Climate Predictability and Prediction on Seasonal, Interannual and Decadal Scales

Presented by Gabriel Vecchi

Frontiers in Climate and Earth System Modeling: Advancing the Science

Geophysical Fluid Dynamics Laboratory

May 20, 2013

Sources of & Limitations on climate predictability

years to decade

hours to a month

Climatology
(what happens typically, including randomness)
need good observations, models

Evolution of initial conditions
(*e.g.*, weather or El Niño forecast)
need good observations, models, initialization schemes

Many decades to centuries

Climatology

Climate response to forcing
(*e.g.*, CO_2, aerosols, sun, volcanoes)
need good models and estimates of forcing

OUTLINE

1) Predictability and Prediction of Large-scale

2) Prediction of Tropical Cyclones Across Timescales

3) High-resolution Coupled Prediction

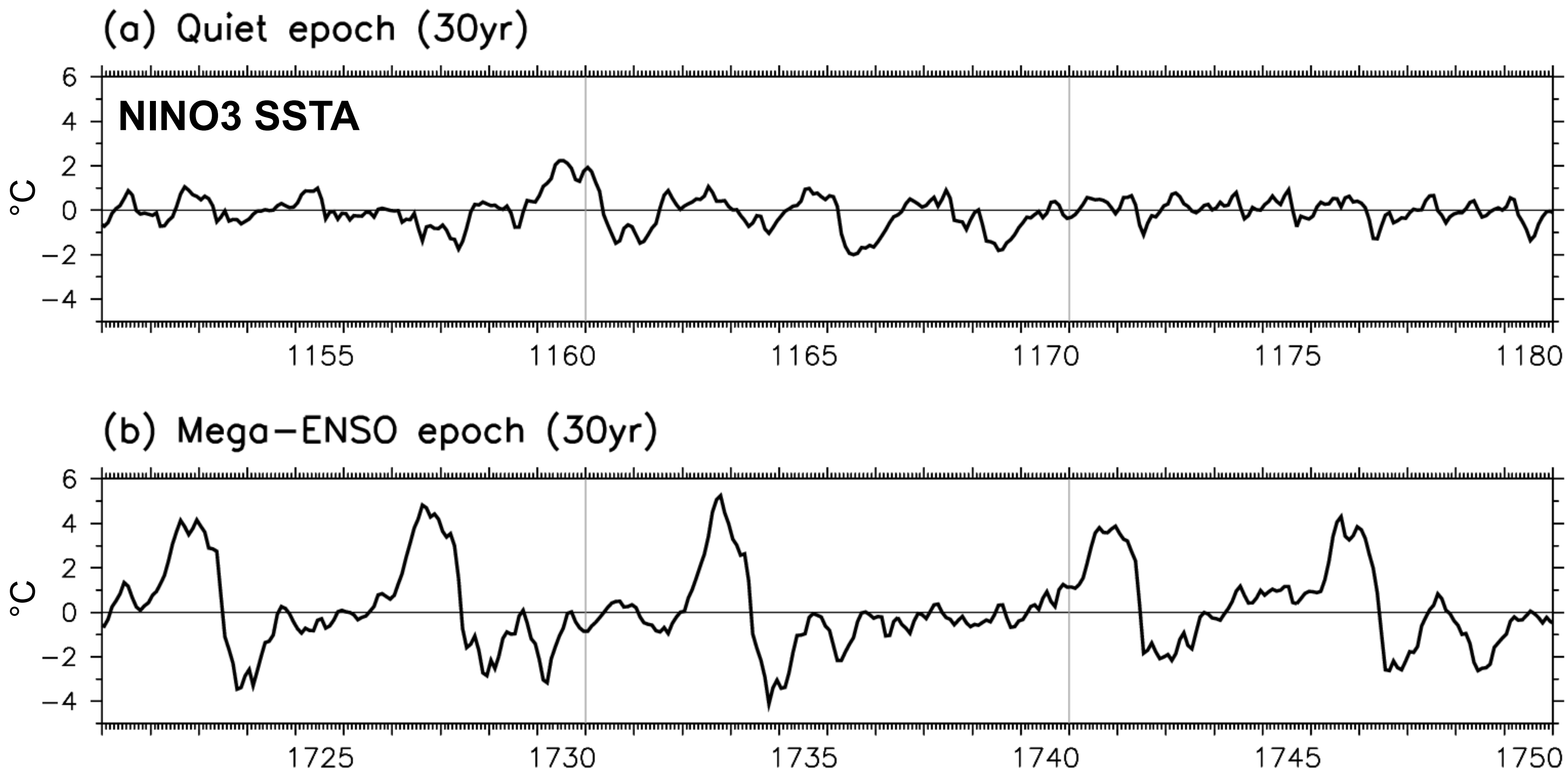
Predictability and Prediction of Large-scale

Multi-year ENSO Predictability

Multi-year North Atlantic Predictions

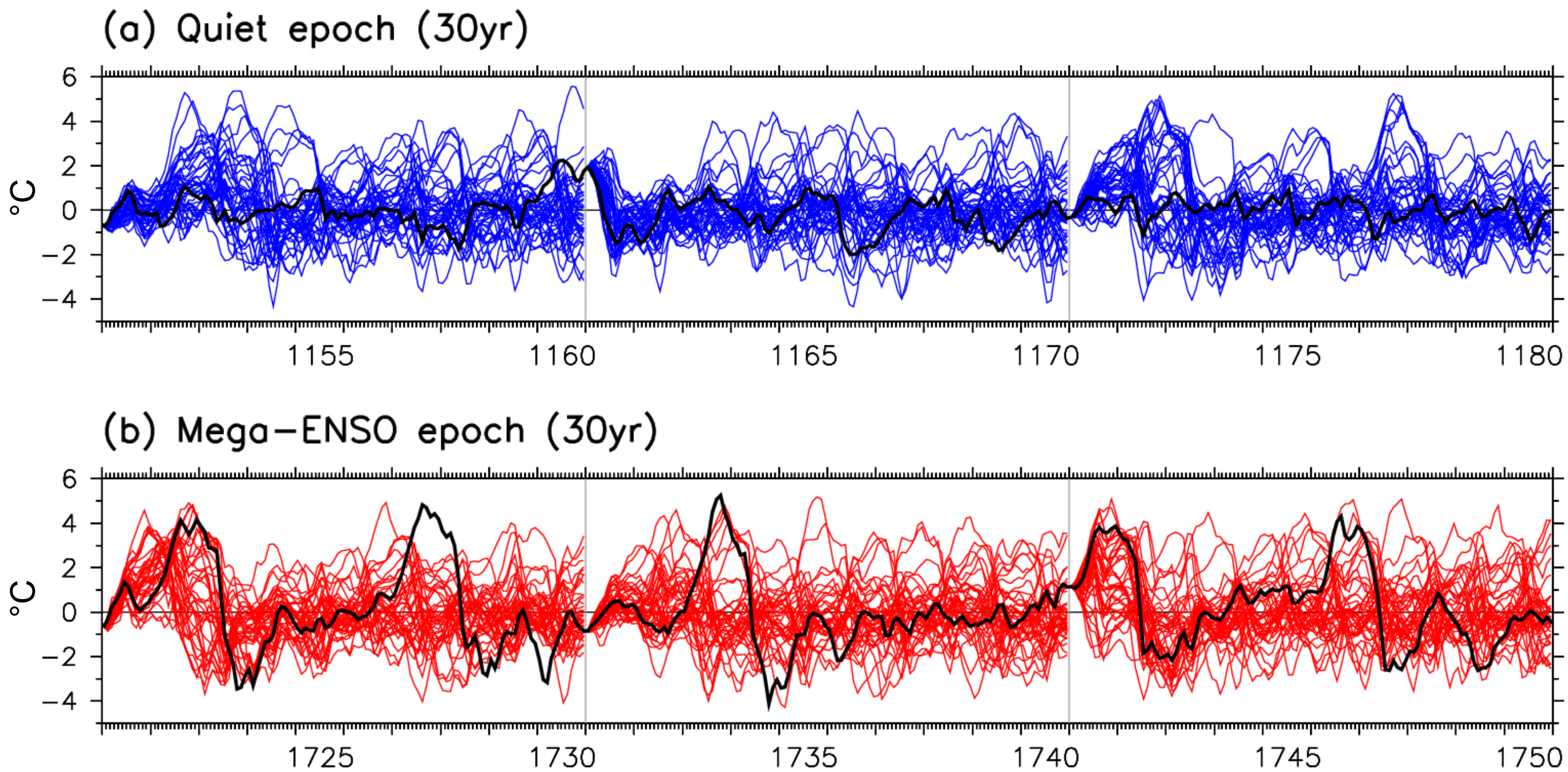
How predictable are decades of extreme ENSO?

Tiny perturbation:
+0.0001C at one gridcell (equator, 180W, top 10m)



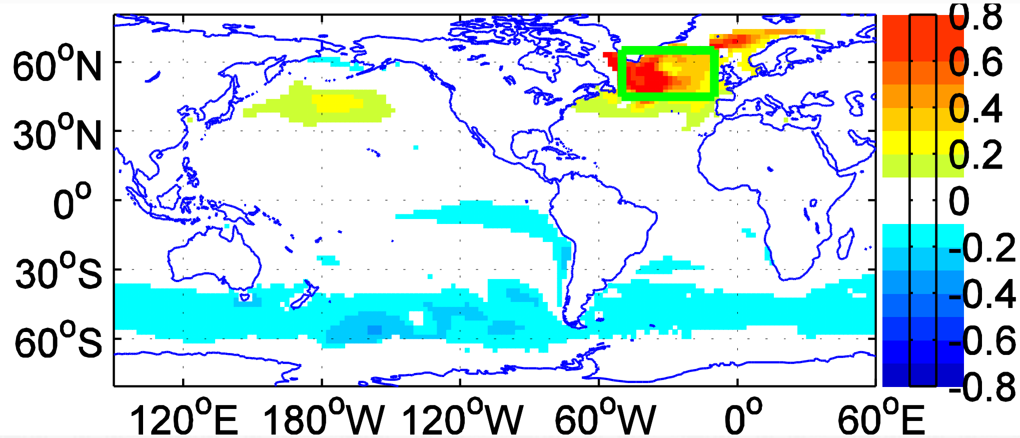
“Perfect” ensemble reforecasts

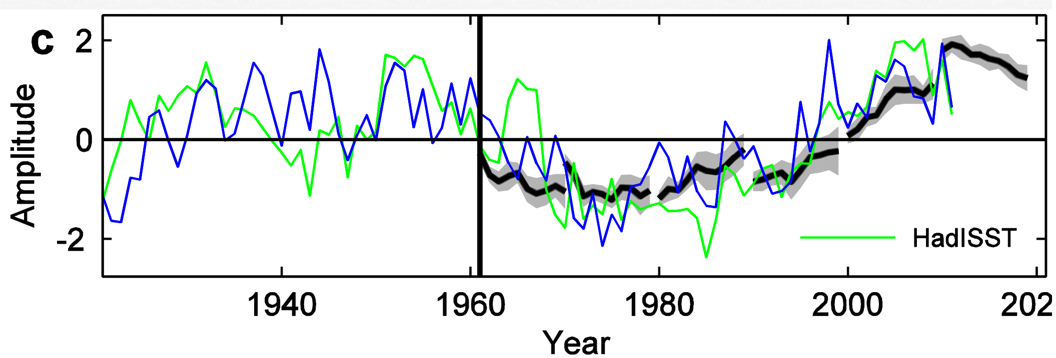
This is what *perfect* probabilistic forecasts look like!
(perfect model, near-perfect initial conditions, 40 members)



A predictable AMO-like pattern in GFDL's decadal hindcasts

Most Predictable SST Pattern



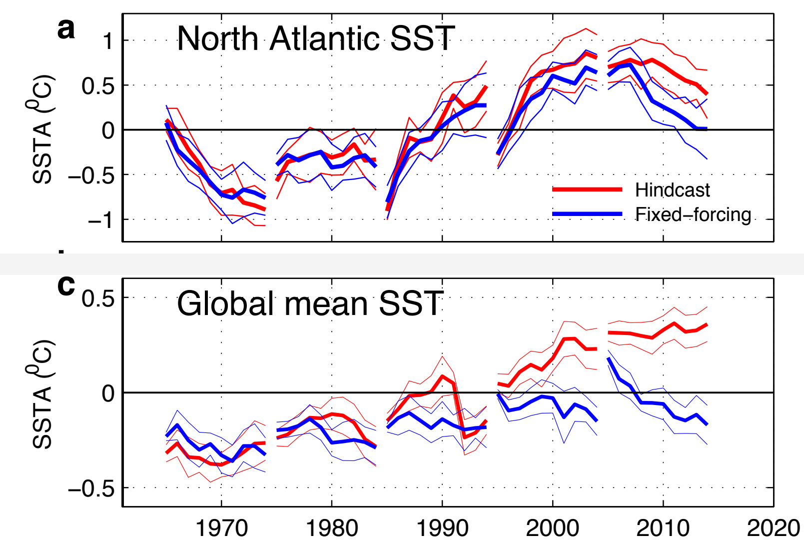


Yang et al. (2013, J. Climate)

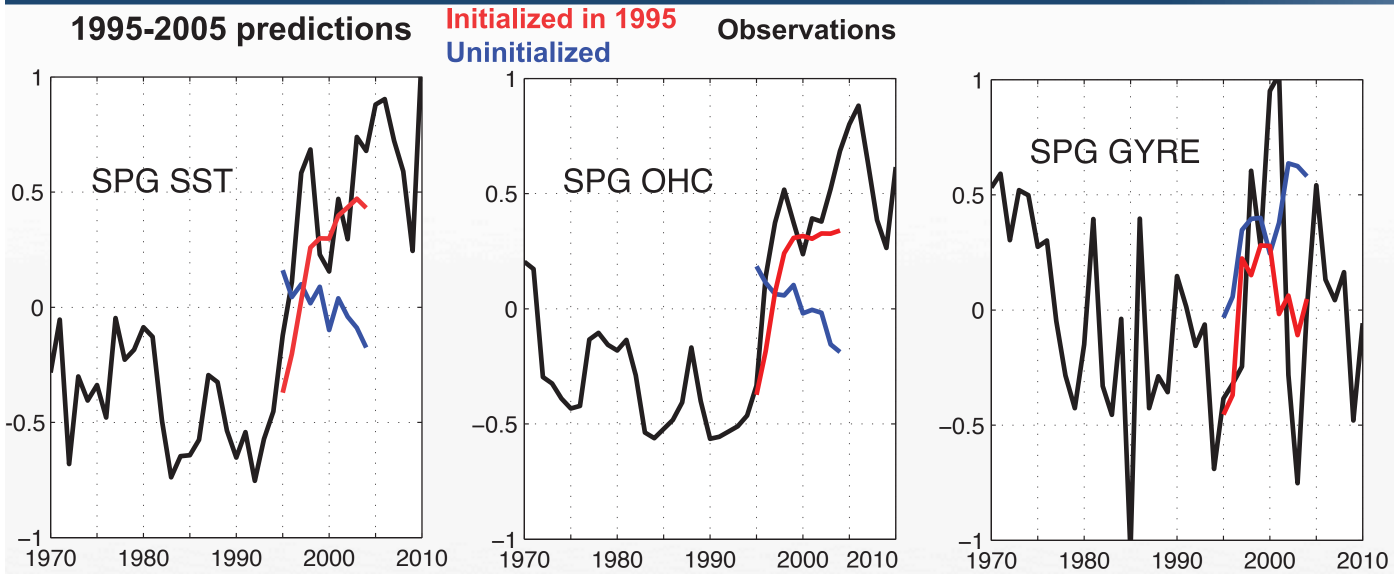
Inter-hemisphere dipole; strong in North Atlantic

Time series well correlated with the AMO index & Hindcasts follow observations

N. Atl. Predictability due to Internal Variability

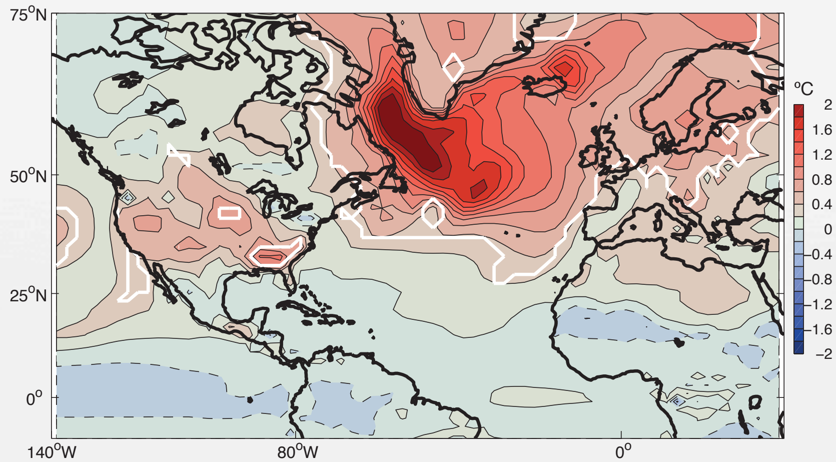


Initialization Enables Prediction on Shift in Sub-Polar Gyre



Initialization leads to skillful predictions of sub-polar gyre (SPG) shift in 1994-1995. Uninitialized predictions fail.

Successful predictions due to the initialization and prediction of enhanced AMOC.



JJA surface air temperature associated with the SPG warming (lead 6-10 years)

Msadek et al. (2013)

Hurricane Prediction Across Timescales

DAYS (GFDL Hurricane Model)

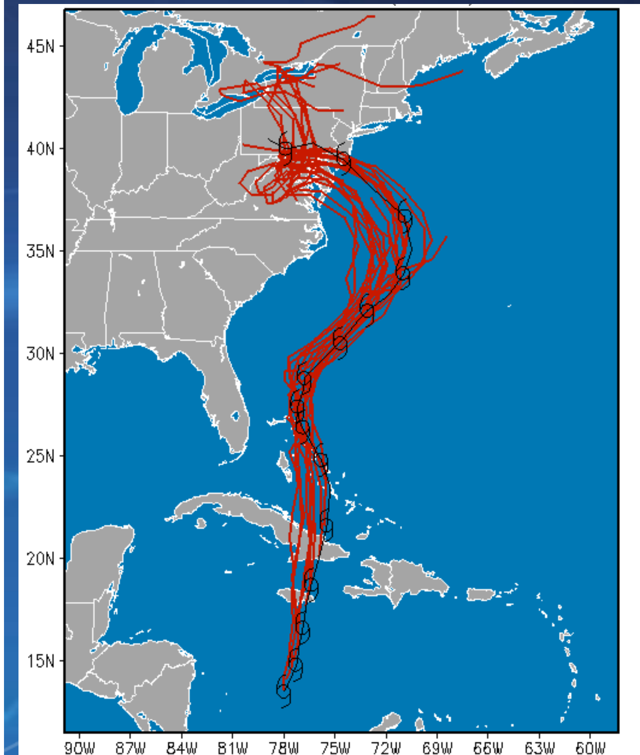
MONTHS (HiRAM 25km Seasonal Forecasts)

SEASONS (HyHuFS Hybrid Forecast System)

YEARS (Decadal HyHuFS)

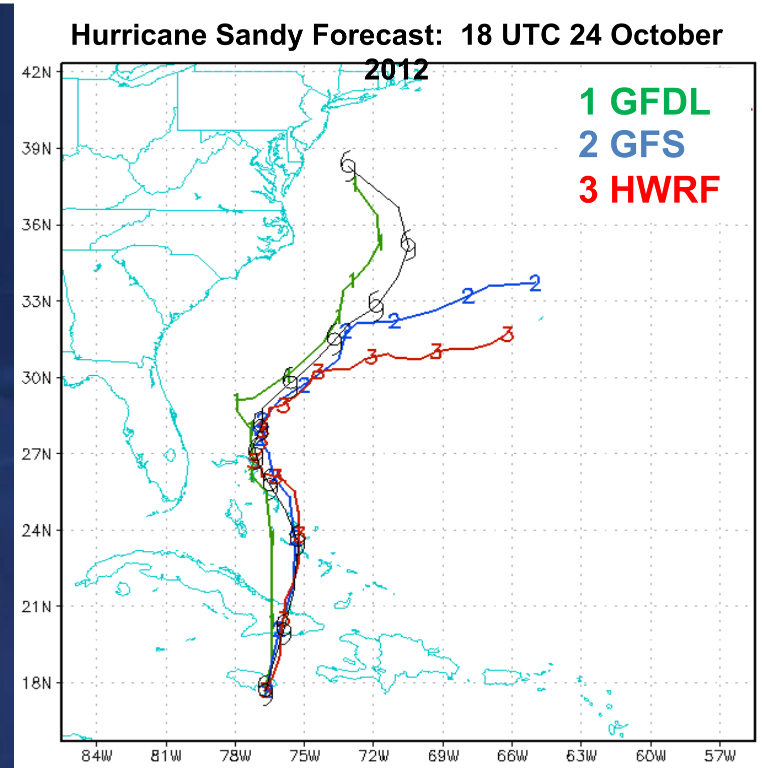
DECADES

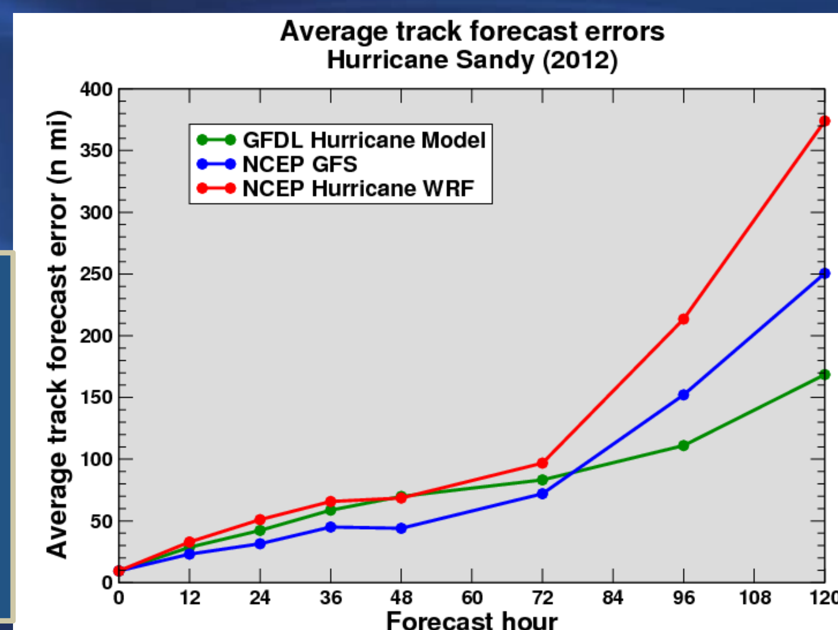
DAYS: GFDL Hurricane Model



All GFDL track forecasts for Hurricane Sandy, beginning 12 UTC 23 October 2012

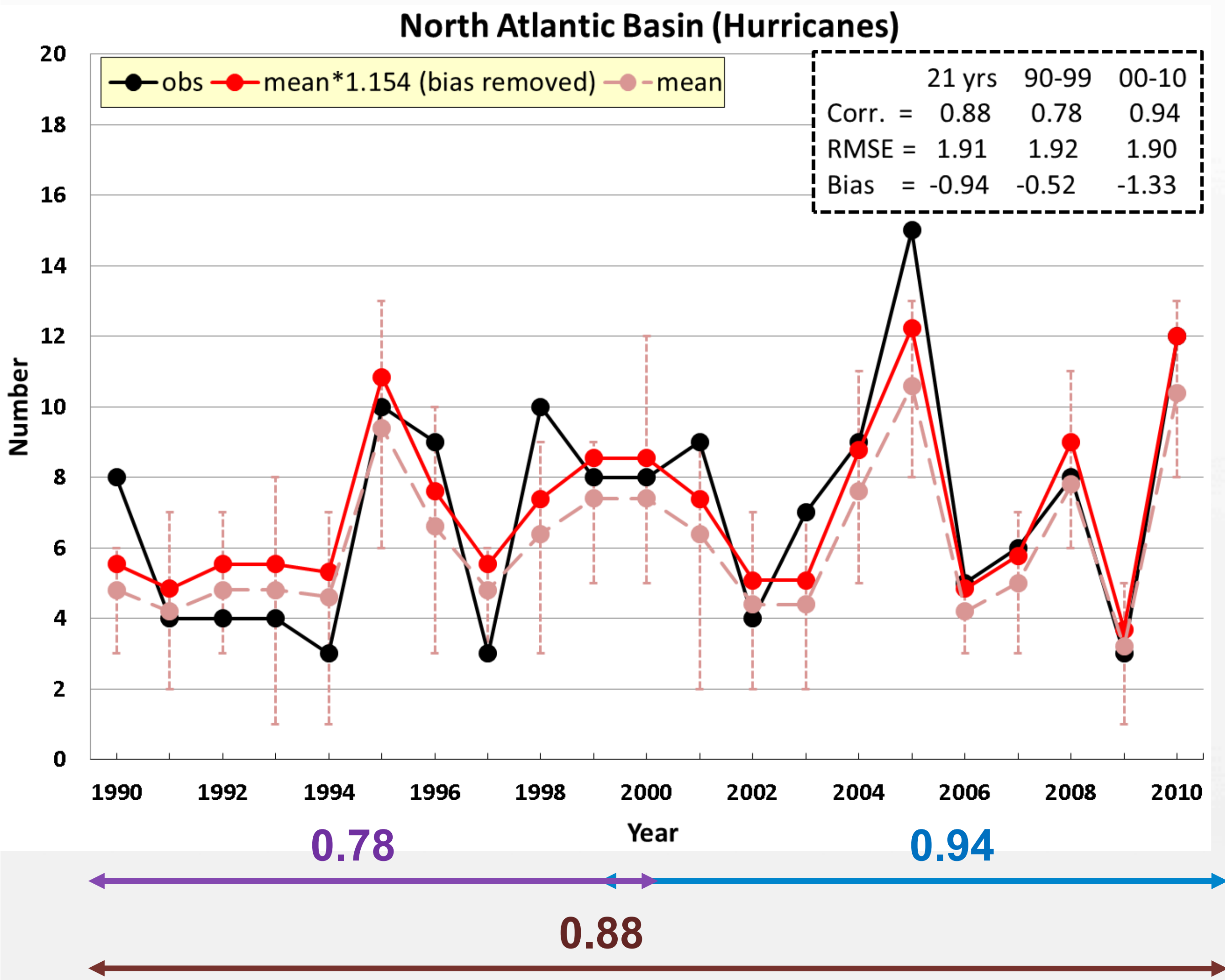
Track Forecast Performance of GFDL Hurricane Model for Hurricane Sandy





- First operational U.S. forecast model to correctly predict Sandy's "left turn"
- GFDL model significantly more skillful than the other two NWS forecast models (GFS, HWRF) at 4- and 5-day lead time.

MONTHS: 25km HiRAM Seasonal hurricane predictions – initialized July 1 1990-2010

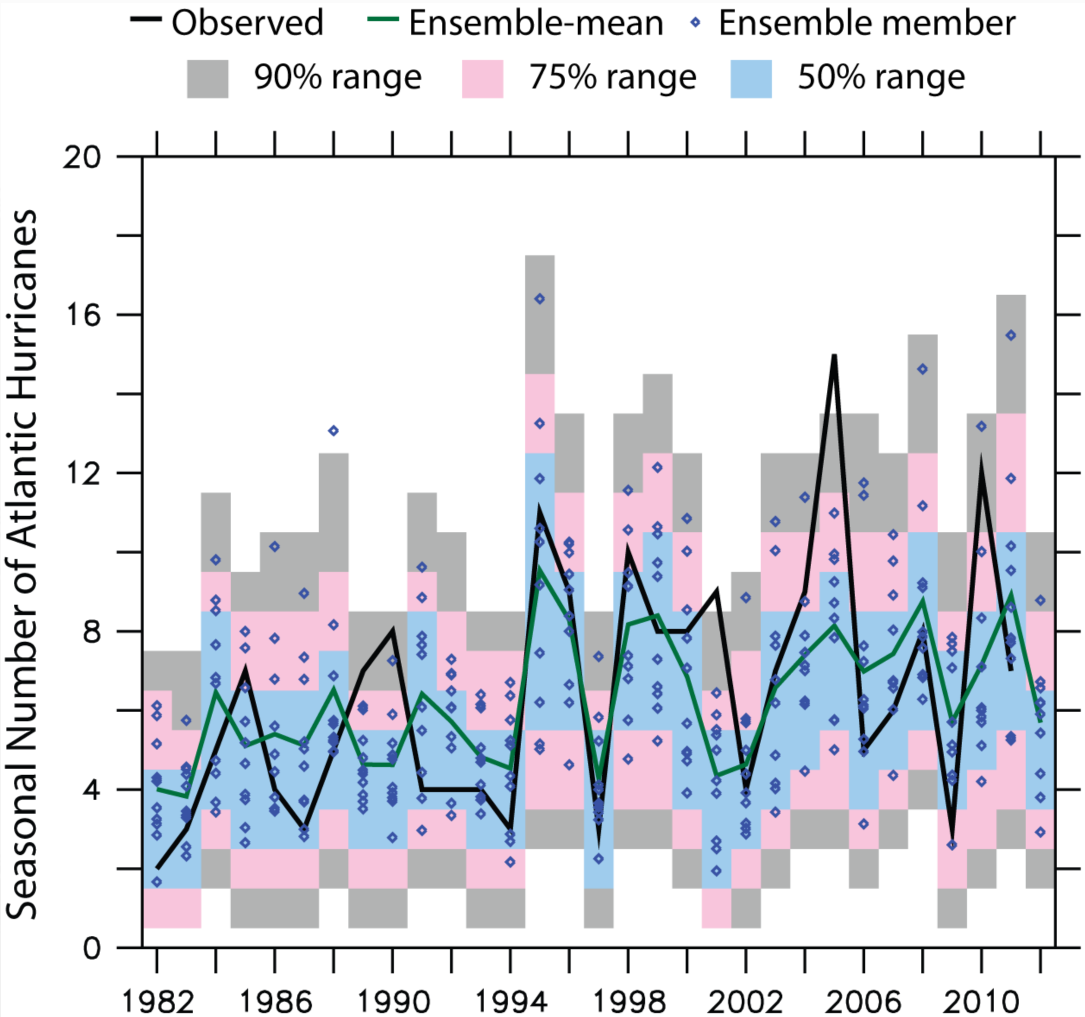


Resolution: 25 km, 32 levels

- 5-members initialized on July 1 with NCEP analysis
- SST anomaly is held constant during the 5-month predictions
- Climatology O3 & greenhouse gases are used

Zhao et al. 2010
Chen and Lin 2011
Chen *et al*., 2012

SEASONS: HyHuFS long-lead forecasts system. Skill from as early as October of year before



Initialized January: r=0.66

May & onward forecasts fed to NOAA Seasonal Outlook Team

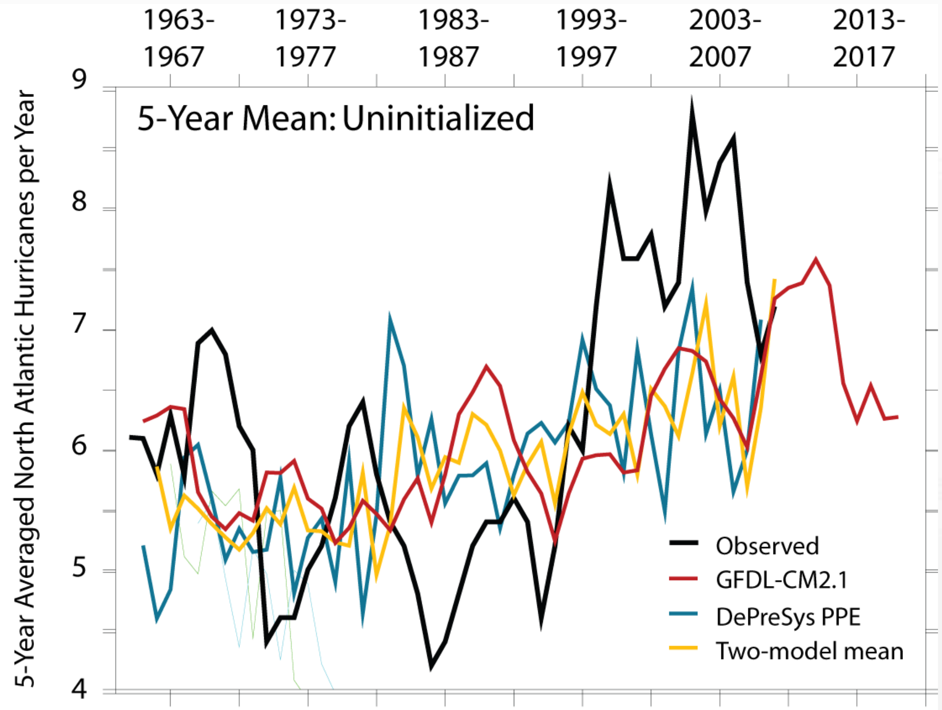
http://gfdl.noaa.gov/HyHuFS

Vecchi et al. (2011), Villarini and Vecchi (2013)

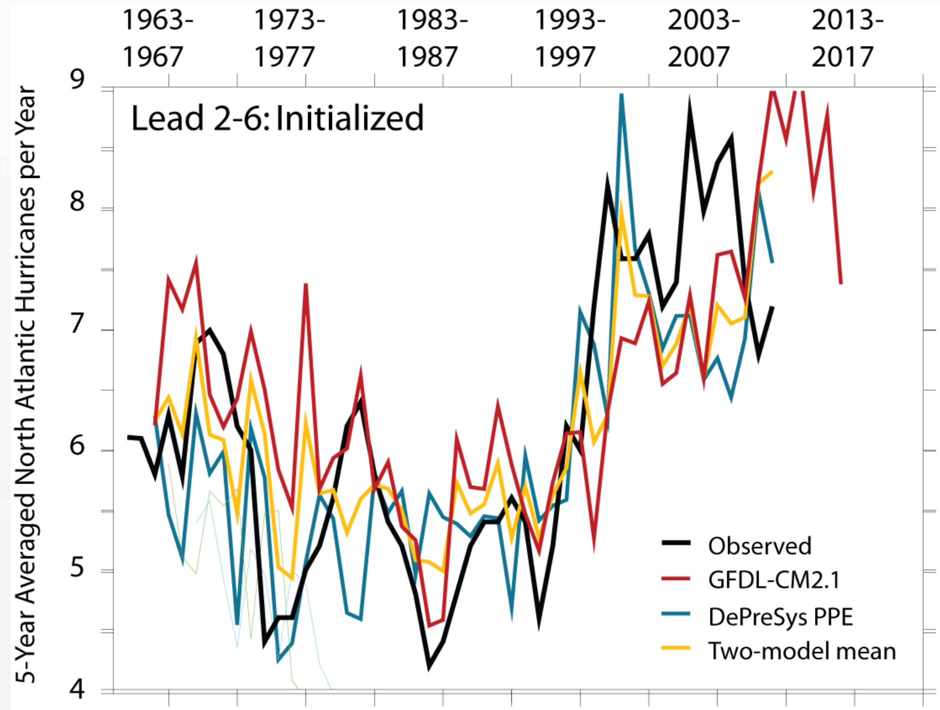
YEARS: Initialization improves 5-year predictions

Hybrid system: statistical hurricanes, dynamical decadal climate forecasts

FORCED



FORCED & INTIALIZED



- Retrospective predictions encouraging.
- However, small sample size limits confidence
- Skill arises more from recognizing 1994-1995 shift than actually predicting it.

EXPERIMENTAL: NOT OFFICIAL FORECAST

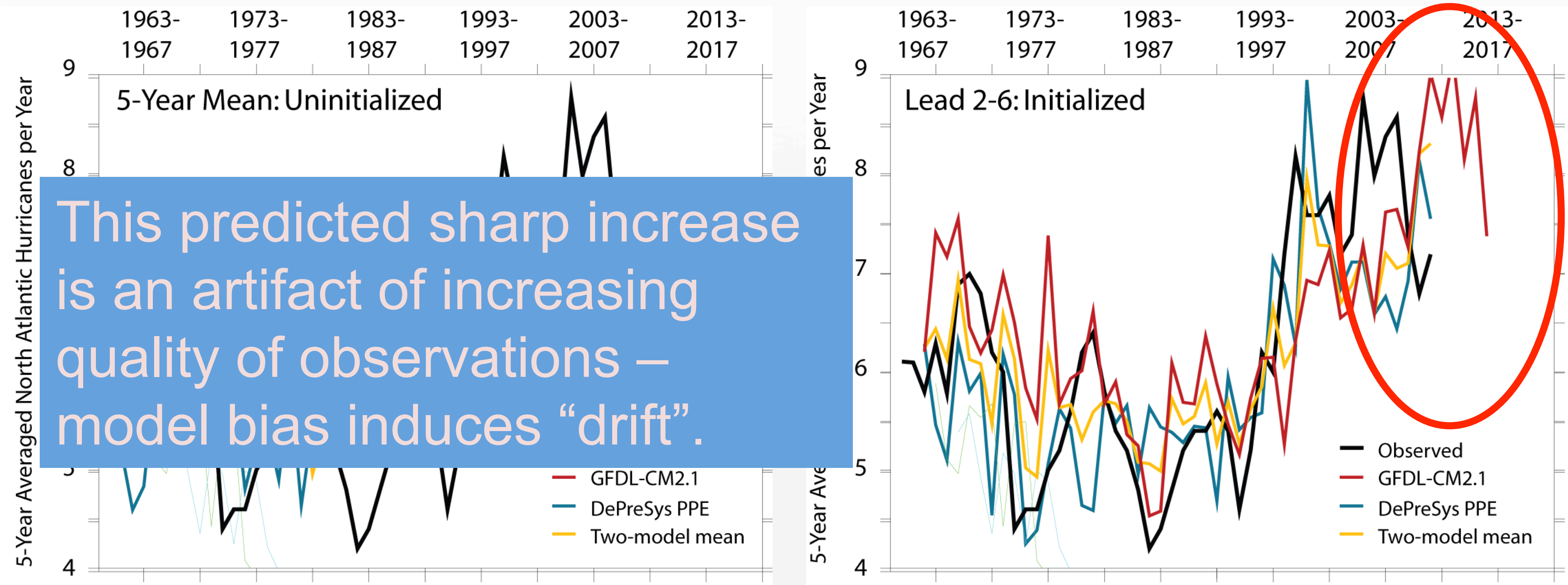
Vecchi et al. (2013.a, J. Clim. in press)

YEARS: Initialization improves 5-year predictions

Hybrid system: statistical hurricanes, dynamical decadal climate forecasts

FORCED

FORCED & INTIALIZED



This predicted sharp increase is an artifact of increasing quality of observations – model bias induces “drift”.

- Retrospective predictions encouraging.
- However, small sample size limits confidence
- Skill arises more from recognizing 1994-1995 shift than actually predicting it.

EXPERIMENTAL: NOT OFFICIAL FORECAST

Vecchi et al. (2013.a, J. Clim. in press)

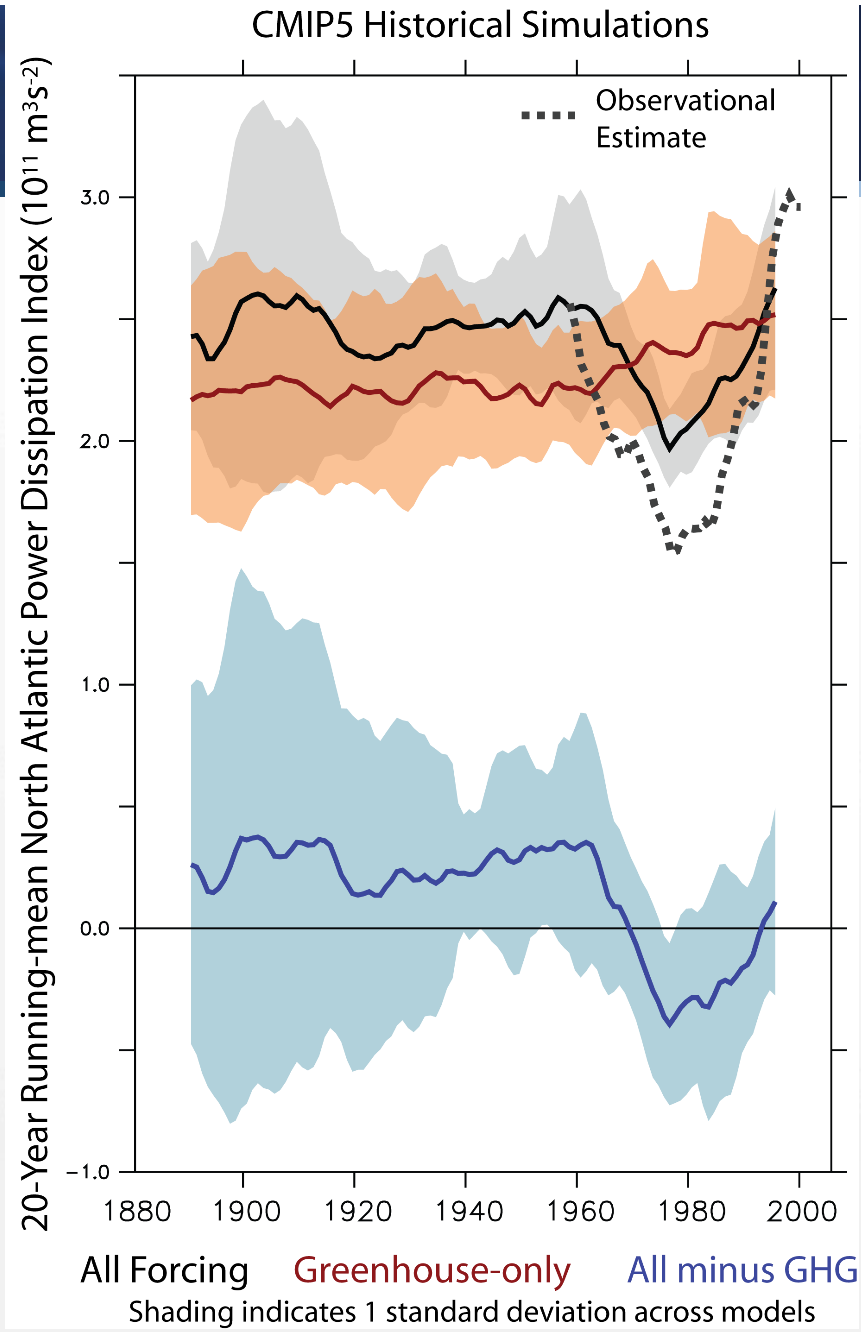
DECADES: Hurricane Attribution and Projection

Historical aerosol forcing may have masked century-scale greenhouse-induced intensification in Atlantic

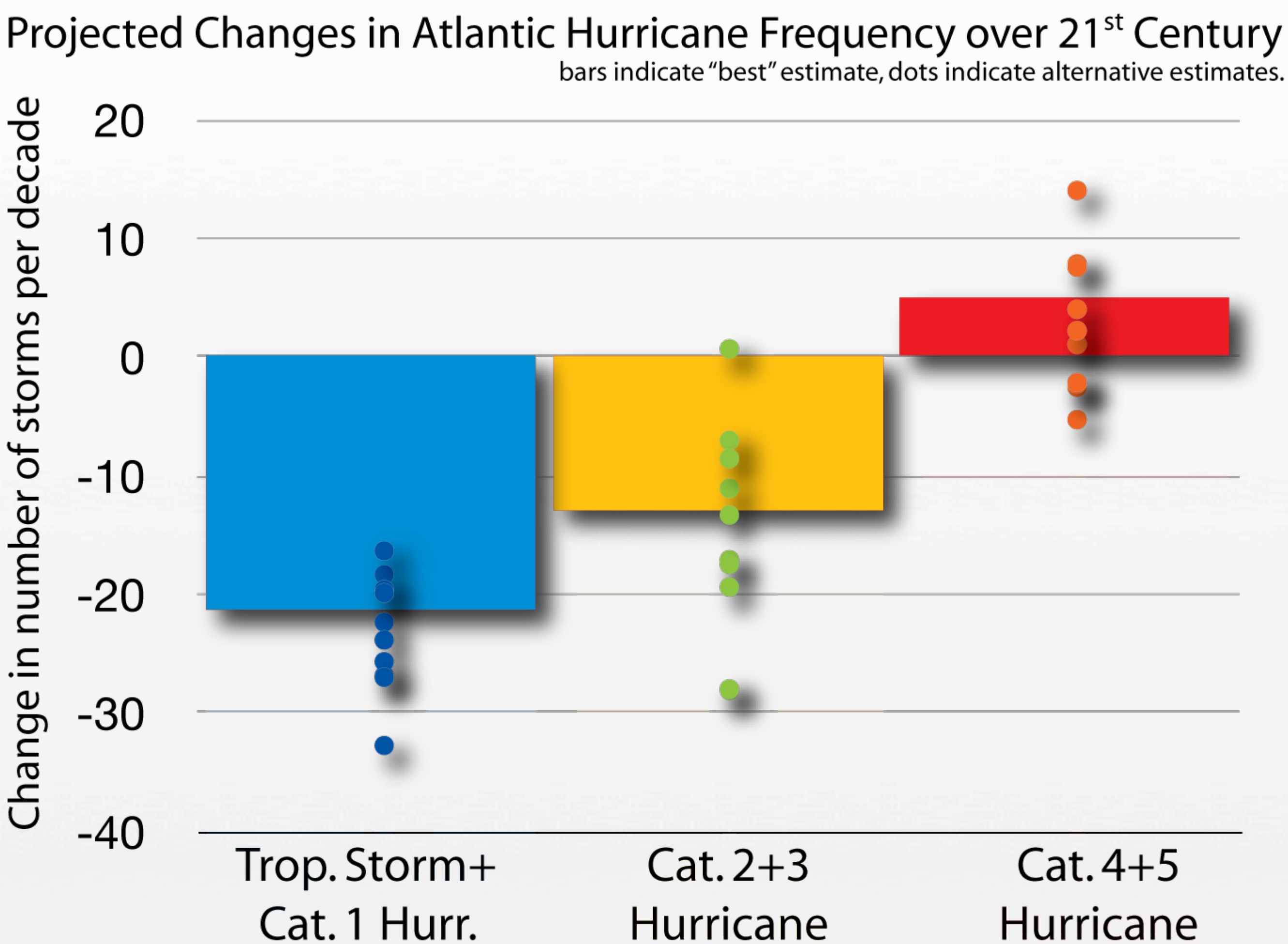
Power Dissipation Index

$$PDI = \sum_{storms} U_{max}^3$$

Villarini and Vecchi (2013, J. Climate)



North Atlantic frequency decrease & intensity increase, so strongest storms may become more frequent



Adapted from Knutson et al (2008, Nature Geosci.), Bender et al (2010 Science), Knutson et al. (2013, J. Climate)

High-resolution coupled prediction: FLOR

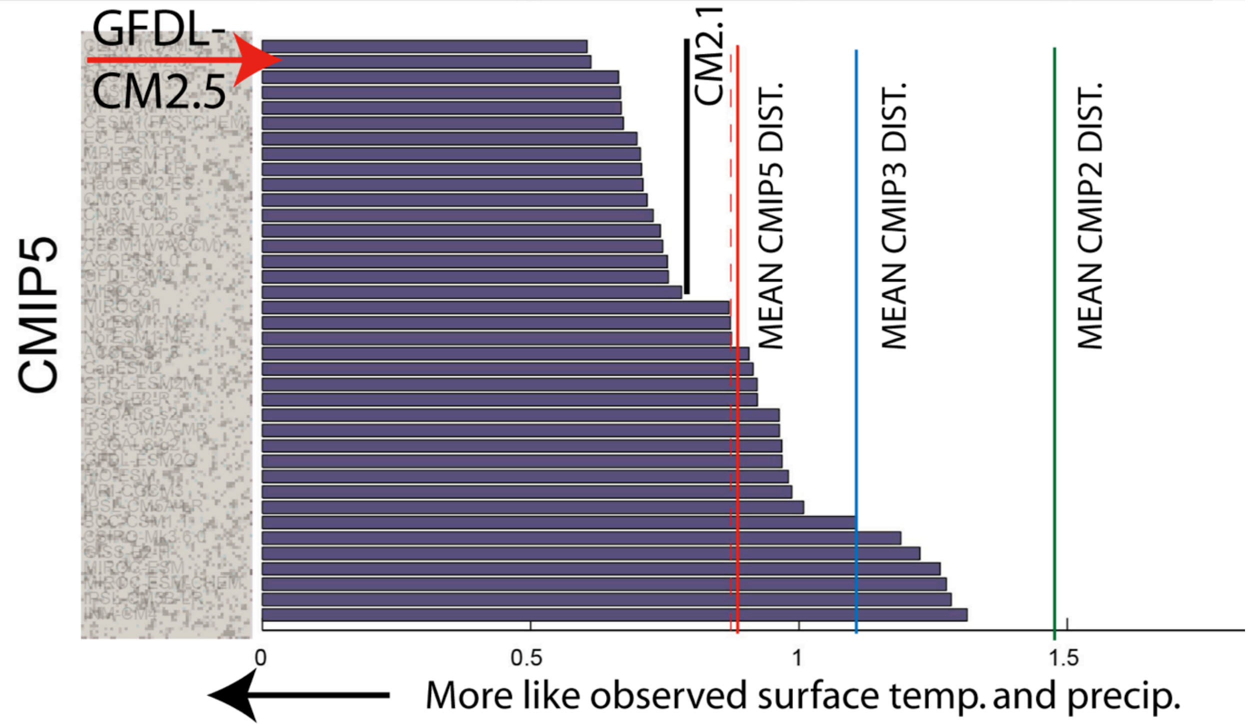
FLOR (Forecast-oriented Low Ocean Resolution version of CM2.5)

Goal is to build seasonal to decadal forecasting system to:

Yield improved forecasts of large-scale climate

Enable forecasts of regional climate and extremes

Faster computer (GAEA) allows improved resolution that translates into significantly reduced biases in CM2.5 relative to CM2.1

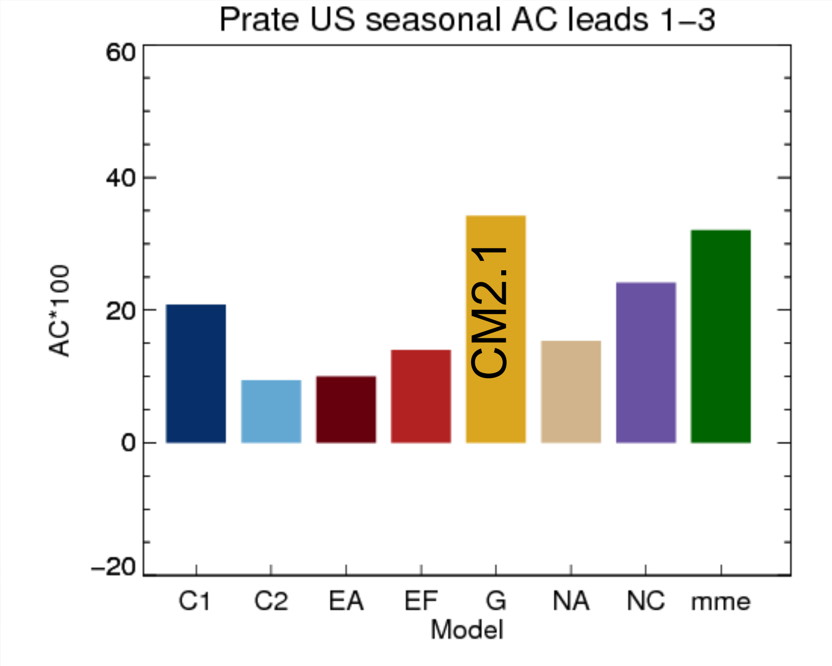


Knutti et al. (2013)

Resolution over land of GFDL SI forecast systems

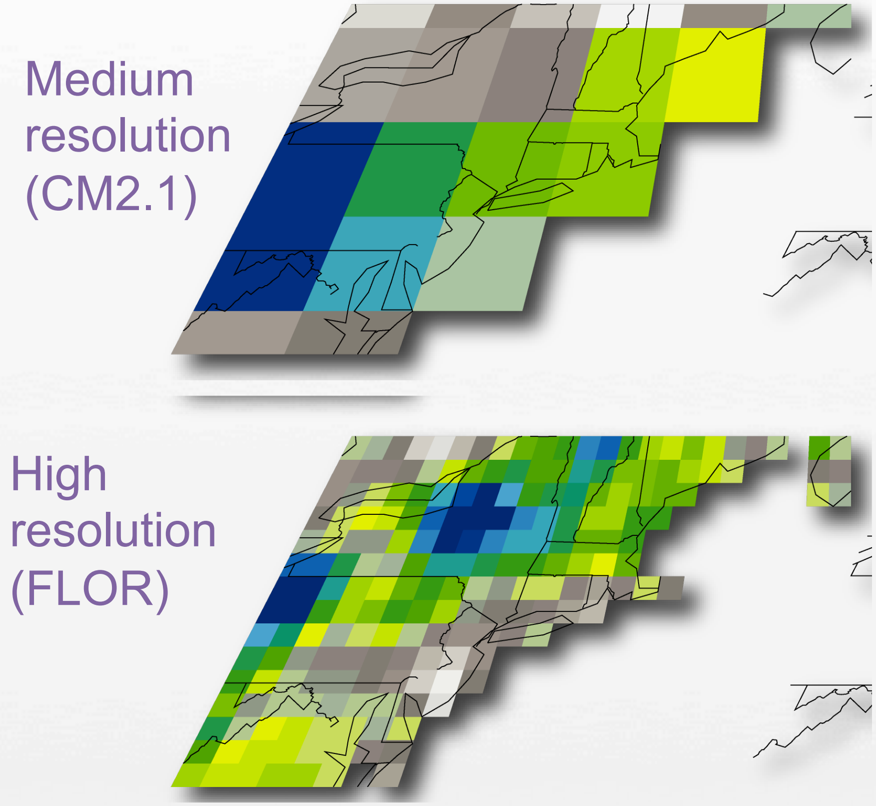
One goal: to outperform CM2.1

"Real-time" skill of first year of NMME Continental US Precip Forecasts



Van den Dool et al. (2013)

High-res enables exploration of regional hydroclimate (including extremes)



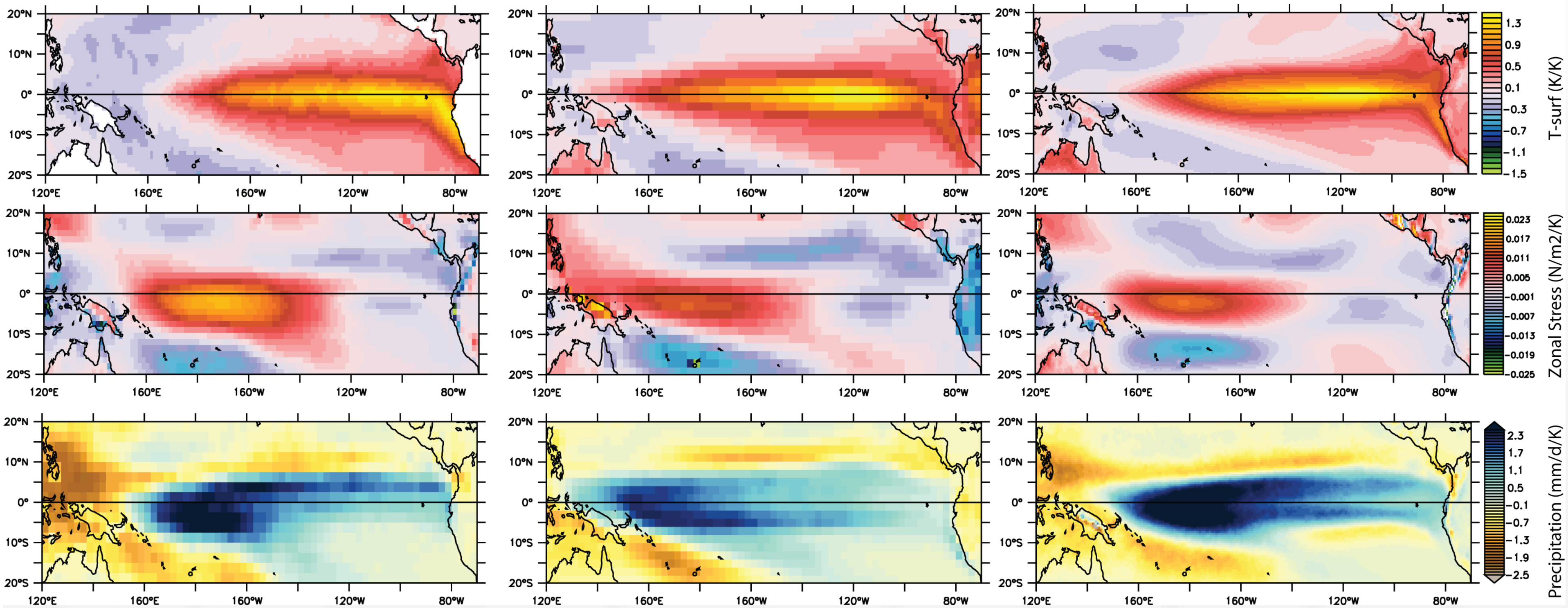
Precipitation in Northeast USA

Adapted from Delworth et al. (2012, J. Clim.)

Structure of ENSO anomalies improves in FLOR (captures much of CM2.5's improvement)

Regressions onto NIÑO3 SSTA

HadISST1, ERA-Interim, CMAP (1980-2005) | CM2.1R (0101-0200) | CM2.5-FLOR-A07 (0001-0100)

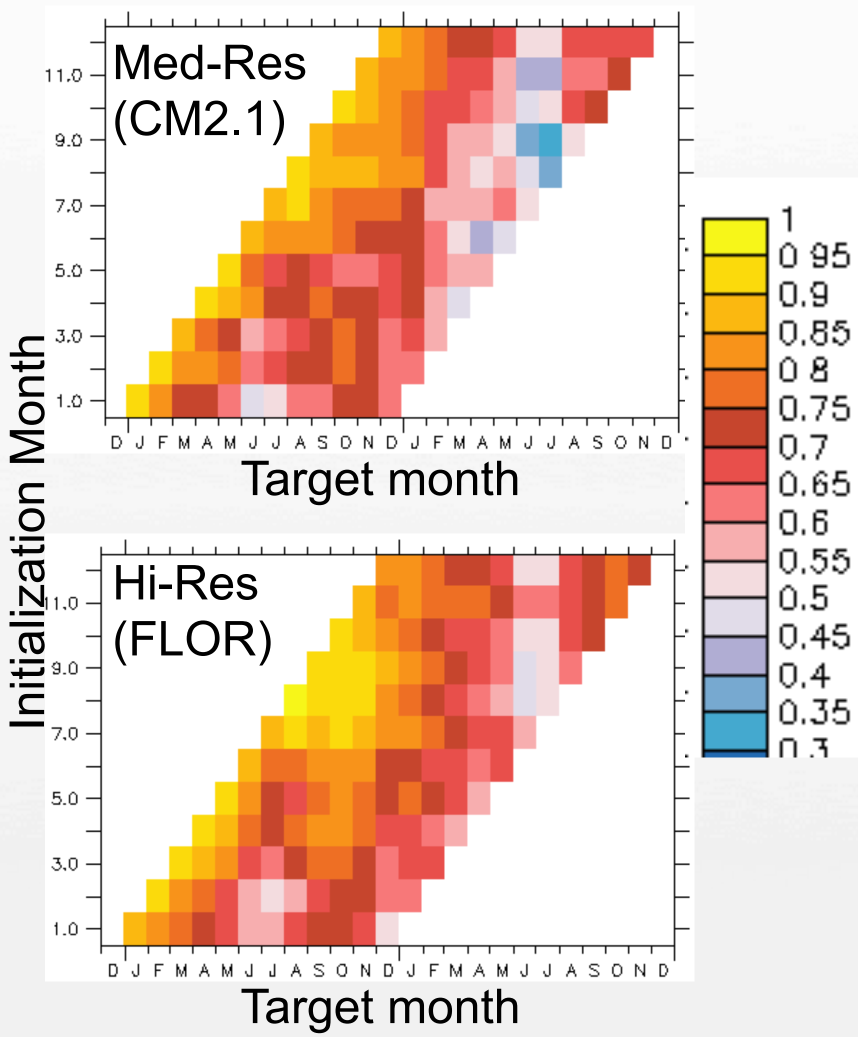


OBS | Med. Resolution | New high-res model

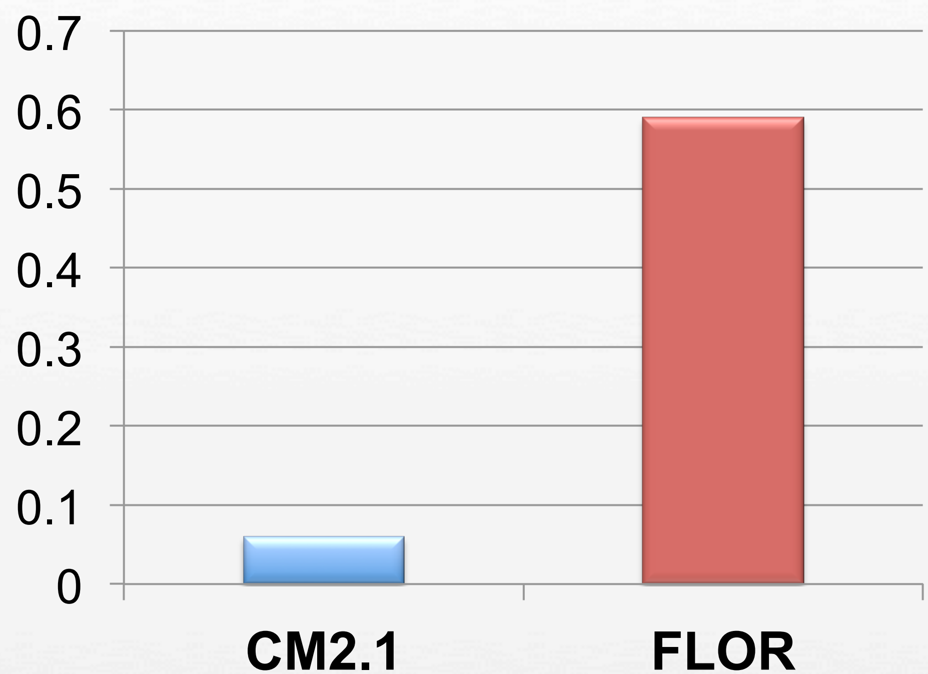
CM2.1 | FLOR

Preliminary FLOR forecast results: Improved skill relative CM2.1
(both using CM2.1 I.C.s – not our "best shot")

Correlation 1982-2012 NIÑO3.4



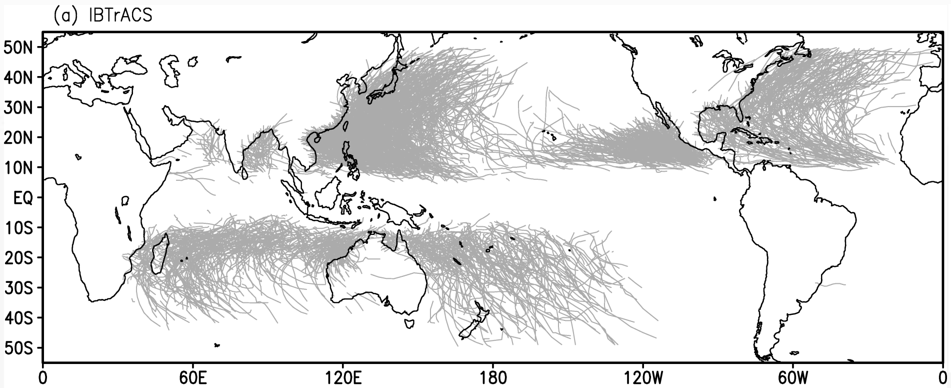
Global Land Precipitation Pattern Correlation 1997-1998 Difference Oct-Dec Predicted 1-Jan



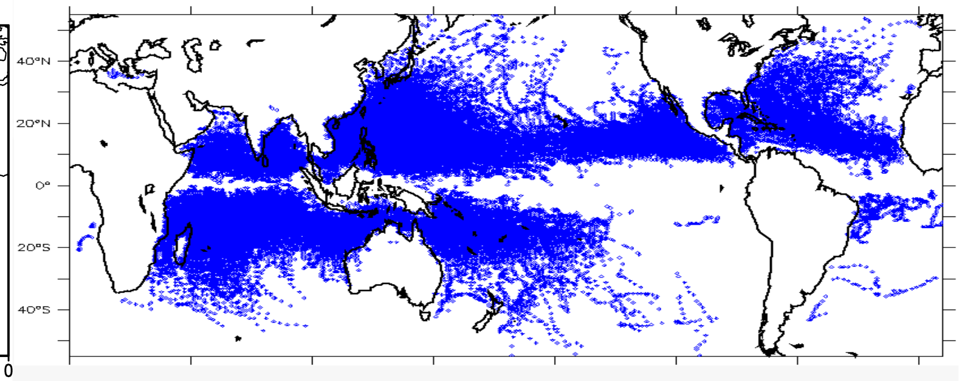
Increase in skill for global and regional surface temperature and precipitation over land (Jia et al. 2013, in prep.)

Prediction of TCs in high-resolution global coupled model (FLOR)

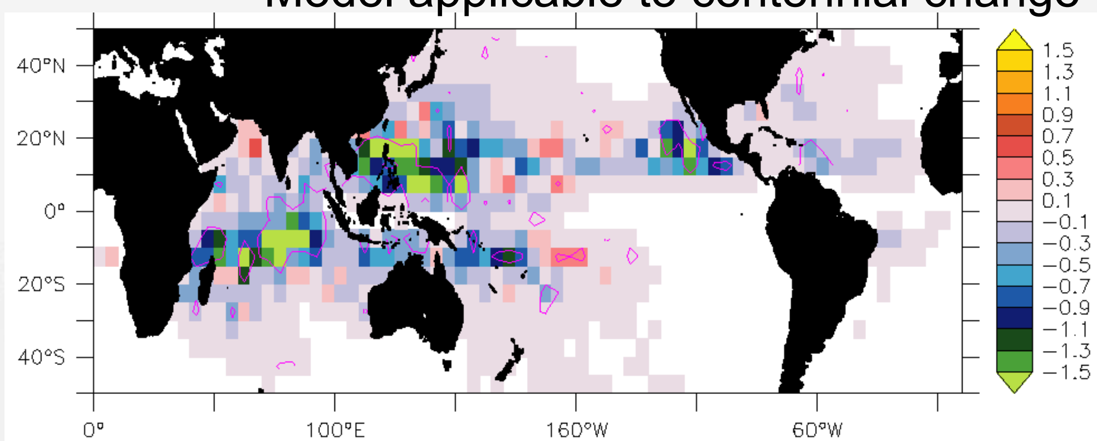
Observed Tracks



Coupled Model Tracks (actual seasonal forecasts)



Model applicable to centennial change



CM2.5 Tropical storm density response to CO_2 doubling

More storms

Fewer storms

(Kim et al. 2013)

External Footprint of Predictability Effort

GFDL Intra-seasonal to Decadal Predictions contribute to operational missions through:

- 3-5 day hurricane forecasts (GFDL hurricane model)
- Regular interactions with NCEP (Provided high-res ocean, research papers)
- North American Multi-model Ensemble (**NMME, via NCEP)**
- International Research Institute for Climate and Society (**IRI**)
- Asia-Pacific Climate Center (**APCC**)
- NOAA Seasonal Hurricane Outlook (**NCEP/CPC**)
- CMIP5 Decadal Experiments
- UKMet decadal MME

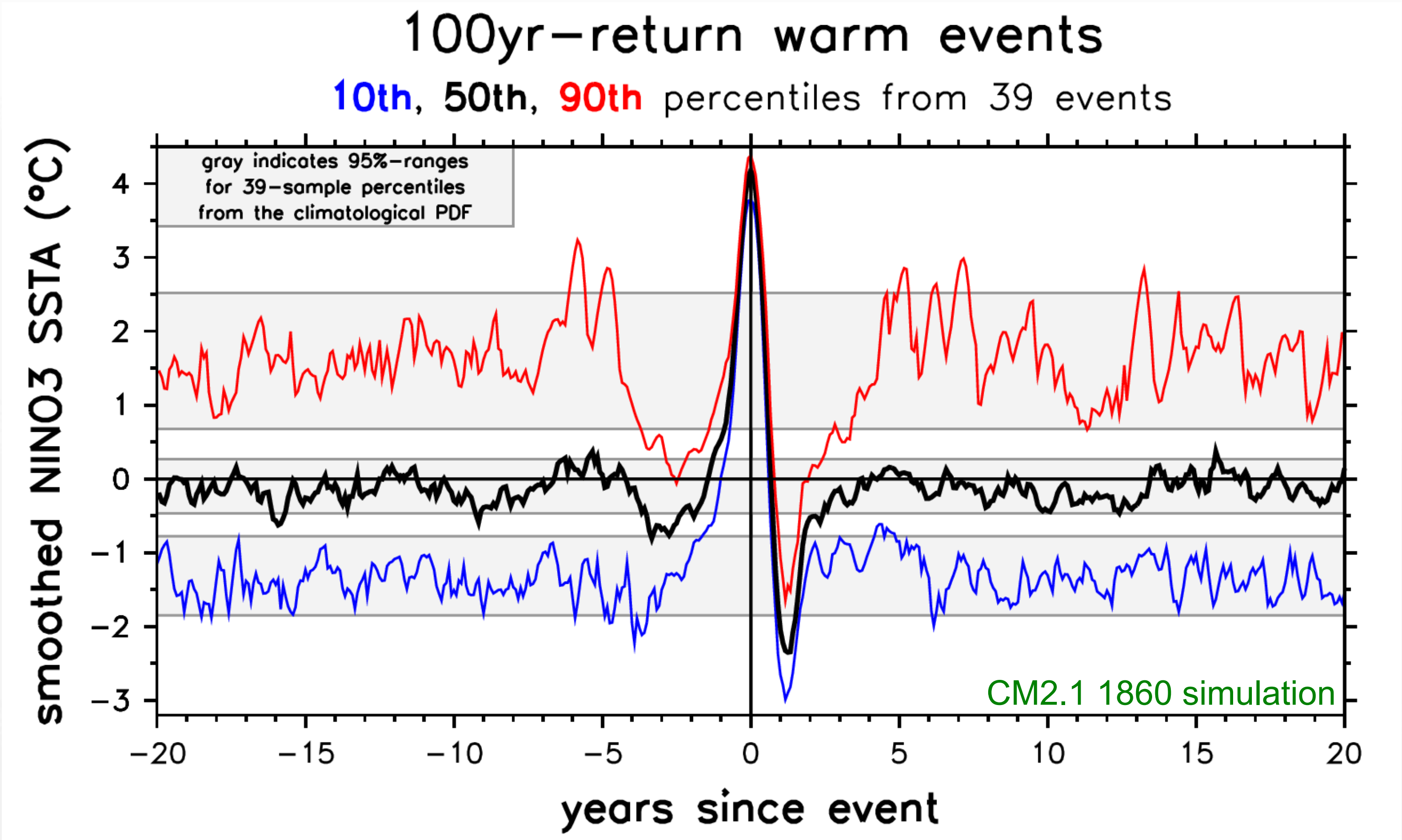
- NCEP-GFDL-NASA OSE project to assess forecast impact of observations

For state estimate:

- NOAA-CPO-OCO
- GCOS & Various U.S.-CLIVAR and CLIVAR Panels and Working Groups

"El Niño of the century."

Strong events induce long-lasting memory in the climate system.



ENSO predictability: Karamperidou et al. (CD 2013); Wittenberg et al. (in prep); Chen et al. (in prep)

GFDL Hurricane Model Development

Recent Advances

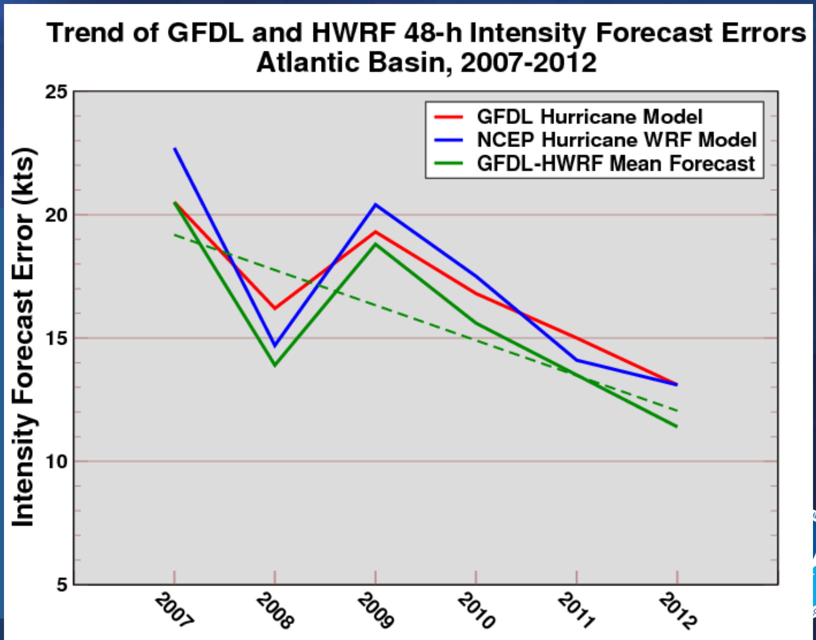
- Improved formulation of Surface exchange coefficients (ch, cd)
- Implementation of GFS Shallow Convection and improved deep convection scheme
- Improved PBL structure
- Semi-operational forecasts from a GFDL hurricane ensemble, run on the NOAA / Jet computer as part of the NOAA / HFIP program.

Planned Upgrades

- Increase resolution of innermost nest from 1/12° to 1/18°
- Upgrade radiation package
- Include coupling with wave model improved surface fluxes and sea spray formulation
- Improved micro-physics

Intensity Forecast Improvement

- Trends over the past 6 seasons indicate an improvement in intensity forecasts
- GFDL and HWRF exhibit comparable improvements, with their mean showing further improvements



SEASONS: HyHuFS long-lead forecasts system. Skill from as early as October of year before

May & onward forecasts fed to NOAA Seasonal Outlook Team

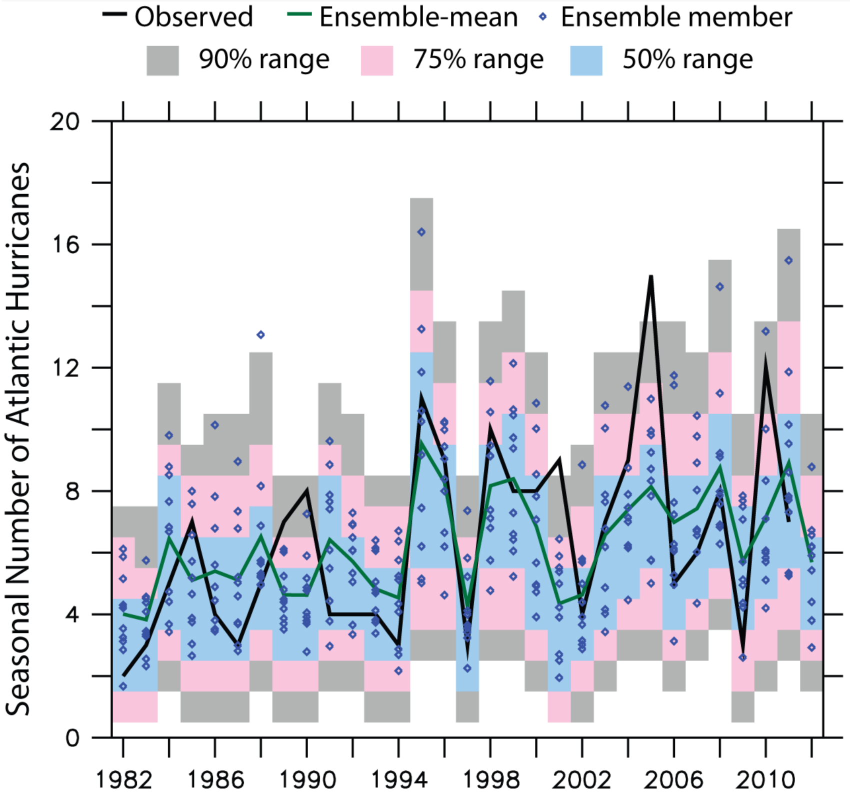
Run Hi-Res AGCM in many different climates. Count storms.

Build statistical model of the response of hurricanes in HiRAM

Use CM2.1 (and CFS) to forecast future values of Atlantic and Tropical SST

Apply Stat model to Predicted SST

Make Prediction of Full PDF of Hurricane Activity

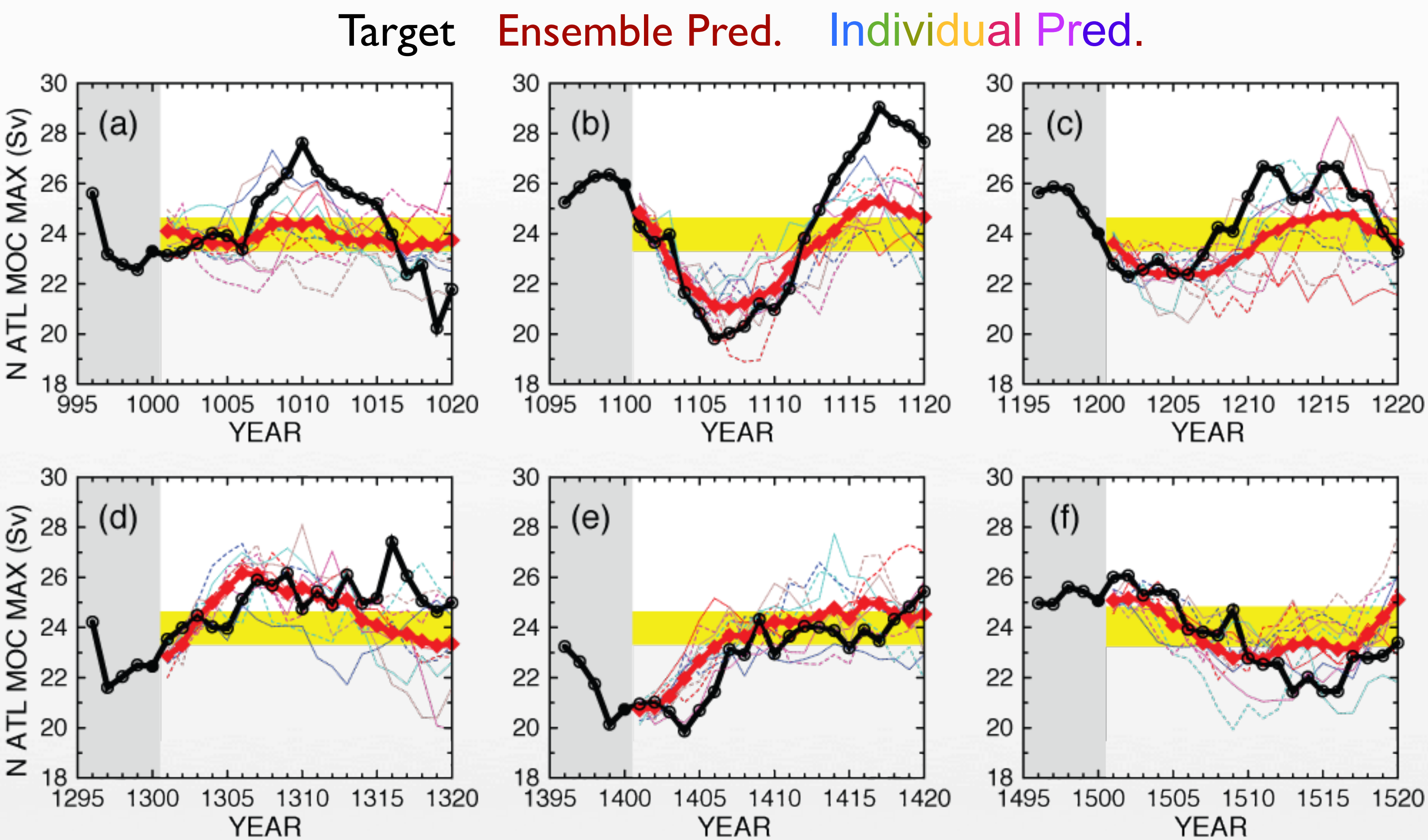


Initialized January: r=0.66

http://gfdl.noaa.gov/HyHuFS

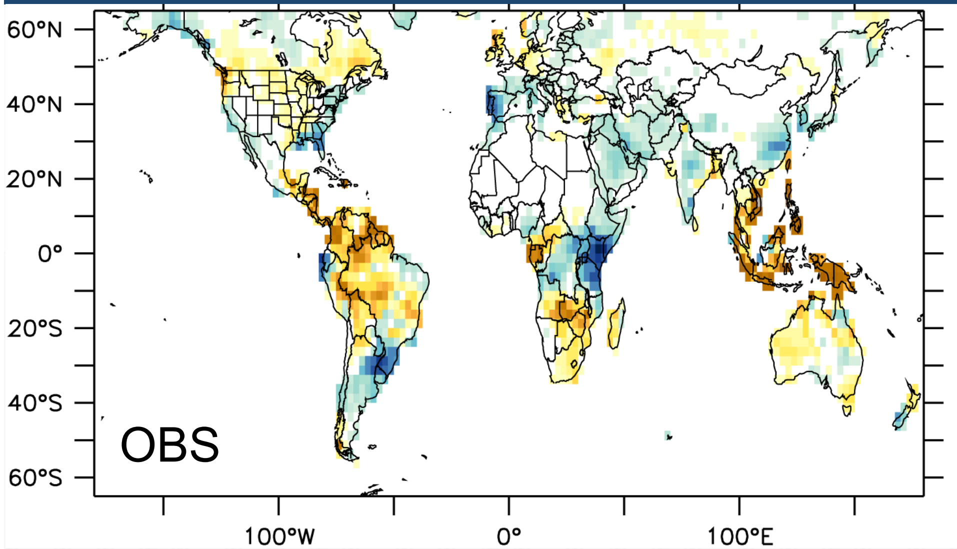
Vecchi et al. (2011), Villarini and Vecchi (2013)

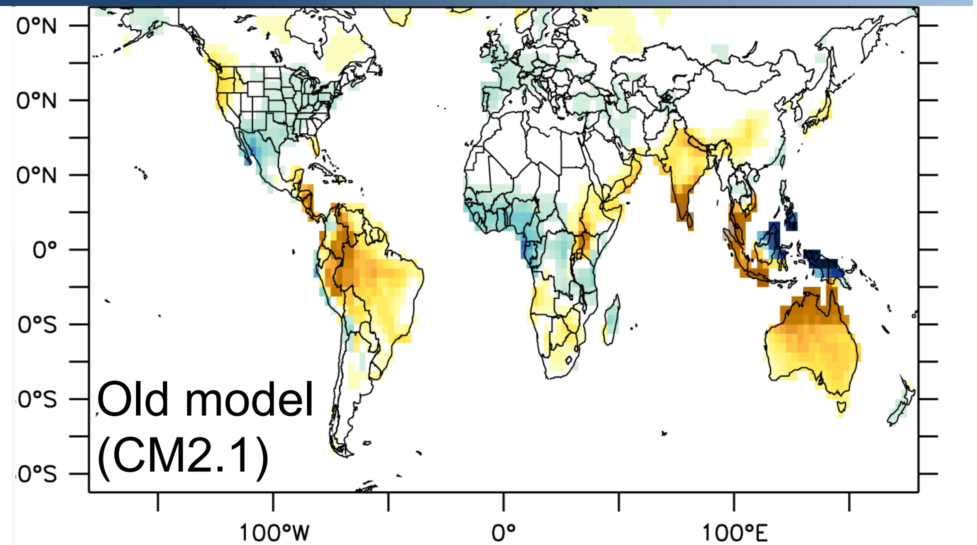
In GFDL-CM2.1 Perfect Model/Perfect Obs. Experiments: MOC Predictability Appears to Vary

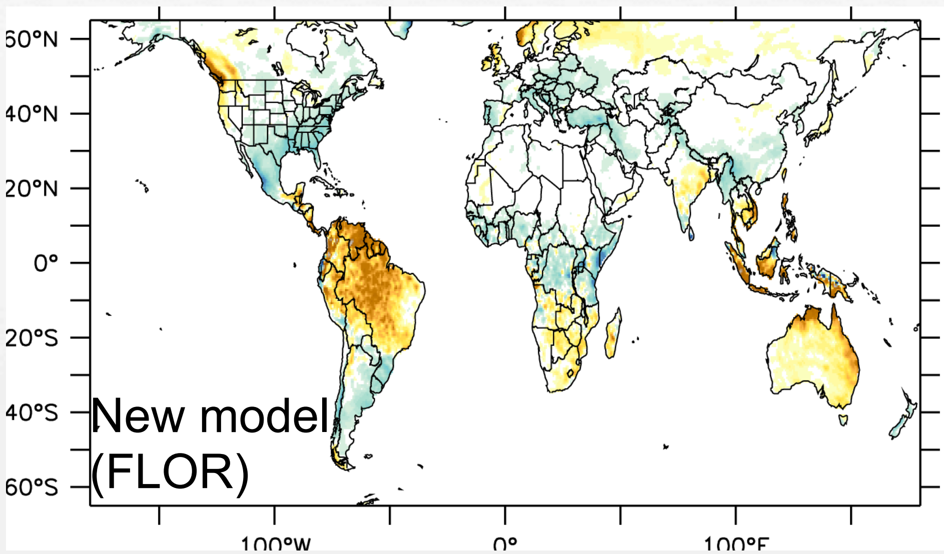


Msadek, Dixon, Delworth and Hurlin (2010, GRL).
ASSESSING THE PREDICTABILITY OF THE AMOC

Preliminary precipitation results: test 1997 & 1998 forecasts







Climate Predictability on Seasonal, Interannual and Decadal Scales

- Research Advances on Climate Estimation and Prediction Initialization

Presented by Shaoqing Zhang

Frontiers in Climate and Earth System Modeling: Advancing the Science

Geophysical Fluid Dynamics Laboratory

May 20, 2013

Motivations of Data Assimilation for Climate Studies

Goal

Understanding climate variability to better estimate and predict climate on seasonal-interannual to decadal scales

Challenges

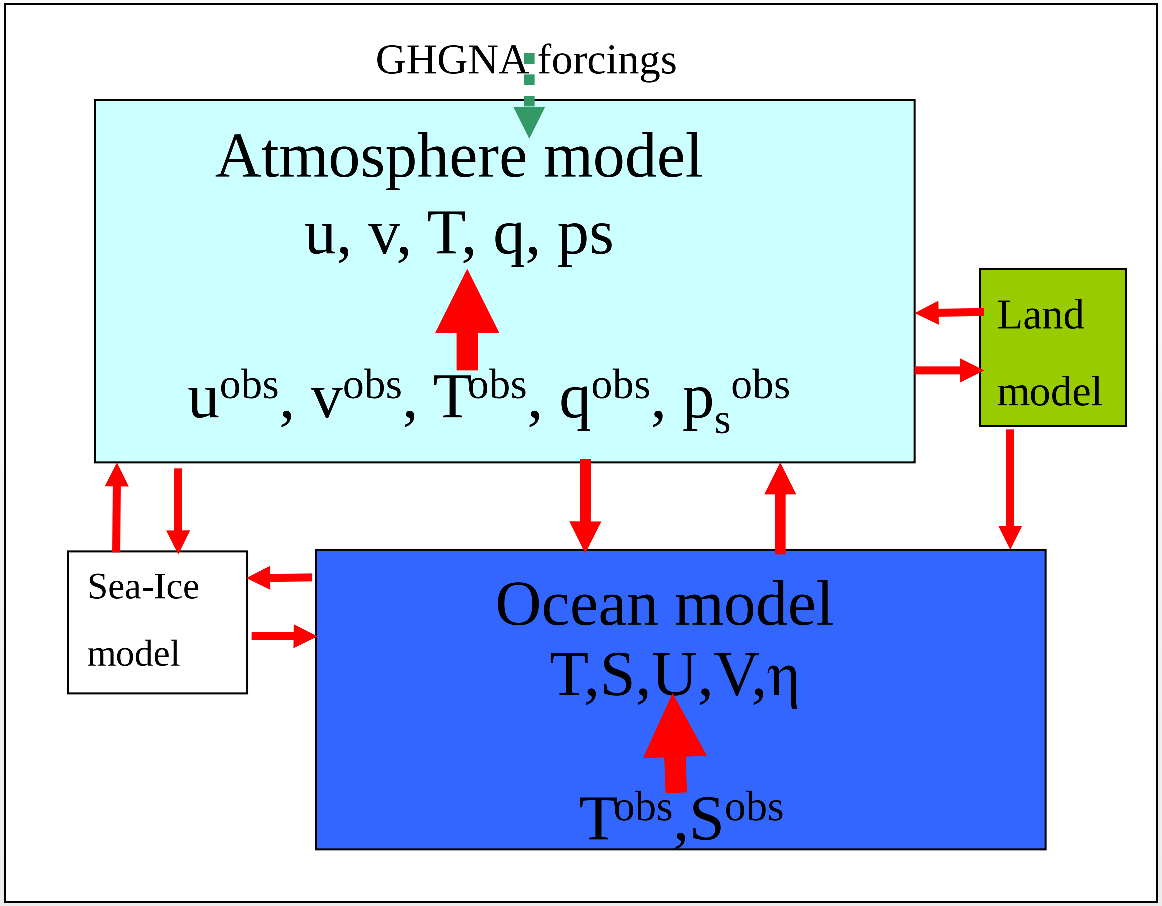
- Models produce different climate features and variability from the real world due to modeling errors and uncertainties.
- Observations have sampling and representation errors.

Methodology

Combining observed data with a climate model using Ensemble Coupled Data Assimilation

Coupled Data Assimilation (CDA)

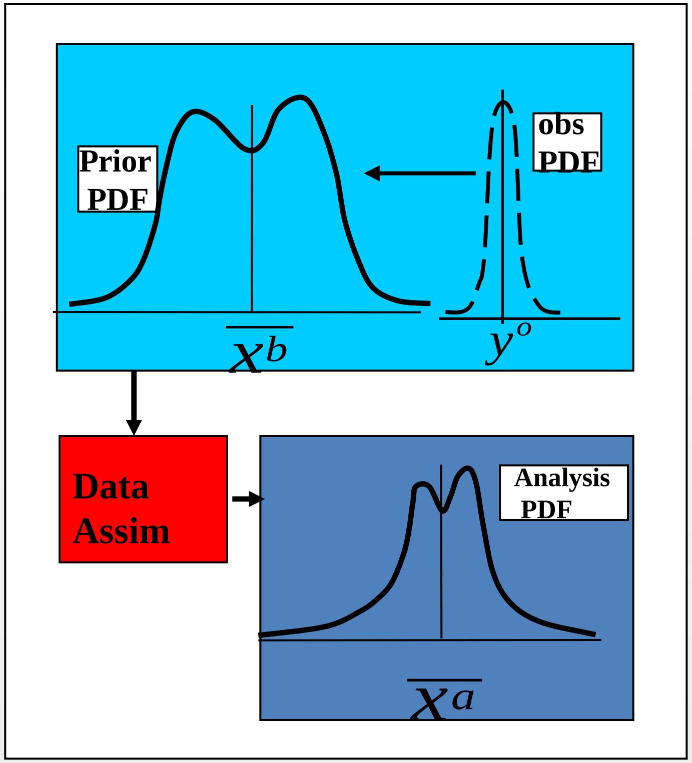
CDA is good for climate studies – All coupled components adjusted by observed data through instantaneously-exchanged fluxes



Ensemble Coupled Data Assimilation (ECDA)

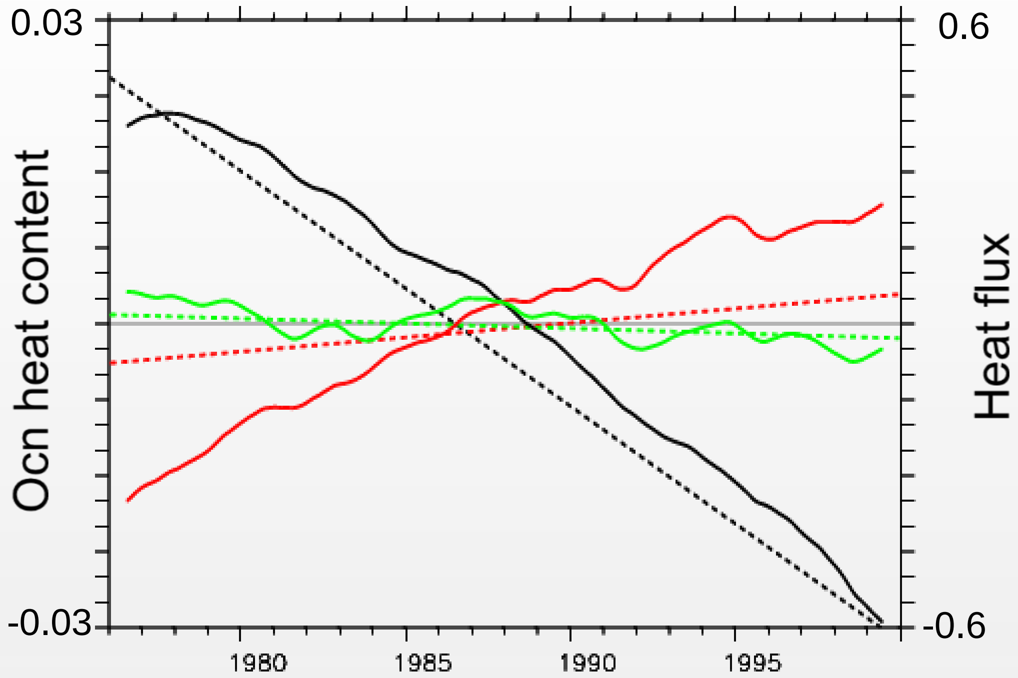
ECDA is optimal for climate studies – An ensemble of model integrations establishing the background error statistics to extract the observational information, addressing the probabilistic nature of climate evolution.

- ✓ Ensemble statistics provide multivariate relationships, such as temperature-salinity relationship and geostrophic balance
- ✓ A set of self-balanced and coherent initial coupled states generates optimal ensemble initialization of coupled model with minimum initial shocks



Combining data with an imperfect coupled model for energy-balanced climate estimation

Using one model results as truth and another model to assimilate the “truth” to illustrate the advantage of coupled data assimilation



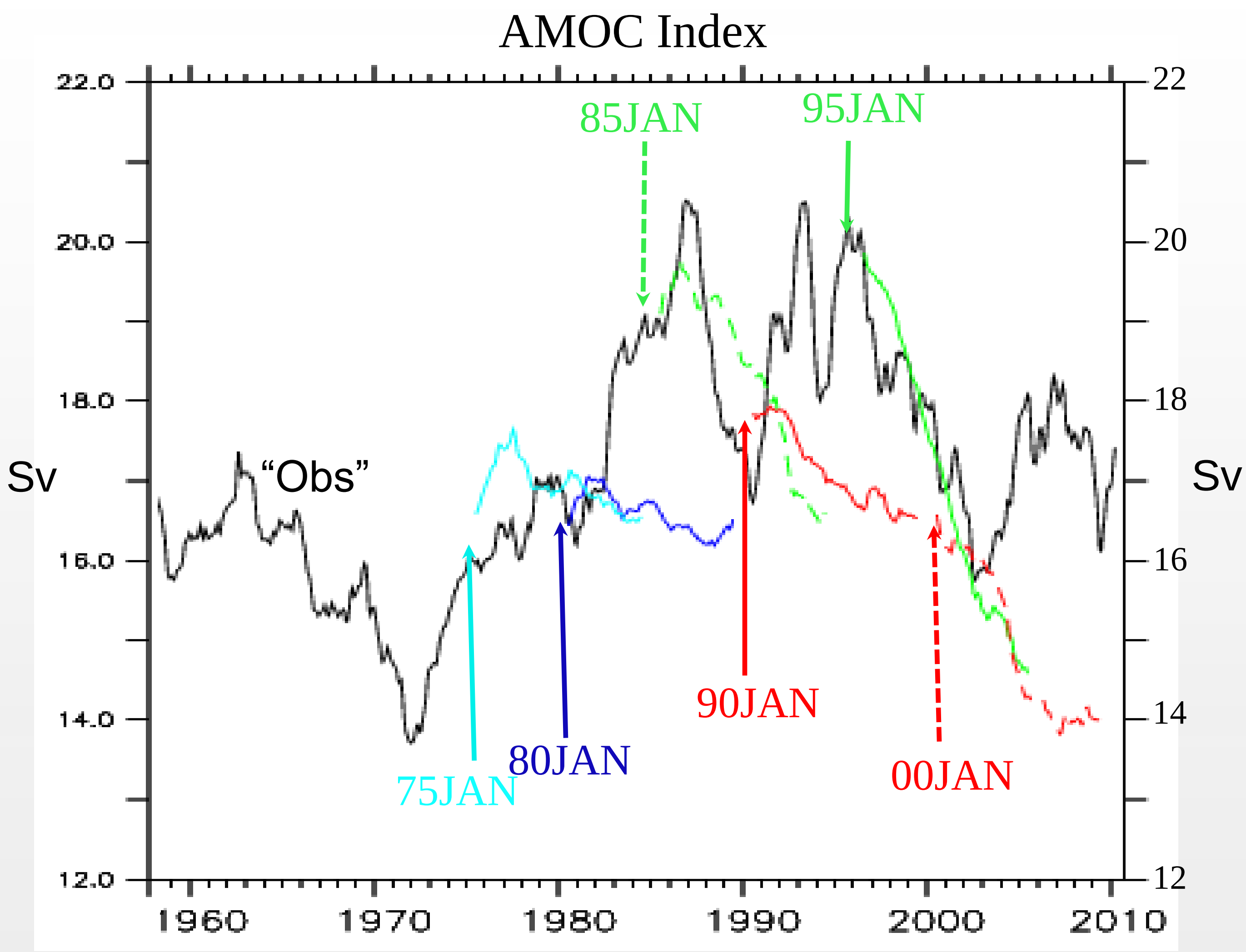
HF in Atm-data-assim — HC in Atm-data-assim

HF in Ocn-data-assim — HC in Ocn-data-assim

HF in A&O-data-assim — HC in A&O-data-assim

(Thanks to XYang, YChang & ARosati)

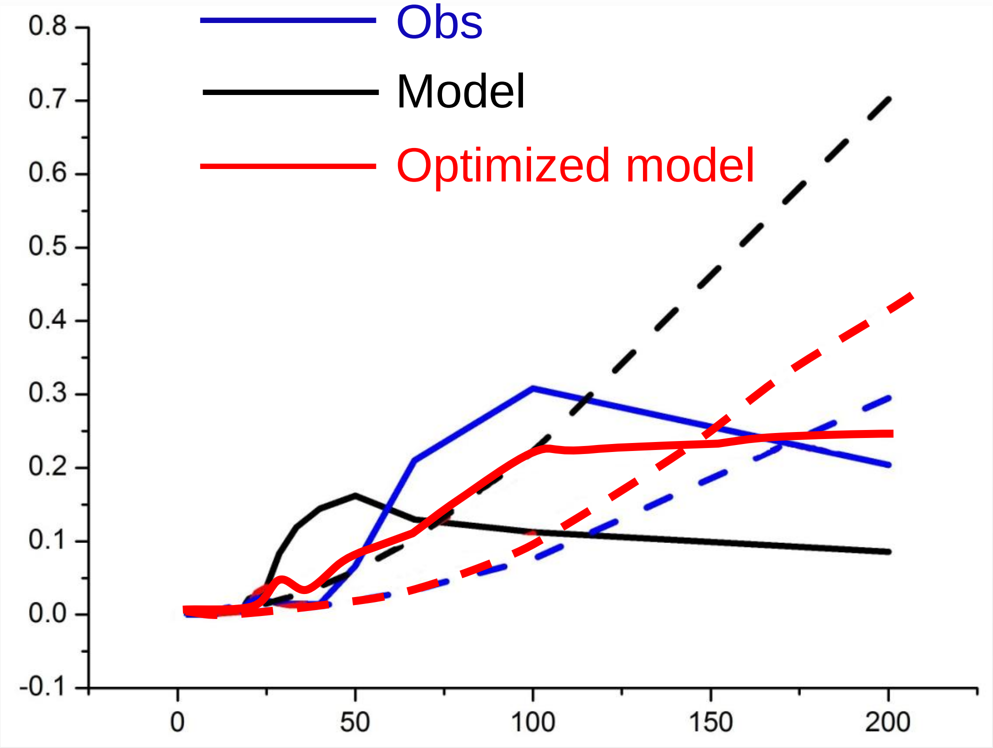
Challenge: model bias causing climate drift hinders prediction



Impact of parameter estimation on model simulation

- ✓ Two different long-wave radiation parameterization schemes in a coupled model simulate a biased climate problem caused by biased physics
- ✓ Scheme-I: Obs
- ✓ Scheme-II: **Model**
- ✓ Optimized model: parameters are optimized using Ensemble Coupled Data Assimilation

power spectrum of ocean temp variability



Period (year)

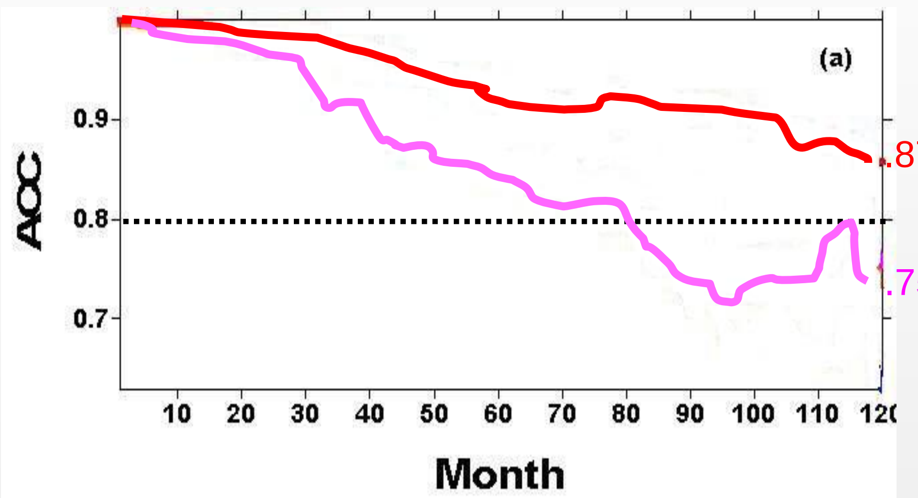
------- 95% confidence

(Thanks to XZhang, GVecchi & IHeld)

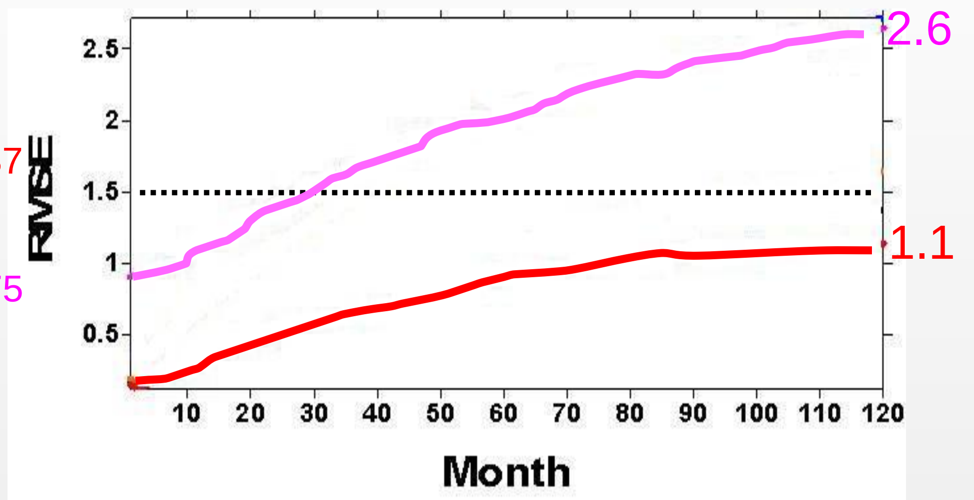
Impact of parameter estimation on model predictability

Ocean temperature forecast skill

Traditional State Estimation — New State Estimation+Parameter Estimation



Forecast lead time



Forecast lead time

Reconstruction of tropical storm statistics in high-resolution coupled data assimilation

A high-resolution coupled model at GFDL: CM2.5 (½° x ½ ° Atm & ¼° x ¼ ° Ocn)

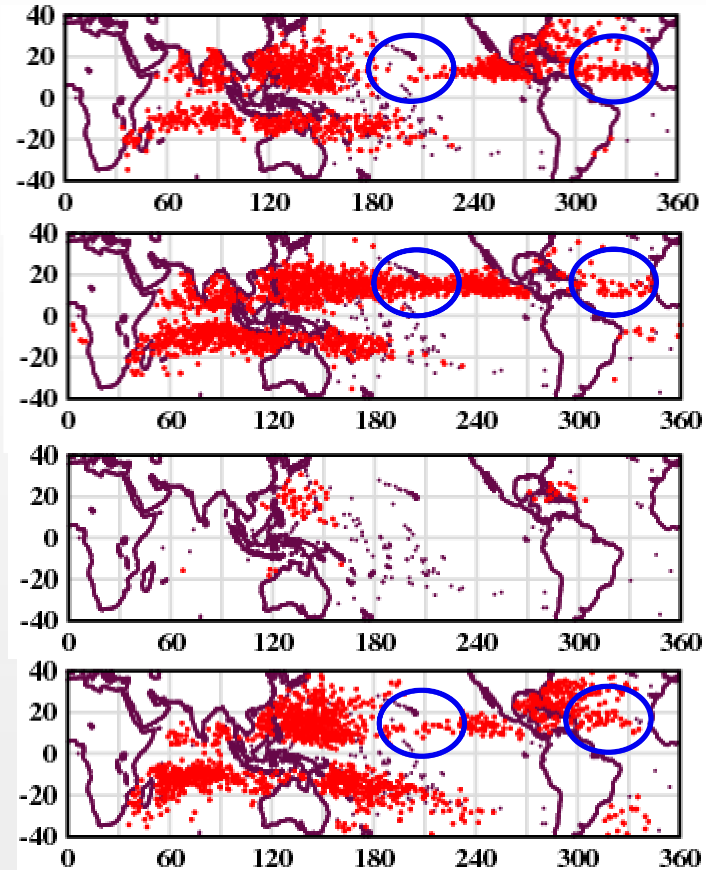
Total TCs (99-11)

Obs

Free model

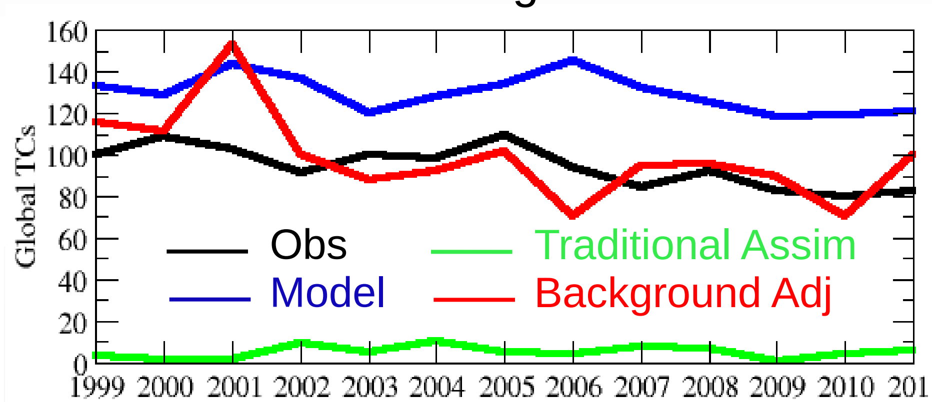
Traditional scheme

New scheme



(*Thanks to MZhao & S-J Lin*)

Time Series of global TCs



- ✓ Low-resolution observations can wipe out tropical storms
- ✓ Background adjustment can reconstruct TC statistics by correcting large-scale background & retaining small-scale perturbations
- ✓ Minimize model forecast errors allowing interactions of TCs & large-scale background

Future directions

1. Complete coupled model data assimilation system by including assimilations of sea ice and land obs, extending to estimation of ecosystem fluxes.

2. Implement coupled model parameter estimation into the climate prediction system, continuously improving the forecast skills in SI-decadal scales.

3. Refine the idea that separately processes the large-scale background and small-scale perturbations to advance high-resolution coupled model initialization, pursuing seamless numerical weather-climate studies.