ATM 265, Spring 2019
Lecture 12
Model Intercomparison and Evaluation
May 6, 2019

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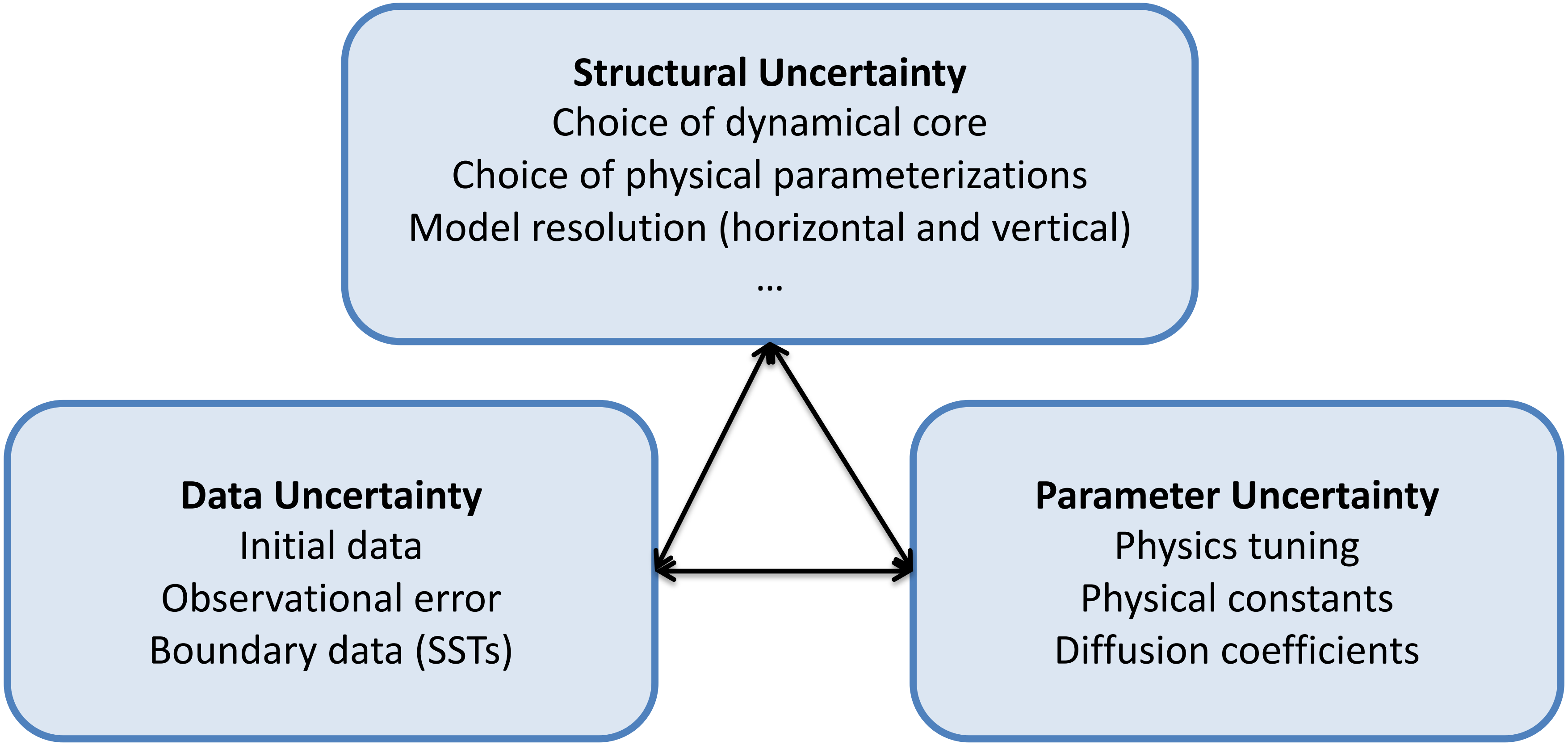
Sources of Uncertainty in GCMs

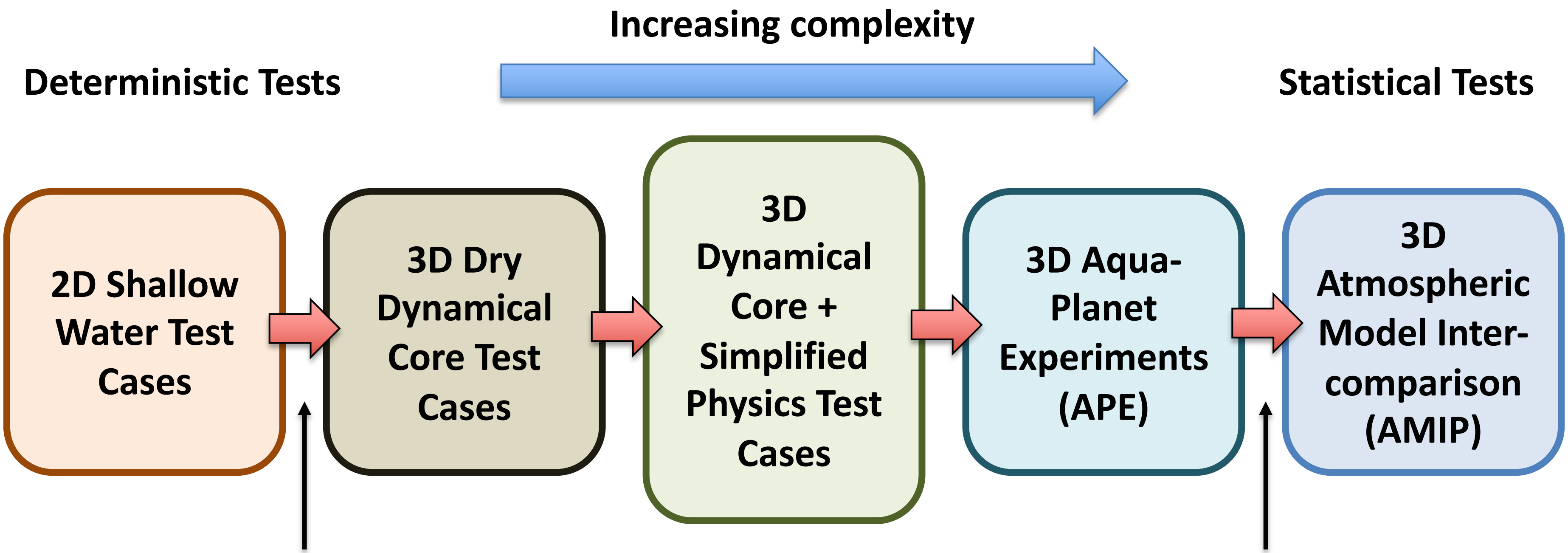


Structural Uncertainty
Choice of dynamical core
Choice of physical parameterizations
Model resolution (horizontal and vertical)
…

Data Uncertainty
Initial data
Observational error
Boundary data (SSTs)

Parameter Uncertainty
Physics tuning
Physical constants
Diffusion coefficients

Test Hierarchy



Increasing complexity

Deterministic Tests

Statistical Tests

2D Shallow Water Test Cases

3D Dry Dynamical Core Test Cases

3D Dynamical Core + Simplified Physics Test Cases

3D Aqua-Planet Experiments (APE)

3D Atmospheric Model Inter-comparison (AMIP)

2D Shallow Water plus physics
(Jablonowski et al.)

Intermediate complexity

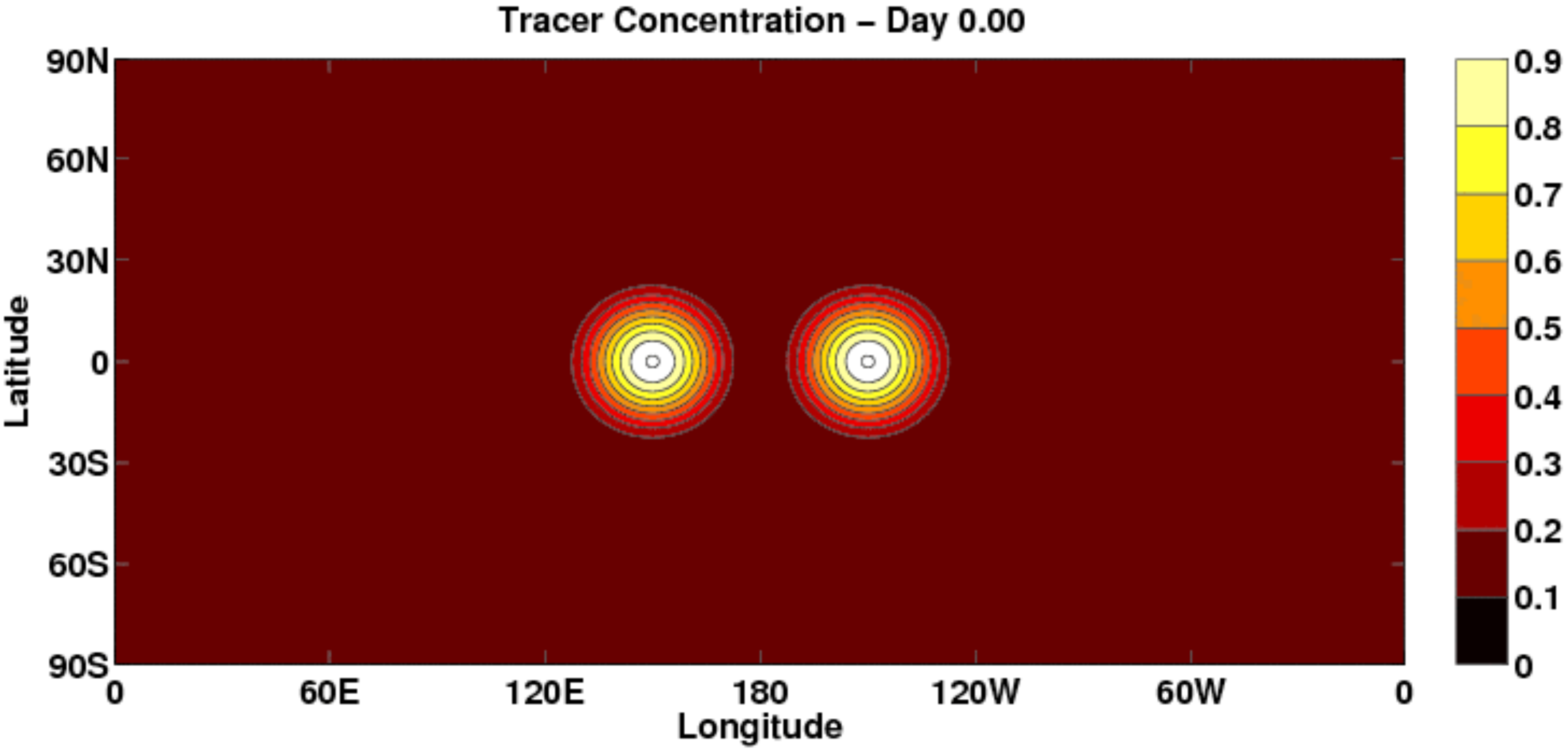
3D Aqua-Planet plus real topography
(Lauritzen et al.)

Williamson et al.
Galewsky et al.
Nair et al.

2D Shallow Water Test Cases

Deformational Flow

(Advection Test)

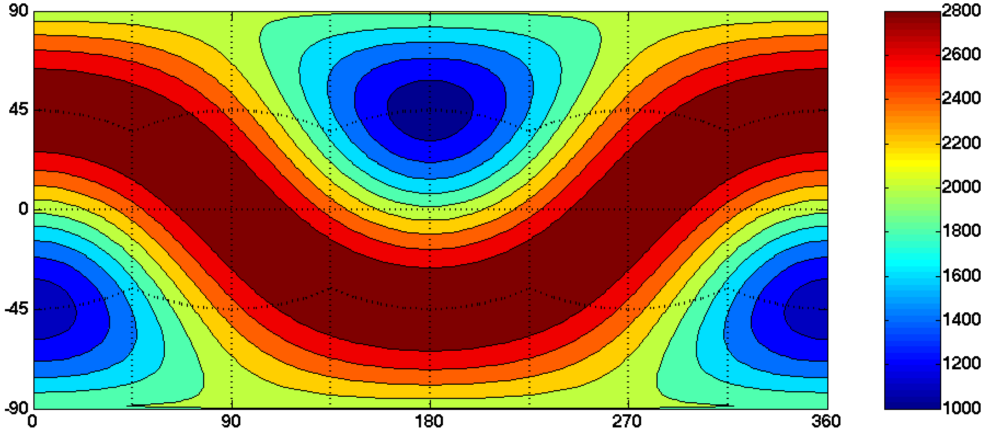


Deformational flow on the sphere (tests accuracy of the numerical method, preservation of monotonicity and functional relationships)

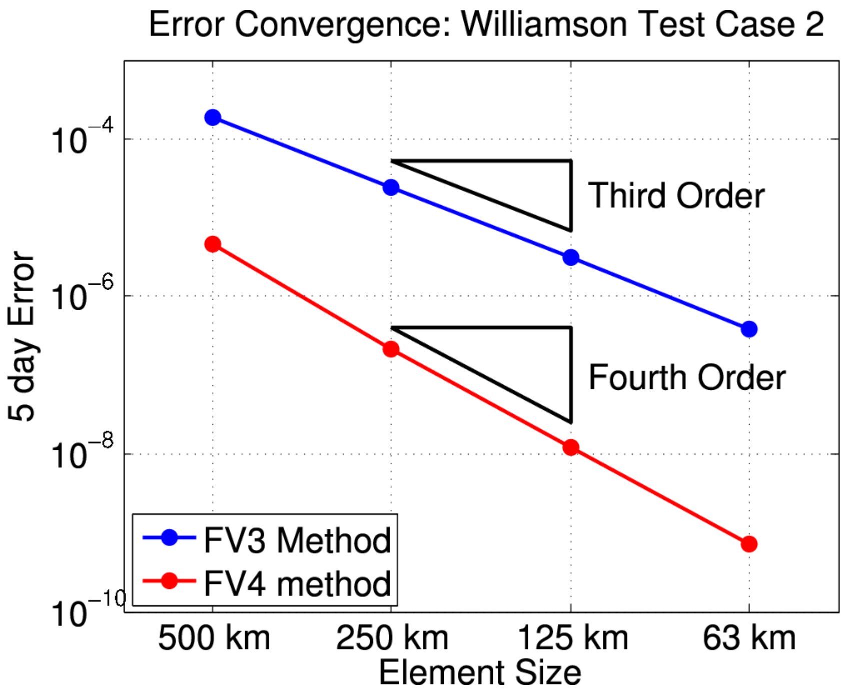
2D Shallow Water Test Cases

Williamson Test Case 2

Steady-state geostrophically balanced flow which is not aligned with the grid. Errors ar measured after five days again the initial state.

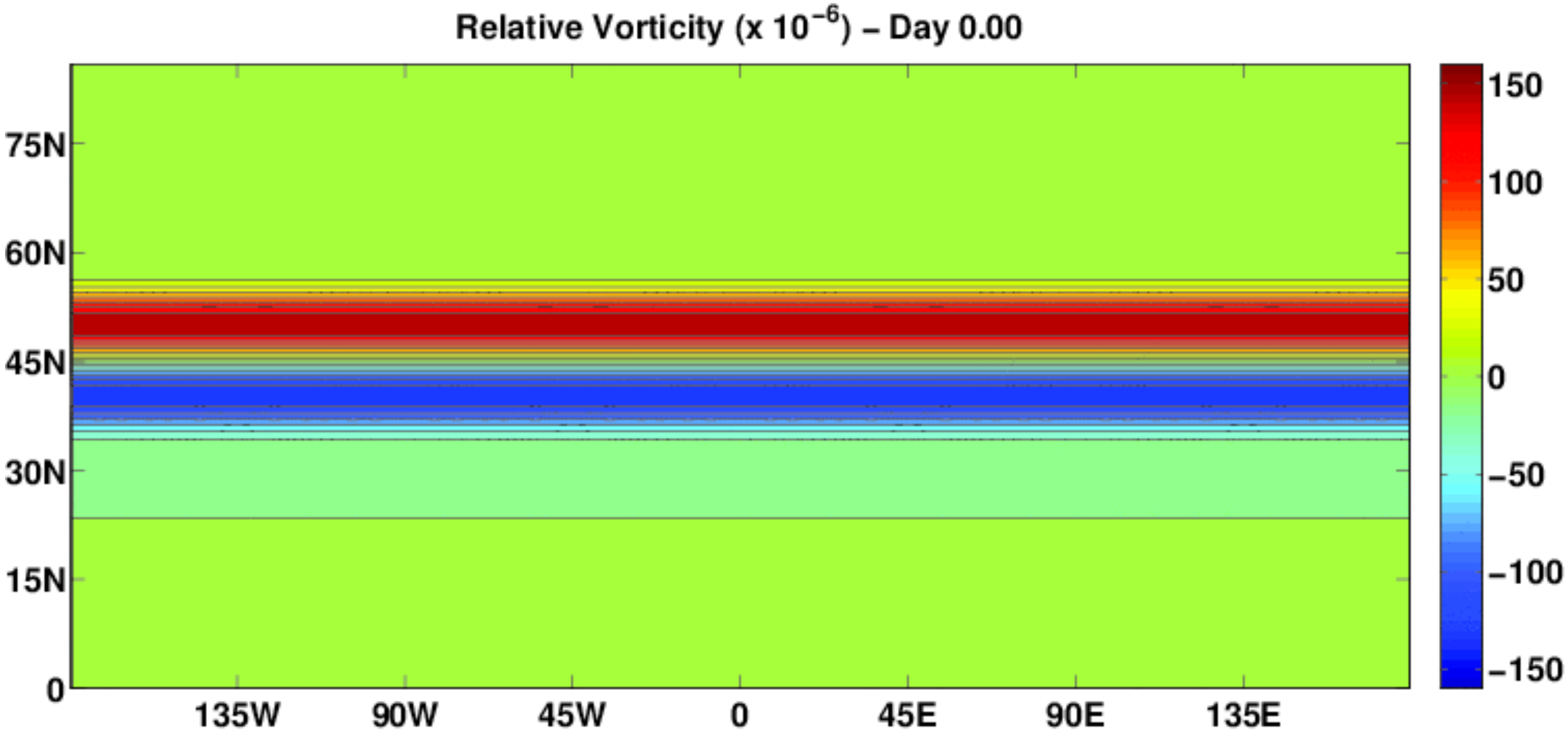


Source: Ullrich, Jablonowski and van Leer (2010) "High-order finite-volume methods for the shallow-water equations on the sphere." J. Comp. Phys.



Galewsky et al. Shallow-Water Barotropic Instability

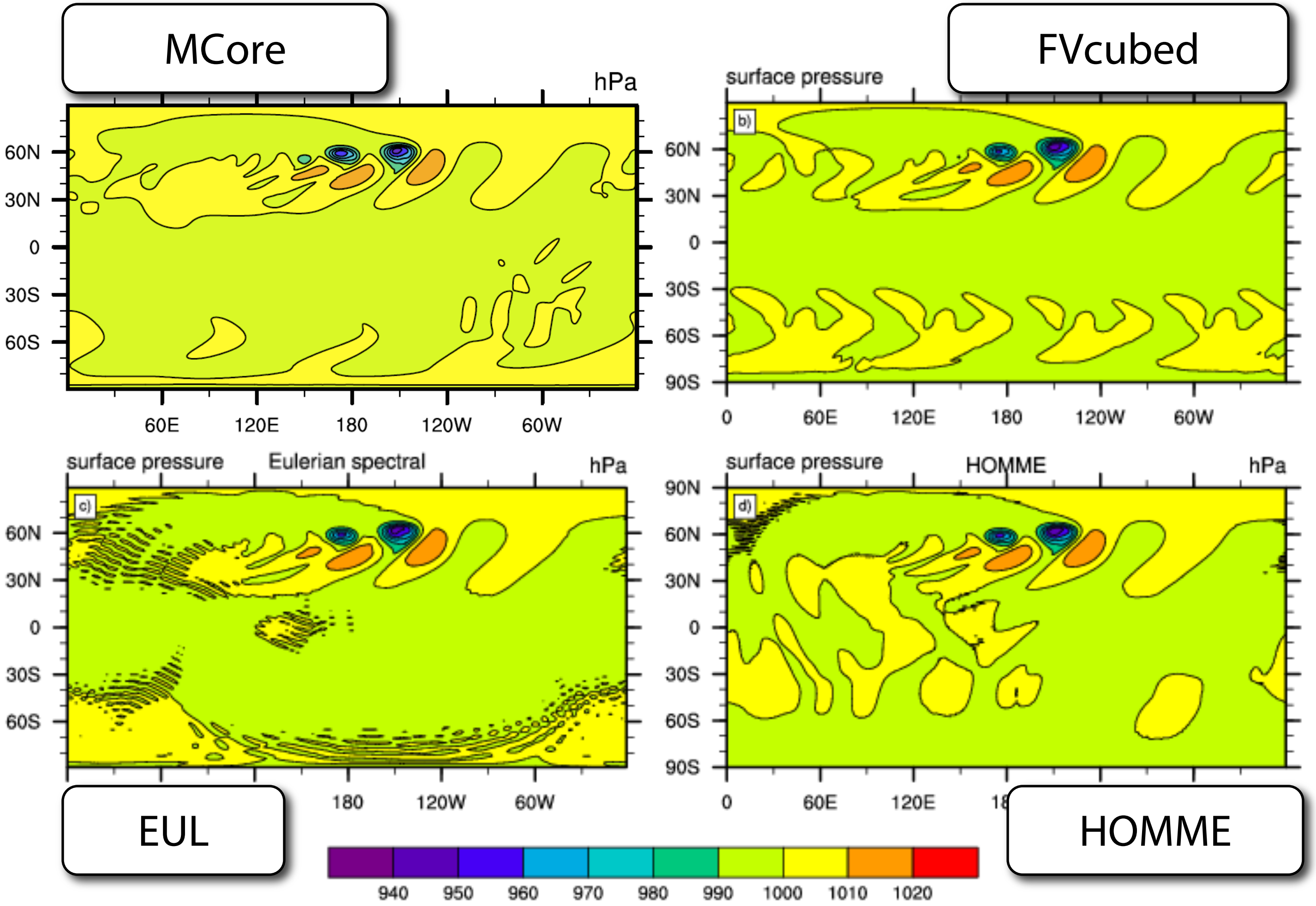
2D Shallow Water Test Cases



Galewsky et al.: Geostropically balanced shallow water jet which is perturbed and leads to the development of a vortical instability.

Baroclinic Instability

3D Dry Dynamical Core Test Cases



MCore

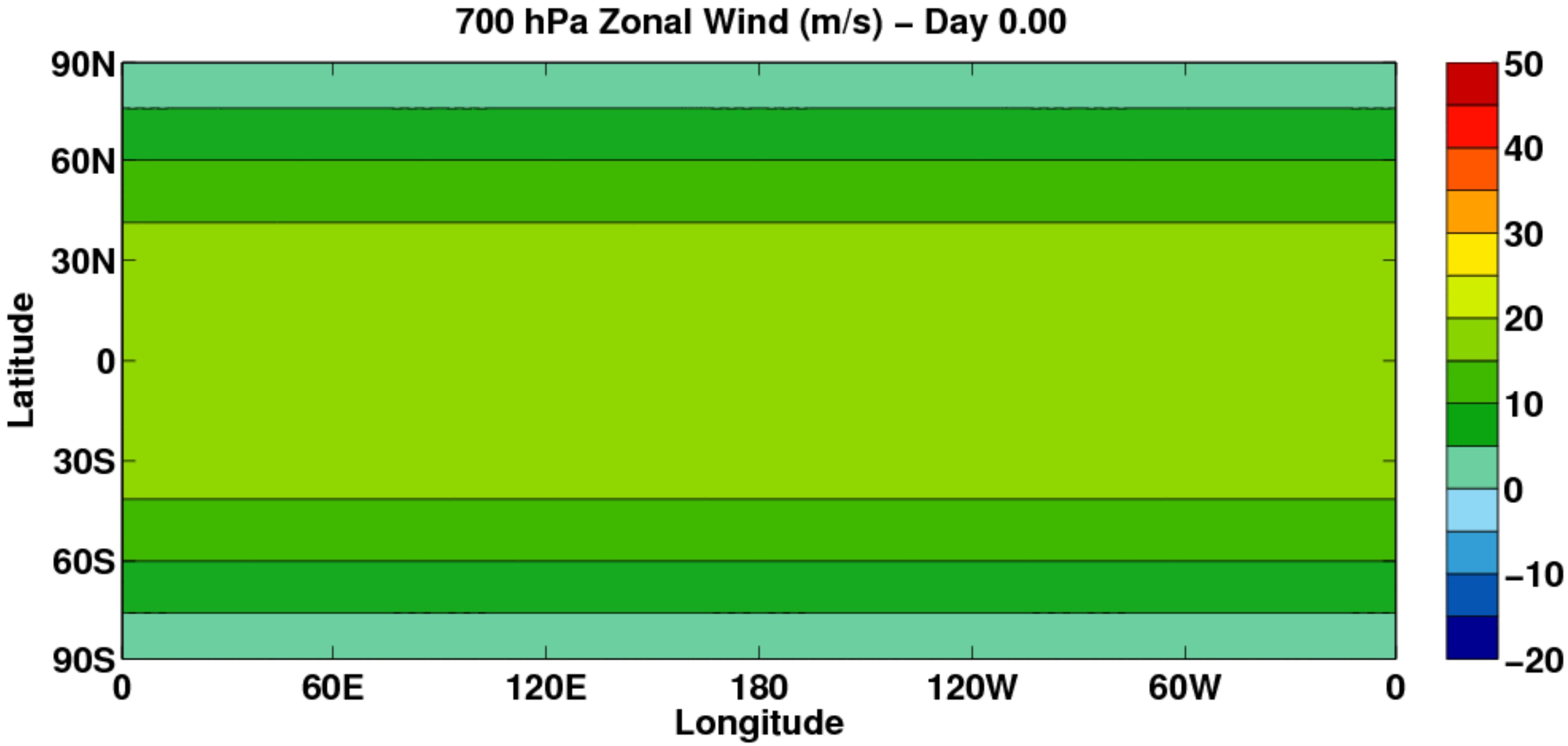
FVcubed

EUL

HOMME

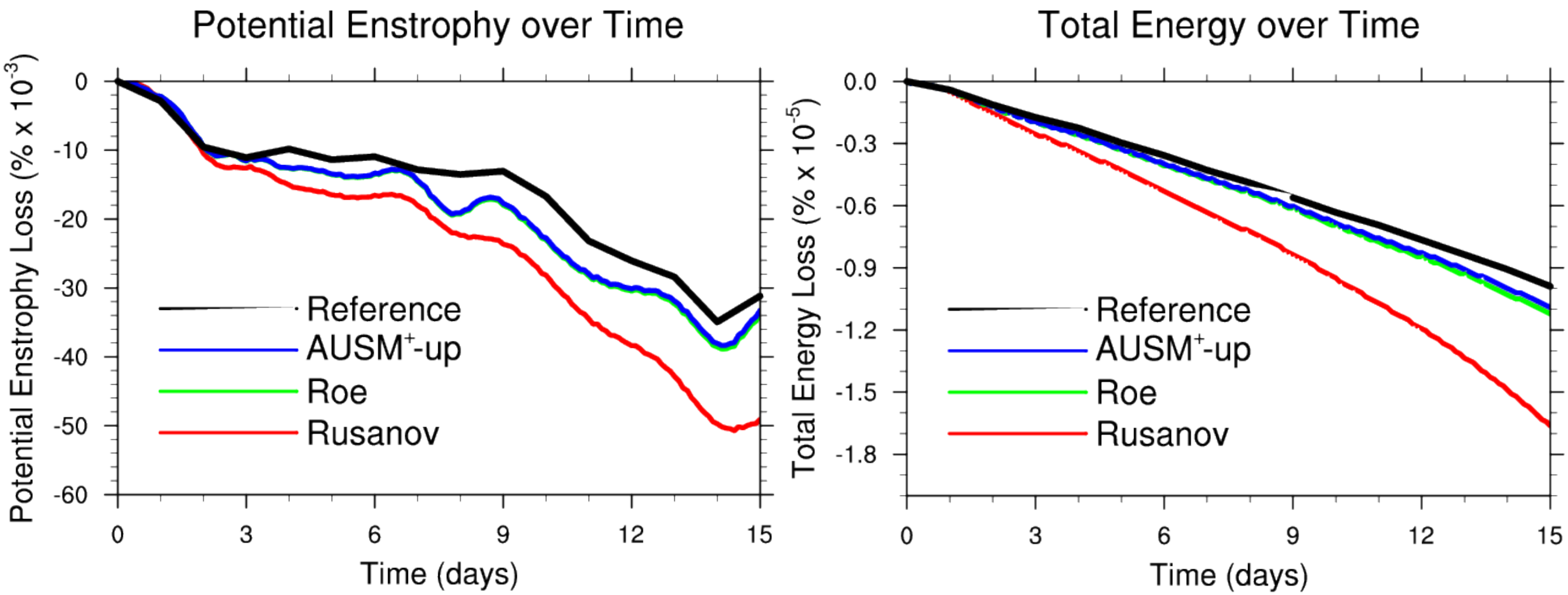
Flow over Topography

3D Dry Dynamical Core Test Cases



Source: Ullrich, Jablonowski and van Leer (2010) "High-order finite-volume methods for the shallow-water equations on the sphere." J. Comp. Phys.

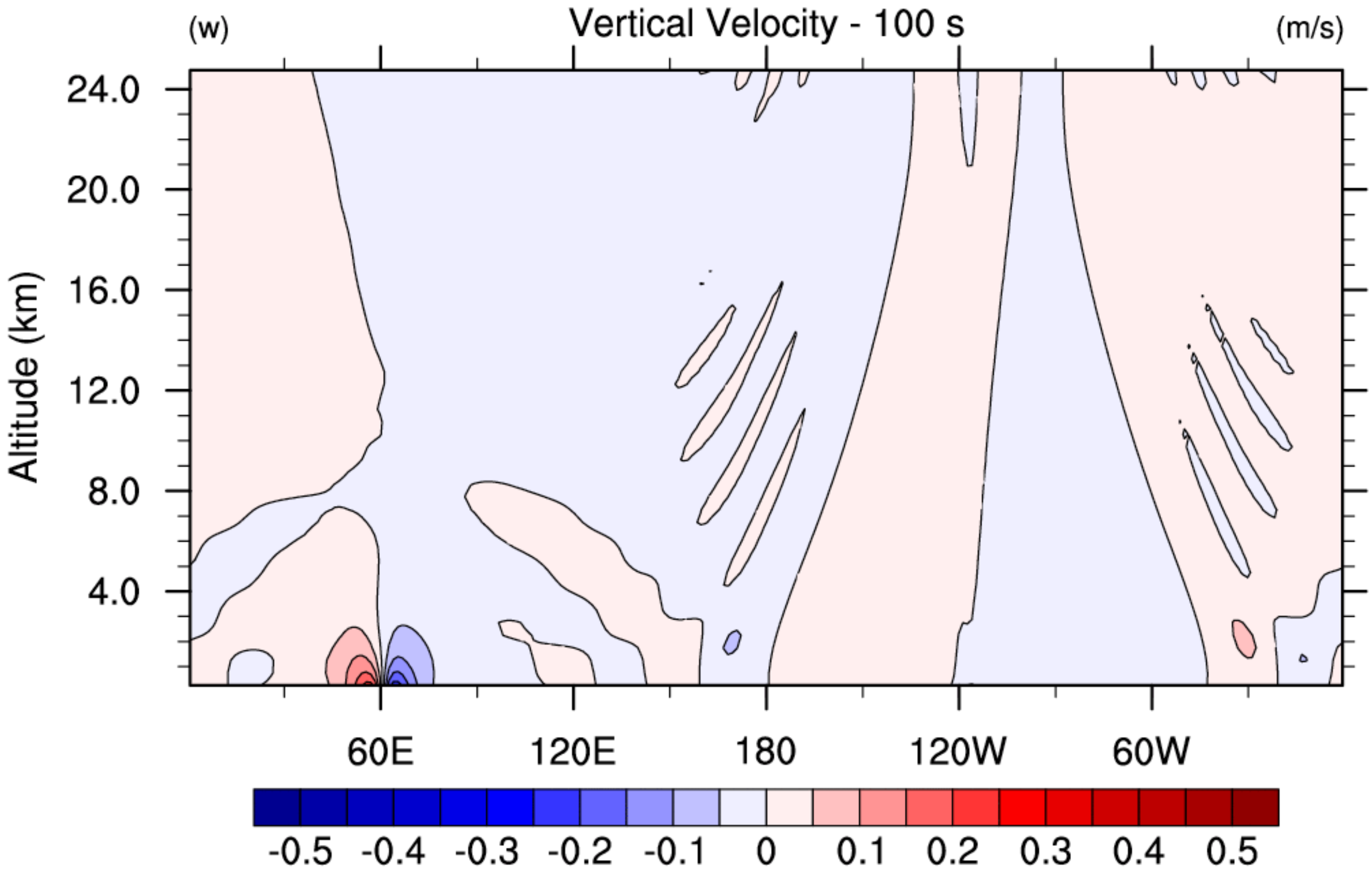
Conservation of Invariants



Source: Ullrich, Jablonowski and van Leer (2010) "High-order finite-volume methods for the shallow-water equations on the sphere." J. Comp. Phys.

Non-Hydrostatic Mountain Waves

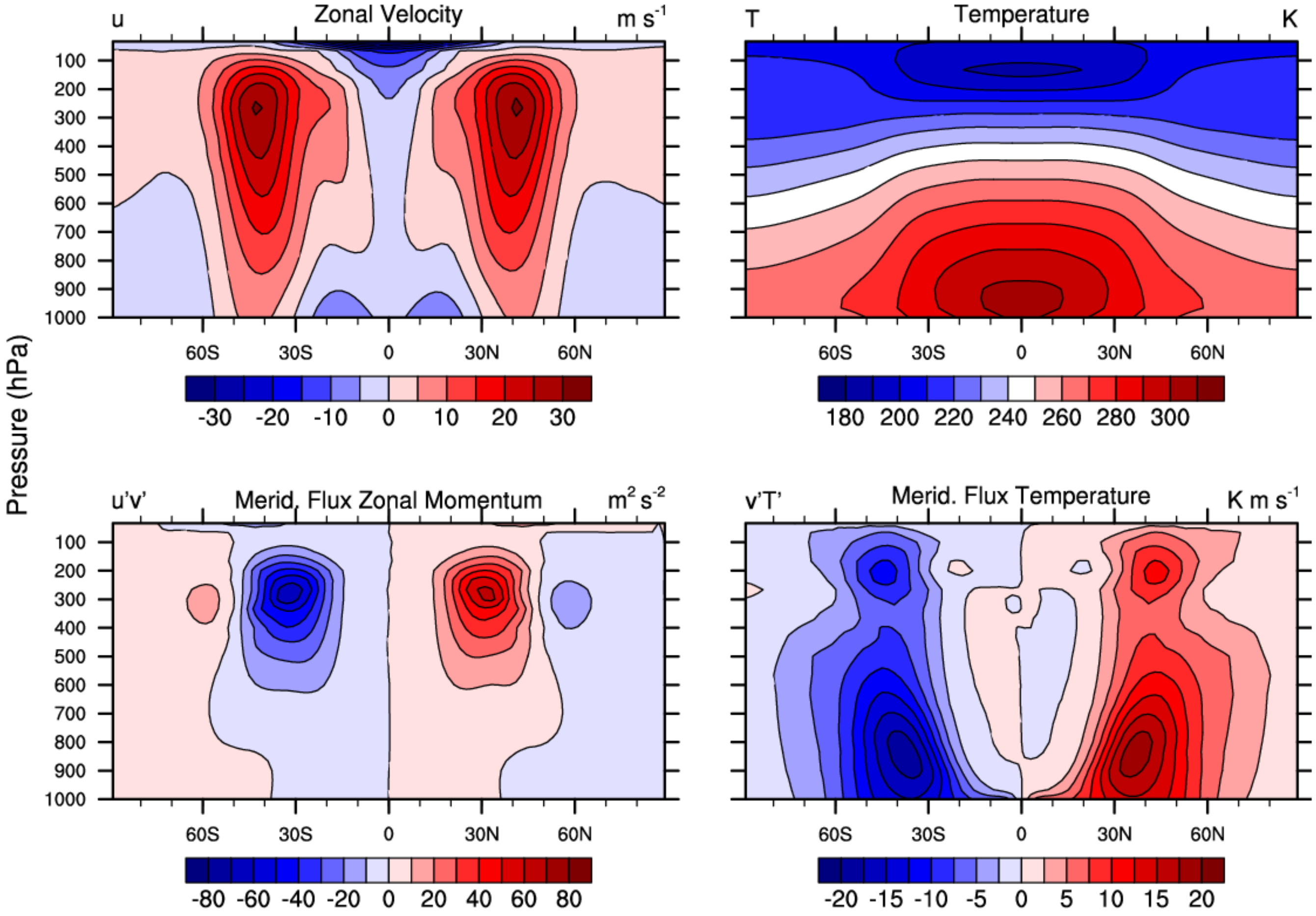
3D Dry Dynamical Core Test Cases



Tests the response of atmospheric models to topography in the non-hydrostatic regime.

Held-Suarez Climatology

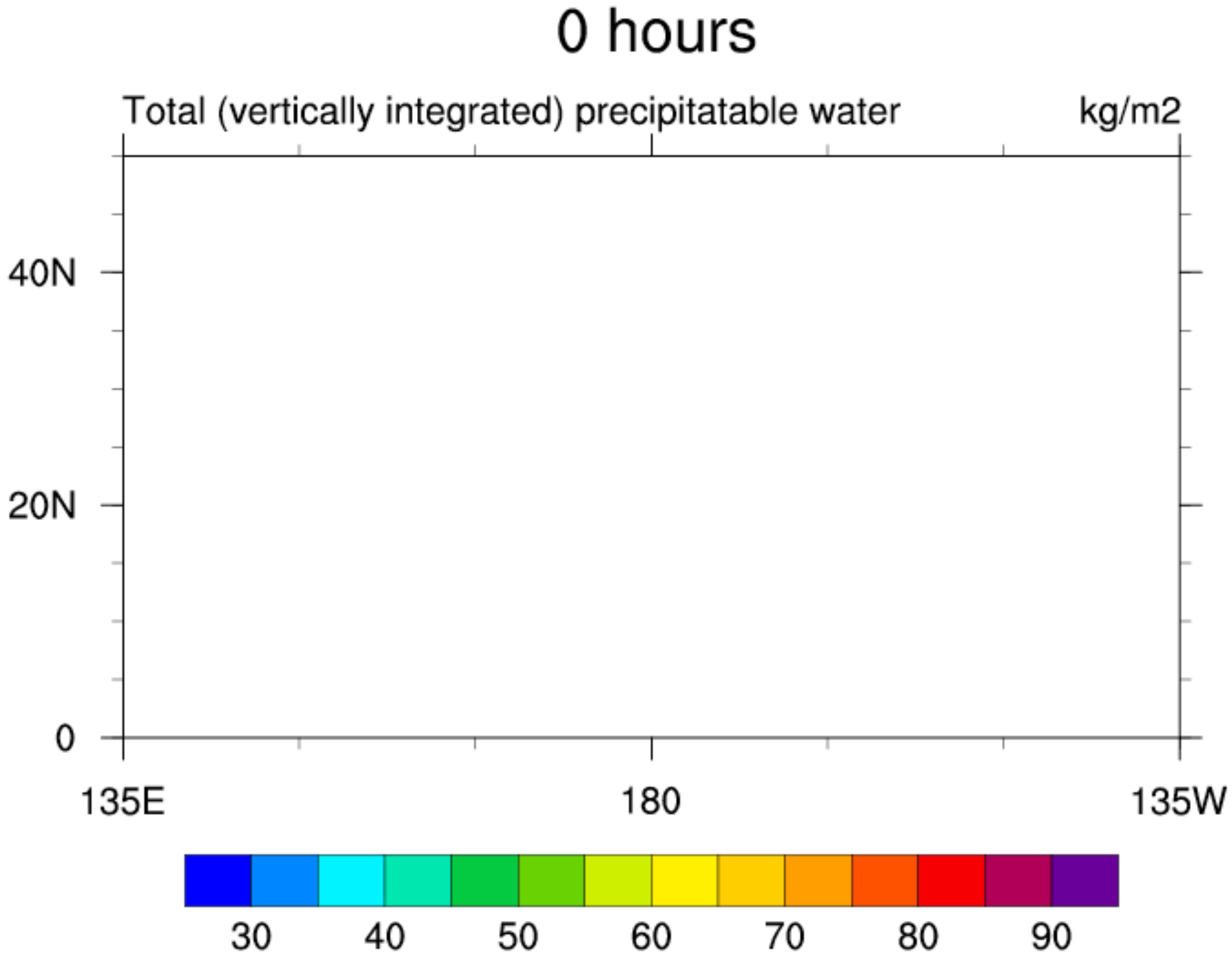
3D Dynamical Core + Simplified Physics Test Cases



Held-Suarez: Heating is prescribed plus a simple velocity relaxation scheme. Climatology is measured using statistics over a 1000 day simulation.

Reed Tropical Cyclone

**3D Dynamical Core +
Simplified Physics Test Cases**

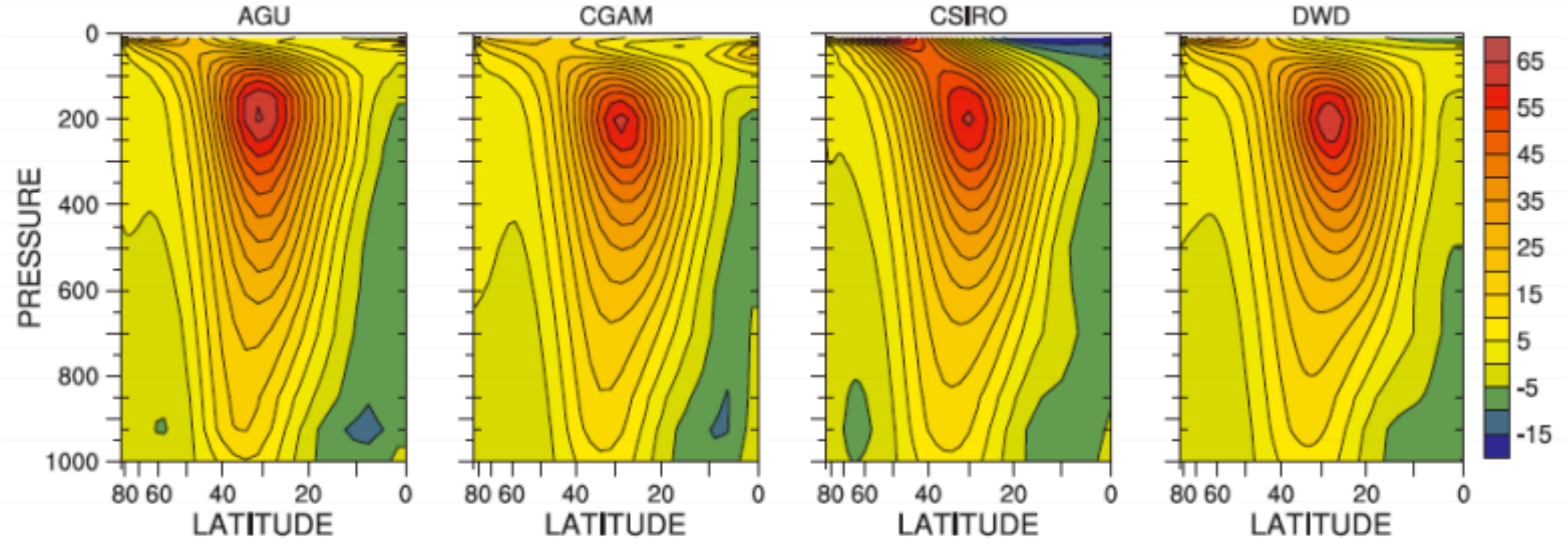


Reed Tropical Cyclone: Simplified physics package (surface fluxes, boundary layer and large-scale condensation) plus an isolated low pressure system

Aqua-Planet Experiments

3D Aqua-Planet Experiments (APE)

3D aqua planet tests evaluate the interaction between the dynamical core and complex physical parameterizations using a simplified lower boundary (flat ocean-covered Earth with analytically prescribed sea-surface temperatures (SSTs)

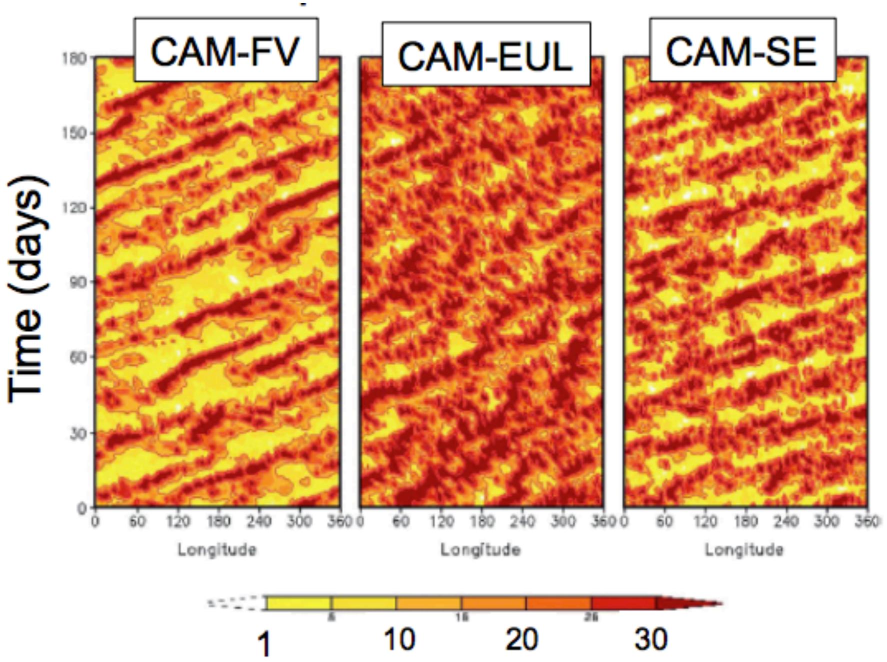


Zonal mean 3-year mean zonal wind: Snapshots of 4 GCMs that participated in the Aqua-Planet Experiment (APE).

Source: Williamson et al., NCAR Technical Note TN-484+STR (2012)

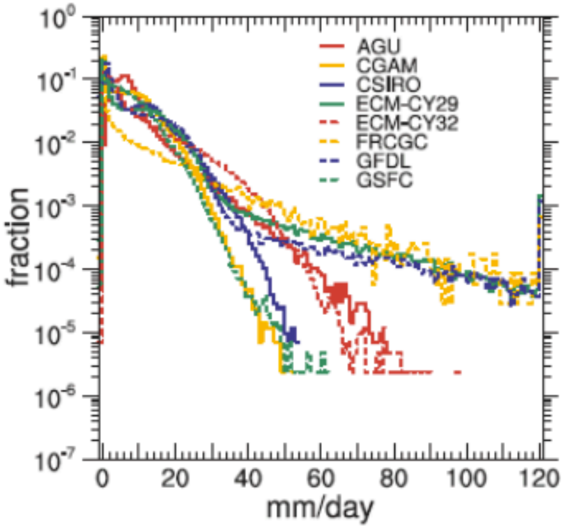
Aqua-Planet Experiments

3D aqua planet tests give insights into the characteristics of moisture processes. What drives these differences?



Daily rainfall rate (mm/day) in the tropics

Mishra et al., J. Climate (2011)



Fraction of time precipitation in the tropics is between 0-120 mm/day

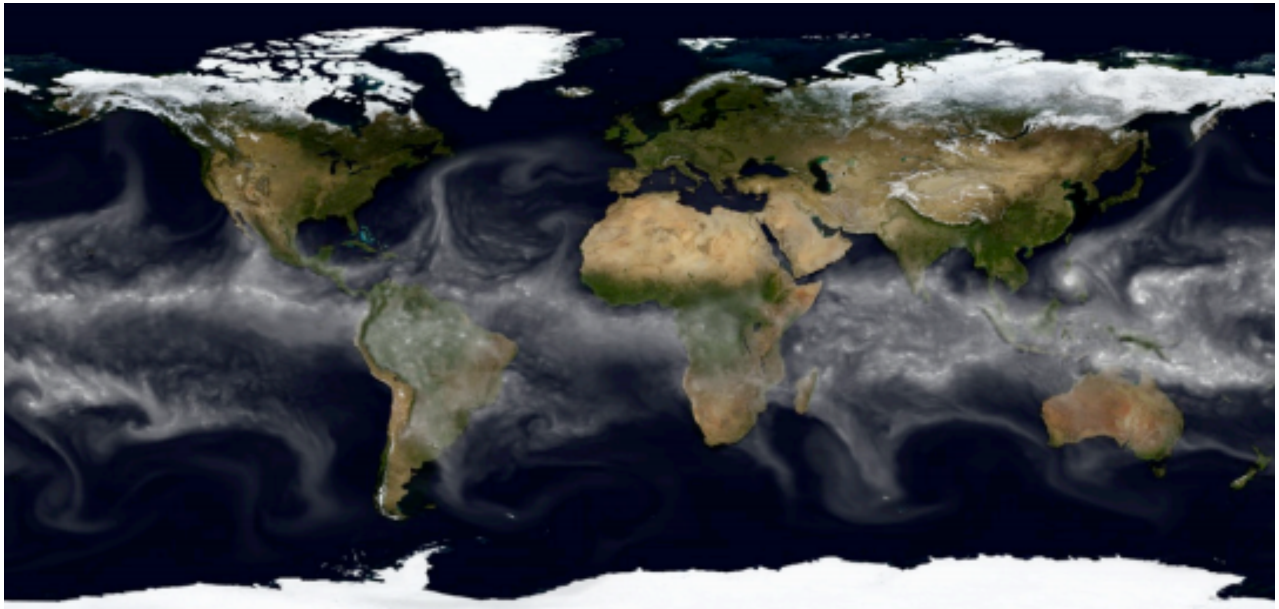
Williamson et al., NCAR Technical Note TN-484+STR (2012)

Source: Christiane Jablonowski, DCMIP 2012

AMIP Simulations

3D Atmospheric Model Intercomparison (AMIP)

3D AMIP tests evaluate the interaction between the dynamical core and complex physical parameterizations (maybe even including chemistry packages) using a complex but prescribed lower boundary (orography, prescribed observation-based SSTs and sea-ice) over 25-year time frames



Source: Christiane Jablonowski, DCMIP 2012

AMIP Simulations

3D Atmospheric Model Intercomparison (AMIP)

Michael Wehner et al.:
Total column-integrated water vapor.
http://www.youtube.com/watch?v=MrRpSzHkx40

1979 Hurricane Season:
Total column-integrated water vapor.
http://www.youtube.com/watch?feature=endscreen&v=VKoZCzlBoDk&NR=1

Fully Coupled

- The most complex GCM evaluations utilize a fully coupled atmosphere (ocean – ice – land – chemistry – carbon-cycle – Earth system) sometimes with prescribed greenhouse gas concentrations are used (CLIVAR runs)
- Fully coupled simulations of past time periods are typically compared against observations, sometimes in the form of re-analysis data
- Differences between simulations are very hard to understand due to the complexity and non-linear interactions
- Fully coupled GCMs are used for the assessment of future climate scenarios (e.g. for the Intergovernmental Panel on Climate Change, IPCC, assessments)

Source: Christiane Jablonowski, DCMIP 2012

Ensembles

- Ensembles are one way to assess the robustness of the simulations, and to gain insight into the uncertainty of the model simulations.

Perturbed Parameter Ensembles

- Variations of empirical tuning factors in the physical parameterizations
- Diffusion coefficients or physical constants in the dynamical core

Initial Data and Boundary Value Ensembles

- Slight variations in the initial data
- Different topography datasets
- Different sea-surface temperatures

Multi-Model Ensembles

- Different atmospheric models (or different versions of the same model)

Source: Christiane Jablonowski, DCMIP 2012

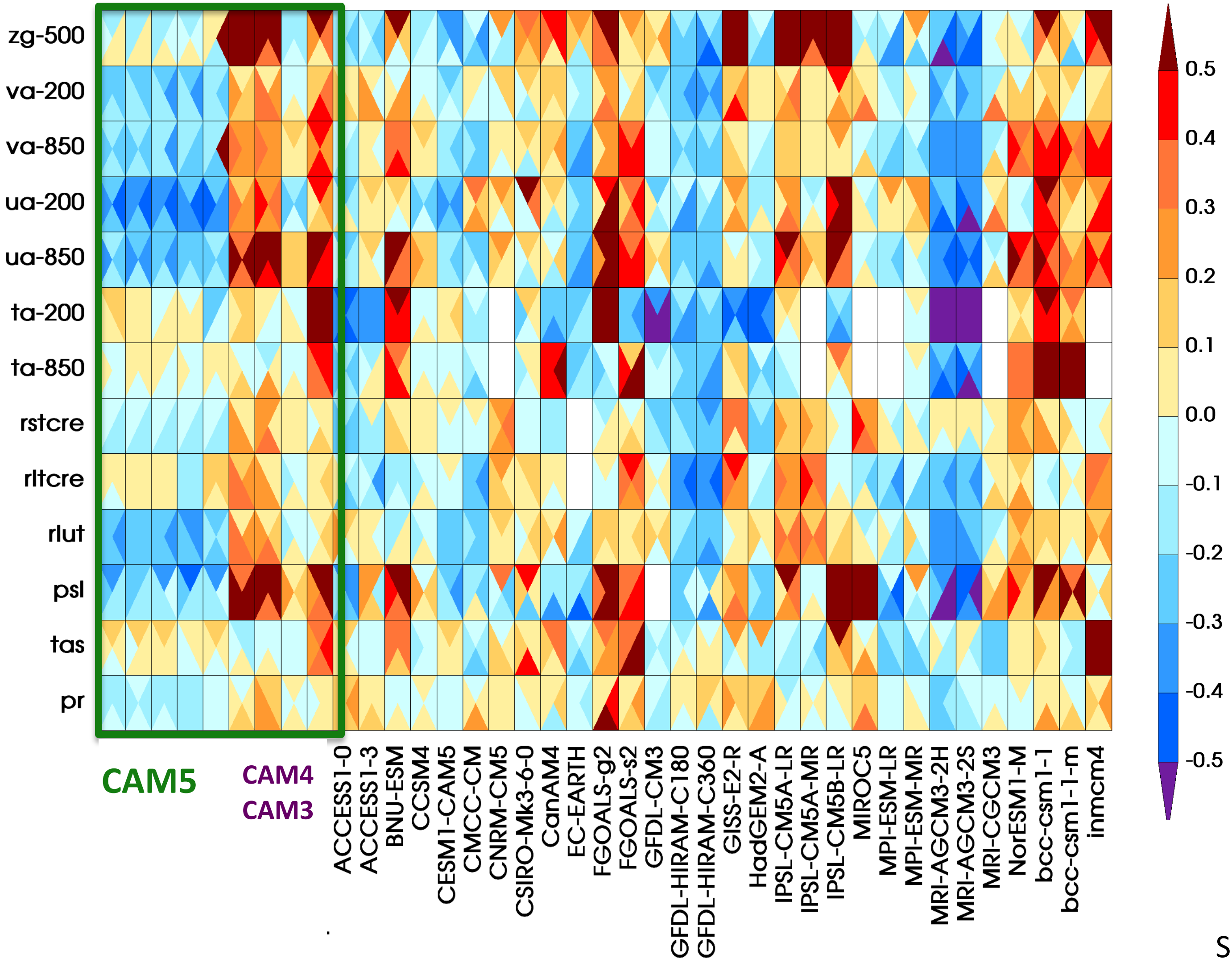
Perturbed Physics Ensembles

CAM5 2°, 22 parameters, 1100 simulations, 5 year AMIP
Latin Hyper-Cube Sampling

	modelSection_modelVariable	variable description	low value	default	high value
Large-Scale Cloud	cldfrc_rhminh	Threshold RH for fraction high stable clouds	0.65	0.8	0.85
	cldfrc_rhminl	Threshold RH for fraction low stable clouds	0.8	0.8875	0.99
	cldwatmi_ai	Fall speed parameter for cloud ice	350	700	1400
	cldwatmi_as	Fall speed parameter for snow	5.86	11.72	23.44
	cldwatmi_cdnl	Cloud droplet number limiter	0	0	1e+06
	cldwatmi_dcs	Autoconversion size threshold for ice to snow	0.0001	0.0004	0.0005
	cldwatmi_eii	Collection efficiency aggregation of ice	0.001	0.1	1
	cldwatmi_qcvar	Inverse relative variance of sub-grid cloud water	0.5	2	5
Aerosol	dust_emis_fact	Dust emission tuning factor	0.21	0.35	0.86
PBL Turb.	eddydiff_a2l	Moist entrainment enhancement parameter	10	30	50
Large-Scale Cloud	micropa_wsubimax	Maximum sub-grid vertical velocity for ice nucleation	0.1	0.2	1
	micropa_wsubmin	Minimum sub-grid vertical velocity for liquid nucleation	0	0.2	1
Shallow Conv.	uwshcu_criqc	Maximum updraft condensate	0.0005	0.0007	0.0015
	uwshcu_kevp	Evaporative efficiency	1e-06	2e-06	2e-05
	uwshcu_rkm	Fractional updraft mixing efficiency	8	14	16
	uwshcu_rpen	Penetrative updraft entrainment efficiency	1	5	10
Deep Conv.	zmconv_alfa	Initial cloud downdraft mass flux	0.05	0.1	0.6
	zmconv_c0_lnd	Deep convection precipitation efficiency over land	0.001	0.0059	0.01
	zmconv_c0_ocn	Deep convection precipitation efficiency over ocean	0.001	0.045	0.1
	zmconv_dmpdz	Parcel fractional mass entrainment rate	0.0002	0.001	0.002
	zmconv_ke	Evaporation efficiency parameter	5e-07	1e-06	1e-05
	zmconv_tau	Convective time scale	1800	3600	28800

Source: Richard Neale

Model Intercomparison: Z Scores



- CAM performs well and is improving
- No exceptional scores
- Good models
  - Good physics
  - High resolution
- Does not give broad indication of performance
- Some “red-line” poor performance may be crossed e.g., ENSO

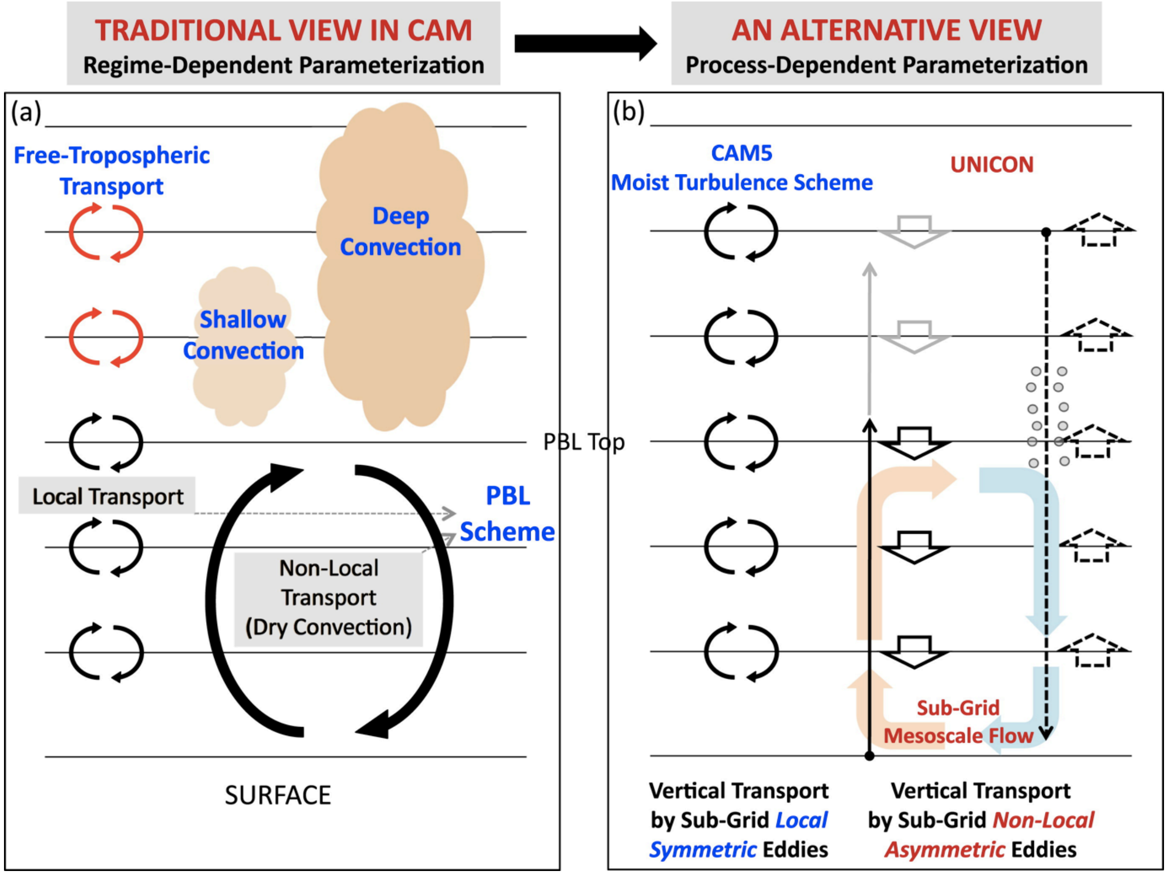
Source: Rich Neale, DCMIP 2016

Summary

- How do we define success?
- Metrics are hard, diagnostics are too many
- Hierarchy of approaches for validation
- Examine variability and process oriented diagnostics
- “Red-line” diagnostics (ENSO, 20th C, sea-ice)
- Model complexity -> more ways to ‘fail’
- The better things get the easier it is to make things worse

Example: UNICON vs. CLUBB

UNICON: Unified Convection Scheme



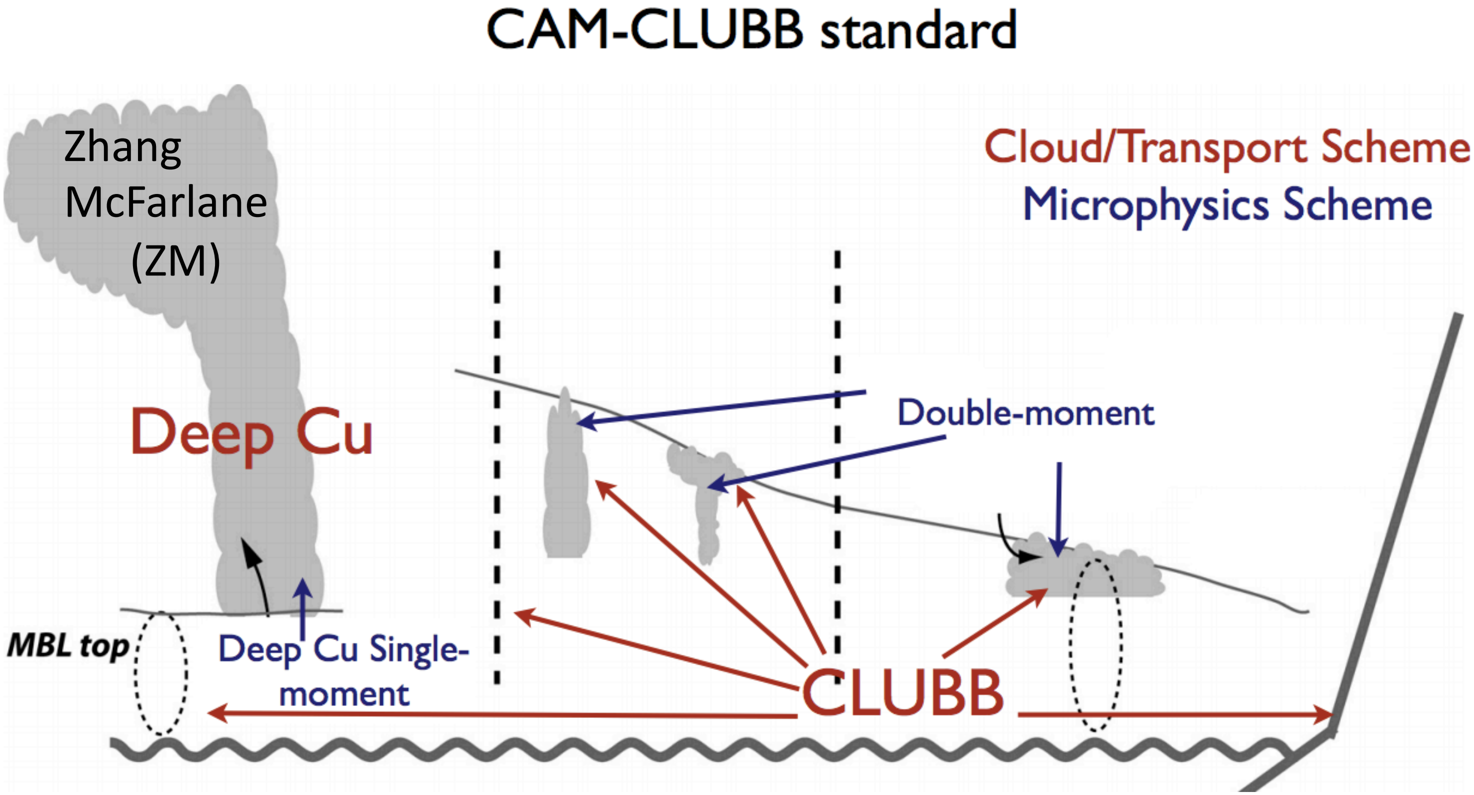
Park 2014a,2014b, J. Climate

- Unifies deep and shallow convection schemes
- Generates forced/free/dry shallow convection + deep convection
- Removes quasi-equilibrium and small area approximations
- Accounts for sub-grid mesoscale flows (prognostic)

Source: *Rich Neale*

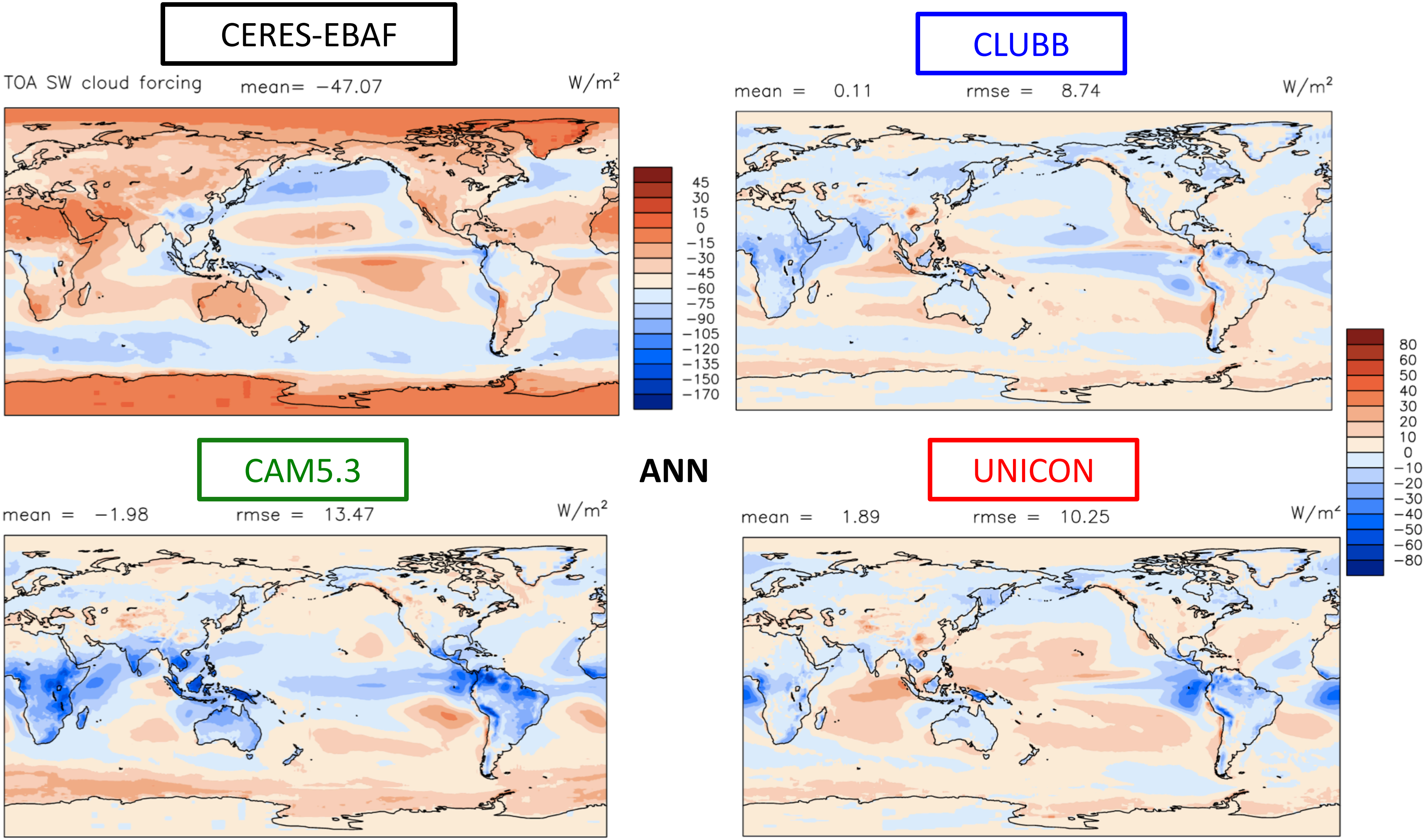
CLUBB: Cloud Layers Unified by Binormals

Golaz 2002b, J. Atmos. Sci.

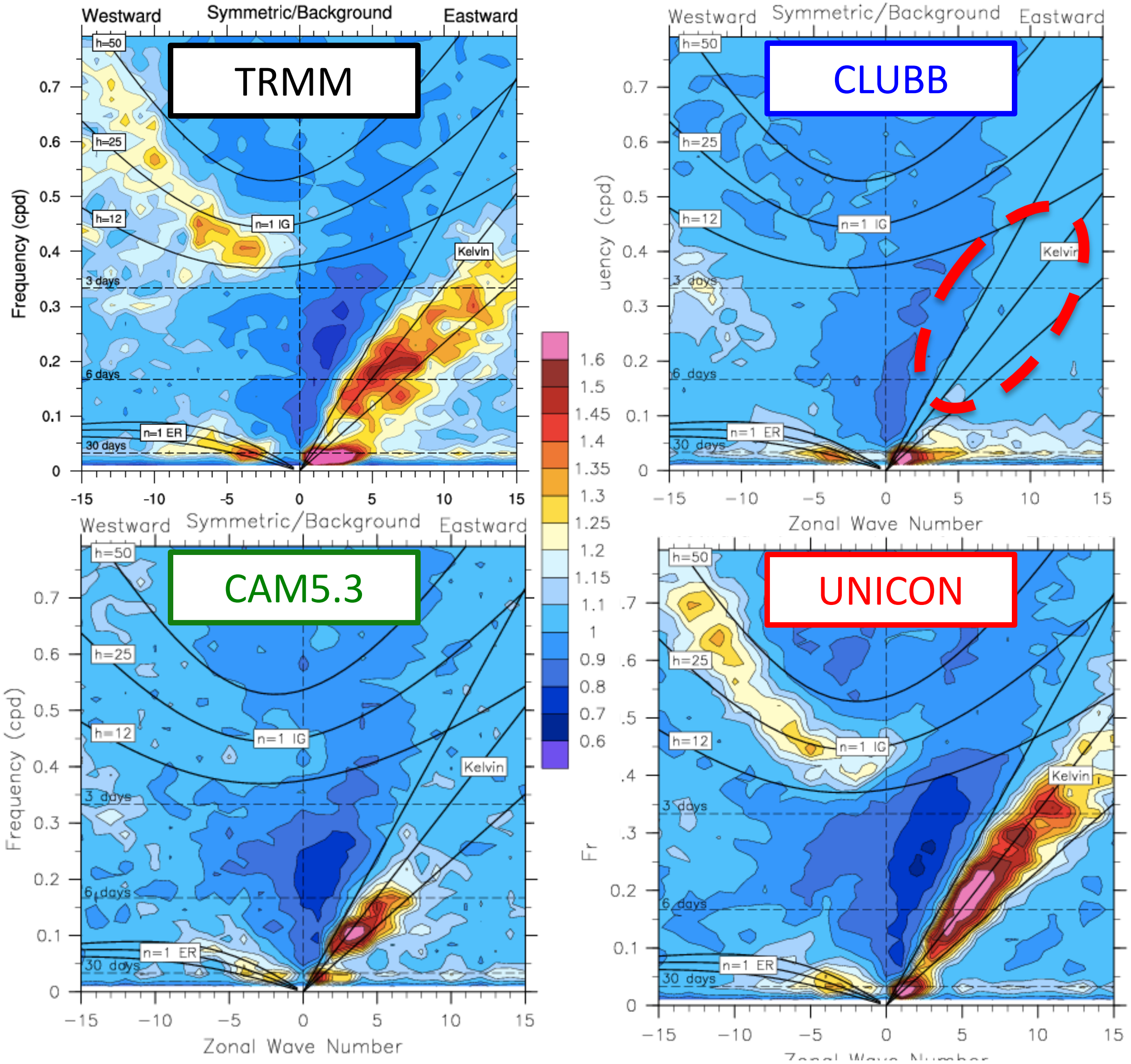


- Unifies moist and dry turbulence (except deep convection)
- Unifies microphysics
- High order closures (1 third order, 9 second order)
- Use two Gaussians to described the sub-grid multivariate PDF: $P=P(w,q_t,\theta_L)$

Clouds: Short-wave cloud forcing (AMIP)



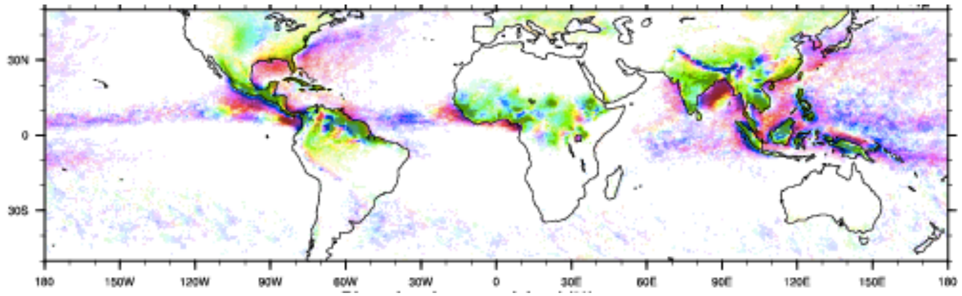
Precipitation: Equatorial Waves



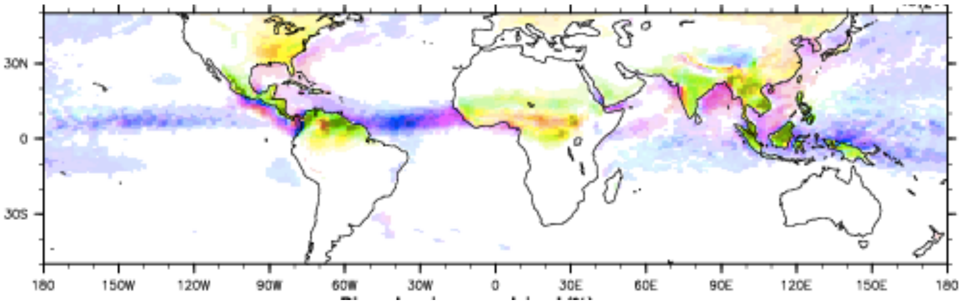
- Madden Julian Oscillation peak improved (still too weak)
- Kelvin wave too strong in UNICON
- Kelvin waves very damped in CLUBB rainfall
- UNICON captures westward gravity waves

Precipitation Diurnal Cycle: Better Phase

TRMM



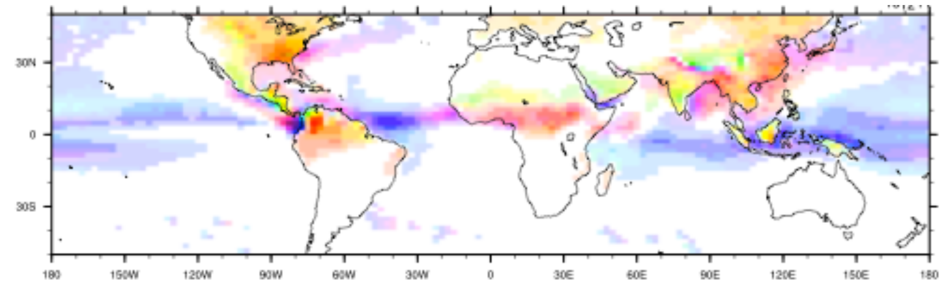
CLUBB

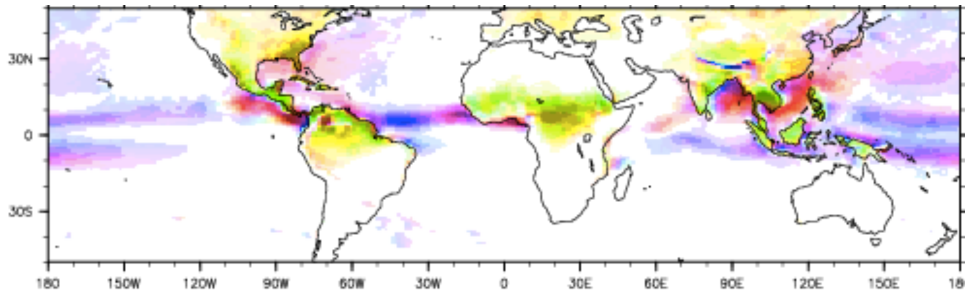


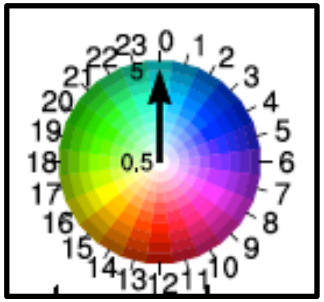
CAM5.3

JJA

UNICON

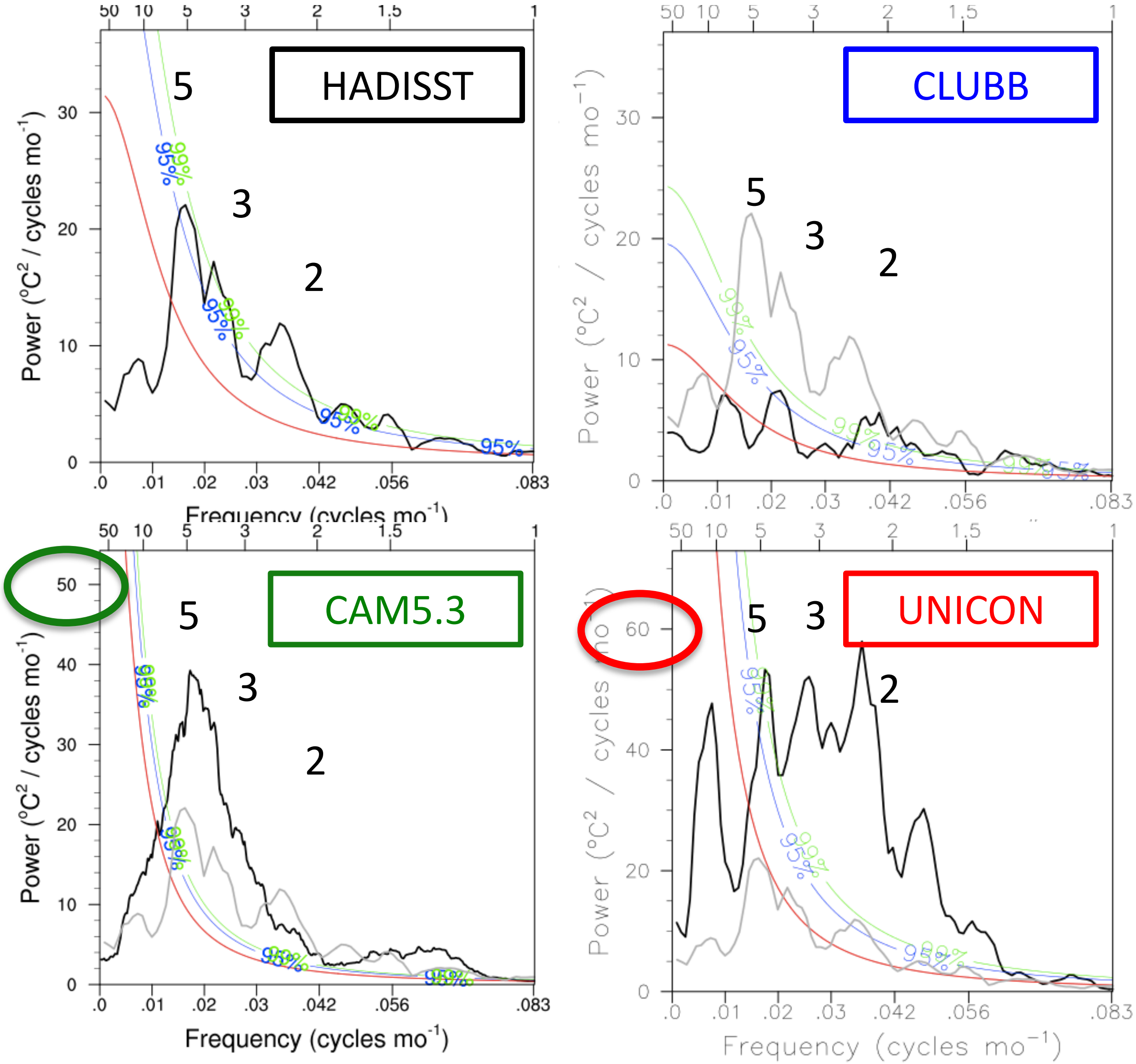






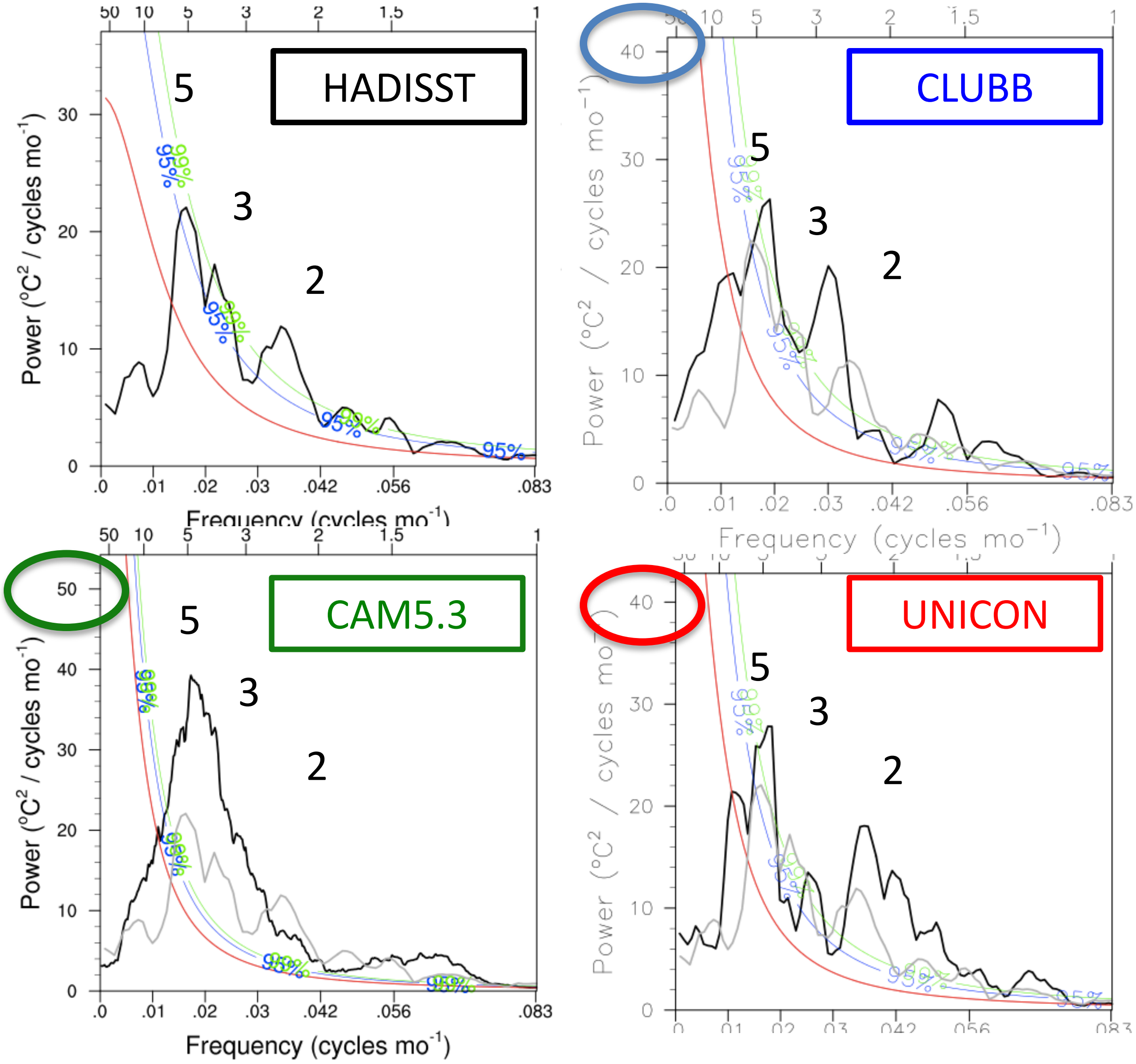
- Diurnal cycle peak remains too early
- Shifts from 12pm to 4pm over land (both)
- Shifts from 2am to 8am over ocean (UNICON better)
- US mid-western rainfall still deficient (at 1°)

ENSO: Cause for concern?



- ENSO not well simulated
- UNICON too strong amplitude at too wide a frequency
- CLUBB has very weak amplitude and no preferred frequency

ENSO: Updated



- ENSO not well simulated
- UNICON too strong amplitude at two wide a frequency
- CLUBB has very weak amplitude and no preferred frequency

Evaluating Against Observations

Does your model reflect reality?

Direct measurements

- **Satellite data products** (TRMM, MODIS, etc.)
- **In-situ measurements** (NOAA meteorological stations, buoys, tethersondes)

Reprocessed products

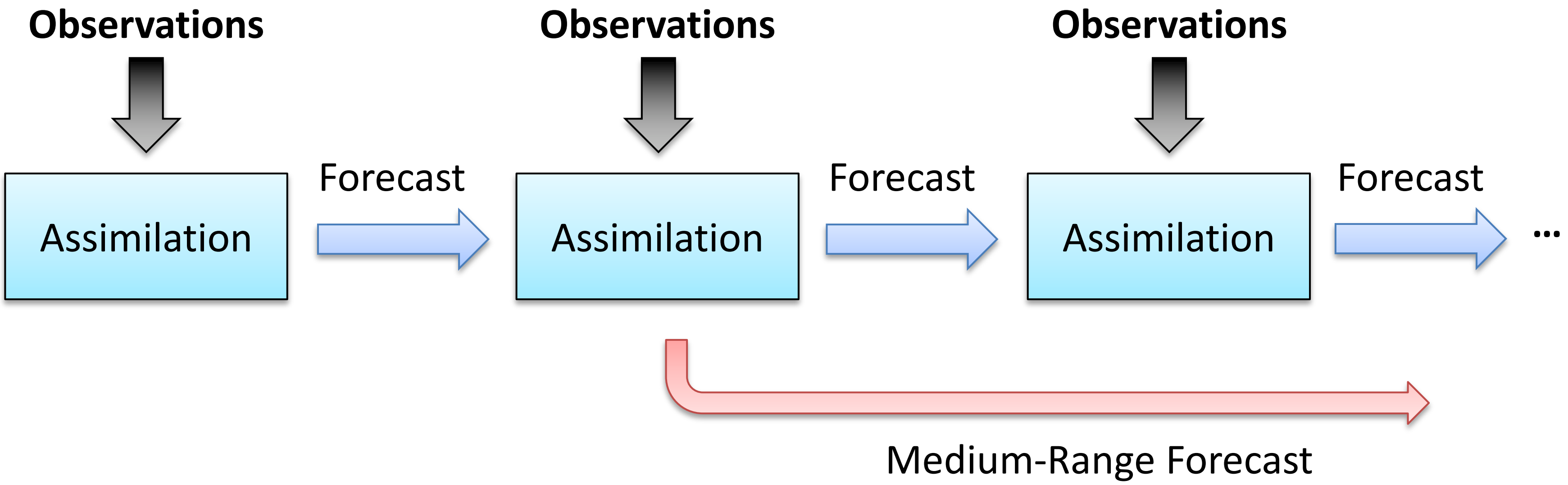
- **Gridded data products** (PRISM, CPC, etc.)
  - i.e. interpolated versions of direct measurements.
- **Reanalysis data** (CFSR, JRA-55, ERA-Interim, MERRA2)
  - Model runs which are initialized with data assimilation and/or “nudged” to be close to direct measurements.

Data Assimilation

Source: Kevin Trenberth

Data assimilation is a process for merging observations and model predictions to provide a superior state estimate.

Observations of state (temperature, wind, soil moisture, etc.) are blended with the state of the system as forecast by a model based on the previous set of observations. It provides a dynamically consistent estimate of the state of the system using a blend of past and current observations.



Data Assimilation

Source: Kevin Trenberth

Four dimensional data analysis (3D space + time) is used to assimilate observations that are sparse in space and staggered in time.

This requires complicated assimilation strategies (i.e. 4DVAR)

“Reanalysis has been applied to atmospheric data covering the past five decades. Although the resulting products have proven very useful, considerable effort is needed to ensure that reanalysis products are suitable for climate monitoring applications.”

- From Executive Summary of “The Second Report on the Adequacy of The Global Observing Systems for Climate in Support of the UNFCCC”

Atmospheric Reanalyses

Source: Kevin Trenberth

Reanalysis	Horiz. Res.	Dates	Vintage	Status
NCEP/NCAR R1	T62 (191km)	1948-now	1995	Ongoing
NCEP-DOE R2	T62 (191km)	1979-now	2001	Ongoing
CFSR (NCEP)	T382 (31km)	1979-now	2009	Ongoing
C20r (NOAA)	T62 (191km)	1875-2008	2009	Complete
ERA-40	T159 (75km)	1957-2002	2004	Done
ERA-Interim	T255 (46km)	1979-now	2009	Ongoing
JRA-25	T106 (112km)	1979-now	2006	Ongoing
JRA-55	T319 (37km)	1958-2012	2009	Underway
MERRA (NASA)	0.5° (55km)	1979-now	2009	Ongoing
MERRA2 (NASA)	0.5° (55km)	1980-now		

More Information

Climate Data Guide: https://climatedataguide.ucar.edu/

Reanalysis.org: http://reanalyses.org/