Chesapeake Hypoxia Analysis & Modeling Program (CHAMP)

Predicting impacts of climate change on the success of management actions in reducing Chesapeake Bay hypoxia

CHAMP PIs:

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CBP Modeling Workgroup Quarterly Meeting, April 10, 2018

CHAMP goals

Develop a Chesapeake Bay scenario-forecast modeling system to:

- Isolate future impacts on Chesapeake hypoxia of *climate change* from those due to *anthropogenic nutrient inputs*

- Determine whether the WIPs/TMDLs will successfully reduce hypoxia (and meet WQS) under future climate conditions

CHAMP models

Use ***multiple models*** in Chesapeake scenario-forecast modeling system:

- Three watershed models:
  - CBP WSMp6 (**CBP: Bhatt/Shenk**)
  - DLEM (**Auburn: H. Tian**)
  - Sparrow (**USGS: Ator**)
- Two estuarine models:
  - CBP WQSTM (**CBP: R. Tian/Linker**)
  - ChesROMS-ECB (**VIMS: Friedrichs**)

Up to six model combinations

- Oyster population model (**ODU: Hofmann**)
  - To examine impact of hypoxia on living resources

CHAMP simulations

Four types of watershed + estuarine simulations:

- Realistic hindcasts (1985-2016)
- Future simulations (2017-2050)
- Factorial future simulations (2017-2050), climate change vs. land use/population change
- Decision support: alternative management scenarios

Forcing fields for future simulations:

For an “apples to apples comparison” all model combinations must use same future forcing fields:

- Atmospheric deposition change (**Bash**)
- Population/land use change (**Claggett**)
- Climate change (**Najjar**)

CHAMP Preliminary Climate Change Results

The competing impacts of climate change and nutrient reductions on dissolved oxygen in Chesapeake Bay

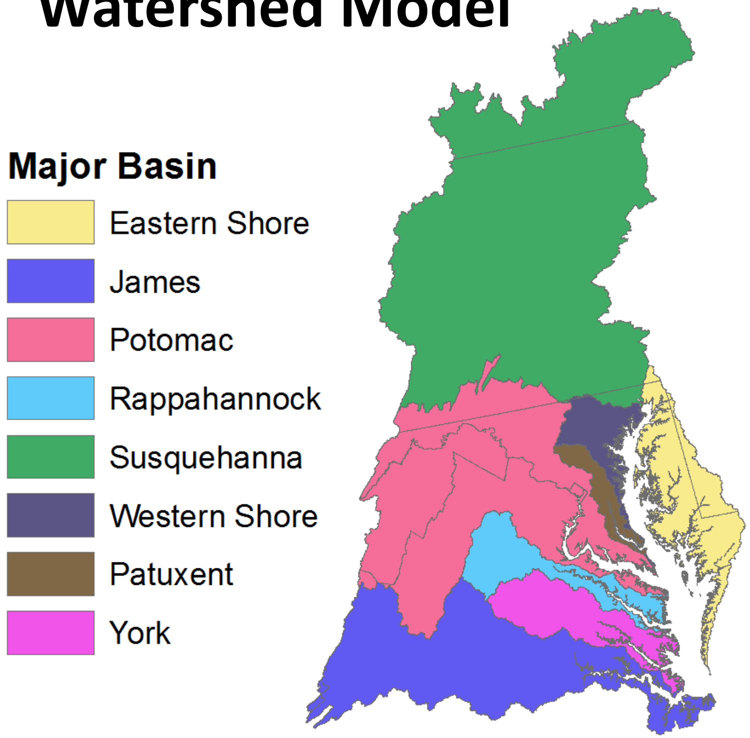
Isaac D. Irby[1], Marjorie A. M. Friedrichs[1], Fei Da[1] and Kyle E. Hinson[1]

[1] Virginia Institute of Marine Science, College of William & Mary, Gloucester Point, VA 23062

Irby et al., accepted, April 2018

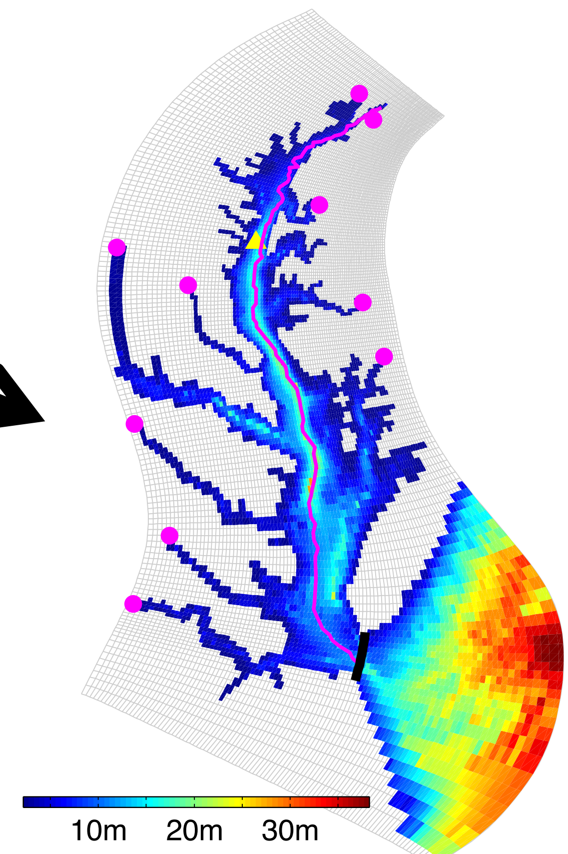
Methods: Modeling Framework

Chesapeake Bay Program's
Watershed Model



(Shenk and Linker, 2013)

ChesROMS-ECB



- **Base Run (realistic 1993-1995 nutrients)**
- **TMDL Run (reduced nutrients)**

(Feng et al., 2015; Irby et al., 2016, 2018)

Methods: 2050 climate change

In 2050, relative to 1990s, we assume:

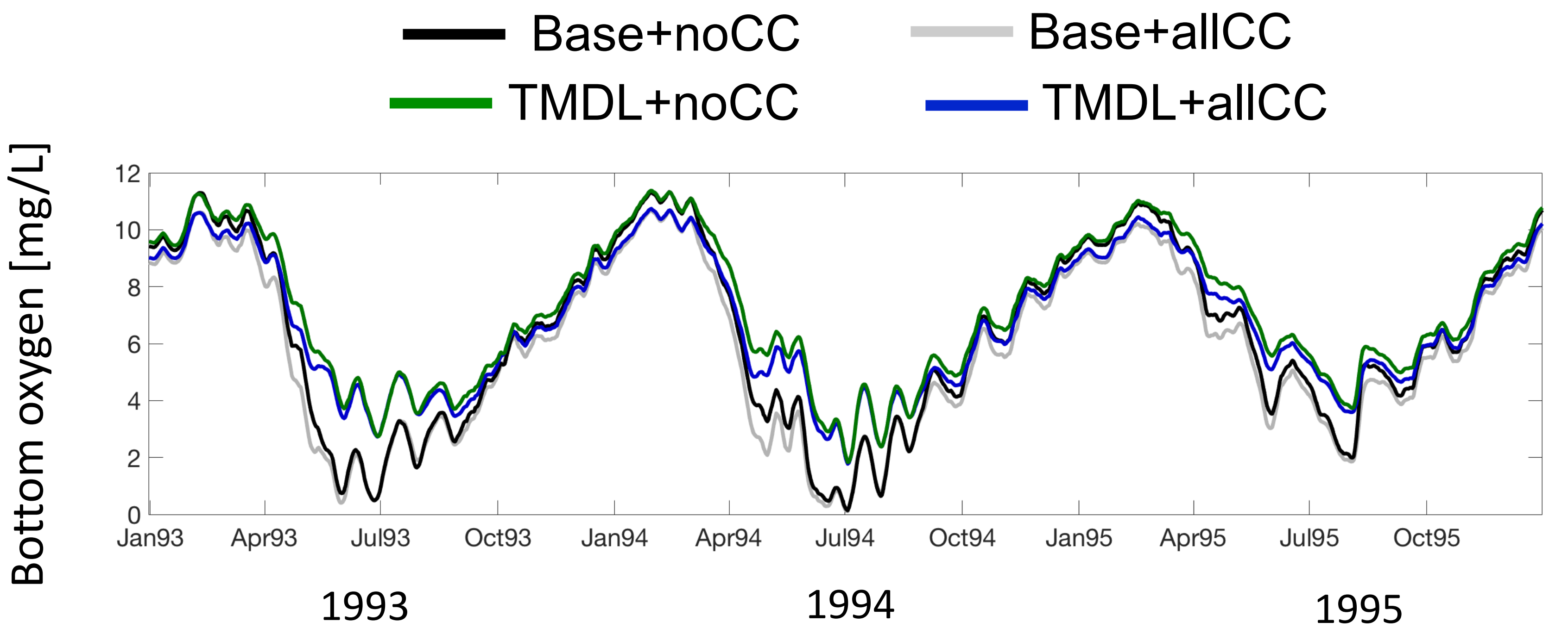
Water Temperature	**Sea Level Rise**	**Rivers**
1.75 °C	0.5 m	~15% flow
Throughout water column	At open boundary	Mostly in winter

(From Hinson, Bhatt & Shenk)

Climate Change Scenarios:

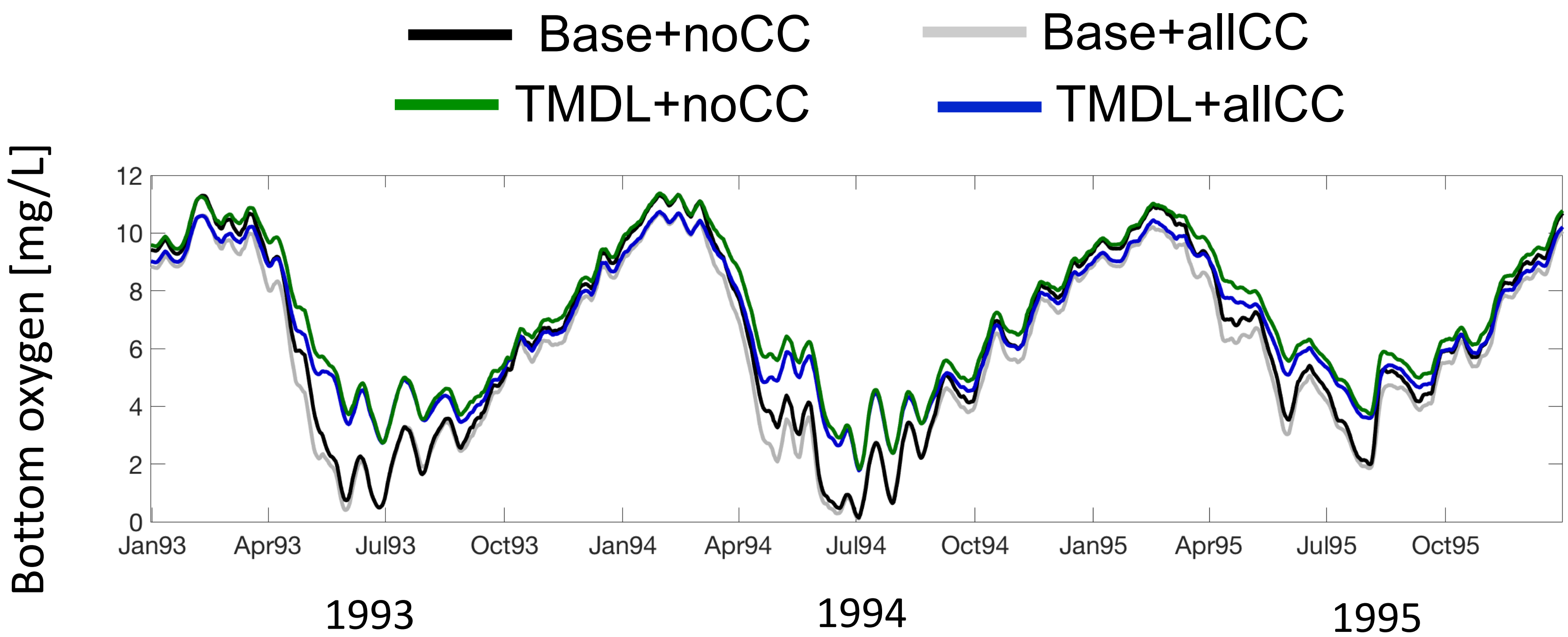
- **Temperature**
- **Sea Level Rise (SLR)**
- **Rivers (precip/temperature/evapotranspiration)**
- **All**

Results: Mesohaline Bay



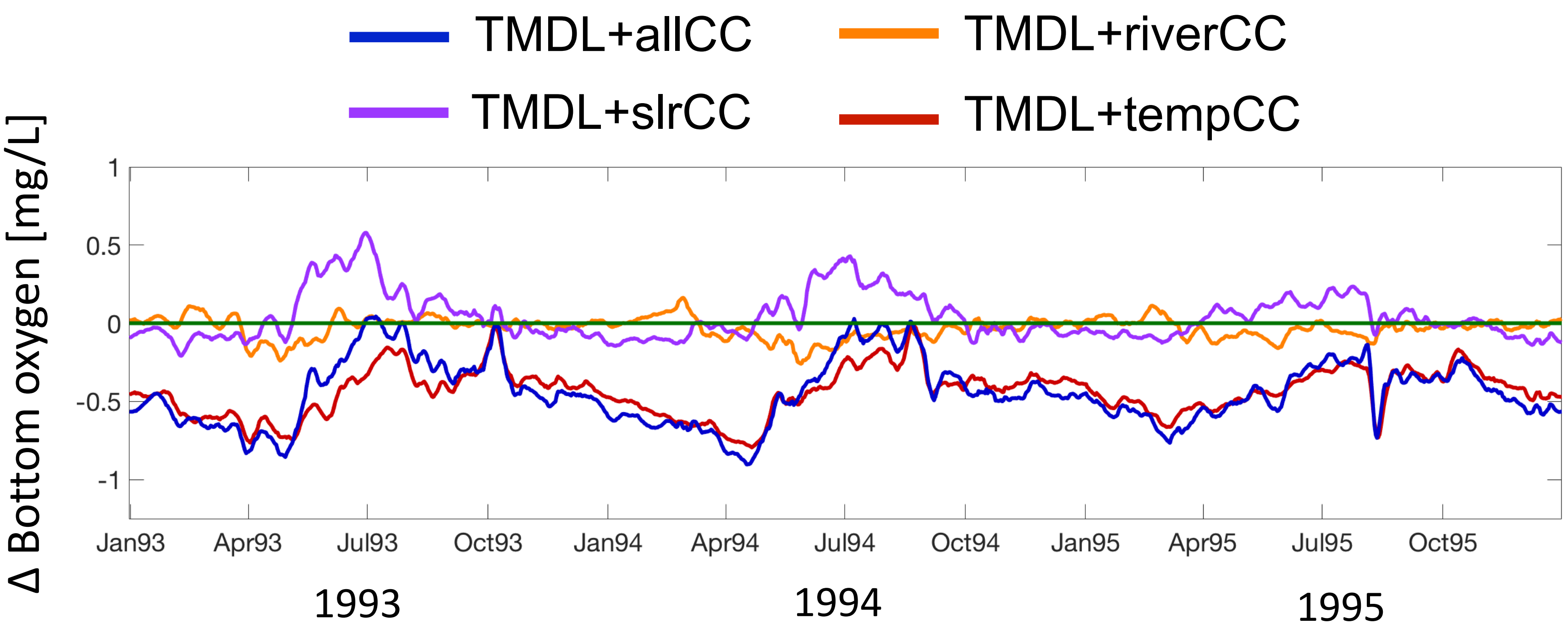
- Climate change exacerbates hypoxia (opposite to WQSTM results)
- Climate change impact on bottom DO << impact of TMDL nutrient reductions (same as WQSTM results)

Results: Mesohaline Bay



What causes hypoxia to get worse?
Temperature? SLR? Rivers?

Results: Mesohaline Bay



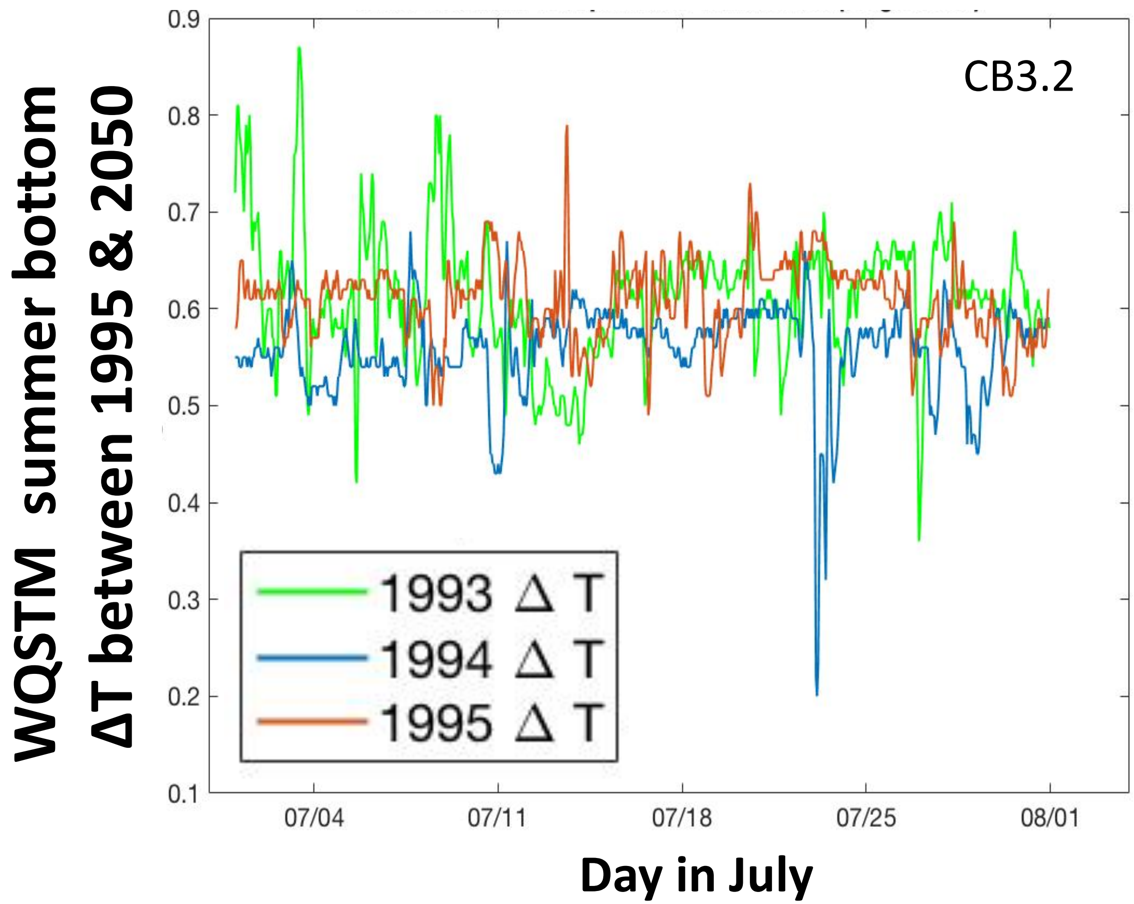
- **SLR** reduces hypoxia – **same as WQSTM**
- **Rivers/precip** increase hypoxia – **same as WQSTM**
- **Temperature** causes large increase in hypoxia – <u>**different from WQSTM**</u>

→ **Of three climate impacts, here we see Temperature is greatest**

Why opposite results?

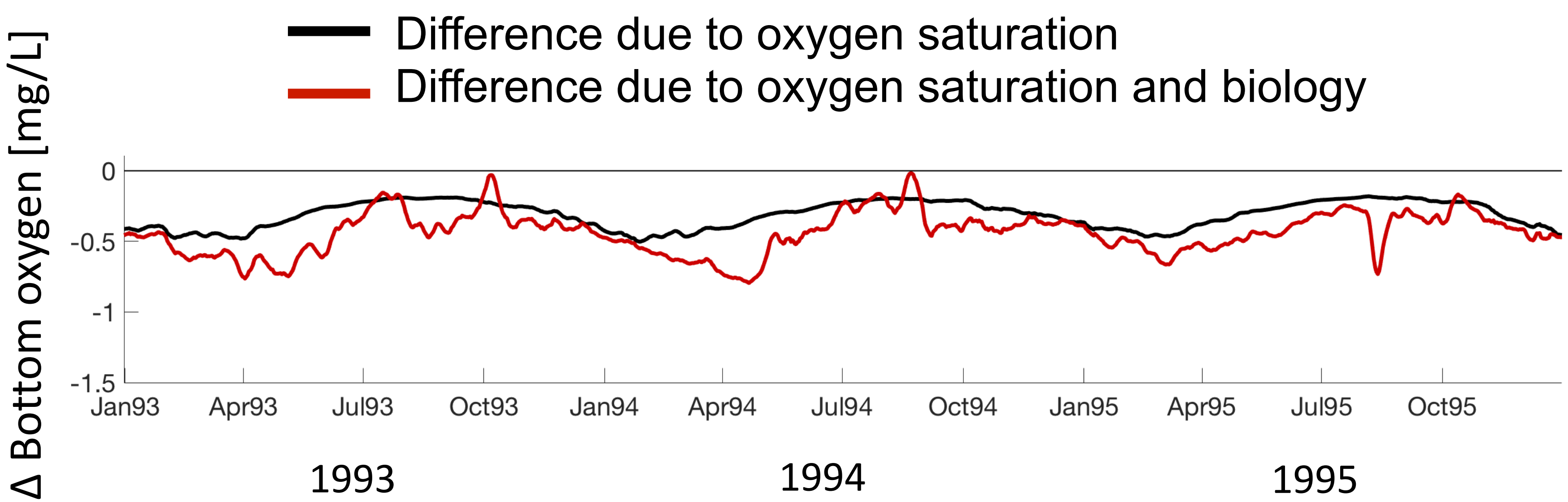
WQSTM:
ΔT_{bot} ~ 0.6°C
(other stations are ~0.7-0.8°C)

ChesROMS:
ΔT_{bot} = 1.75°C



- ChesROMS: ΔT_w = 1.75°C throughout water column, based on literature
- WQSTM: ΔT_w ~ 0.6°C at the bottom, based on realistic ΔT_{atm} (***but ΔT_{rivers} and ΔT_{OBC} may need to be re-examined***)

Results: Mesohaline Bay



- Most (~75%) of Δ oxygen due to warming results from solubility
- Largest change in rate processes (biology) in spring/summer

Climate Change Conclusions

- Increasing sea level will *slightly* *increase* oxygen via:

  → **increased estuarine circulation**

- Increasing precip will *slightly* *decrease* oxygen via:

  → **higher winter/spring nutrient loads that will increase respiration/remineralization in spring**

- Increasing water temp will *significantly* *decrease* oxygen via:

  → **decreased solubility year-round, throughout Bay**

  → **increased respiration/remineralization rates in spring/summer**

Other CHAMP results (preliminary)

Hindcasts with/without TMDL reductions:

- WSMp5 + WQSTM produces similar WQS as WSMp5 + ChesROMS-ECB

(Irby & Friedrichs, Estuaries and Coasts, in review)
→ Increases our confidence in the TMDL

Coming next:

How will WSMp6 + WQSTM compare to WSMp6 + ChesROMS-ECB?

How will DLEM + ChesROMS-ECB compare to WSMp6 + ChesROMS-ECB?

CHAMP Summary

- ✧ Opportunity for academic research to impact management decisions
- ✧ Opportunity for Modeling Workgroup to suggest management-oriented (hypoxia focused) research questions that need addressing

Climate projections for the Chesapeake Bay and Watershed based on Multivariate Adaptive Constructed Analogs (MACA)

Raymond Najjar and Maria Herrmann

The Pennsylvania State University

CBP Modeling Workgroup Quarterly Meeting

April 10, 2018

CHAMP project needs

- Climate projections to serve as inputs to the Chesapeake watershed and estuarine models
- Climate variables:
  - air temperature
  - precipitation
  - humidity
  - downwelling shortwave and longwave radiation
  - wind (magnitude and direction)
- Spatial resolution: at least 1/8^{o}
- Temporal resolution: at least daily

Statistical downscaling solves two problems presented by GCMs:

- Spatial resolution is too coarse
- The models are biased

Why we use MACA among the many statistical downscaling choices:

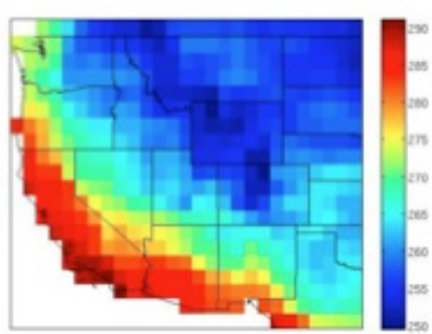
- It has all the variables we need, except for downwelling longwave radiation
- It has the highest spatial resolution available ($1/24^{o}$)

MACA uses constructed analogues

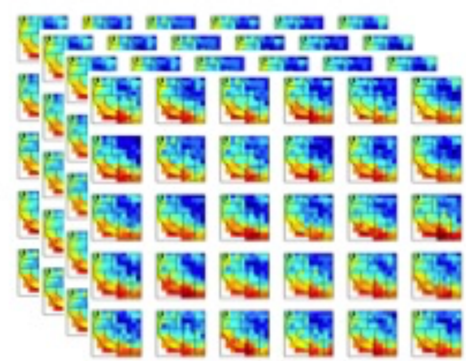
Step 1. For a given day of GCM output, find the top 10–100 days in the historical record that are closest (most analogous) to that GCM day

Single GCM day

Library of coarse observations within 45 calendar days of the GCM day



Z^{GCM}



Z_n^{OBS}

Method description: Abatzoglu and Brown (2012)

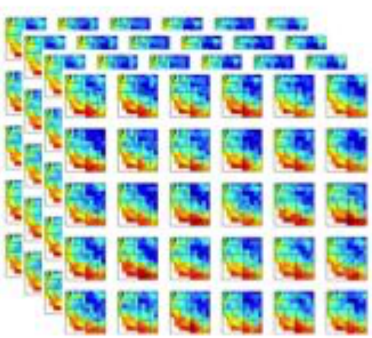
Step 2. Find the weights a_n for the top 10–100 days that best reconstruct the GCM day

$$Z^{GCM} \approx \sum_{i=1}^{i=N} a_n Z_n^{OBS}$$

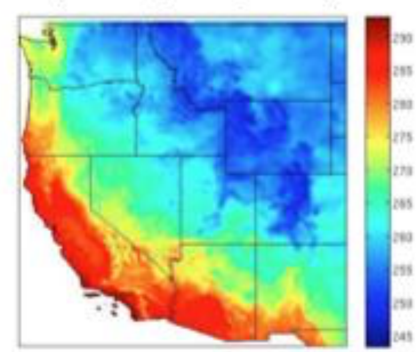
Step 3. Apply those weights to the high-resolution observational data to get a high-resolution projection

Corresponding fine OBS patterns from N best coarse OBS patterns

Downscaled GCM target pattern (1 day, 1 year)



$$\sum_{i=1}^{i=N} a_n Y_n^{OBS} = Y^{GCM}$$



Y_n^{OBS}

Y^{GCM}

Additional MACA details

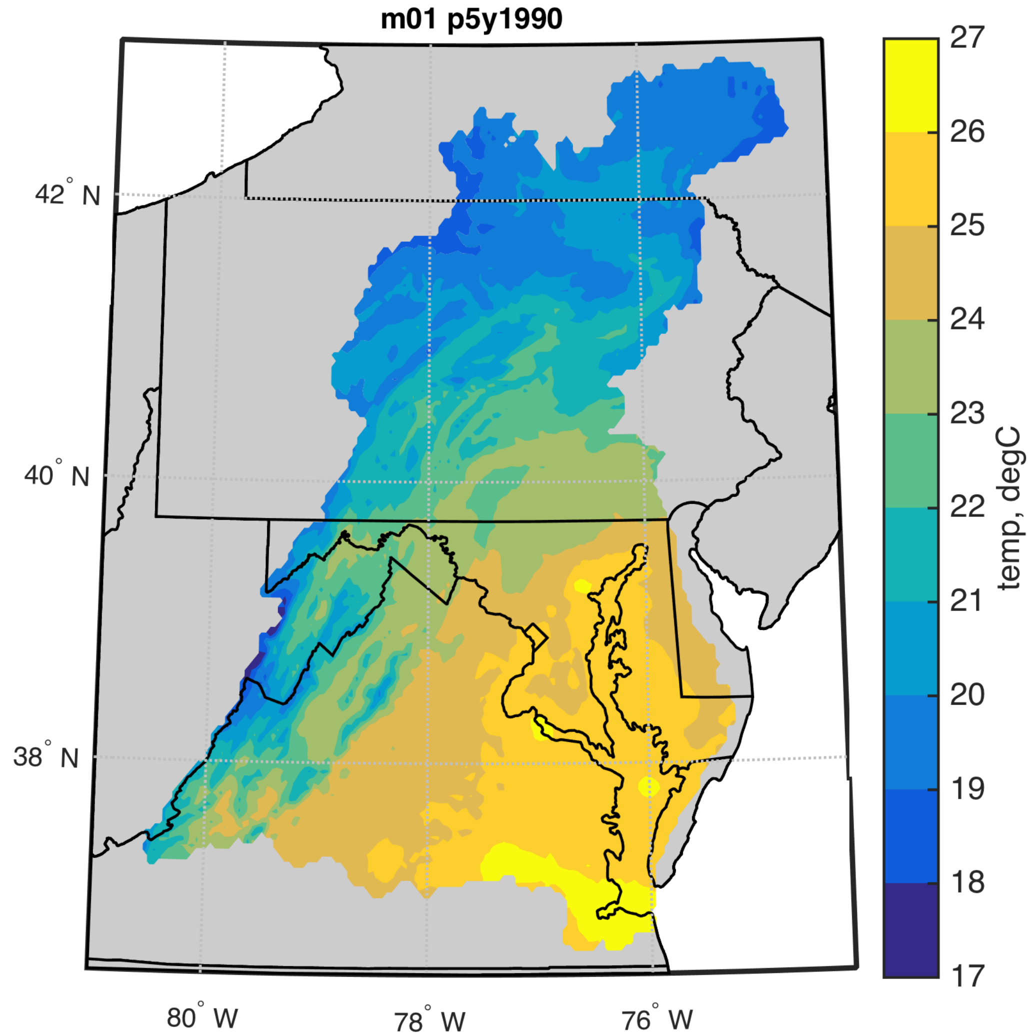
- Bias correction using quantile mapping
- Epoch adjustment to solve the problem of disappearing analogues (”adaptive”)
- 20 CMIP5 GCMs
- 2 emissions scenarios (RCP 4.5 and 8.5)
- 2 meteorological training data sets
- 2 versions of the downscaling (using slightly different approaches for the constructed analogues, bias correction, and epoch adjustment)

Processing of MACA product for CHAMP

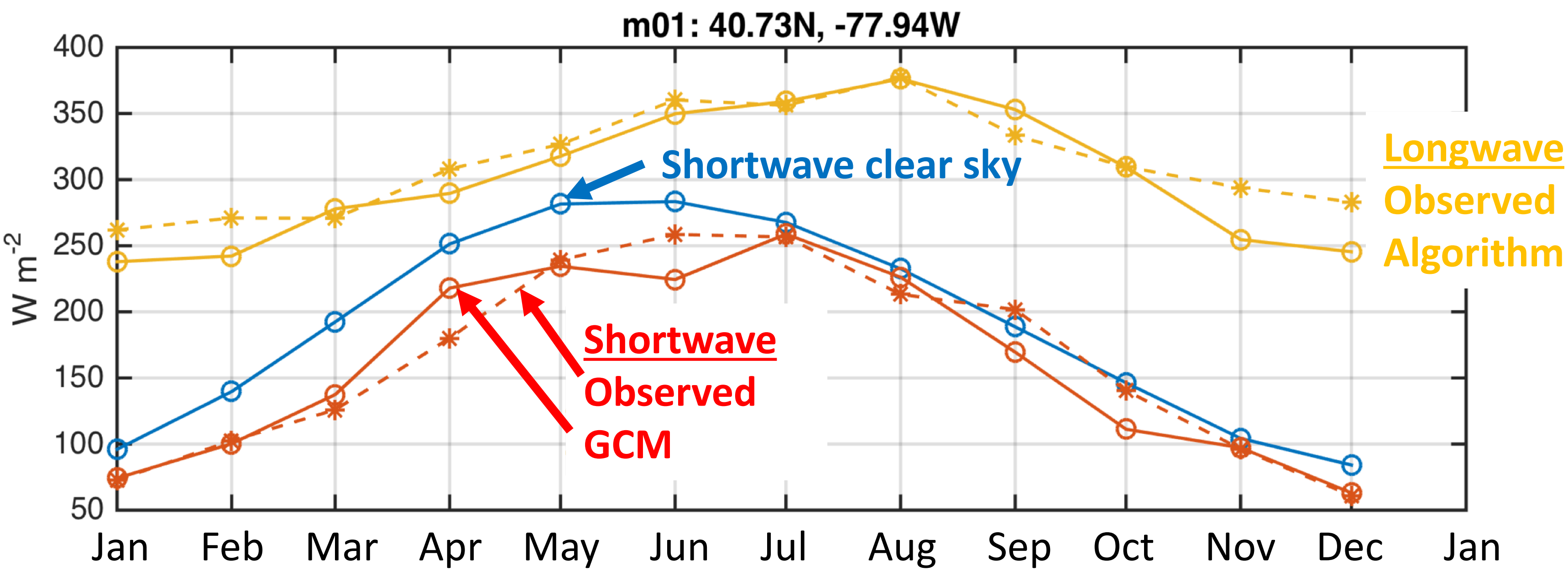
- MACAv2 with METDATA training data
- RCP8.5
- All 20 models
- Monthly longwave radiation computed from monthly temperature, humidity, and shortwave radiation (Najjar and Herrmann, 2018)
- Delta approach
- Mean annual cycles at monthly resolution in 5-year averages: 1981–1985, 1986–1990, … , 2046–2050

Example output:

- daily average temperature
- August, 1986–1990
- GCM BCC-CSM1-1



Longwave radiation algorithm works well

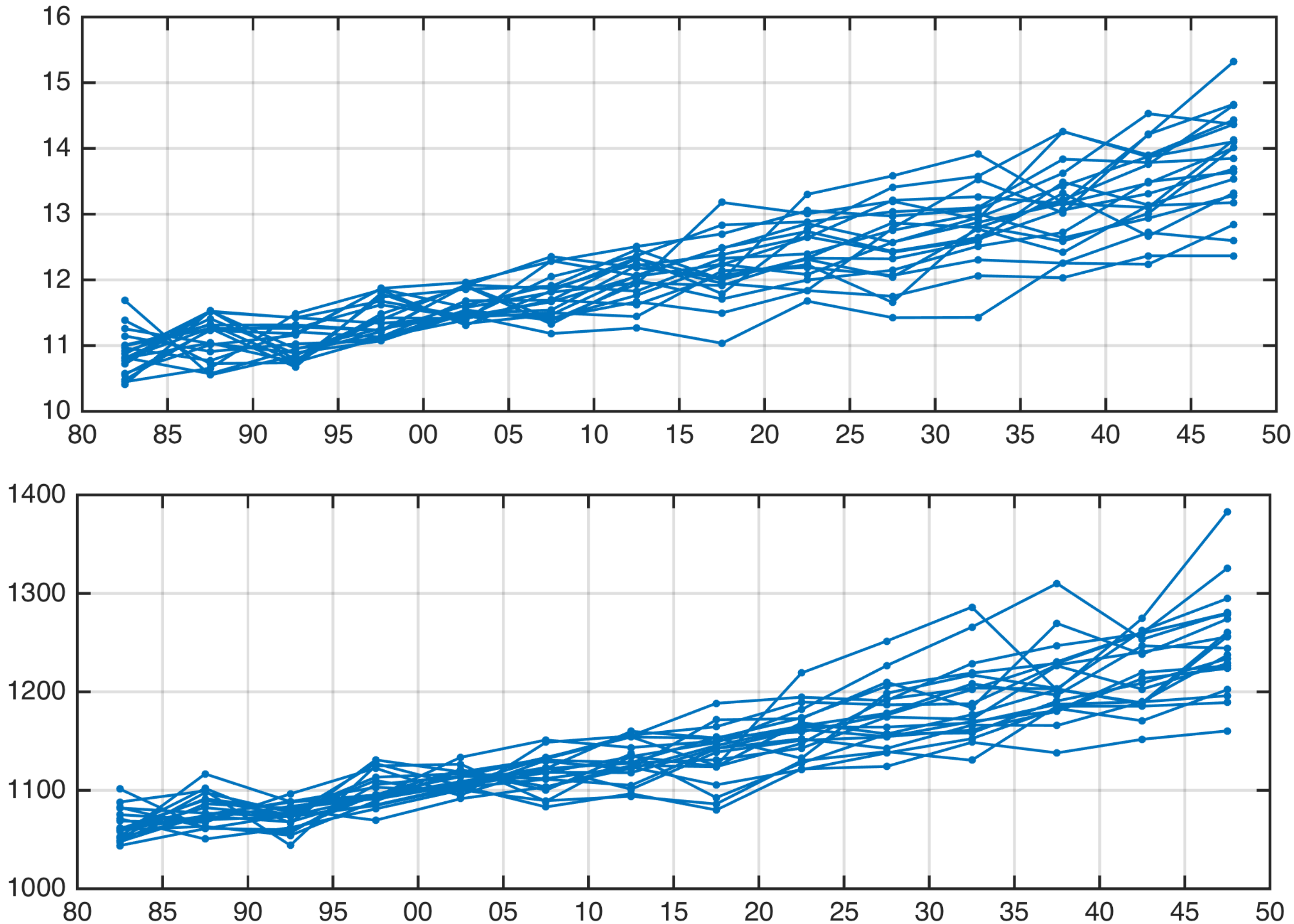


GCM is bcc-csm1-1, output is 2000-2004, observations from State College for 2001

Models consistently simulate increases in temperature and humidity

Temperature (^oC)

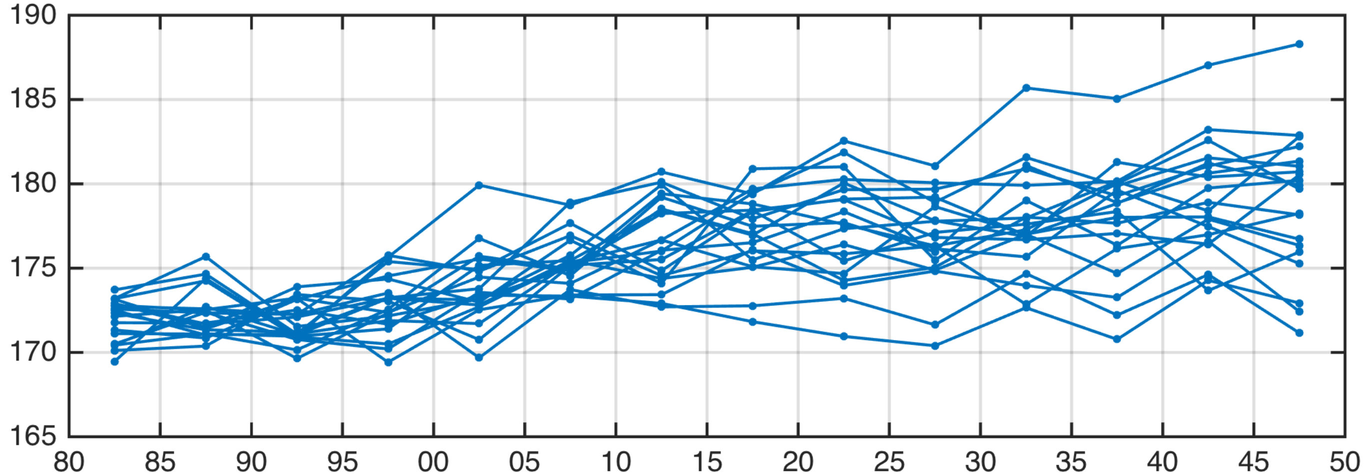
Vapor pressure (Pa)



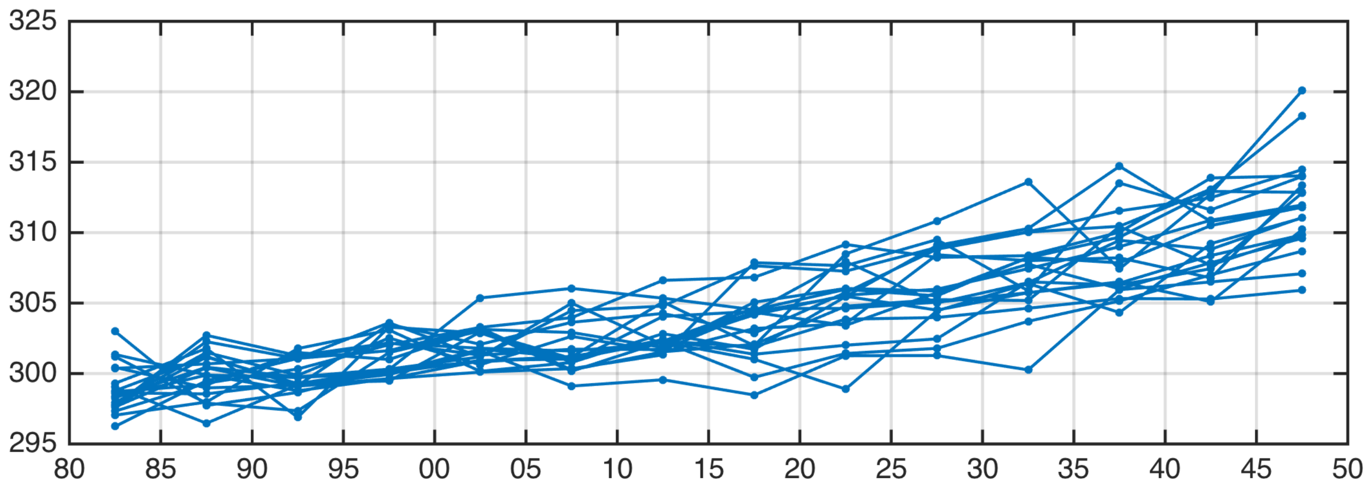
Year, 1980 to 2050

Models consistently simulate increases in shortwave and longwave radiation

Downwelling shortwave radiation ($W\ m^{-2}$)

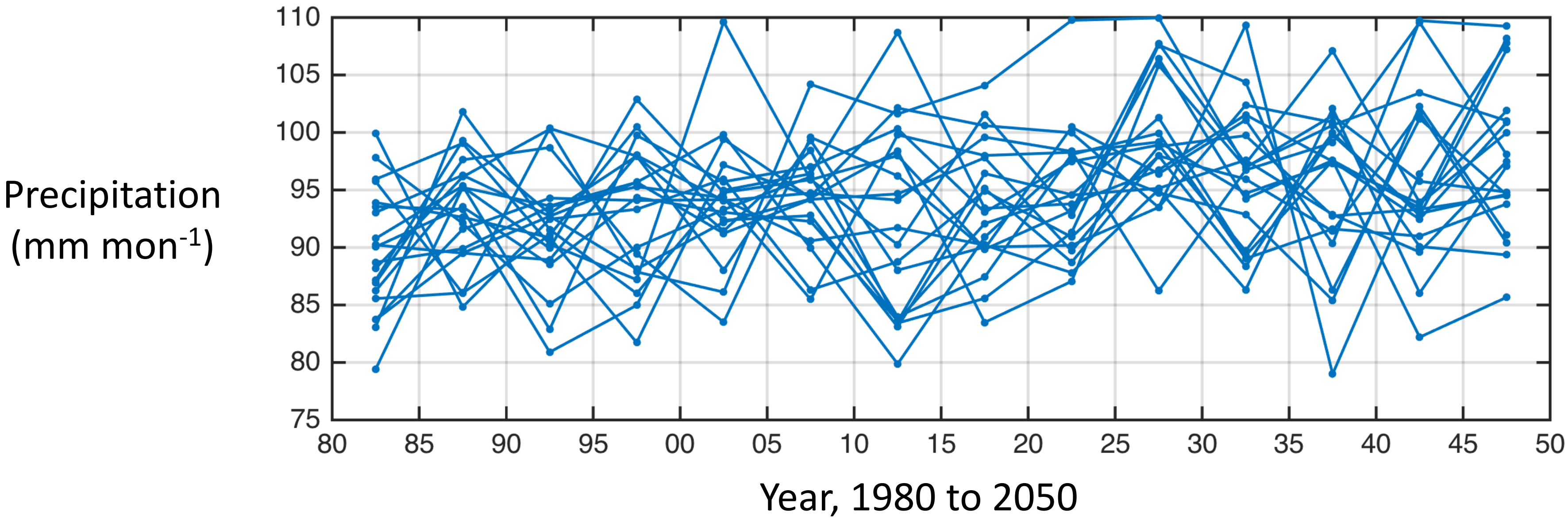


Downwelling longwave radiation ($W\ m^{-2}$)



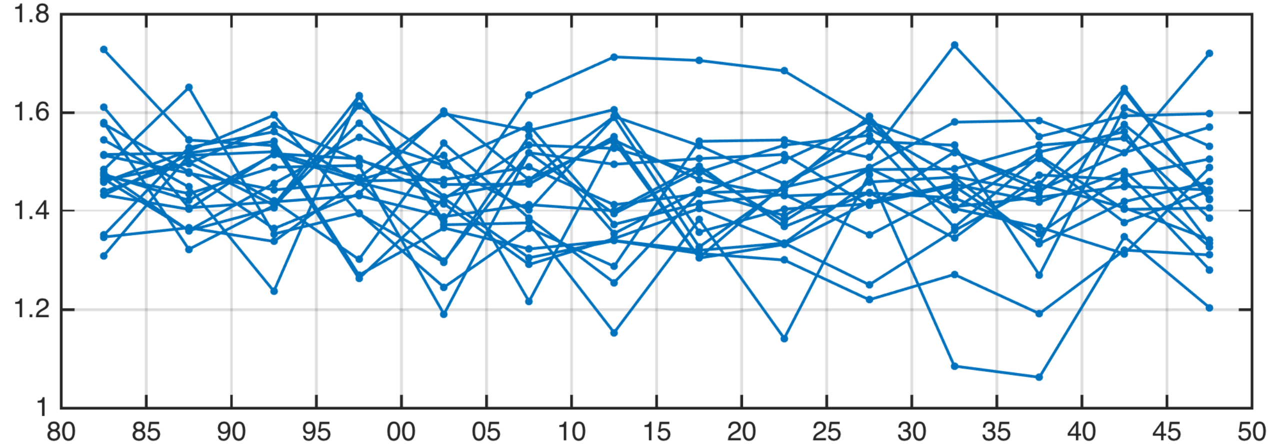
Year, 1980 to 2050

Model precipitation secular change is small compared to natural variability

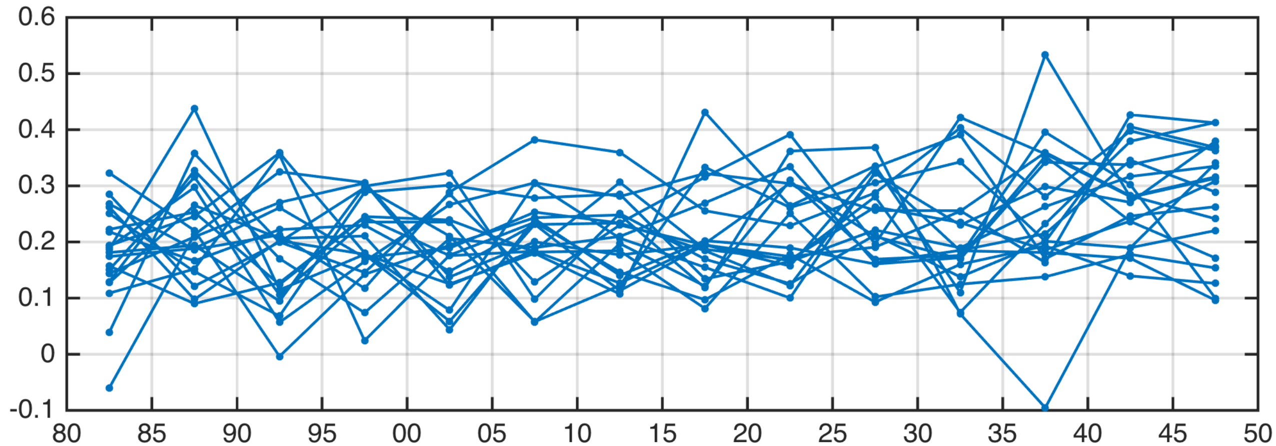


Model wind component secular change is small compared to natural variability

Westerly wind component (m s^{-1})



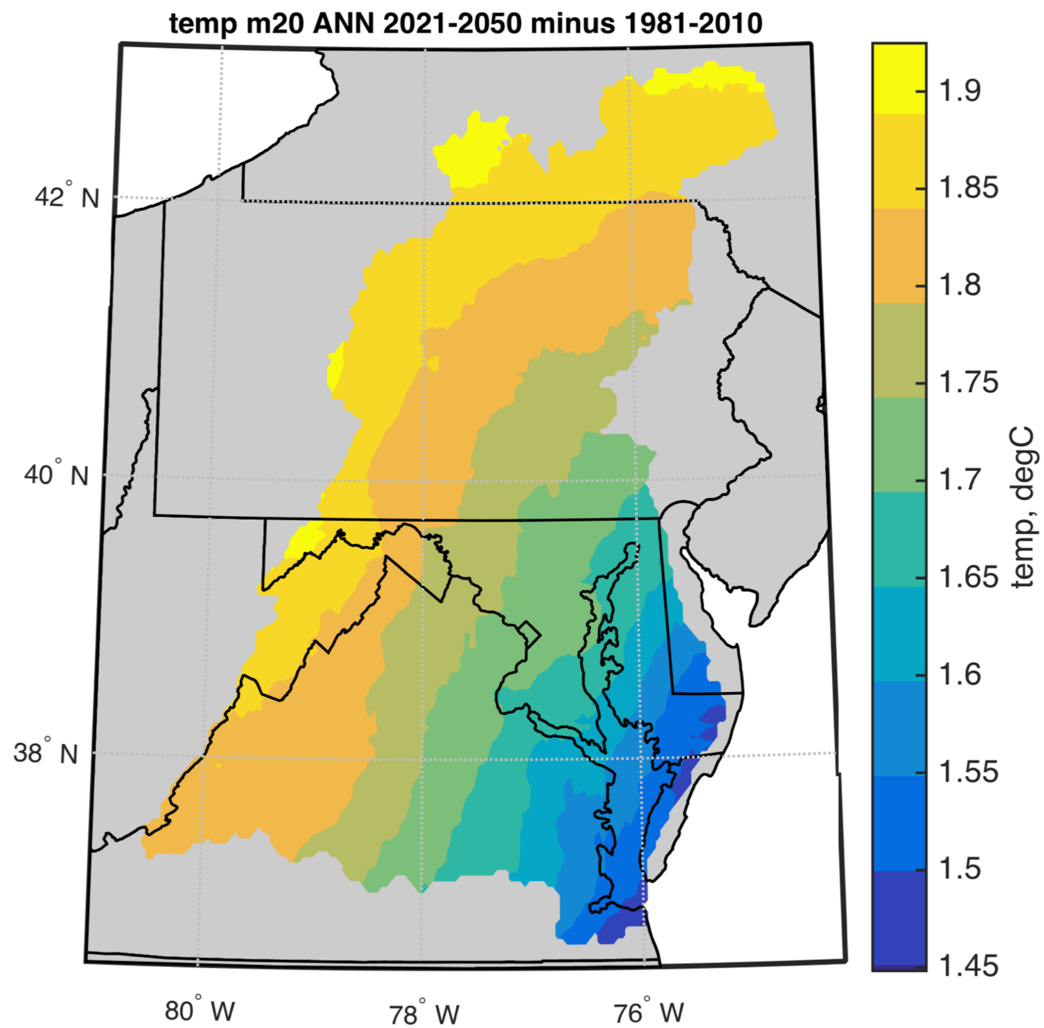
Southerly wind component (m s^{-1})



Year, 1980 to 2050

Warming increases with distance from the coast

Annual temperature change from 1981-2020 to 2021-2050 simulated by NorESM2



Next steps for climate model analysis in CHAMP

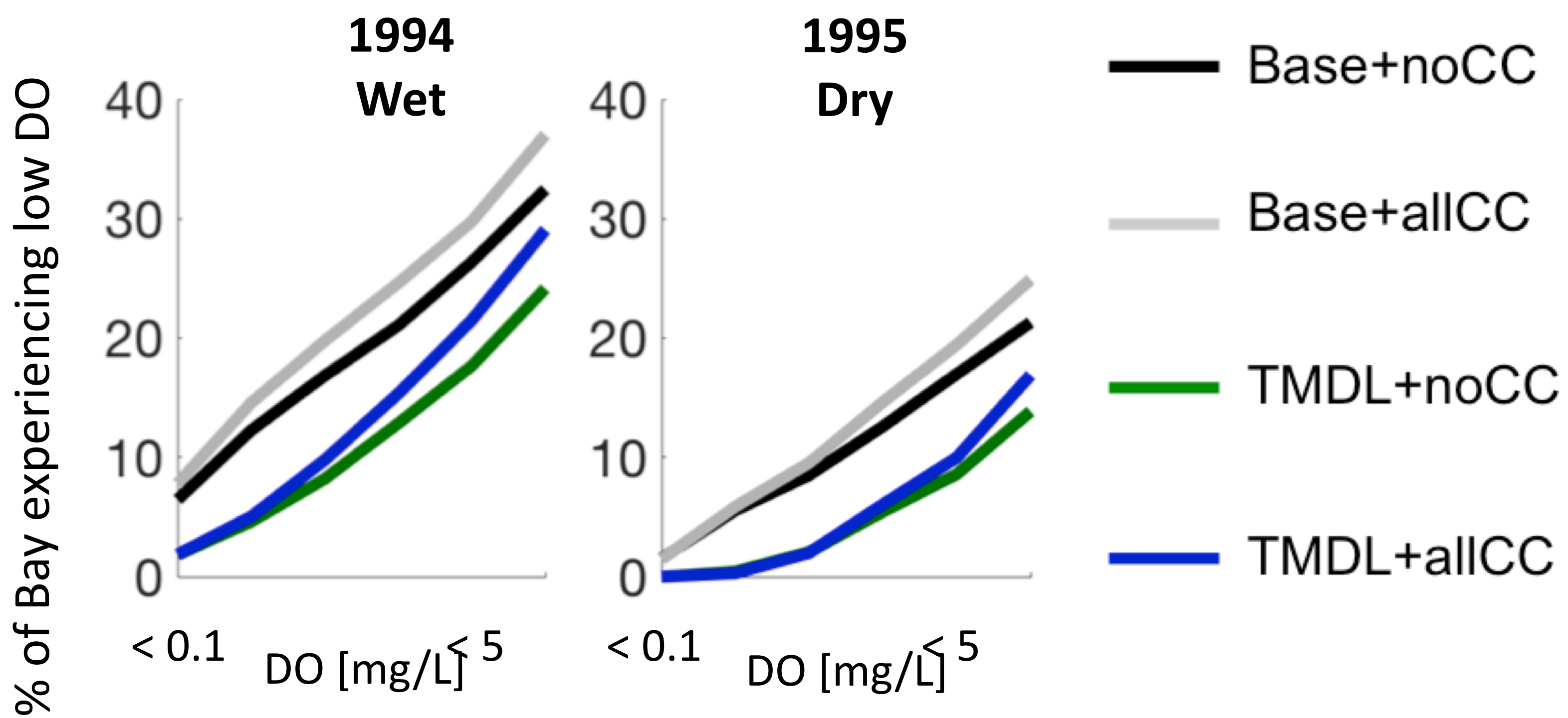
- Select a limited number of climate models
- Use winter precipitation and summer temperature as selection criteria
- Investigate causes of some simulated climate changes (e.g., projected solar radiation increase)

Discussion points regarding CBP’s potential use of MACA

- MACA has almost all meteorological variables needed for input to watershed and estuarine models
- MACA has high resolution
- MACA is available over Chesapeake Bay
- We (PSU) have not thoroughly evaluated the product
- We (PSU) have not done a thorough comparison of MACA to other products as such the product of Brekke et al. (2014)
- We (PSU) are not sure how much use the MACA product is getting
- Most applications of MACA appear to be in the Western U.S.

Extra slides

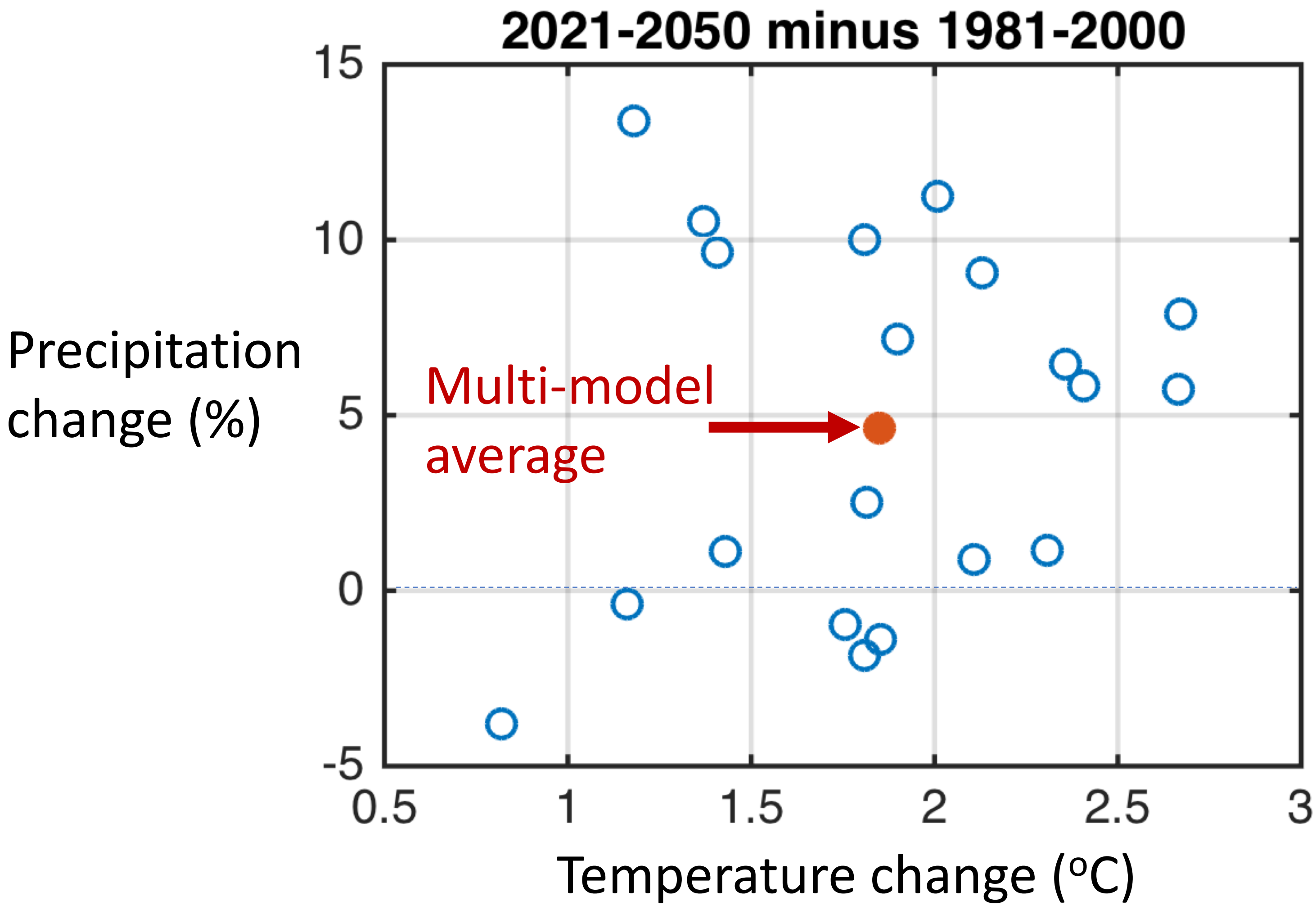
Results: wet vs. dry years

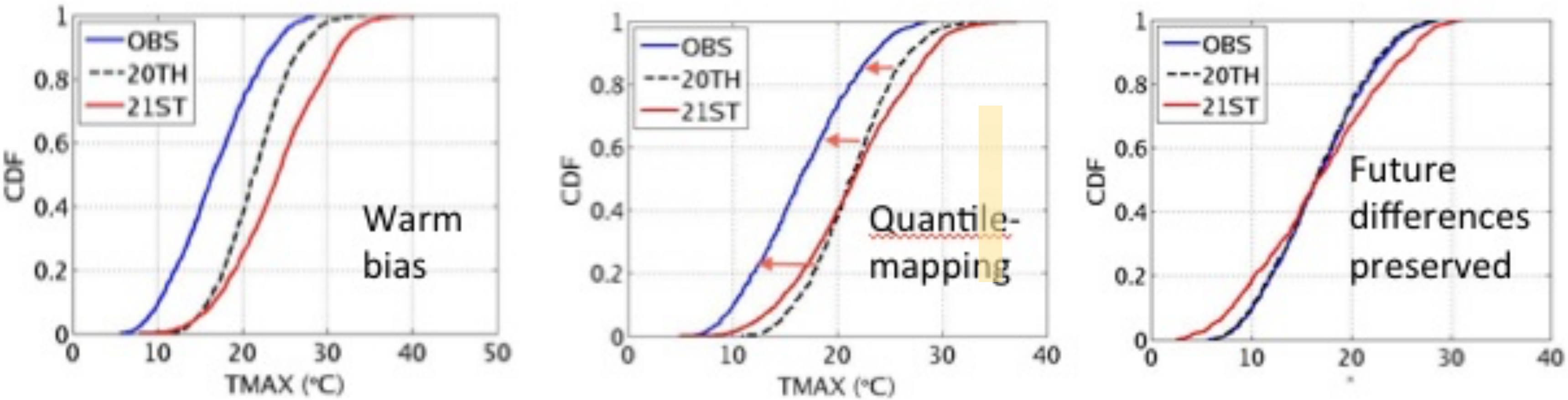


- Larger impacts at higher DO levels (DO < 5 mg/L, change ~6%)
- Hypoxia in the TMDL scenarios (both with and without climate change) is always less than Base case hypoxia

- But… **dry year** + noTMDL+allCC (worst case scenario)
  = **wet year** + TMDL+noCC (best case scenario)!

Projected annual temperature and precipitation change by the 20 GCMs





Raw GCM Data

After Epoch Adjustment

After Bias Correction

Differences between MACAv1 and MACAv2 downscaling

Epoch adjustment: variables
In v2, the trend in all variables is removed at the start.
In v1, the trend for only tasmax/tasmin,uas/vas was removed at the start.

Epoch adjustment: periods
In v2, the trend is removed for both the historical and future periods.
In v1, the trend was only removed in the future period.

Bias correction at coarse scale: preserving trends
In v2, after the coarse bias correction of the multiplicative variables (i.e. pr, huss,wind speed), the trend is removed again (as the coarse bias correction can modify this trend).

Constructed Analogs: number of patterns
In v2, we use 10 patterns.
In v1, we use 100 patterns(there may be some overfitting here).

Constructed Analogs: the error
In v2, we interpolate the error in the constructed coarse pattern and add it to the constructed downscaling at the fine level.
In v1, we throw away the coarse error from the constructed analogs method.

Bias Correction at Fine Scale: independently or jointly
In v2, we bias correct pr, huss, rsds independently, but bias correct tasmax and tasmin jointly with the corrected precipitation.
In v1, we bias correct all variables independently.

METDATA

- Spatial resolution of 1/24-degree (~4-km)
- Daily timescales
- Variables: near-surface minimum/maximum temperature, minimum/maximum relative humidity, precipitation, downward solar radiation, **wind components**, and specific humidity.

This dataset was created by bias-correcting daily and sub-daily mesoscale reanalysis and assimilated precipitation from the NASA North American Land Data Assimilation System (NLDAS-2, Mitchell et al., 2004) using monthly temperature, precipitation and humidity from Parameter-elevation Regressions on Independent Slopes Model (PRISM, Daly et al., 2008). The data were validated against an extensive network of weather stations including RAWS, AgriMet, AgWeatherNet, and USHCN-2 showing skill in correlation and RMSE comparable to that derived from interpolation using station observations.

Comparison of the three available MACA data products

	MACAv1-METDATA	MACAv2-LIVNEH	MACAv2-METDATA
Status	Available	Available	Available
Training Dataset	Abatzoglou et. al, 2012 (Years 1979-2010)	Livneh et. al, 2013 (Years 1950-2011)	Abatzoglou et. al, 2012 (Years 1979-2012)
Resolution	4-km (1/24-deg)	~6-km (1/16-deg)	4-km (1/24-deg)
Spatial Extent	WUSA (31.02-49.1N, -124.77 to -103.02E)	Contiguous USA (CONUS) and Columbia Basin into Canada	Contiguous USA (CONUS)
Spatial Projection	WGS 1984 datum	WGS 1984 datum	WGS 1984 datum
Temporal Resolution	daily(on METDATA grid) monthly aggregations (adjusted to 4-km PRISM grid)	daily	daily
Temporal Extent	1950-2100	1950-2099	1950-2099
Downscaled Variables	tasmax,tasmin,rhsmax, rhsmin,pr,rsds, uas,vas,huss	tasmax,tasmin,pr, rsds,was,huss	tasmax,tasmin,rhsmax, rhsmin,pr,rsds, uas,vas,huss
Leap Days	No leap days	Yes, even if model excludes leap days	Yes, even if model excludes leap days
Size of individual netcdf files	3GB-daily, 100MB-monthly	2-4GB compressed-daily,0.1GB compressed-monthly	2.5GB-daily
Size of total dataset	13.7TB-daily, 0.3TB-monthly	5TB-daily,0.5TB-monthly	20TB-daily

List of CMIP5 GCMs used in MACA product

Model Name	Model Country	Model Agency	Atmosphere Resolution(Lon x Lat)	Ensemble Used
bcc-csm1-1	China	Beijing Climate Center, China Meteorological Administration	2.8 deg x 2.8 deg	r1i1p1
bcc-csm1-1-m	China	Beijing Climate Center, China Meteorological Administration	1.12 deg x 1.12 deg	r1i1p1
BNU-ESM	China	College of Global Change and Earth System Science, Beijing Normal University, China	2.8 deg x 2.8 deg	r1i1p1
CanESM2	Canada	Canadian Centre for Climate Modeling and Analysis	2.8 deg x 2.8 deg	r1i1p1
CCSM4	USA	National Center of Atmospheric Research, USA	1.25 deg x 0.94 deg	r6i1p1
CNRM-CM5	France	National Centre of Meteorological Research, France	1.4 deg x 1.4 deg	r1i1p1
CSIRO-Mk3-6-0	Australia	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Centre of Excellence, Australia	1.8 deg x 1.8 deg	r1i1p1
GFDL-ESM2M	USA	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5 deg x 2.0 deg	r1i1p1
GFDL-ESM2G	USA	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5 deg x 2.0 deg	r1i1p1
HadGEM2-ES	United Kingdom	Met Office Hadley Center, UK	1.88 deg x 1.25 deg	r1i1p1
HadGEM2-CC	United Kingdom	Met Office Hadley Center, UK	1.88 deg x 1.25 deg	r1i1p1
inmcm4	Russia	Institute for Numerical Mathematics, Russia	2.0 deg x 1.5 deg	r1i1p1
IPSL-CM5A-LR	France	Institut Pierre Simon Laplace, France	3.75 deg x 1.8 deg	r1i1p1
IPSL-CM5A-MR	France	Institut Pierre Simon Laplace, France	2.5 deg x 1.25 deg	r1i1p1
IPSL-CM5B-LR	France	Institut Pierre Simon Laplace, France	2.75 deg x 1.8 deg	r1i1p1
MIROC5	Japan	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies,and Japan Agency for Marine-Earth Science and Technology	1.4 deg x 1.4 deg	r1i1p1
MIROC-ESM	Japan	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	2.8 deg x 2.8 deg	r1i1p1
MIROC-ESM-CHEM	Japan	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	2.8 deg x 2.8 deg	r1i1p1
MRI-CGCM3	Japan	Meteorological Research Institute, Japan	1.1 deg x 1.1 deg	r1i1p1
NorESM1-M	Norway	Norwegian Climate Center, Norway	2.5 deg x 1.9 deg	r1i1p1