Downscaling Climate Models for Ecological Forecasting In Northeast U.S. Estuaries

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PRINCETON UNIVERSITY

AOS Atmospheric and Oceanic Sciences

GFDL Geophysical Fluid Dynamics Laboratory

NOAA FISHERIES NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION

National Ocean Service

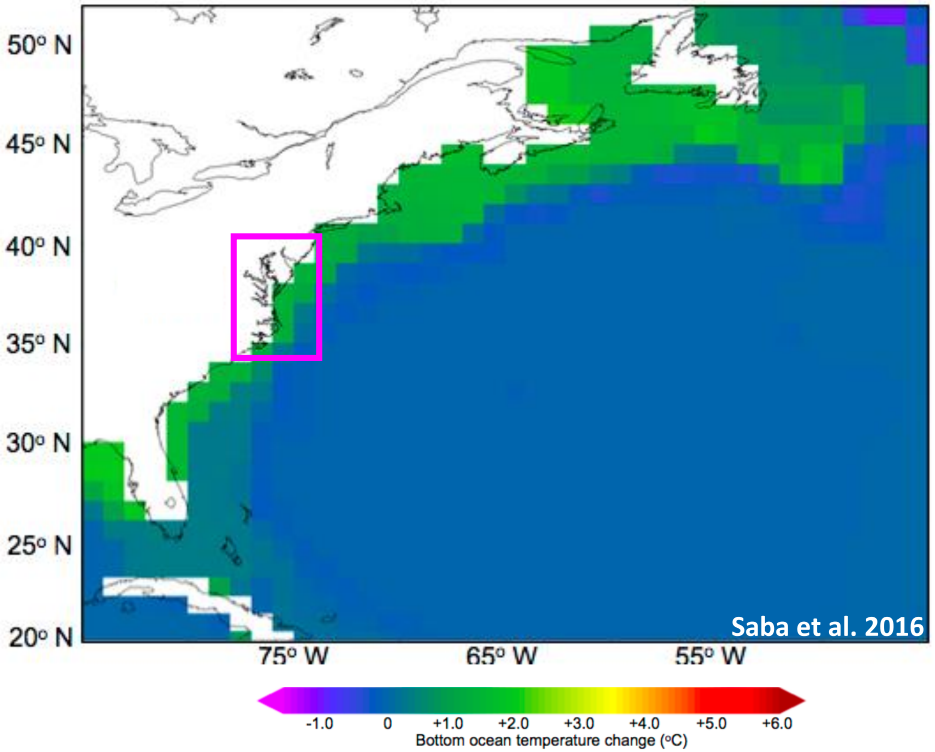
Overall Project Aims

- We are aiming to:
  - *Develop future projections* of estuarine habitats, and responses of living marine resources, using statistically downscaled climate models for the northeast US region
  - Rather than developing a comprehensive suite of projections, we are particularly interested in assessing the sensitivity of projections to the *downscaling method used*
- Potential biological impacts include:
  - <u>Distribution</u>: how will target species be distributed?
  - <u>Phenology</u>: when will different life stages of target species be present in different habitats?
  - <u>Thermal stress</u>: at what point will conditions become physiological stressful
  - <u>Recruitment</u>: how favorable will conditions be for juvenile survival?

Climate model resolution and estuarine environments

- Global climate models (GCMs) are generally too coarse to resolve local-scale dynamics, such as those in rivers or estuaries
- Models are often downscaled to a regional study area
  - *Statistical downscaling*: relies on present-day relationships between coarse and fine-scale processes
- Procedure:
  1. Locate long-term, historical *in situ* time series
  2. Extract global climate model historical and future projections for same location
  3. Use regression, quantile mapping or other mathematical techniques to replicate past variability
  4. Apply to future projections
- Assumptions:
  - Stationarity: that past relationships between coarse and fine scale dynamics will continue into the future:
  - See http://www.gfdl.noaa.gov/esd_eval for publications, presentations, and further explanation

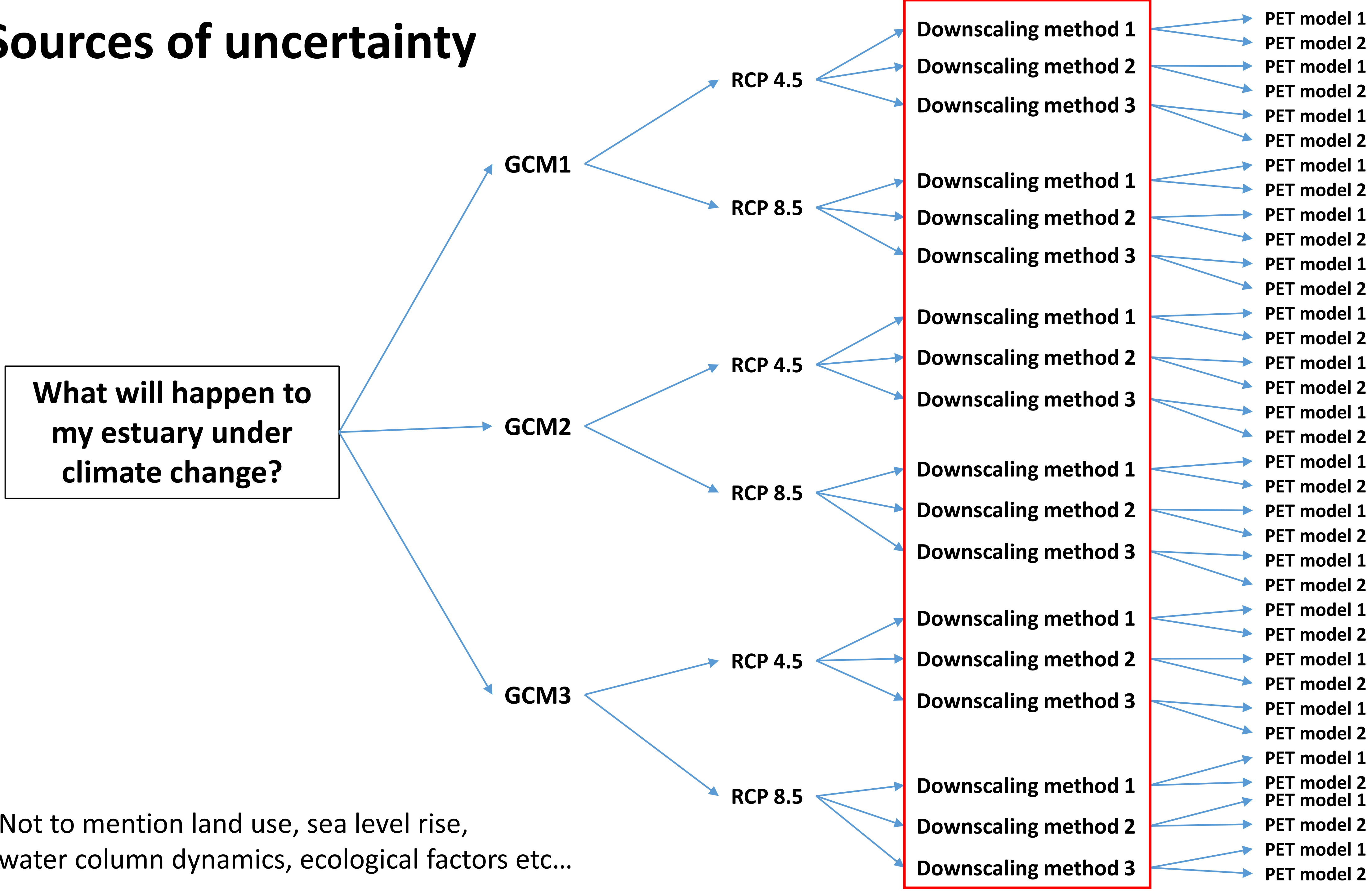
GFDL CM2.1 Global Climate Model



Other GFDL GCMs

Model	Atmosphere	Ocean
CM2.1	2.0°	1.0°
CM2.5 FLOR	0.5°	1.0°
CM2.5	0.5°	0.25°
CM2.6	0.5°	0.1°

Sources of uncertainty



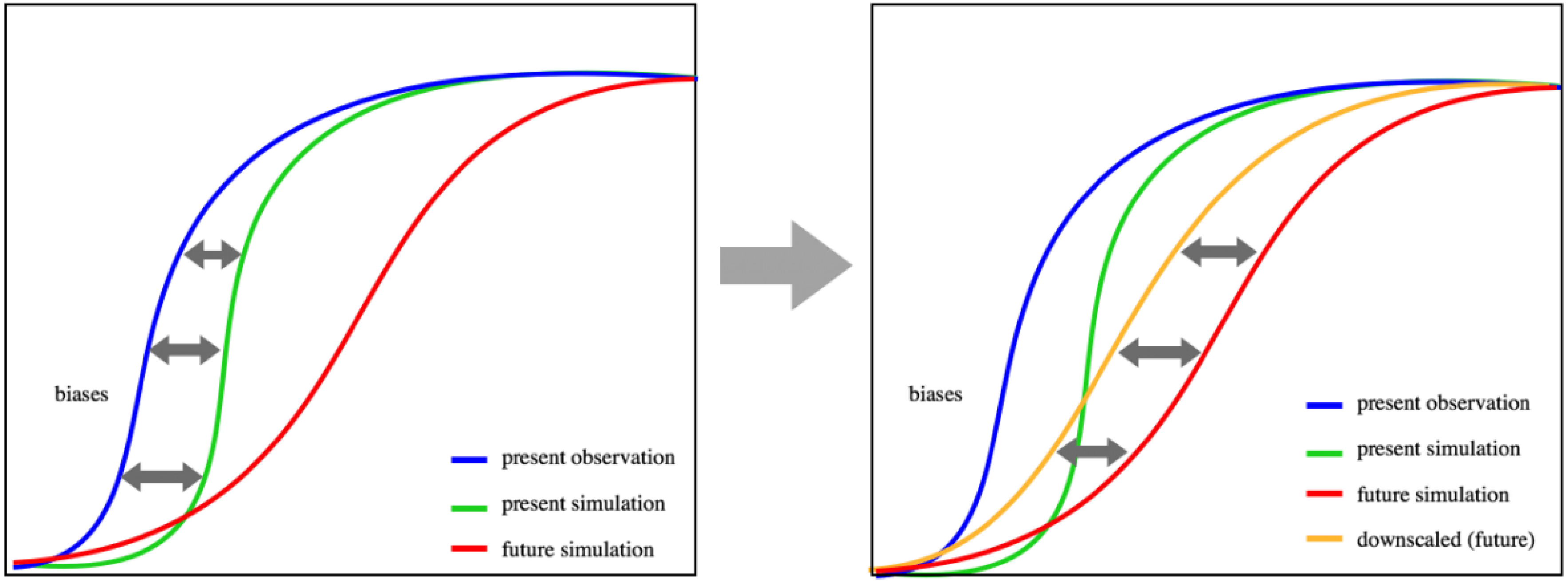
Not to mention land use, sea level rise,
water column dynamics, ecological factors etc…

Statistical downscaling methods

- In this study, global climate model projections were downscaled using five methods:
  - Bias correction quantile mapping (BCQM)
  - Change factor quantile mapping (CFQM)
  - Equidistant quantile mapping (EDQM)
  - Cumulative distribution function transform (CDFt)
  - A modified delta method

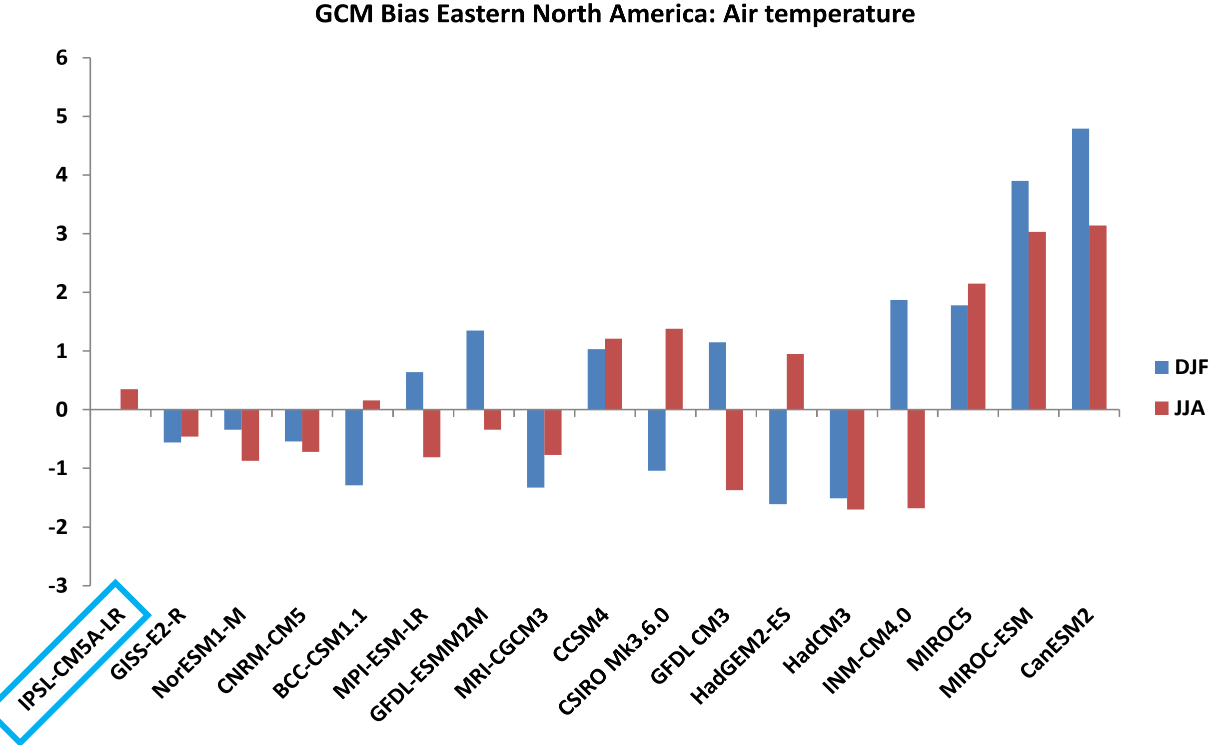
Example: Statistical Downscaling using Quantile Mapping

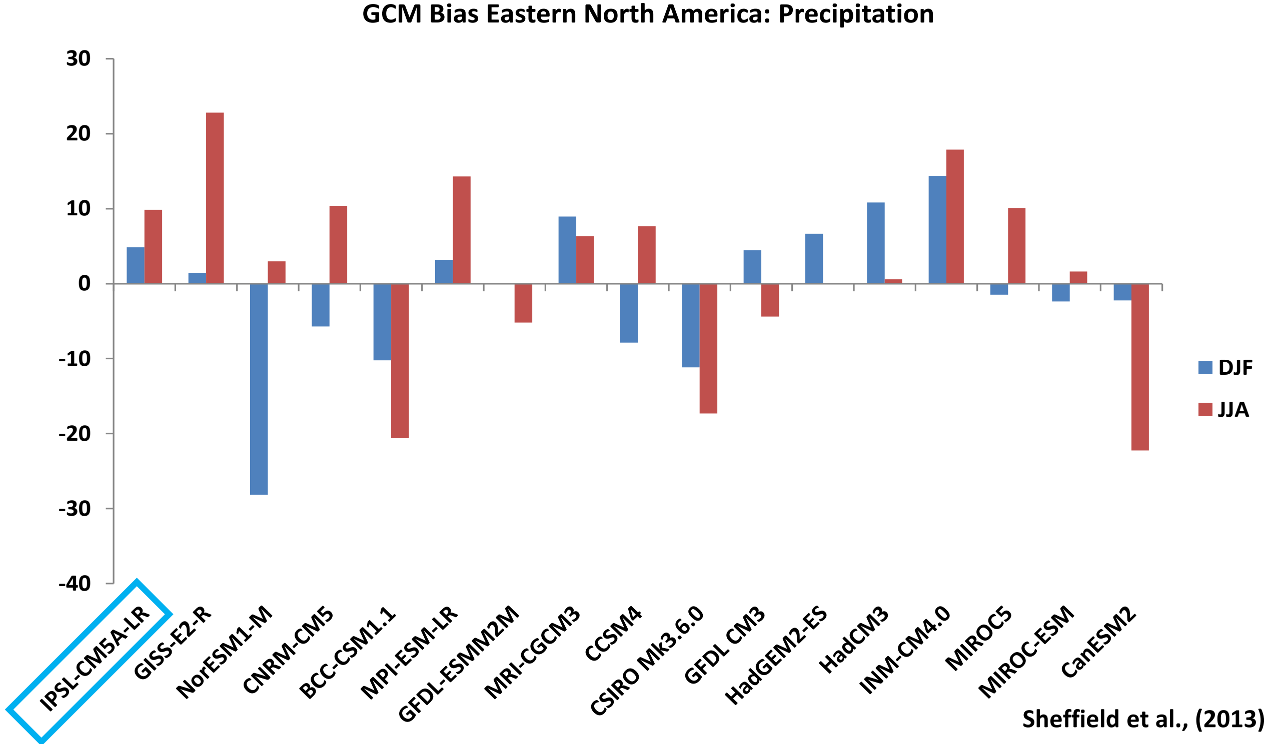
Biases are calculated for each percentile in the cumulative distribution function from present simulation (blue). Then the calculated biases are added to the future simulation to correct the biases of each percentile (NASA JPL)



Selecting global climate models for downscaling

- There are >50 global climate model runs available from CMIP5 from ~28 institutions
- Each of these has different bias characteristics in the northeast US region
- Models which are good at reproducing temperature might not also be good at reproducing precipitation
- We started with the IPSL-CM5A-LR model, due to low temperature bias in the region, and CO_2 representative concentration pathway (RCP) 8.5
  - We will extend our approach to other GCMs (ensembles?) and RCPs (probably 4.5) in the future

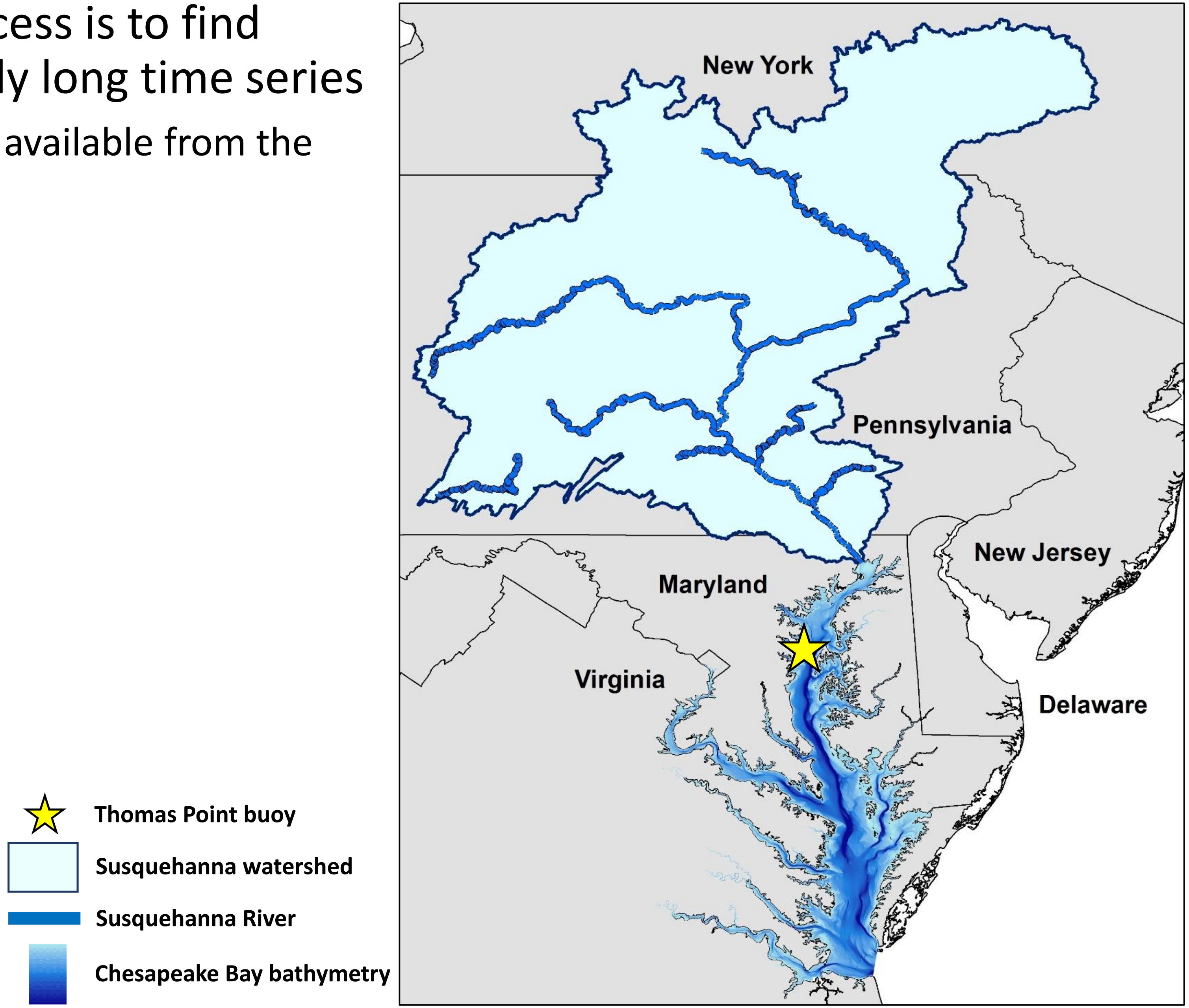




Sheffield et al., (2013)

Downscaling: observations and GCM grid points

- The first step of the downscaling process is to find observation stations with a sufficiently long time series
  - Air temperature in Chesapeake Bay was available from the Thomas Point buoy (1985-present)



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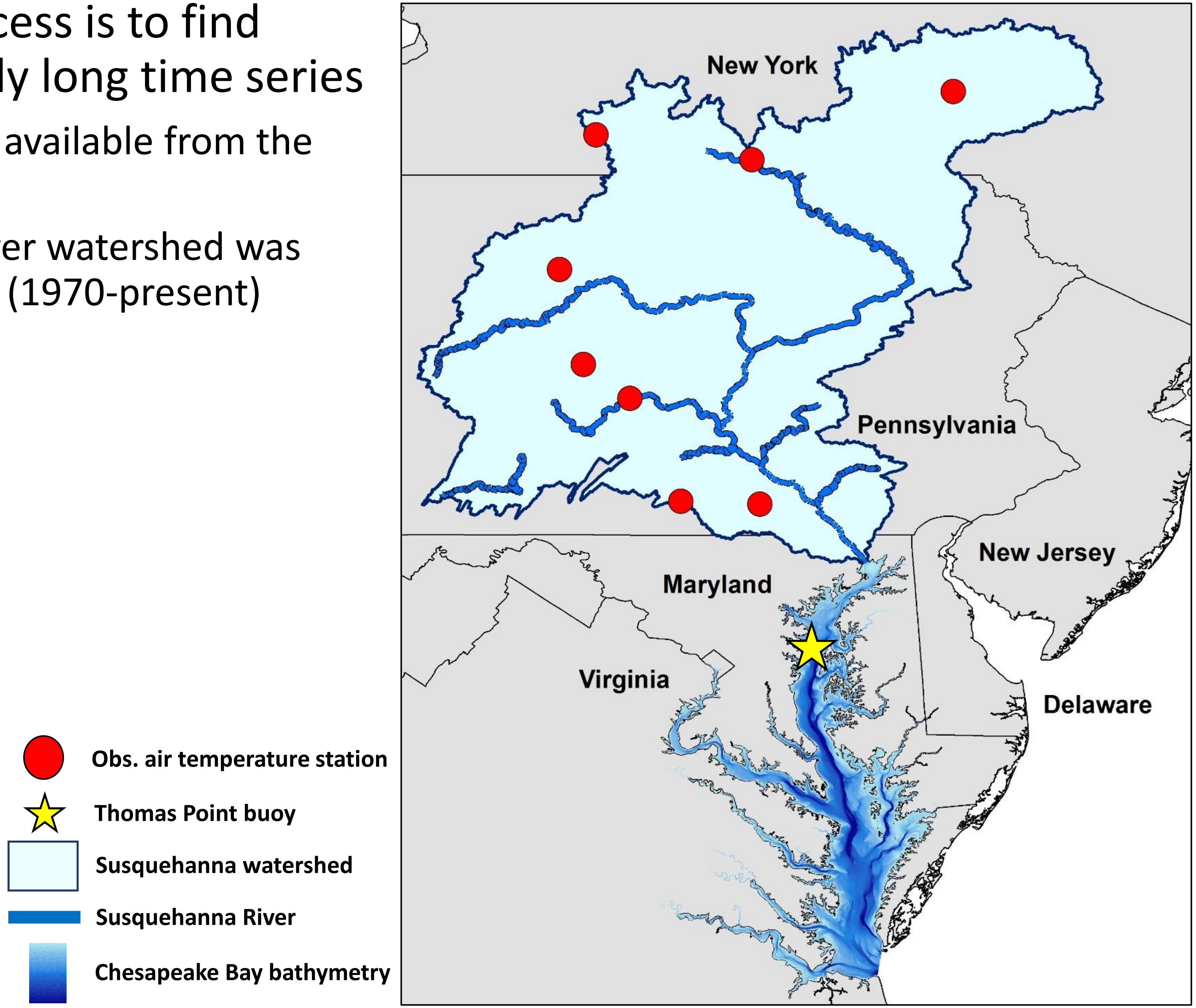

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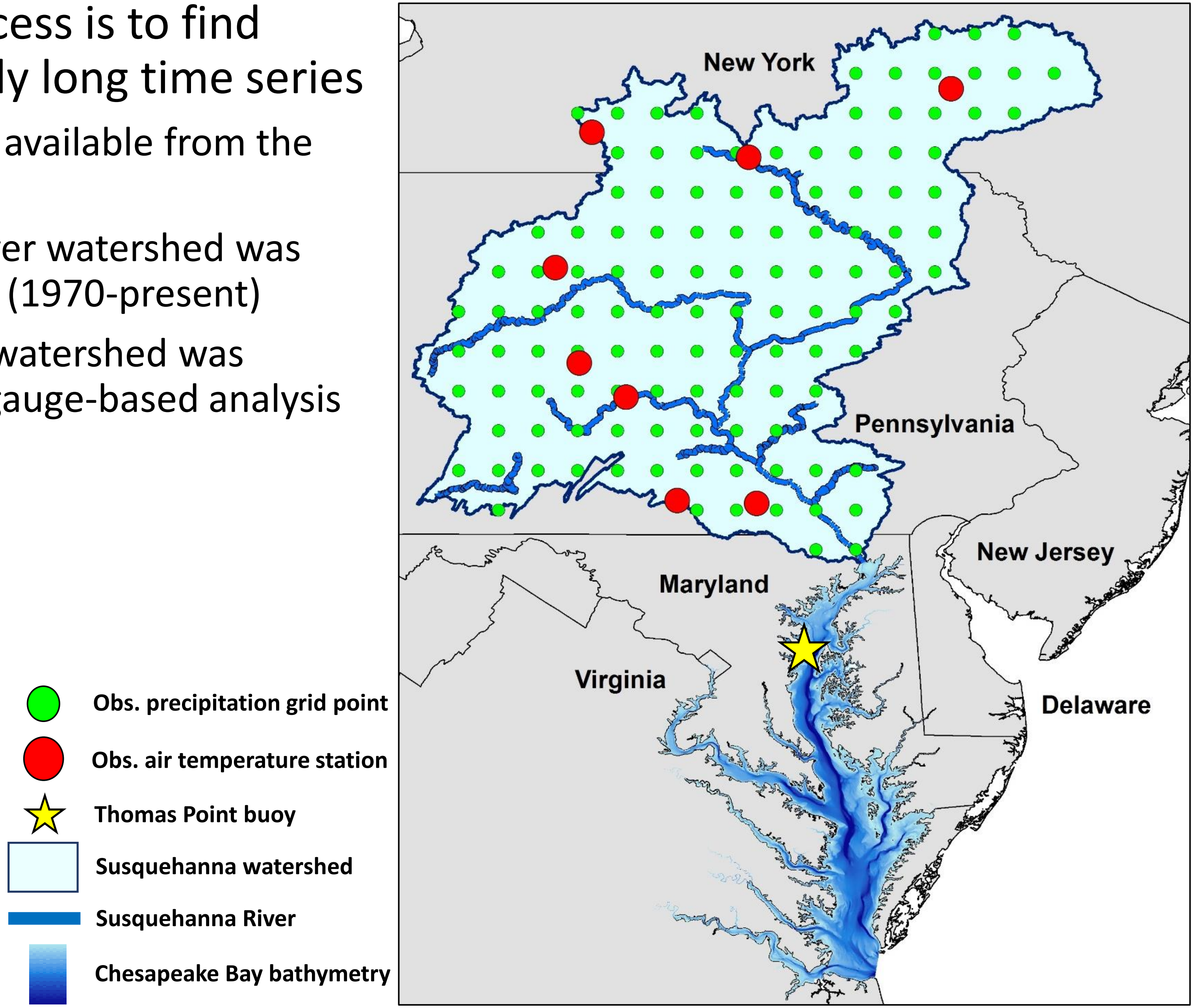

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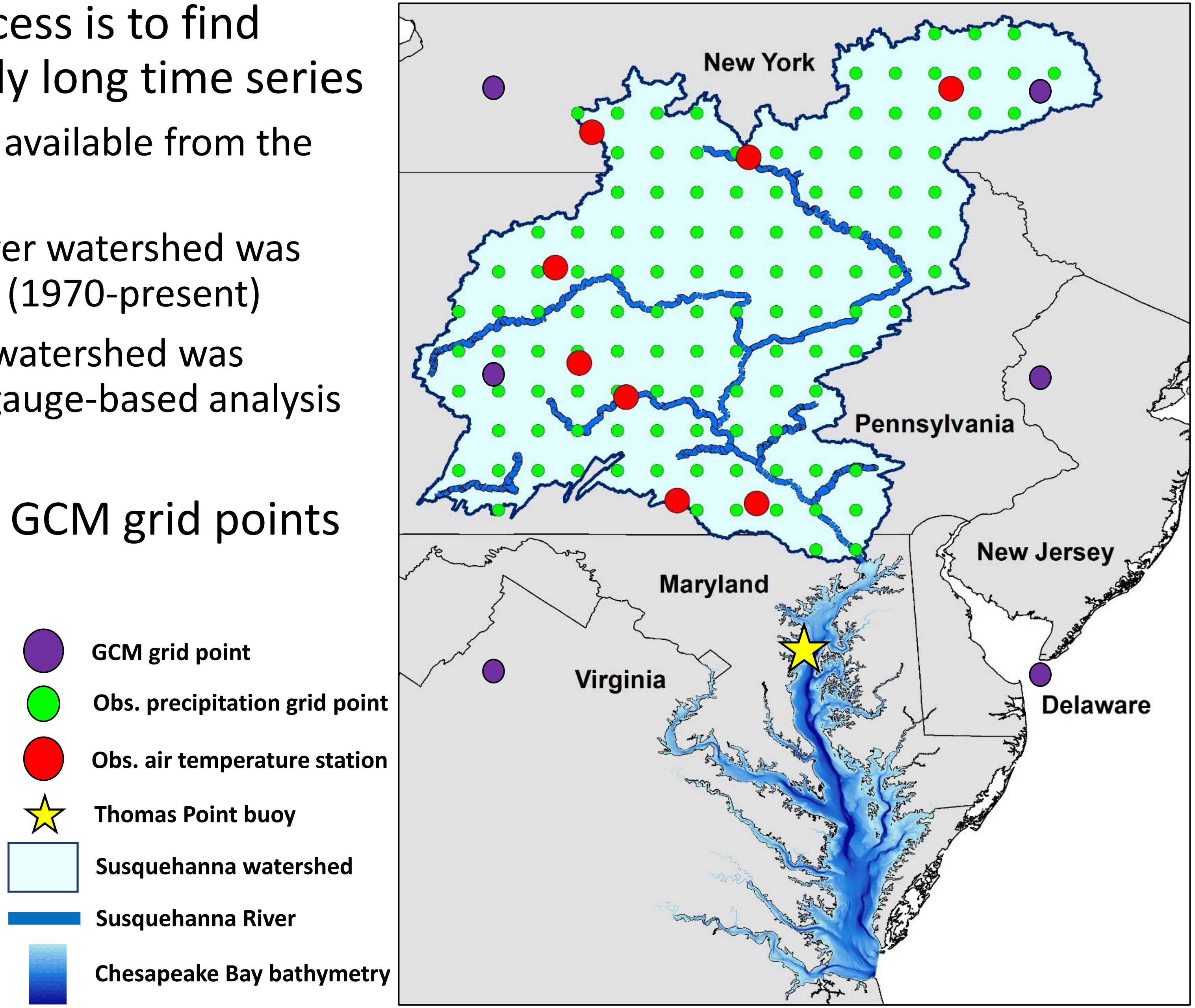
- The next step is to select appropriate GCM grid points
  - We used a point near Delaware Bay to represent estuarine conditions at the Thomas Point buoy
  - Two grid points were located within the Susquehanna River watershed
  - We downscaled the watershed observations to the nearest available grid point

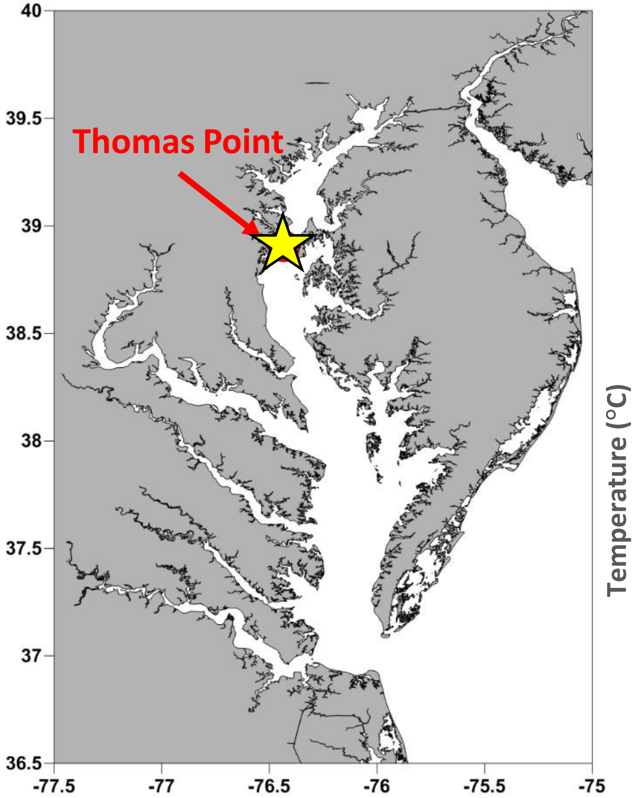


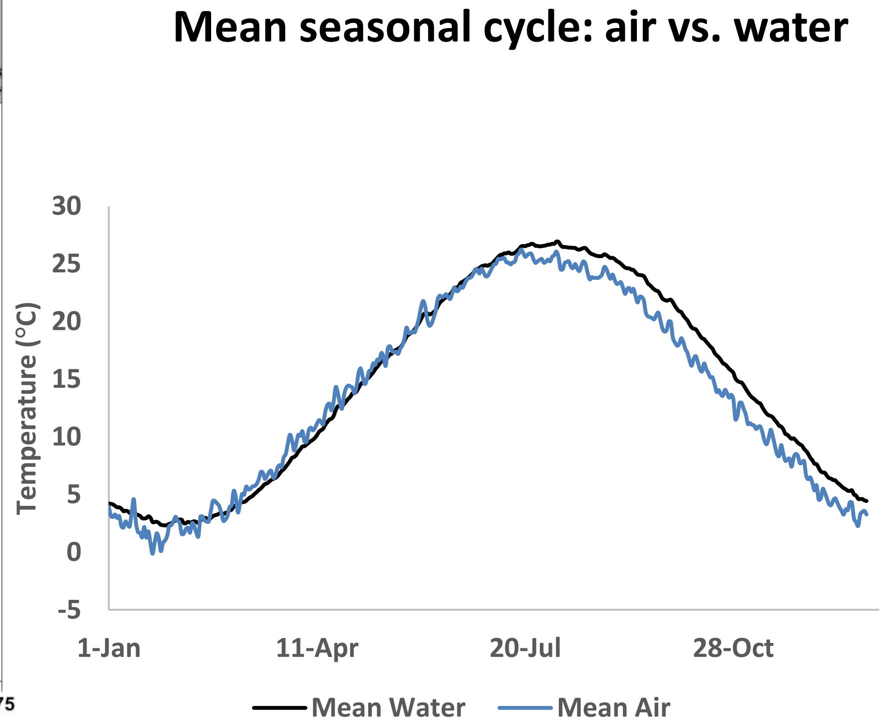
Variables of interest

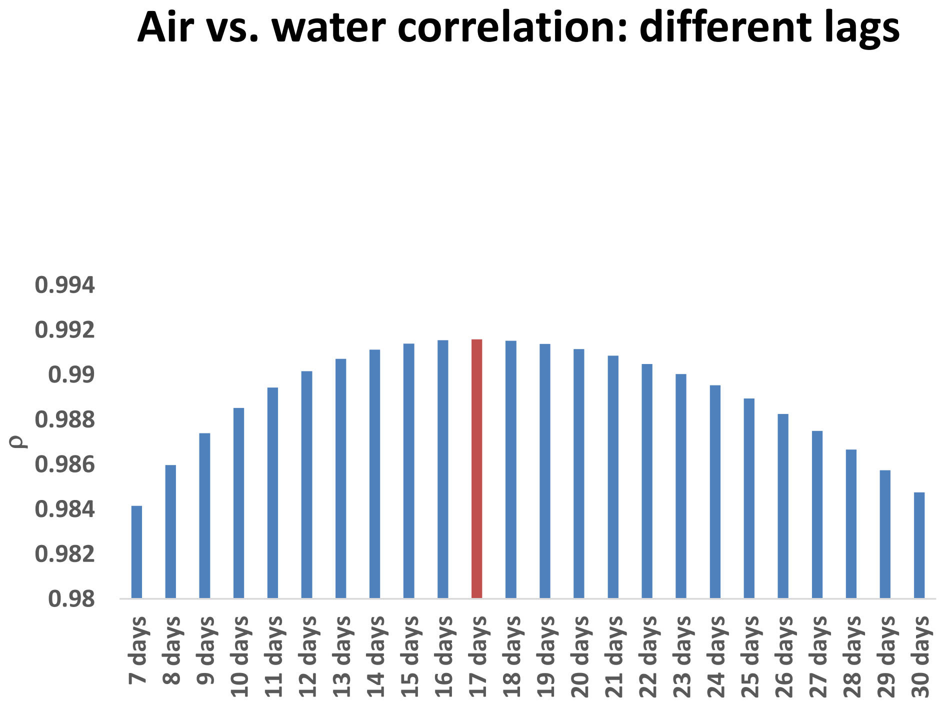
- Air temperature:
  - Drives estuarine surface *water temperature* through heat exchange at water-air interface
  - Influences *evaporation* in the watershed: how much precipitation is converted to runoff
  - Influences *snow* pack dynamics and snow melt in the watershed
- Precipitation:
  - Drives soil moisture, runoff, and *streamflow* into estuary
  - Streamflow influences river and estuarine *salinity*
- Both local estuarine and watershed dynamics are thus important for predicting estuarine conditions
- First step: can we predict estuarine conditions using only these atmospheric variables?

Estuarine water temperature

- Water temperature integrates air temperature through time, and so varies at lower frequency, with a slight seasonal lag
- Data from the Thomas Point buoy showed that a 17 day moving mean of air temperature best predicted water temperature



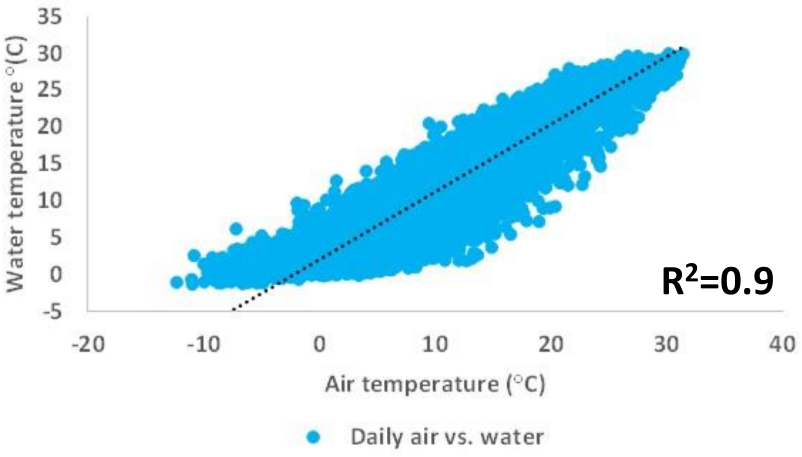




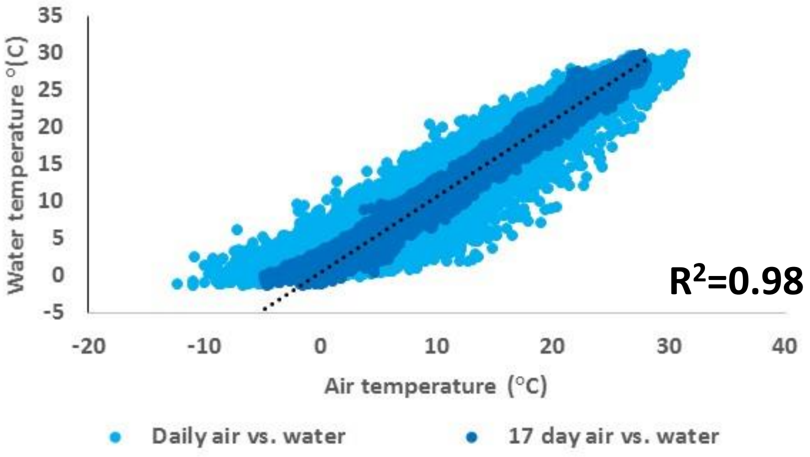
Estuarine water temperature

- The 17 day moving mean of air temperature was well correlated with water temperature
- However, the relationship was non-linear at extreme values
- Following Mohseni & Stefan, 1999, we applied a sinusoidal correction to the relationship, to account for the “leveling off” of water temperature at very cold and very warm air temperatures
- Important for extrapolation as air temperatures exceed current values

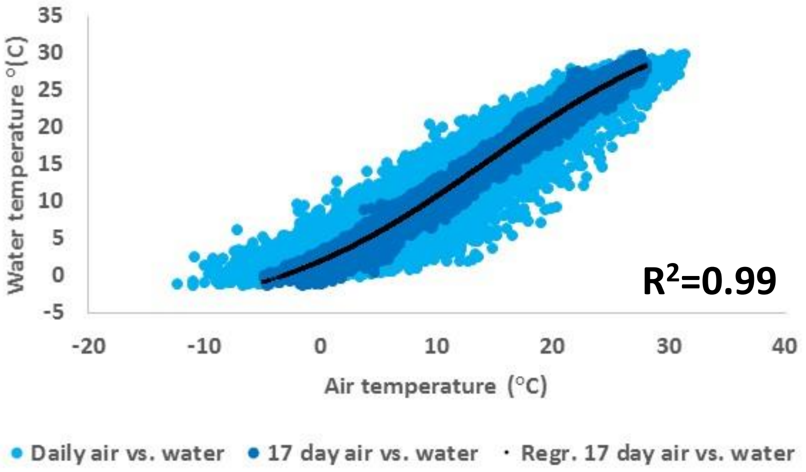
Daily air vs. water temperature



17 day air vs. water temperature



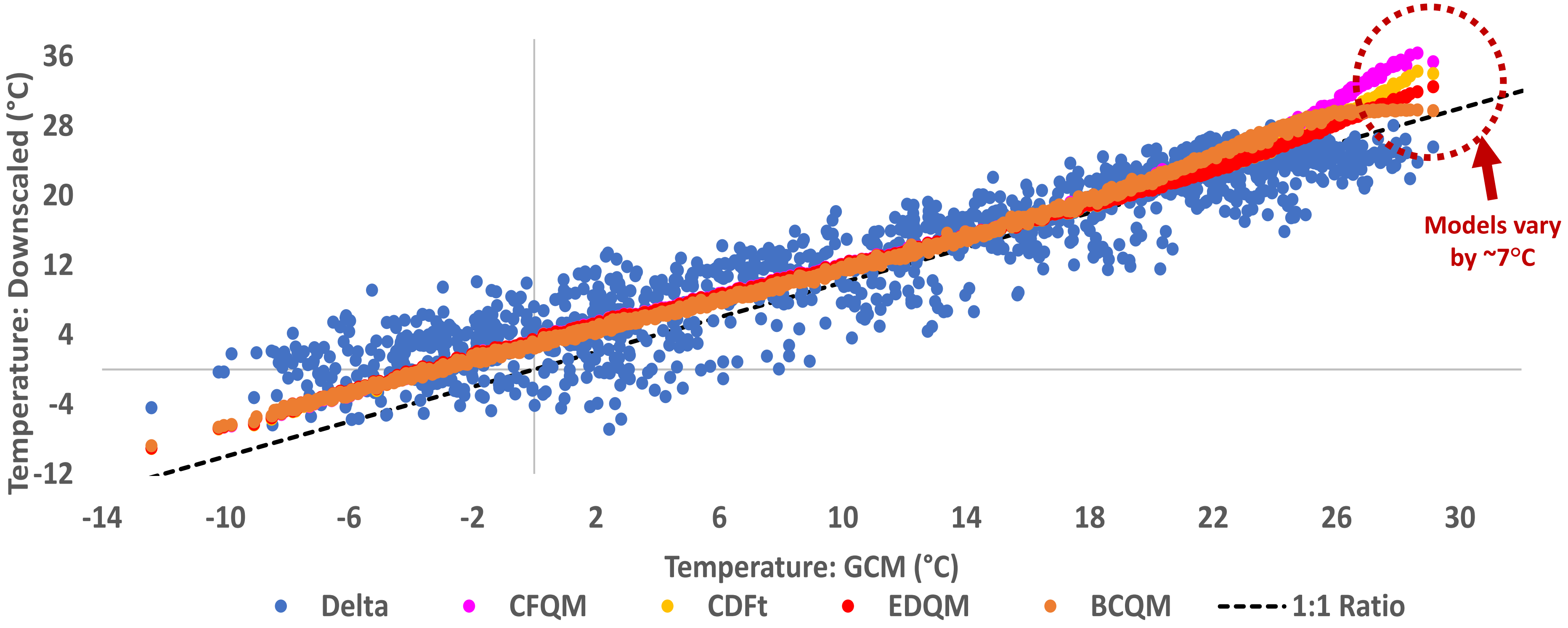
Adj. 17 day air vs. water temperature



Downscaled temperature results

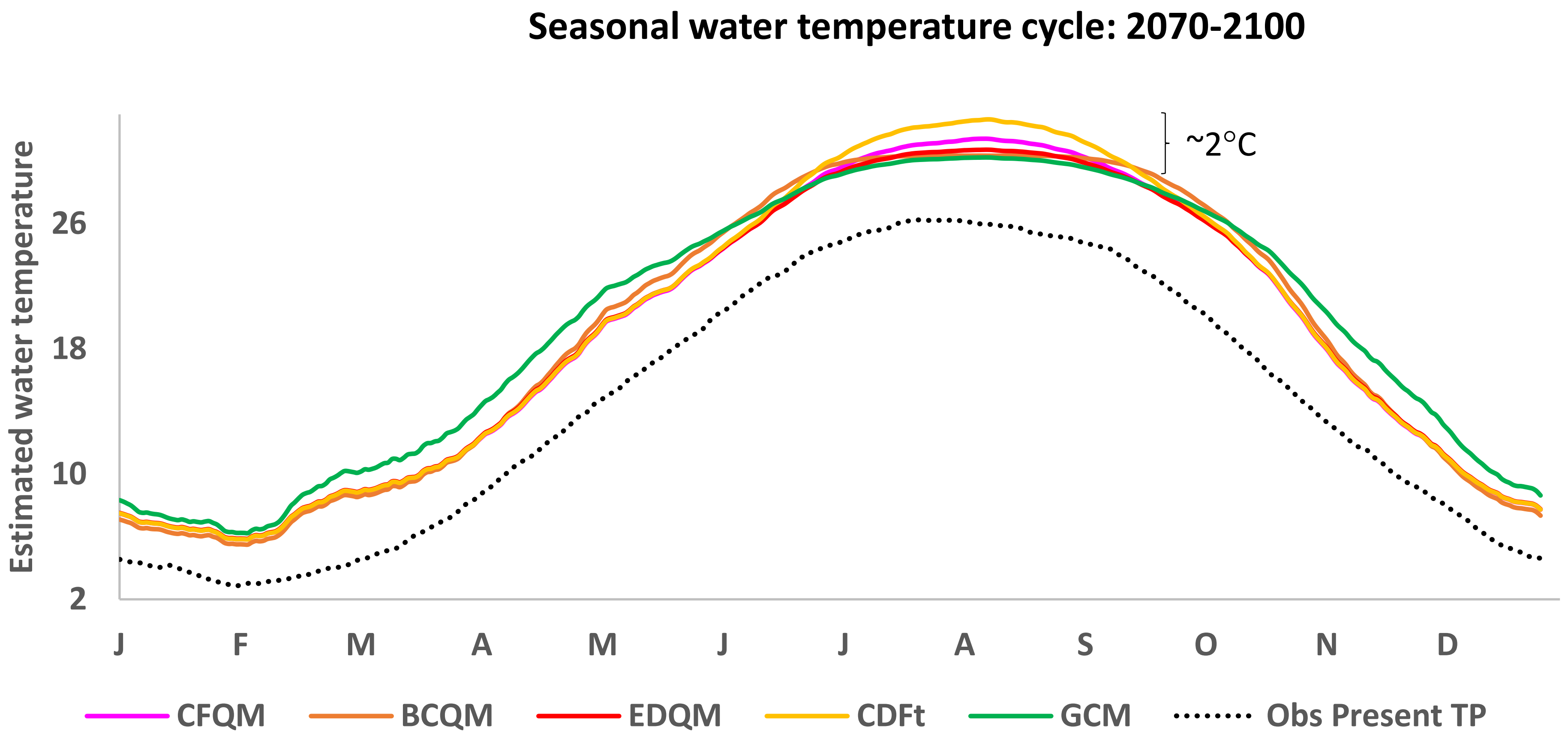
- Air temperature projections using downscaled methods were slightly warmer than those from the GCM at cooler (>14°C) temperatures
- The models diverged significantly at high (>26°C) air temperatures, as a result of the extrapolation procedures allowed by each model

Scatterplot of monthly air temperatures from the IPSL GCM, and the five downscaling methods



Downscaled temperature results

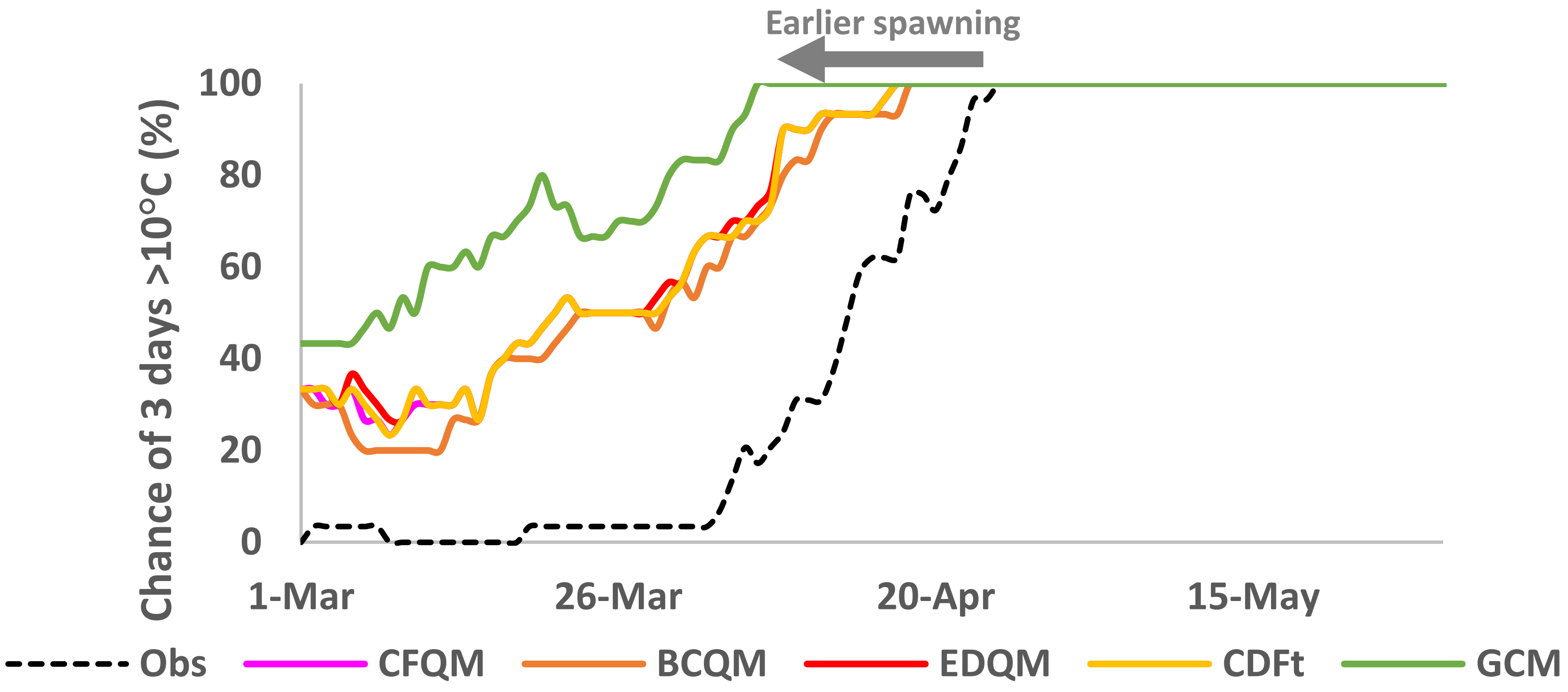
- As a result, projections of seasonal water temperature cycles varied
- The GCM was *warmer* than the downscaled models in spring and fall, but slightly *cooler* in mid-summer



Downscaled temperature and biological models

- Applying temperature projections to simple biological models shows the effects of model divergence
- Model 1: date of alewife spring spawning initiation (based on a 3 day 10°C threshold)
  - All projections showed a shift to earlier spawning by 2100
  - However the downscaled models were *more conservative* than the GCM, due to cooler projected spring temperatures

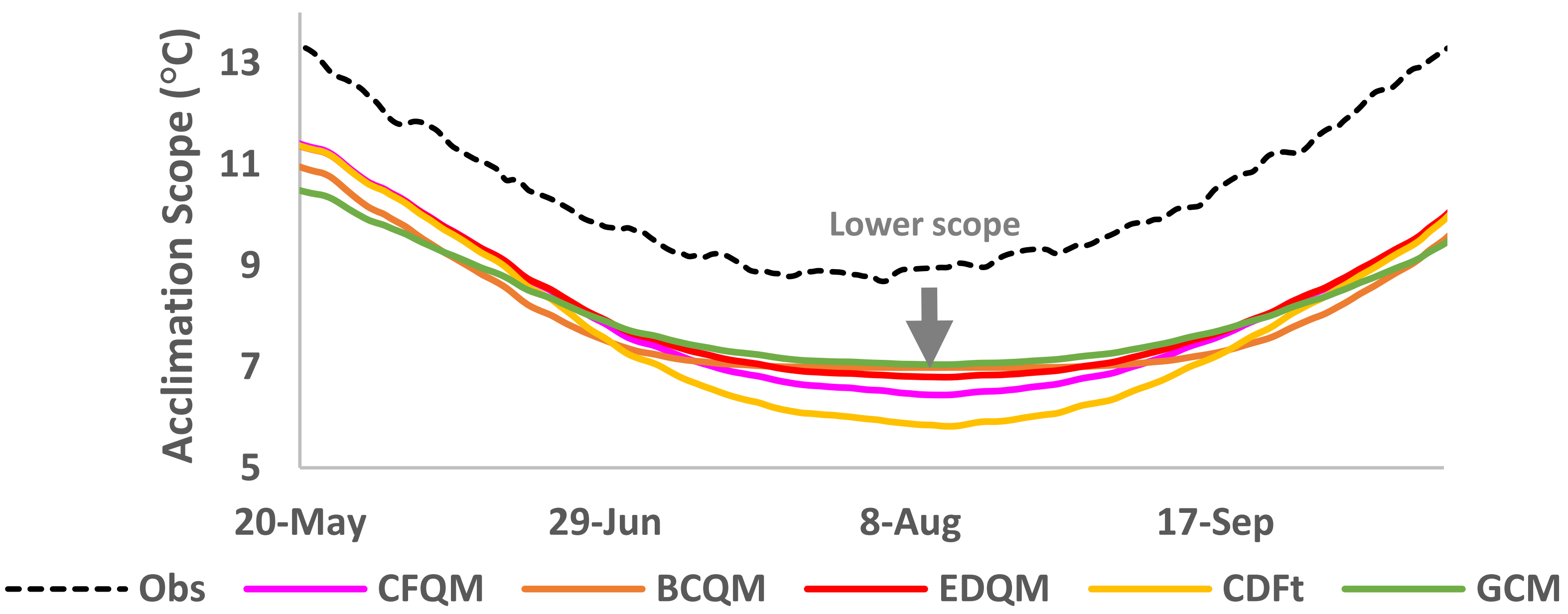
Probability of water temperature >10°C for 3 consecutive days: 2070-2100. Present day (1985-2010) mean also shown



Downscaled temperature and biological models

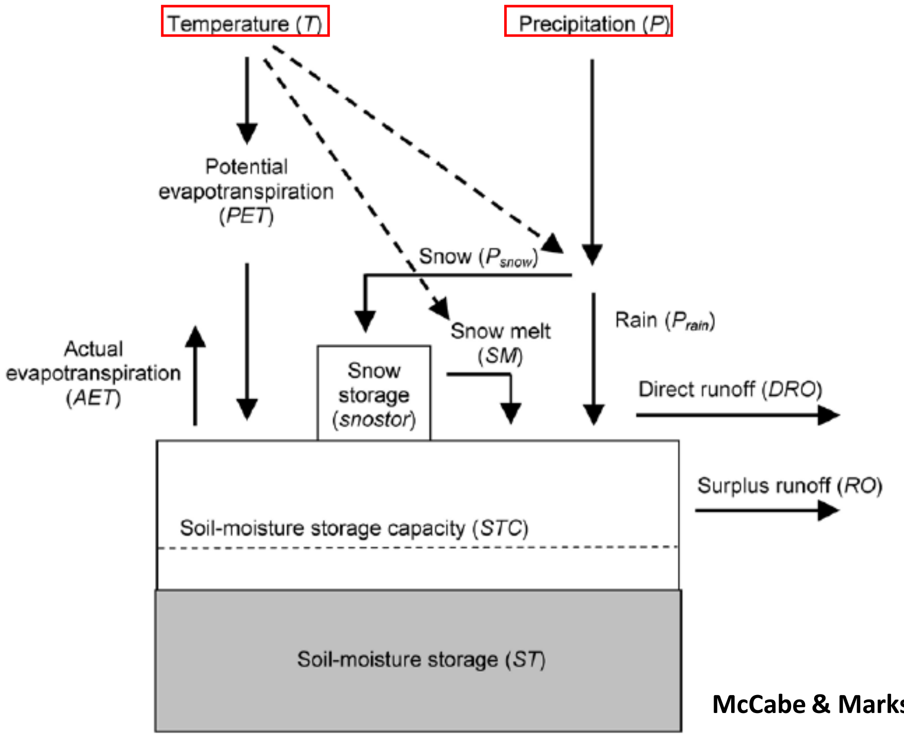
- Applying temperature projections to simple biological models shows the effects of model divergence
- <u>Model 2</u>: thermal acclimation scope of juvenile alewife during summer (based on Otto, 1976)
  - All projections predicted lower thermal scope by 2100
  - However the downscaled models were *less conservative* than the GCM, due to warmer projected summer temperatures

Thermal acclimation scope for juvenile alewife: 2070-2100. Present day (1985-2010) mean also shown

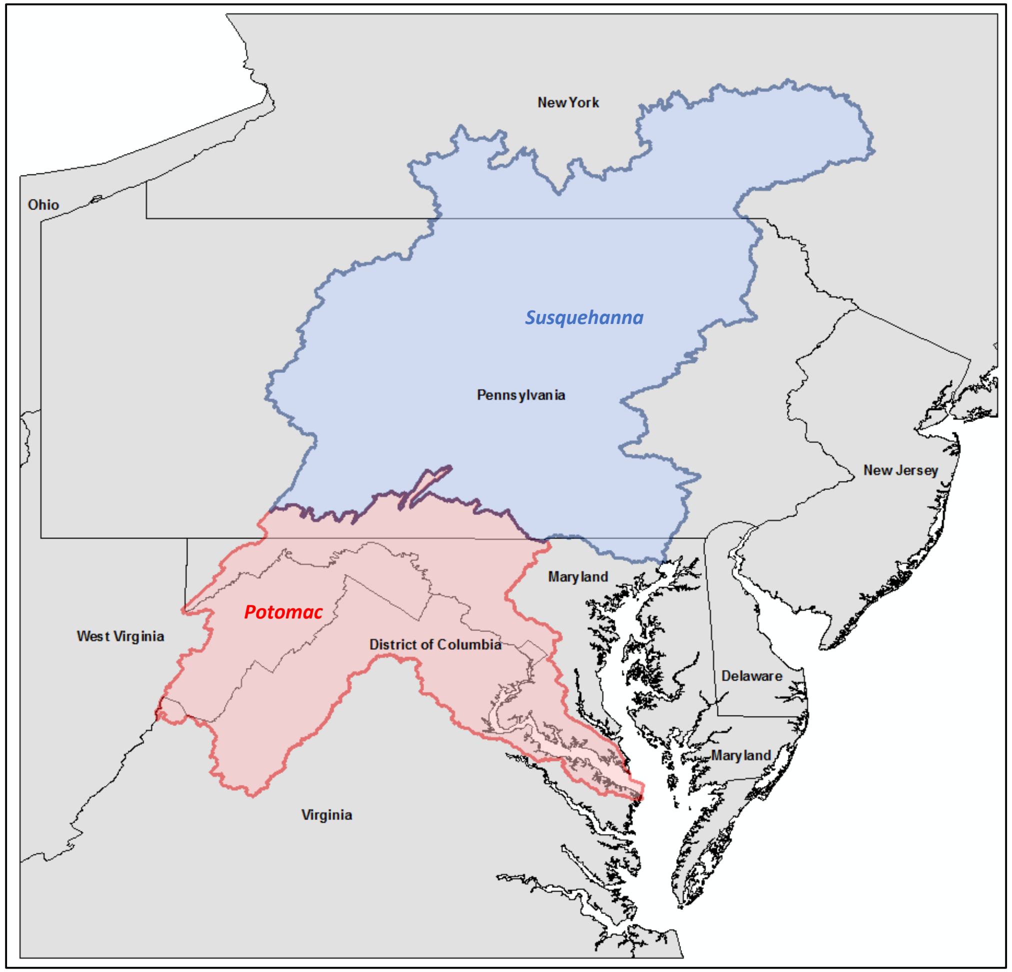


Estimating freshwater flows

- <u>Step 2</u>: can we predict river inflow from precipitation?
- The two largest contributors of freshwater flow to the Chesapeake Bay are the Susquehanna (~50%), and Potomac (~30%) Rivers
- We constructed a monthly water balance model for the Susquehanna watershed using observed precipitation and temperature from 1970 – 2006
- The model assigns precipitation to soil storage, runoff or snowpack depending on calculated evapotranspiration

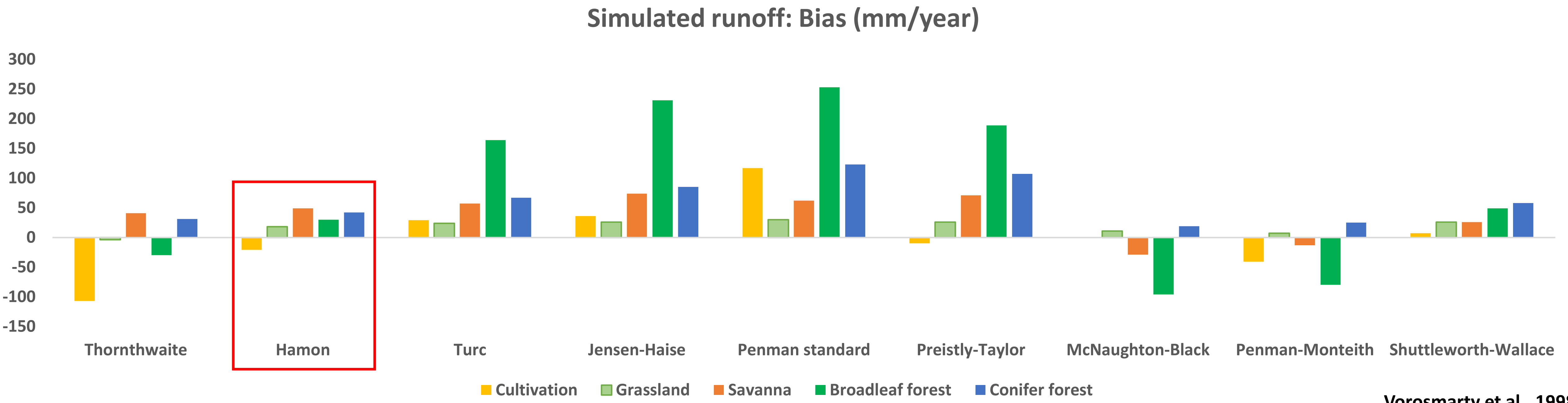


McCabe & Markstrom, USGS



Potential evapotranspiration

- Many models are available, with varying complexity and temperature-dependence (see Milly presentation)
  - Simple is better for our purposes … but may introduce additional bias
- Bias and error characteristics vary depending on watershed vegetation (Vorosmarty et al., 1998)
- Results shown here for Hamon only

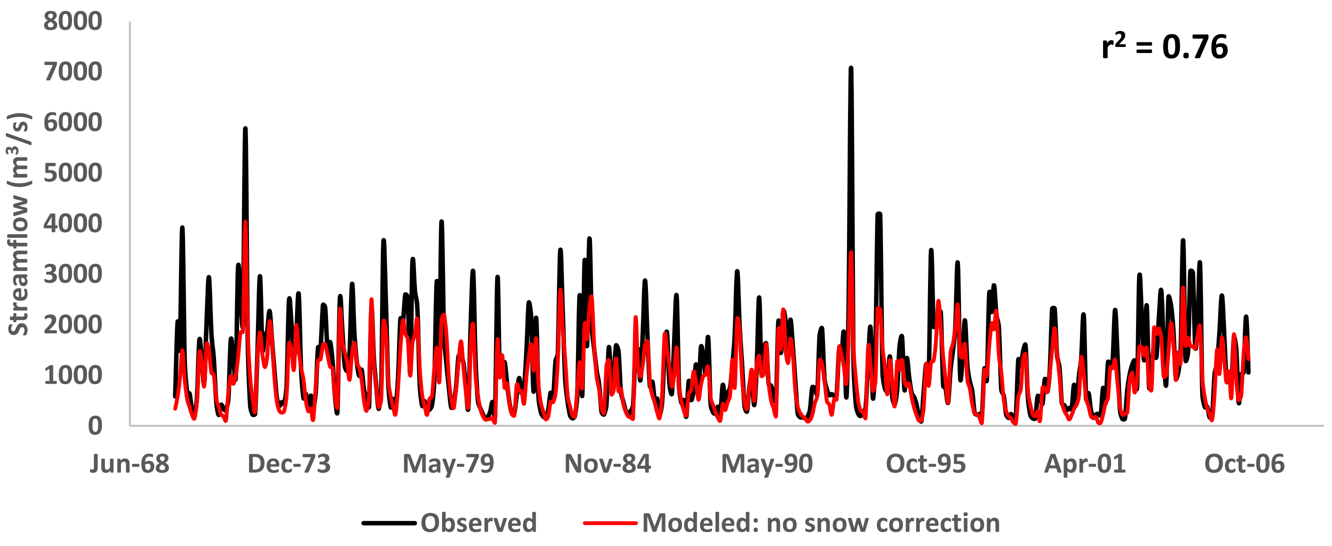


Vorosmarty et al., 1998

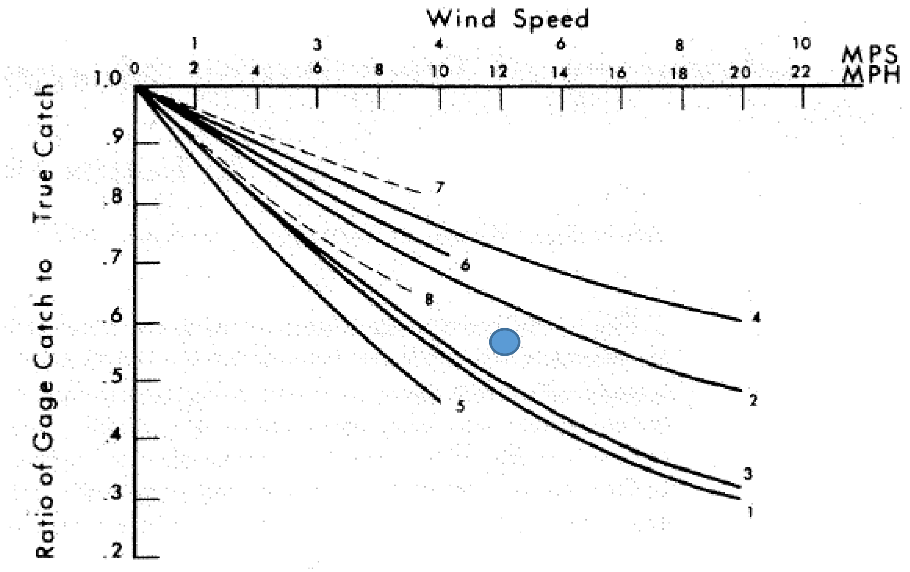
Water balance model results

- The initial water balance model showed good correlation with observations, but had a negative bias during winter and spring
- We determined that this was most likely due to wind-induced under-catch of snowfall in precipitation gauges
  - We used the CPC Unified Gauge-Based Gridded Precipitation dataset as observations
- A snow correction assuming 55% snow catch ratio was applied, based on mean winter-spring wind speeds (4-6 m/s)

Water balance model vs. observations: 1970-2006

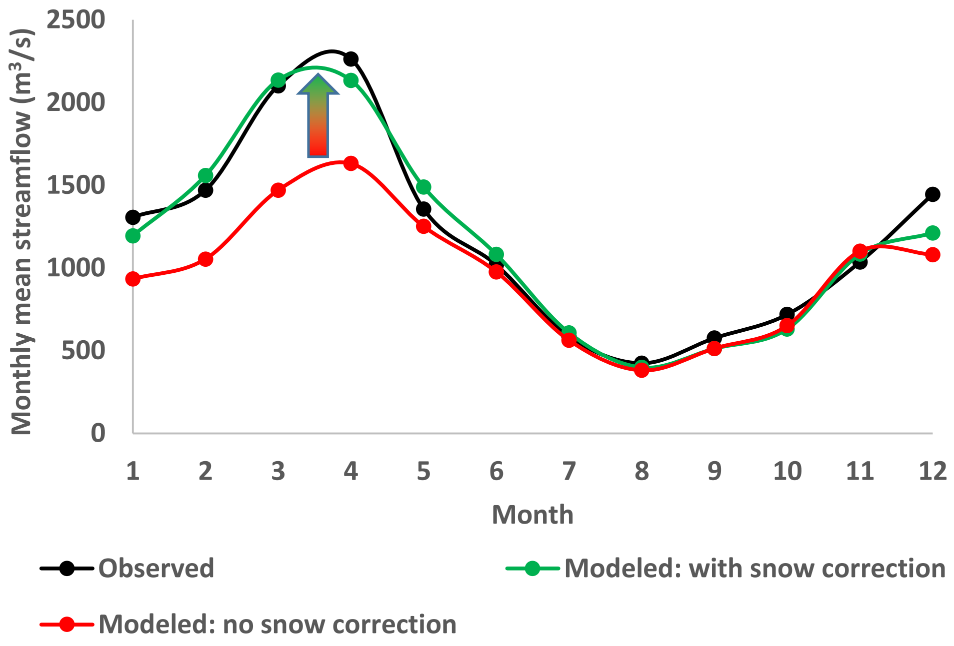


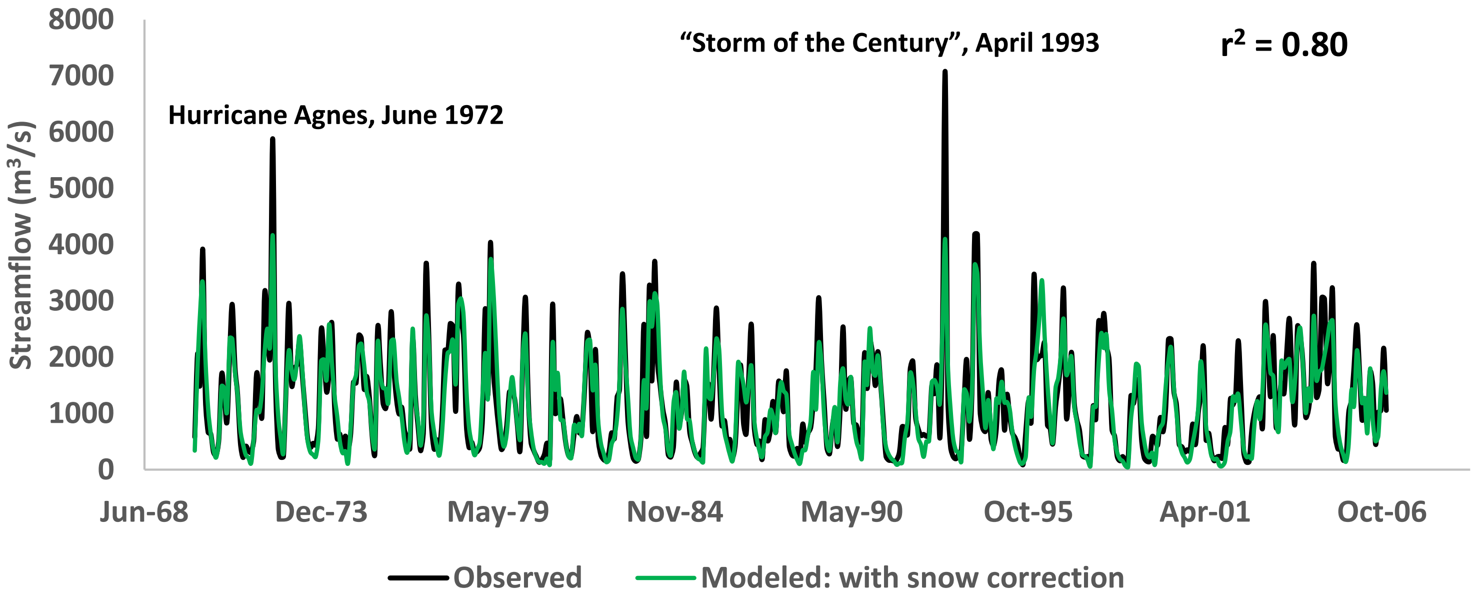
Snow catch vs wind (Larsen, 1974)



Water balance model results

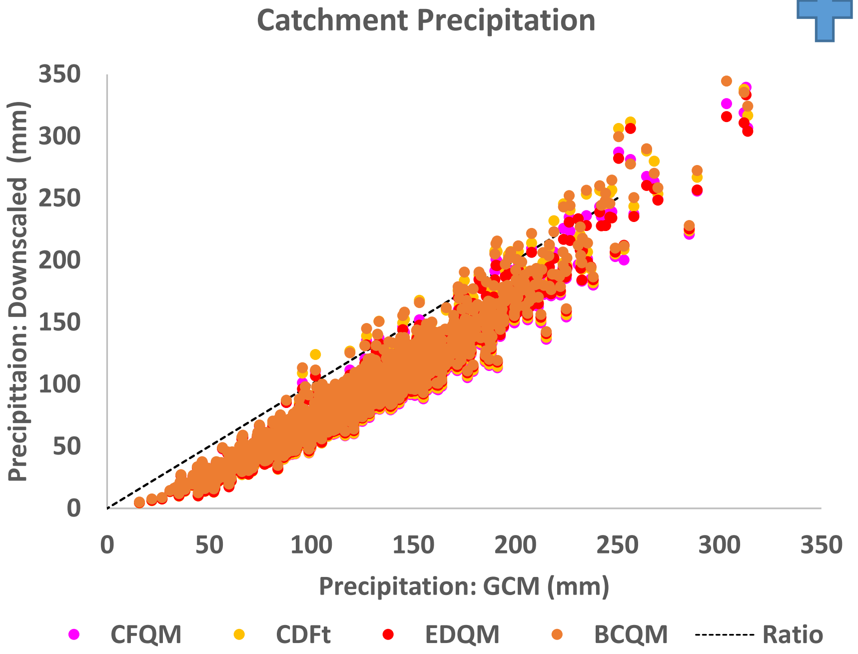
- The snow correction improved the winter-spring bias in the model substantially
- The water balance model now showed good correlation and low bias across the 30 year observation series
- Only very large flood events (e.g. hurricanes) were now under-estimated
- (This correction was not applied to GCM fields)

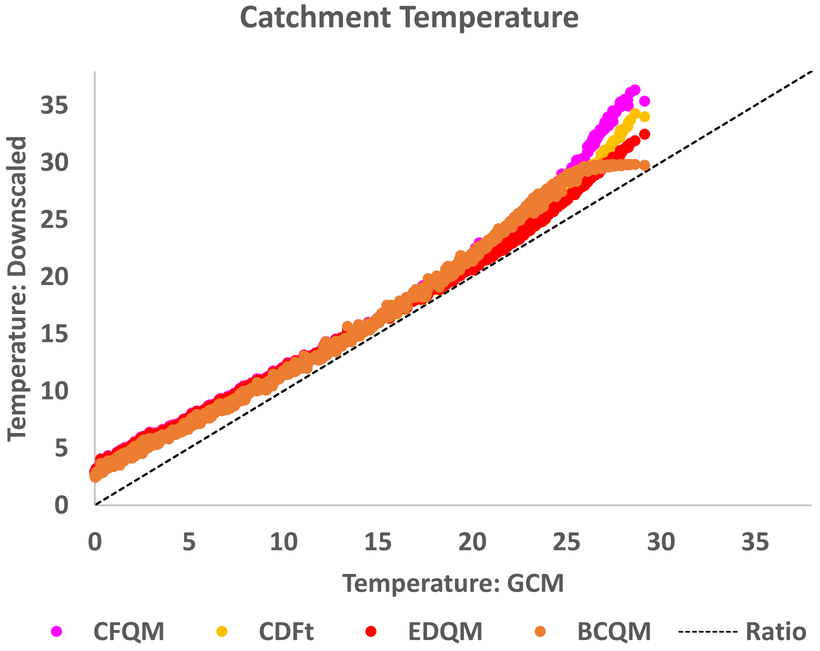


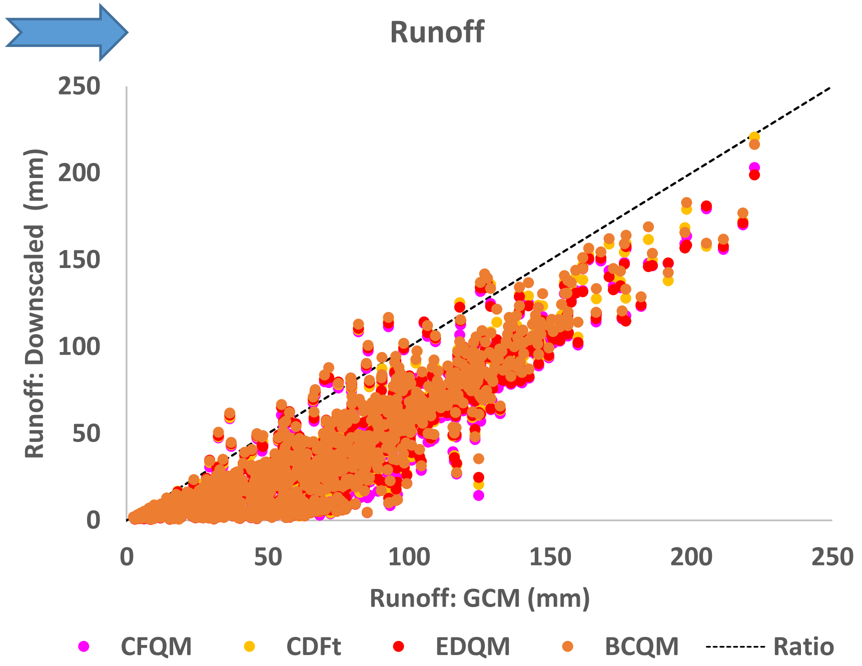


Downscaling precipitation and streamflow

- Catchment precipitation was over-estimated by the GCM in the historical period
- As a result, downscaled precipitation projections were lower than those from the GCM
- Similarly to estuarine temperature, downscaled temperatures were warmer than those from the GCM, and diverged strongly at >26°C
- A combination of lower precipitation and warmer temperatures in the downscaled projections resulted in lower projected streamflow than in the GCM

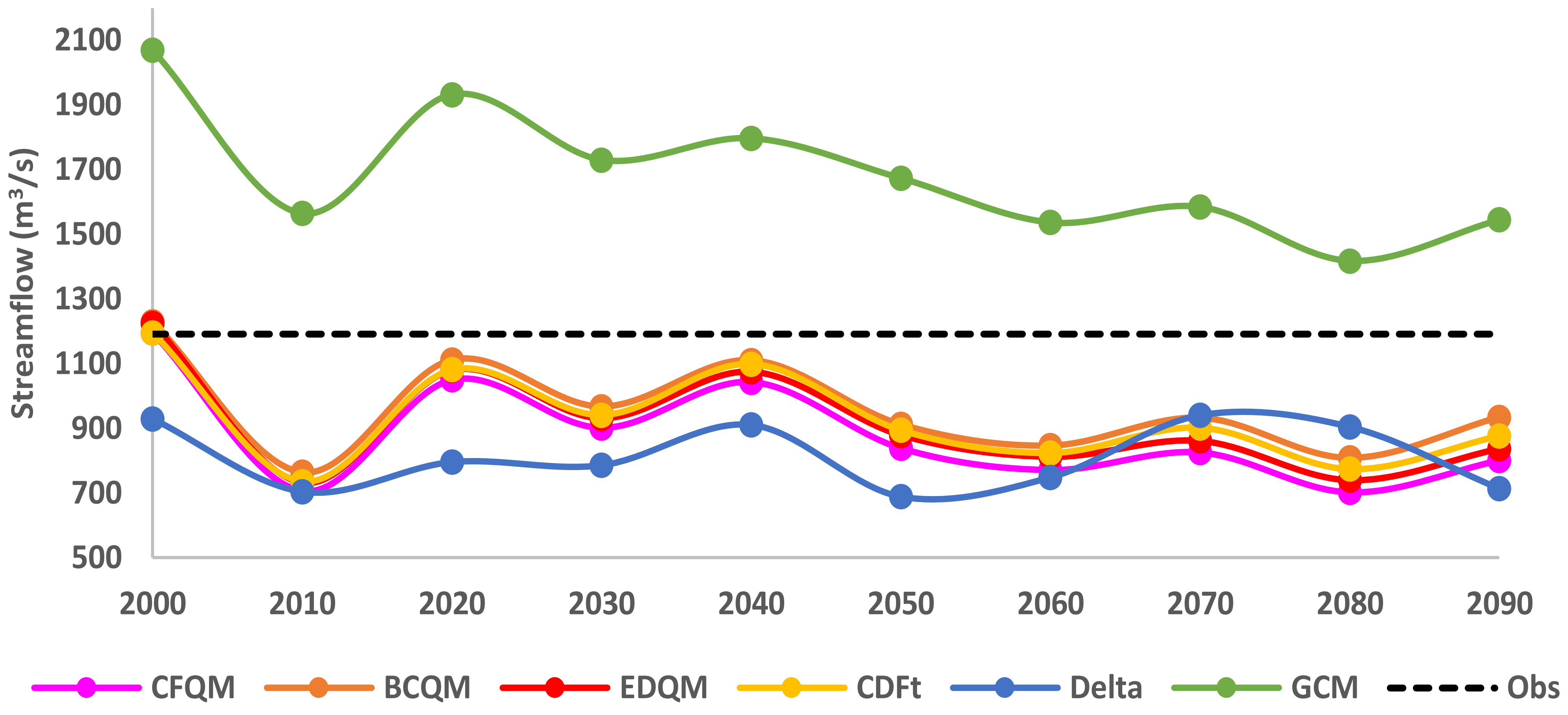






Downscaling precipitation and streamflow

- Both the GCM and downscaled models (except Delta) projected a modest decrease in annual Susquehanna River streamflow through 2100
- Largely due to temperature: precipitation varied without a strong trend through to 2100



Downscaling precipitation and streamflow

- How reliable is this modeled reduction in streamflow?
- We compared results from the water balance model to runoff directly from the GCM
- In winter, the downscaled models showed a reduction in streamflow, while both methods from the GCM (water balance model and direct calculation) did not
- However, trends in other seasons were less clear

Conclusions

- Water temperature and Susquehanna River streamflow could both be predicted from observations of atmospheric variables during the recent past
- Results from downscaled models were similar for both temperature and precipitation, except when air temperatures exceeded ~26°C
  - Implications for biological impact models using temperature
- Downscaled models generally projected warmer temperatures and lower precipitation than the GCM, resulting in lower Susquehanna River streamflow
- Downscaling among these methods (statistical, not dynamical) will likely contribute less to overall uncertainty than choice of GCM, or RCP, except maybe at upper temperature limits (…but still should be considered)
  - Consider and communicate *multiple sources of uncertainty*

Future directions

- We would like to extend this work to consider spatial models of temperature and salinity across the bay
- More complex biological impact models will be investigated, including those with streamflow effects
- The effect of downscaling climate models to drive these, and the effect of using different downscaling techniques, will be further described
- Additional GCMs, additional RCP scenarios, and additional study sites in the US will be included (as a function of available time)

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- Chesapeake Bay Program water quality database
- NOAA National Data Buoy Center
- NOAA NOS, OAR, NMFS, NWS

T Kiser, J Mueller