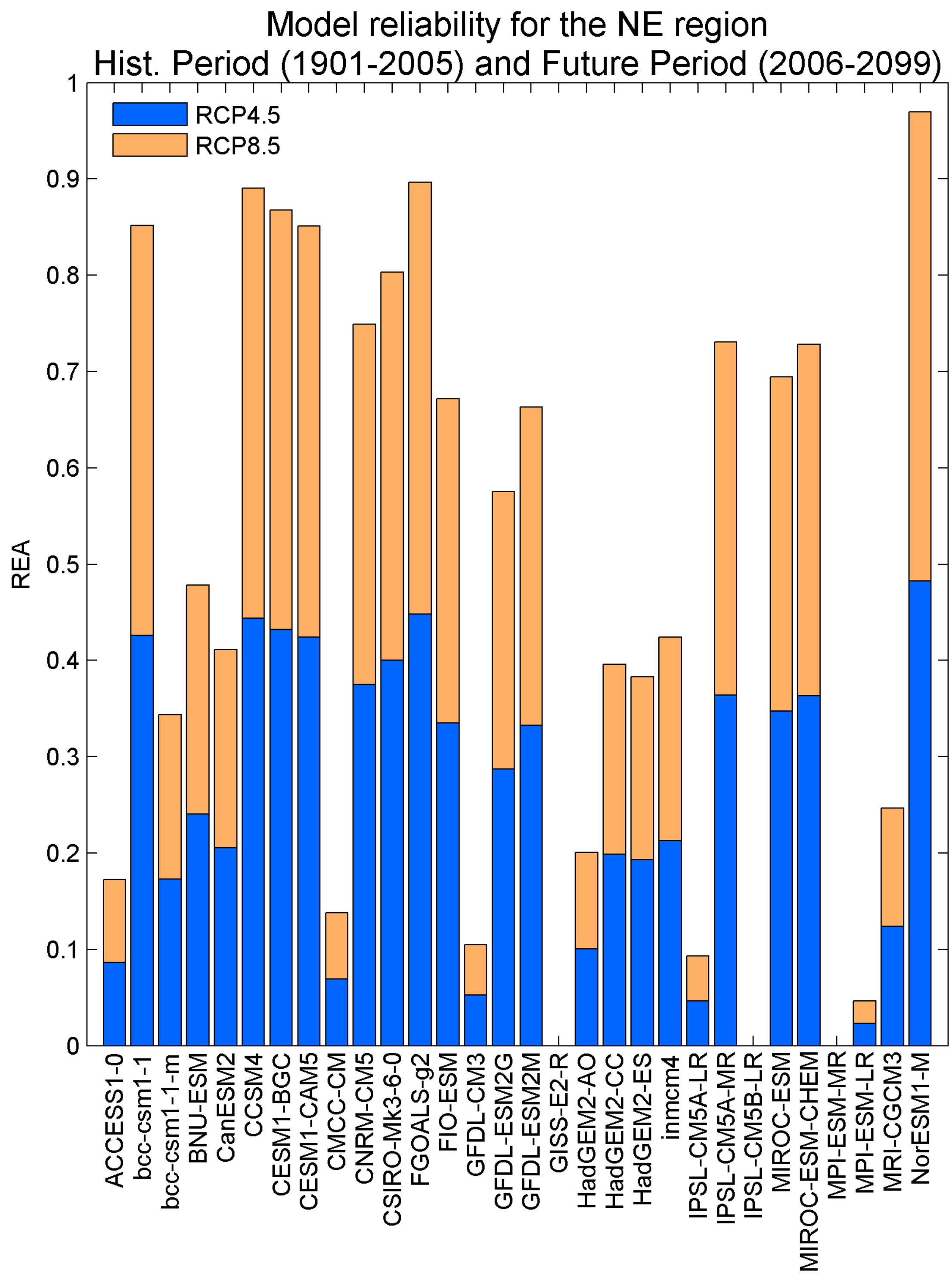

Figure 1. The Reliability Ensemble Average (REA, Dominguez et al. 2010) was calculated for 30 model runs based on the fit to historical data. The 14 best performing models for the Northeast Region were selected.

3.1 WCRP CMIP5 12km BCSD Data

The WCRP's CMIP5 has made publicly available a database of climate predictions downscaled using a BCSD approach, consistently applied across many AOGCMs under 4 RCP scenarios projected to the year 2100. This dataset, derived from CMIP5 data and served at: http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/, was described by Maurer et al. (2007) and consists of monthly average precipitation and monthly average temperature projections at 1/8 degree (12km) resolution across the U.S. Demaria (Northeast Climate Science Center) evaluated 30 models based on their ability to predict historical climate in the northeast region and selected 14 of these models to downscale temporally to daily values (**Fig. 1**).

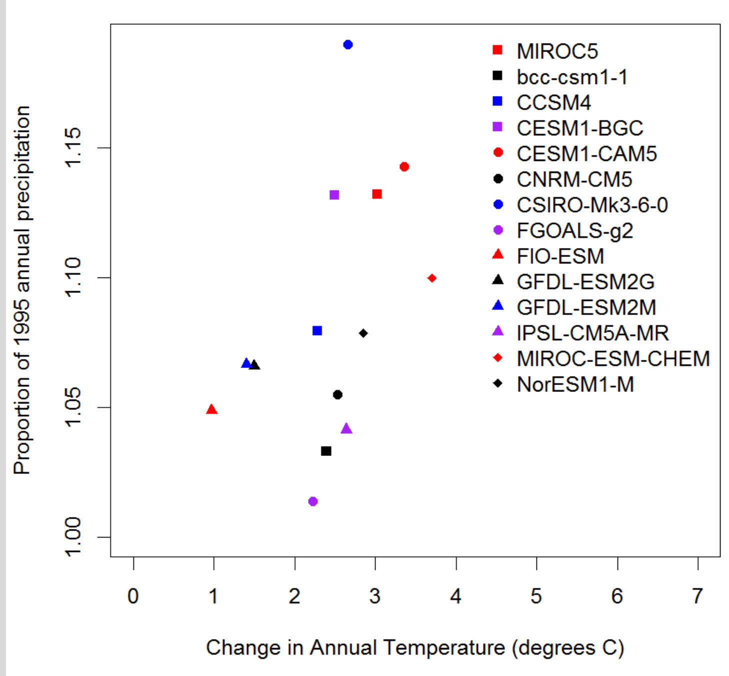

Figure 2. Average projected change in annual temperature and precipitation across the Northeast Region between "1995" and 2080 for each AOGCM under RCP 4.5.

We processed the output from those 14 AOGCM model runs to create an ensemble average AOGCM projection under each of 2 RCP scenarios (RCP4.5 and RCP8.5). Key features of the WCRP CMIP5 dataset include:

- *Ensemble of many models*.—The WRCP CMIP5 dataset uses results from many AOGCMs, each run 1-4 times under each RCP scenario (outlined below). We used an ensemble average of the 14 model runs that best predicted historical climate within the northeast region. The 14 model runs used and their sources are listed in **Table 1**. The variability of each of these model runs was assessed for both temperature and precipitation. Under all emissions scenarios, the range in temperature increase between model projections was about 3 degrees. Under the lowest RCP (4.5), the various models project an increase of 1 to 4 degrees C across the Northeast between 1995 and 2080 (**Fig. 2**) and under the highest RCP (8.5) the projected increase is 3 to 6 degrees C (**Fig. 4)**. The range of projections for precipitation under all scenarios is an increase of 1 to 20 % (**Figs. 2-3**). Because the model projections were fairly normally distributed with no real outliers, we used an ensemble average of all model runs.
- *RCP scenarios*.—RCP's 4.5 and 8.5 were the only two RCPs available for every CMIP5 model and they represent two different climate outcomes. They are similar through 2020 in both predicting increasing atmospheric forcing but then diverge; under RCP 4.5, the increase in atmospheric forcing begins to slow around 2020 and the

Table 1. AOGCM model runs used in climate projections.

Modeling Group, Country	**Institute ID**	**WCRP CMIP5 I.D.**
Beijing Climate Center, China Meteorological Administration	BCC	BCC-CSM1-1
National Center for Atmospheric Research, USA	NCAR	CCSM4
National Science Foundation, Department of Energy, National Center for Atmospheric Research, USA	NSF-DOE-NCAR	CESM1-BGC
National Science Foundation, Department of Energy, National Center for Atmospheric Research, USA	NSF-DOE-NCAR	CESM1-CAM5
Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique, France	CNRM-CERFACS	CNRM-CM5
Commonwealth Scientific and Industrial Research Organisation in collaboration with the Queensland Climate Change Centre of Excellence, Australia	CSIRO-QCCCE	CSIRO-Mk3.6.0
LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences; and CESS, Tsinghua University, China	LASG-CESS	FGOALS-g2
The First Institute of Oceanography, SOA, China	FIO	FIO-ESM
NOAA Geophysical Fluid Dynamics Laboratory, USA	NOAA GFDL	GFDL-ESM2G
NOAA Geophysical Fluid Dynamics Laboratory, USA	NOAA GFDL	GFDL-ESM2M
Institut Pierre-Simon Laplace, France	IPSL	IPSL-CM5A-MR
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC	MIROC-ESM-CHEM
Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute	MIROC	MIROC5

for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan		
Norwegian Climate Centre	NCC	NorESM1-M

amount of forcing levels off around 2070. In RCP 8.5, atmospheric forcing increases through 2080. Thus, RCP 4.5 is a more optimistic scenario that might be achieved by large societal, economic, political, or technological changes while RCP 8.5 projects that the historical pattern of increasing atmospheric forcing will continue. However, the RCPs themselves make assumptions only about the concentration of greenhouse gasses in the atmosphere, not about how those concentrations are reached. The RCPs assumptions are reflected in the temperature projections under each RCP (**Fig. 4**). The ensemble average precipitation increases under both RCPs, but increases slightly more under RCP 8.5 (**Fig. 5**).

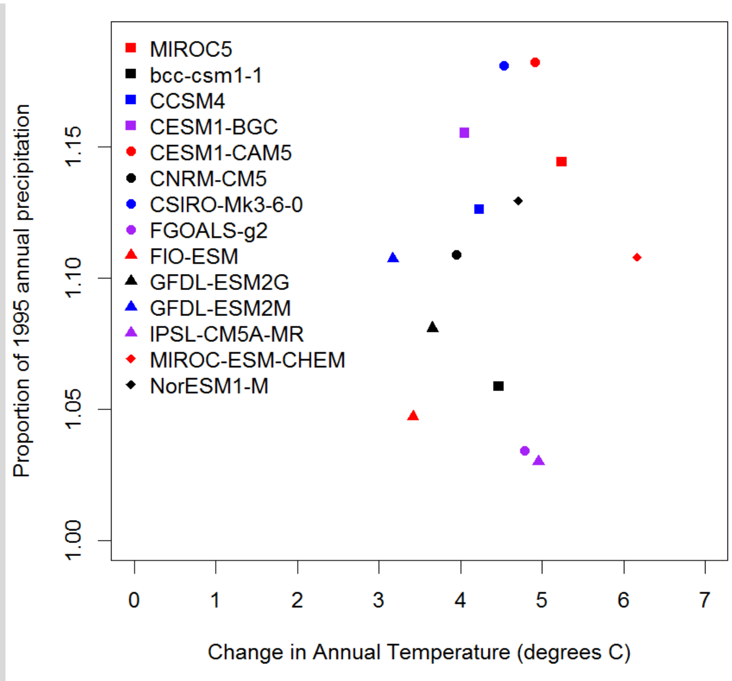

Figure 3. Average projected change in annual temperature and precipitation across the Northeast Region between "1995" and 2080 for each AOGCM under RCP 8.5.

- *BCSD downscaling approach*.—This approach was initially developed to downscale climate data for hydrological applications (Wood et al. 2002), but since has been used for a variety of applications, including the Northeast Climate Impact Assessment (NECIA, Hayhoe et al. 2007). Maurer et al. (2007), in conjunction with the WRCP, has made this dataset readily available. When compared to other downscaling approaches, BCSD performs well (Wood et al. 2004). While regional climate models (RCM) may be better at projecting extreme events, particularly with regard to precipitation in the northeast, computational costs of RCMs are prohibitive, and the BCSD method has been shown to perform comparably well, especially for average temperatures in this region (Hayhoe et al. 2007). Validation performed by previous authors suggests that average simulated precipitation values downscaled using a BCSD method were within 10% of observed climatological data, better than the HadRM3 RCM studied by Tryhorn and Degaetano (2010).

3.2 PRISM

The Parameter-elevation Relationships on Independent Slopes Model (PRISM) dataset was developed by Oregon State University with support from the U.S. Department of Agriculture through the Natural Resources Conservation Service (USDA-NRCS). The model uses a weighted climate-elevation regression approach to model the temperature and precipitation in each digital elevation model (DEM) grid cell. To develop the regression model in each cell, the model considers the most similar of 10,000 and 13,000 stations (for temperature and precipitation, respectively) in physiographic space, including the factors: location, elevation, coastal proximity, aspect, vertical atmospheric layer, topographic position, and orographic effects. The PRISM data are available as 30-year normal grids of the entire U.S. consisting of 800m cells with monthly average precipitation and monthly average minimum and maximum temperatures averaged across the years 1971 – 2000, and 1981-2010. This climate modeling approach outperforms similar datasets such as WorldClim and Daymet (Daly et al. 2008).

3.3 Data processing

The process (detailed below in Section 4 and illustrated in **figure 6**) we used to convert the 12km data to 30m grid cells for each of our climate variables (**Table 2**) consisted of:

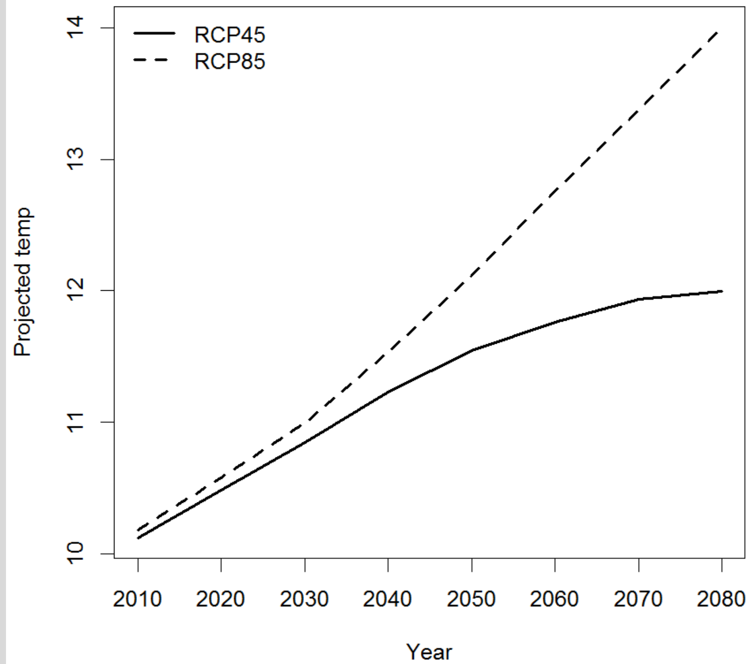

Figure 4. Projected annual average temperature throughout the Northeast Region from 2010 to 2080 under RCP 4.5 and RCP 8.5.

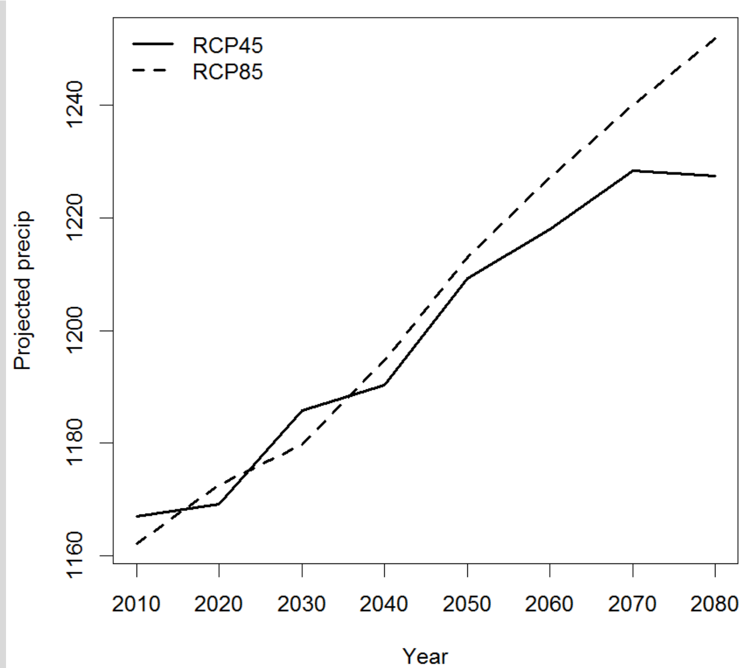

Figure 5. Projected annual average precipitation (mm) throughout the Northeast Region from 2010 to 2080 under RCP 4.5 and RCP 8.5.

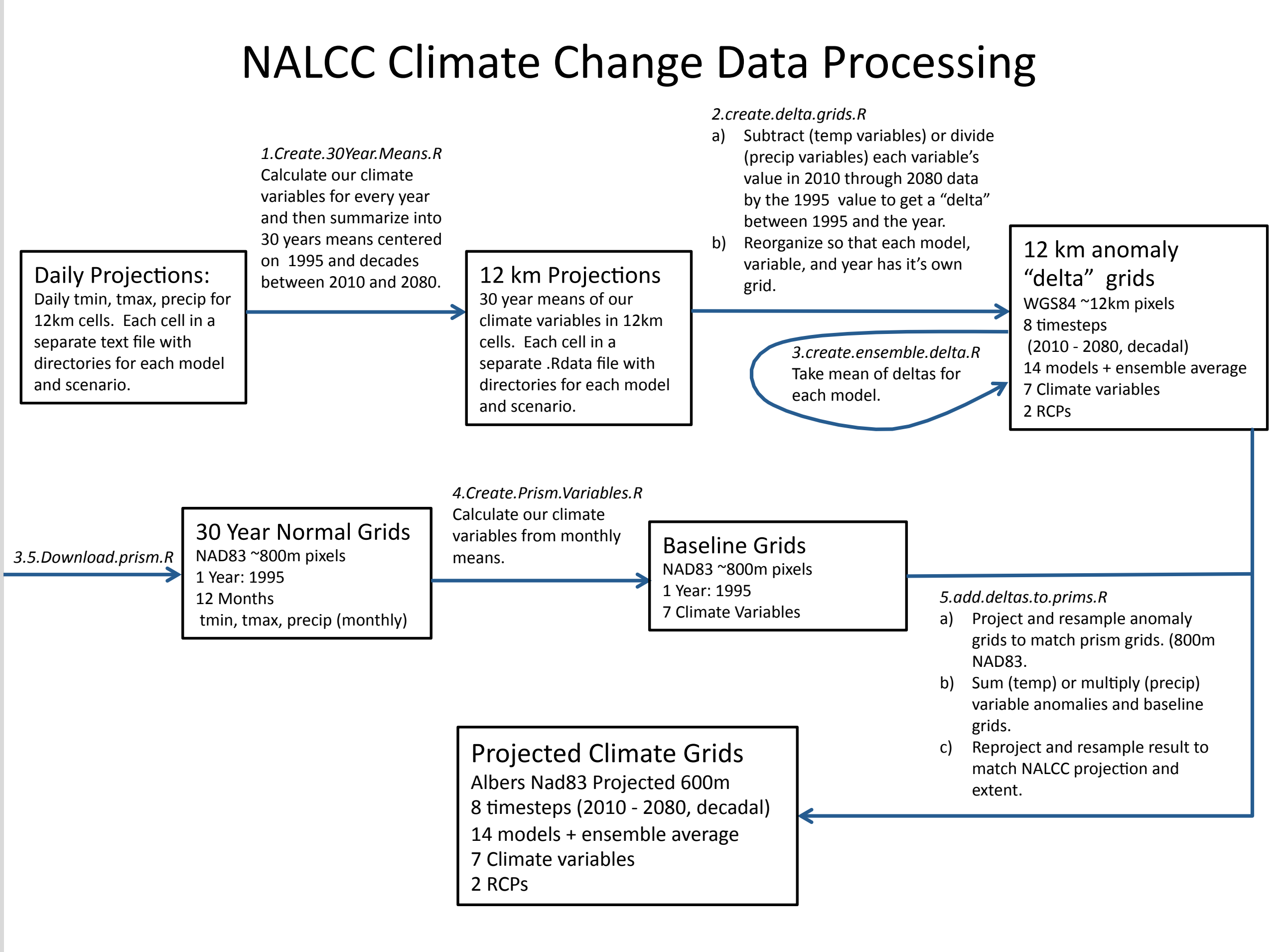

Figure 6. Designing sustainable landscapes project climate change data processing diagram. File reference: NALCC_Climate_Data_Processing_EBP.pptx.

1) Obtaining daily min and max temp, and precipitation data.
2) Summarizing the 30 year averages of our climate variables (**Table 2**) by
3) Creating anomaly ("delta") grids for each AOGCM, RCP, timestep, and climate variable based on the 30 year average for 1995 and the 30 year average for each timestep. These anomaly grids were created by subtracting temperature and dividing precipitation based variables.
4) Create ensemble deltas for each RCP and timestep by averaging across all the AOGCM delta grids.
5) Downloading the 1995 PRISM 30-year normal data.
6) Calculating climate variables from the PRISM data for the 1995 baseline.
7) Combining the 1995 baseline with the anomaly grids to create downscaled climate projections.

Table 2. Climate variables derived from AOGMC's and PRISM data and used in the DSL project. CNE = climate niche envelop modeling for representative species.

Climate Variable	Calculation Details	Alias
Annual Precipitation (Input in soil wetness calculation, CNE)	Total precipitation for the year. The sum of the daily values across all days. mm/year * 100. Note the "delta" in this case is actually a ratio.	precip
Growing Season Precip (CNE)	Sum of daily precipitation for days in May through September mm/year * 100. The "delta" is actually a ratio.	precipgs
Average annual temperature (CNE)	Mean of daily min and max for every day of the year.	temp
Mean Minimum Winter Temperature (Settings Variable, CNE)	Mean of the daily minimum temperatures for everyday in December, January, and February.	tmin
Mean Maximum Summer Temperature (CNE)	The mean of the daily maximum temperature for June, July and August.	tmax
Growing Degree Days (Settings Variable, CNE)	The sum across days of the number of degrees by which the mean daily temperature exceeds a threshold of 10 deg C. Where mean temperature is the mean of the min and max temp for the day. For prism data this is calculated from the 30 year mean temperature for each month by multiplying the exceedance by the number of days in the month.	gdd
Heat Index 35 (Settings Variable)	Uses the same general algorithm as gdd but with a threshold of 35 deg and based on the daily max temperature rather than the daily mean temp.	heat35

3.4 Assessment

In Phase 1 of this project we used a similar process to create projected climate grids from CMIP3 AOGCM projections and PRISM 1985 30 year normals. In that prior phase, we evaluated the error associated with the AOGCM modelling and downscaling; we compared our downscaled and resampled grids to raw station data available from the U.S. Historical Climatology Network (USHCN). Similar to the approach used above for the model data, we downloaded spatially explicit, monthly temperature and precipitation data and averaged them across 30 year intervals for the 1970 and 1980 time-steps. We then compared these 30 year values with those obtained through the modelling and downscaling process.

Temperature R_c values were between 0.97 and 0.99 for all months in both timesteps, suggesting strong agreement between the downscaled modelled temperatures and observed station temperatures. R_c values for precipitation were 0.83 in 1970 and 0.92 in 1980. The full results of that prior assessment are in the **Appendix**. Based on the strength of these phase 1 results and the similarity in data processing approaches used in phase 1 and 2, we chose not to repeat this assessment with the updated results generated from CMIP5 and PRISM 1995 data.

4 Detailed Description of Process

1) We obtained downsampled daily data from Demaria (Northeast Climate Science Center) who used the methods of Wood et al (2002, and 2004) to convert monthly climate data from the WRCP website: http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/#Projections:%20Complete%20Archives into daily values for the variables minimum temperature, maximum temperature, and precipitation. Each individual model run was stored in a directory with a separate text file for each cell in the landscape containing the three columns of climate data for each day from Jan-1-1950 to Dec-31-2099.

2) We created 30-year mean values for each of our climate variables (**Table 2**) centered on the prism normal year of 1995 as well as each of our model timesteps – the decades from 2010 to 2080. The R script : Z:\LCC\Code\Prep\Climate\run\1.Create.30Year.Means.R performed this in two stages:

    a. Calculating the climate variables for each year in the file from the daily min and max temperature and precipitation values.

    b. Average the yearly values of the variable over the 30 years.

    The output was an .Rdata file for each model, RCP, and cell containing the climate variable values for each year.

3) We created anomaly ("delta") grids by subtracting temperature based variables and dividing precipitation variables for each of the focal years by the value in 1995. These were produced for every AOGMC, RCP, and year. Script: Z:\LCC\Code\Prep\Climate\run\2.create.delta.grids.R. The output files were floating point ESRI grids with cells and projection matching those in the WRCP source data.

4) We created an ensemble anomaly grid for each RCP, variable, and focal year by taking the mean of the corresponding grids across all models. Script: Z:\LCC\Code\Prep\Climate\run\3.create.ensemble.delta.R

5) We downloaded PRISM 30 year normals centered on 1995 from: [ftp://prism.oregonstate.edu//pub/prism/us_30s/grids/[type.abr]/Normals/us_[type.abr]_1981_2010.[month].gz](ftp://prism.oregonstate.edu//pub/prism/us_30s/grids/[type.abr]/Normals/us_[type.abr]_1981_2010.[month].gz) Where [type.abr] took the values "tmin" "tmax" "ppt", and month ranged from 01 to 12 using the script: Z:\LCC\Code\Prep\Climate\run\3.5.Download.prism.R

6) We calculated our climate variables for the 1995 prism 30 year normal using the script Z:\LCC\Code\Prep\Climate\run\4.Create.Prism.Variables.R. The output files were ESRI grids representing each climate variable at 1995. With 800 meter cells in NAD83. Adopting the standard used in the PRISM data the value of each climate

variable was multiplied by 100 and then stored in an integer grid. This allows for more efficient data storage with a slight loss of precision.

7) We combined the AOGCM deltas with the PRISM 1995 normal to generate spatially downscaled grids representing our climate variables for the ensemble and each AOGCM, for each RCP and timestep. This allowed us to combine the course (12 km) resolution of the AOGCMs with the fine 800m variability of the prism normal while preserving the changes predicted by the AOGCM's.
    a. We reprojected the delta grids into the prism extent, cell size, and projection. This decreases the cell size from the 12km of the downsampled AOGCMs to the 800 meters of the prism data.
    b. We multiplied the PRISM derived precipitation variables by the anomaly grids and added the anomaly grids to the PRISM derived temperature variables.
    c. We reprojected the result to match the LCC projection and extent with 600 m pixels that snap to the 30 meter pixels used by most of the LCAD input grids.

    The result are predicted values for each climate variable multiplied by 100 and stored as integer grids. There are grids for each combination of variable, AOGCM (plus ensemble), RCP, and timestep with 600m pixels in the LCAD projection (Albers NAD83). A single R script executes this step: Z:\LCC\Code\Prep\Climate\run\5.add.deltas.to.PRISM.R

5 Alternatives Considered and Rejected

Prior to selecting the BCSD data source, we evaluated alternative methods for downscaling AOGCM data, including: 1) dynamical downscaling (regional climate models), 2) regression-based statistical downscaling approaches, and 3) the delta approach:

1) *Dynamical downscaling (regional climate models).*—These models use regional topography and local weather patterns to model future climate with AOGCM data input as "boundary conditions". This method is sometimes described as a model nested within a model. Though more accurate in modelling extremes in some cases (e.g., Hayhoe et al. 2006), they have also been shown to model average precipitation with less skill (Tryhorn and Degaetano 2010) in the northeast. These models are much more computationally intensive, and applying such a model to the entire NALCC for multiple scenarios and nine timesteps from 2000-2080 would have been prohibitive.
2) *Regression-based statistical downscaling approaches*.—While these methods have been shown to be more accurate in some instances (Tryhorn and Degaetano 2010), they are not as readily available as the BCSD data, and would require an extensive modelling effort in order to develop projections. The widely used SDSM software available to downscale station data operates on only one station at a time, and would have been prohibitive to implement over the entire NALCC. Other approaches to developing the regression models would also have been difficult, as the statistical relationships between broad- and fine-scale climate are likely to vary widely across the NALCC region. In addition, this method is not as conducive to developing long-term ensemble AOGCM averages. Regression-based approaches also have the same

limitations as the BCSD approach (discussed below in Section 8); they assume stationarity and are limited by the availability of AOGCM data.

3) *Delta approach.*—The delta approach, also known as the change factor approach (Wilby and Wigley 1997), is the most straightforward means of downscaling climate data from AOGCMs. This method involves subtracting the AOGCM projection for a time in the future from a baseline time in order to develop a "delta" to add to current climate data obtained from station data or other present-day climate models. We used this approach when combining the 12km data with the PRISM data in order to obtain higher resolution climate projections at future timesteps.

Given these factors, the BCSD is the best and most available data source for AOGCM data. The BCSD has been shown to be effective for downscaling data in the northeast region. No other approach has been applied over such a large area for so many timesteps. It does have several assumptions and limitations, but these are not unique to the BCSD approach. See section 8 for additional information.

6 Major Implementation Constraints

One of the major reasons for choosing the BCSD method was the relative simplicity of its implementation and the fact that the BCSD dataset was already available at the 12km scale. Demaria had already selected the 14 model runs that performed best in the Northeast and downscaled them to daily data. However, since Demaria is not a member of our research team, it may be difficult for us to reproduce that aspect of this approach in the future if new CMIP datasets become available. However, we can always fall back on the CMIP5 data she used as the starting point of the temporal downscaling.

Additionally, although the daily downscaling did allow us to calculate our climate variables more accurately for the AOGCM projections, we were unable to do the same with the PRISM data for which we calculated our baseline variables from monthly averages. GDD and Heat35 in particular benefit from the daily data.

7 Major Risks and Dependencies

7.1 Major risks

The WRCP CMIP3 12km BCSD dataset has several assumptions and limitations, most of which are true of all AOGCM data and downscaling approaches.

- Assumptions:
  - Stationarity: the BCSD approach assumes that the relationship between the distributions of broad- and fine-scale temperature and precipitation in the future will be similar to the relationship historically. This assumption is not unique to the BCSD, but is a basic assumption of all other downscaling approaches that use historical climate data.
  - The BCSD approach also assumes that the biases of the AOGCM models will be the same in the future as they have been in the past. Again, this assumption is not unique to this modelling approach.

- Limitations:
  - The BCSD approach models data at the monthly timescale; daily temperature and precipitation projections are not available using this approach. This is a disadvantage for two reasons. First, extreme data points (high and low temperatures and extreme precipitation events) are not included in the projections and therefore cannot be used in the landscape change model. We projected average minimum January temperature by adding the projected January anomaly at each timestep to the average minimum January temperature from the PRISM data. This assumes that the anomalies we calculated apply similarly to minimums and means. Second, typical growing degree day calculations require daily minimum and maximum temperature data, which were not available using this approach. We were able to modify the equation in order to estimate GDD using monthly data, but this is probably not as accurate as a daily calculation would be.
  - The WRCP CMIP5 12km BCSD dataset is only available to the year 2100. Because we are using 30 year projections, this allows a projection only to the year 2080. The temporal limitation is not unique to this dataset. It does, however, limit our ability to project a full 100 years into the future.

As described previously, in phase 1 we evaluated the error and potential bias in the projections by comparing the downscaled projections to data observed at weather stations throughout the Northeast Region. The downscaled temperature data were within 2 degrees C of observed station data in all cases in each month, and on average were 0.15 degrees warmer. Downscaled precipitation data were within 13% of observed station data in all cases, and were an average 2.7% and 5.1% higher than observed station data in the 1980 and 1970 timesteps. We did not repeat this analysis as part of the process of generating the climate data for phase 2, but because the overall approach is similar in phase 2 we felt it to be unnecessary to revaluate the error.

In addition to the limitations of the input data (above), our approach for processing the data imposes additional limitations on the interpretation of the results. Due to the inherent uncertainty in climate change projections, we opted to utilize an ensemble average AOGCM approach, so that our model would not be driven by outliers. In addition, we opted to utilize 30-year average projections for temperature and precipitation data to match the PRISM dataset that we used as a baseline, and to more realistically project trends in climate, rather than the inherent variability in annual weather patterns. This approach safeguards the landscape change model from being overly influenced by outliers and annual variations in weather patterns. However, by averaging away extremes and variability, we may miss the most extreme changes that will occur as a result of climate change. These extremes are inherently difficult to predict, and may be more easily incorporated into the landscape change model as scenarios in a later phase of the project.

Finally, it is important to note that the climate data have not been formally downscaled to the 30m grid cell level that our model runs at. The 800m cell projections have been developed using the PRISM data, which incorporates variation as a result of topography, but the process of converting the projections from 12km to 800m and from 800m to 30m involves only bilinear interpolation. This process assumes that temperature and precipitation vary linearly between the center points of the cells, and that the cell values of the larger grid cells (12km and 800m) were representative of the value at the center point of each cell. This is clearly not entirely true, as the 12km BCSD values (and the larger AOGCM values) represent an average value over the entire cell, rather than the value at the center point of that cell. We chose to resample to match the 30m cell size used for other LCAD grids using bilinear interpolation in order to prevent sharp boundaries between larger cells and potential resulting artifacts in the ecological models, but we recognize that these data are artificially smooth.

7.2 Dependencies

Because we are relying on data from outside sources (WRCP and PRISM), the accuracy of our projections are directly dependent upon the accuracy of the data from these outside sources. In addition, the accuracy of our assessment is dependent upon the quality of the USHCN database and on Demaria's (Northeast Climate Science Center) temporal downscaling of the WRCP data.

8 Acknowledgments

We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modeling groups (listed in **Table 1** of this paper) for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals

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Appendix. Phase 1 Assessment

In Phase 1 of this project we used a similar approach to spatially downscale CMIP3 climate models relative to the PRISM 1985 30 year normal. This appendix outlines the assessment process we performed on those prior results.

We repeated steps 1–7 for the 1970 and 1980 timesteps to compare with raw observation data from United States Historical Climatology Network (USHCN) weather stations. We then downloaded the full monthly temperature and precipitation records for 174 stations in the Northeast Region that are available in the USHCN v.2 database (Menne et al. 2010; available at the site: ftp://ftp.ncdc.noaa.gov/pub/data/ushcn/v2/monthly/). We used the data adjusted for Time of Observation Bias (TOB), but with no other adjustments (i.e. unadjusted for homogenization or urbanization effects).

We used the epi.ccc function in the R package epiR (Stevenson 2011) to calculate the concordance correlation coefficient (R_c, Lin 1989) for average annual precipitation and average monthly temperature for the 1970 and 1980 timesteps. Because results were very similar for the three SRES scenarios (B1, A1B and A2), we report results from the A2 dataset here. Temperature R_c values were between 0.97 and 0.99 for all months in both timesteps, suggesting strong agreement between the downscaled modelled temperatures and observed station temperatures. R_c values for precipitation were 0.83 in 1970 and 0.92 in 1980.

We also evaluated potential bias in the downscaled estimates by calculating the residual difference in temperature and precipitation values between the observed and modelled datasets. On average, the observed station data was lower in temperature and precipitation than the downscaled climate data, suggesting a slight positive bias in the downscaled projections.

One station located at 515m in elevation at Stillwater reservoir in the Adirondacks, NY (Station ID # 308248), measured an average of 4 degrees C lower than the modelled values. Upon further investigation, the latitude and longitude of this station were incorrect in the USHCN database, so this point was dropped from subsequent comparisons. All other stations were within 2 degrees C for all months, and the average difference, excluding the outlier, was 0.15 degrees C in 1970 and 0.125 in 1980, suggesting a slight positive bias in the modelled temperature data. Similarly, the two stations with the greatest differences in observed and modelled precipitation values (Station # 308248, Stillwater Reservoir and Station #301401, Chazy, NY) were located at incorrect coordinates in the USHCN database, and they were dropped from subsequent comparisons. Downscaled precipitation projections for all other stations were within 13% of observed values and were on average 2.7% higher in 1980 and 5.1% higher in 1970 than the observed station data. A similar bias in downscaled precipitation projections was observed by Hayhoe et al. (2007) who also noted that BCSD projected precipitation rates were too high in the northeastern U.S. Overall, given the unanticipated locational errors in the USHCN database, it is quite likely that additional stations were incorrectly located. Thus, our estimates of accuracy of our downscaled climate estimates are probably conservative (i.e., the true discrepancy between observed weather station data and our downscaled model estimates are probably slightly less than we report here).

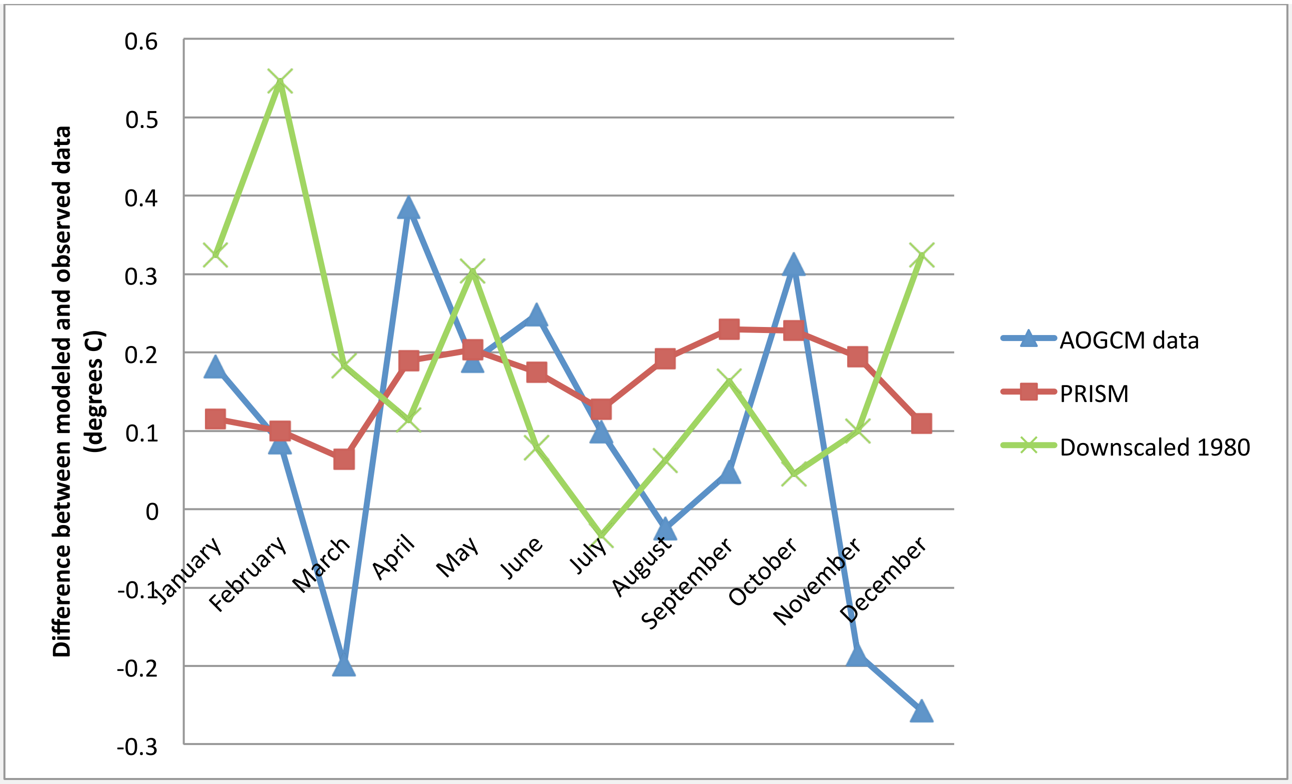

Figure 7. Residual difference between modelled average monthly temperature data and temperature observations at 174 weather stations throughout the NALCC. The 1980 downscaled data (green X's) are the difference between the completely processed downscaled projections for the 1980 timestep and the weather station data. This dataset has an average bias of 0.15 degrees C (i.e., the projections are on average 0.15 degrees C higher than the observed values), though it varies greatly by month. These projections are built from the other two datasets presented in the figure. The AOGCM data (blue triangles) are the differences between the raw ensemble AOGCM projections and the weather station data. The residual error in this dataset also varies greatly by month. The PRISM (red squares) data are the differences between the raw PRISM data and the weather station data, which has a consistently positive bias.

To further evaluate the source and nature of the bias, we examined the residual difference between the PRISM dataset and the station data, as well as the residual difference between the raw downscaled AOGCM ensemble output for the year 1985 and the station data. The PRISM data, excluding the Stillwater, NY outlier were on average 0.13 degrees C higher than the station data. The raw downscaled AOGCM ensemble data were on average 0.04 degrees higher than the observed station data, suggesting a positive bias from both data sources. The spatial and temporal variation in the bias was also visually inspected. The bias in the AOGCM data was much more variable by month, while the PRISM data were consistently higher over all months (**Fig. 7**). In summer months, the magnitude and direction of the error between modelled and observed temperature data were interspersed throughout the NALCC, with no regions modelling consistently higher or lower than other regions (**Fig. 8**). In the winter months, however, there was a gradient, with northern areas modeling cooler than observed and southern areas modeling warmer (**Fig. 9**). Precipitation projections were consistently higher than observed across the NALCC (**Fig. 10**).

This bias is difficult to correct without incorporating additional error from other sources. Overall, although there is a slight positive bias in the downscaled temperature and precipitation values, it is quantifiable, the modelled and observed data are highly correlated, and for the temperature, the bias is small compared to the projected increase in temperature expected over the course of the 80 year simulation. For precipitation, the bias is larger and slightly more problematic. However, for both temperature and precipitation, we will be using a similarly biased dataset to create the initial habitat models and derive starting ecological settings variables at timestep 0 in the simulation, so the bias should not influence the projected trends over time.

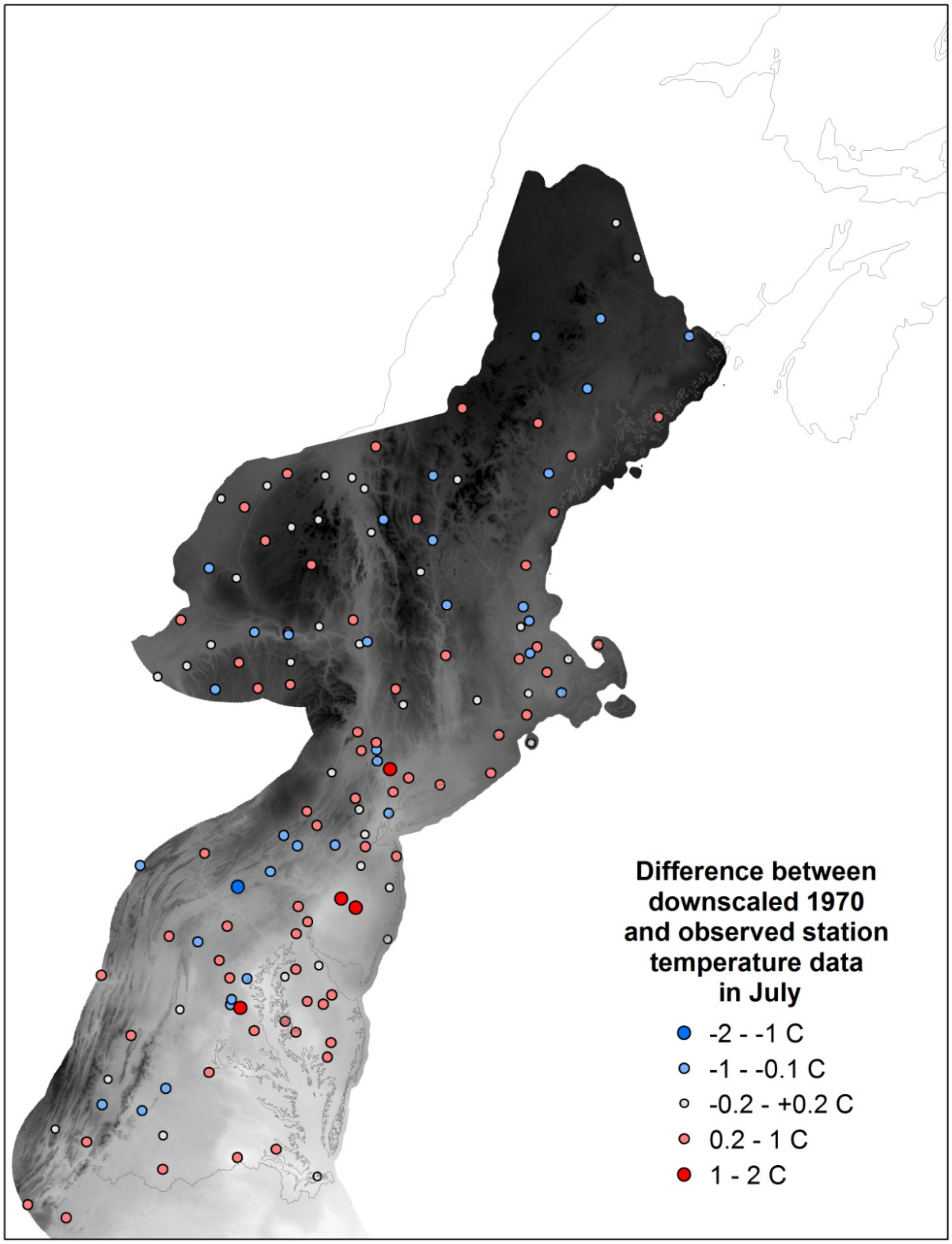

Figure 8. Spatial distribution of residual differences between downscaled temperature projections in July for the 1970 timestep and observed weather station data across the NALCC. Larger dots indicate larger differences between modelled vs. observed. Red dots indicate stations that modelled higher than observed, blue modelled lower.

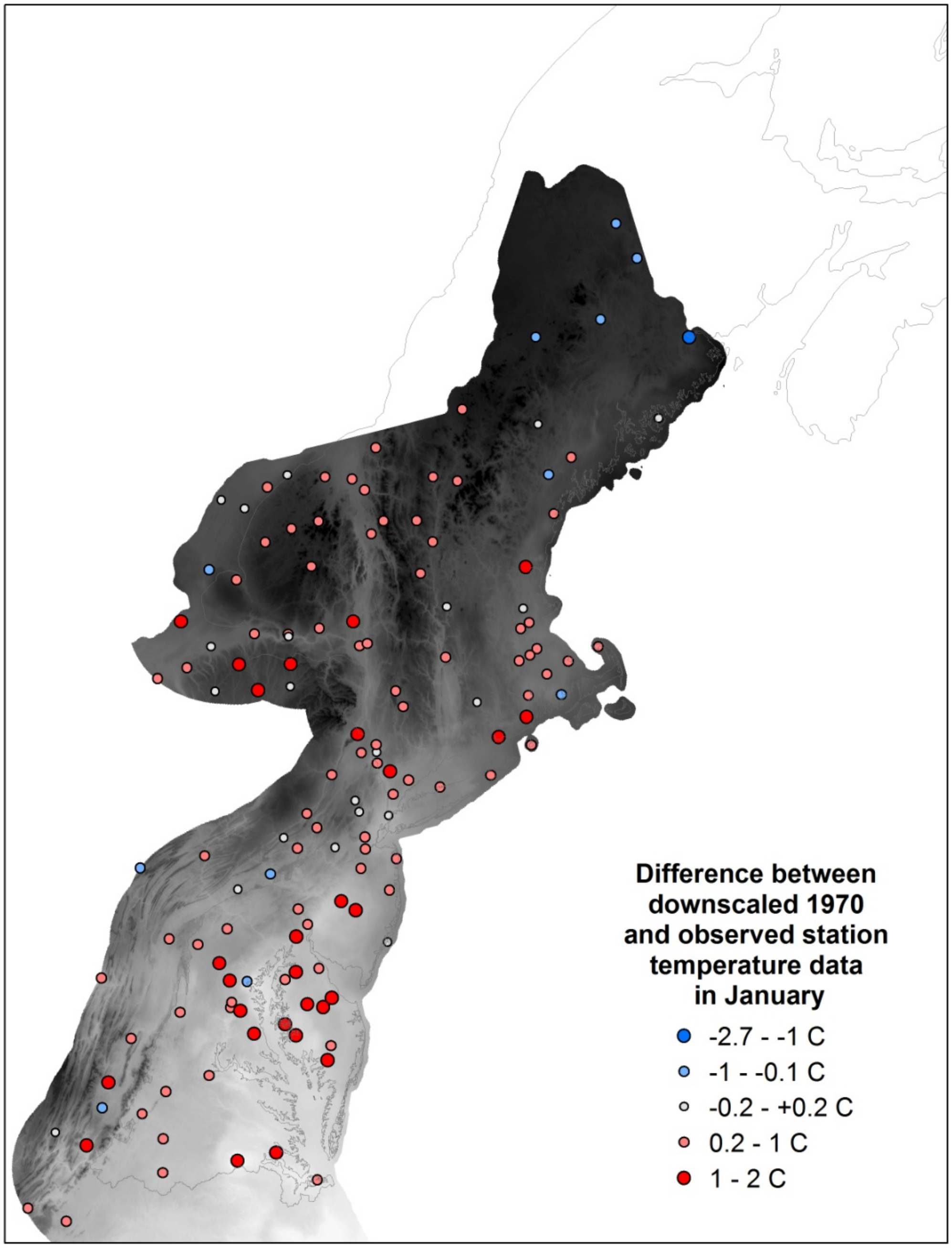

Figure 9. Spatial distribution of residual differences between downscaled temperature projections in January for the 1970 timestep and observed weather station data across the NALCC. Larger dots indicate larger differences between modelled vs. observed. Red dots indicate stations that modelled higher than observed, blue modelled lower. There is a gradient from north to south of temperatures that modelled increasingly warmer than observed.

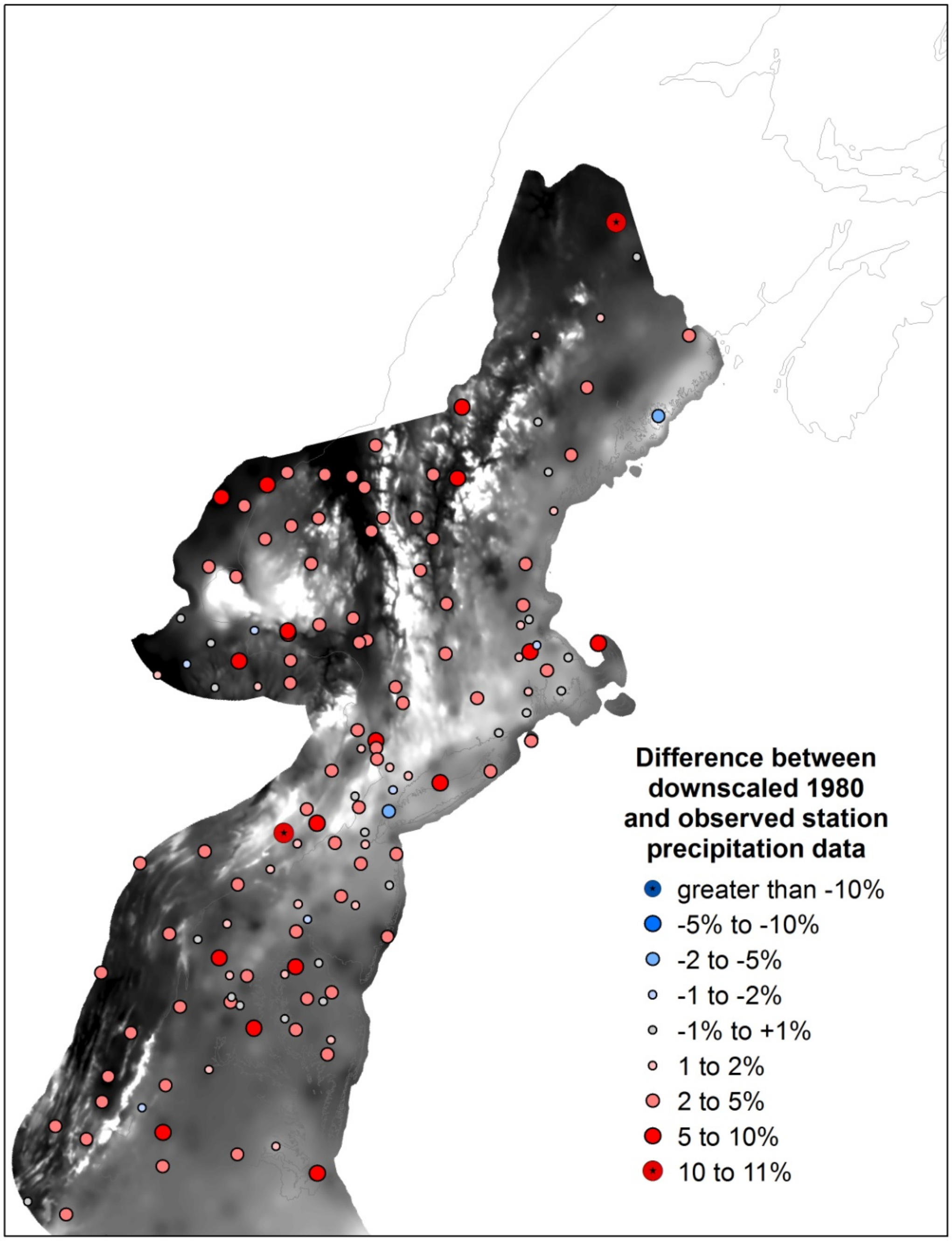

Figure 10. Spatial distribution of residual differences between downscaled annual precipitation projections for the 1970 timestep and observed weather station data across the NALCC. Larger dots indicate larger differences between modelled vs. observed. Red dots indicate stations that modelled higher than observed, blue modelled lower. Precipitation projections are consistently higher than observed throughout the NALCC.