Diagnosing systematic numerical weather prediction model bias over the Antarctic from short-term forecast tendencies

Steven Cavallo[1]

ECMWF/WWRP Workshop: Model Uncertainty

12 April 2016

Reading, UK

[1] University of Oklahoma, School of Meteorology, Norman, OK

1. Background and method
   - Antarctic weather and climate prediction
   - Using ensemble data assimilation to diagnose sources of model bias in a limited area model

2. Application to Antarctic numerical weather prediction
   - Model and experimental setup

3. Results
   - A-DART experiments
   - Adjustment from initial conditions

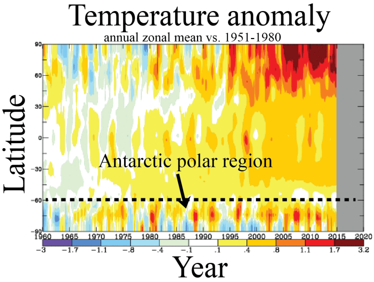
4. Summary and future work

Outline

1. Background and method
   - Antarctic weather and climate prediction
   - Using ensemble data assimilation to diagnose sources of model bias in a limited area model
2. Application to Antarctic numerical weather prediction
   - Model and experimental setup
3. Results
   - A-DART experiments
   - Adjustment from initial conditions
4. Summary and future work

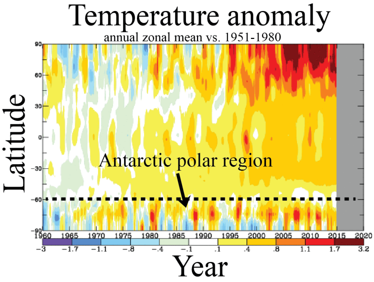
Antarctica: Why do we care?

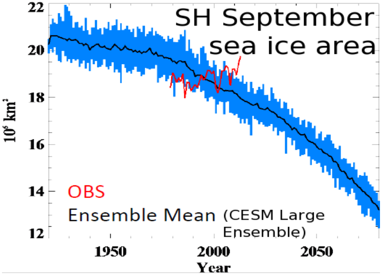
- Climate is changing more rapidly in polar regions than global average



Antarctica: Why do we care?

- Climate is changing more rapidly in polar regions than global average
- Ice mass budget is poorly understood:
  - ➔ Most of atmospheric warming is localized over the Western Antarctic Peninsula.
  - ➔ Ocean currents likely play a significant role in ice melt/freezing.
  - ➔ Moisture transport via extratropical cyclones = ???





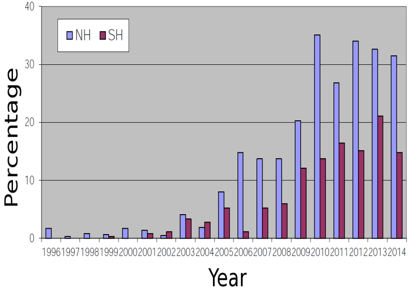
Holland and Landrum 2014

Antarctica: Why do we care?

Sparse population $\Rightarrow$ few permanent observation stations, relatively large errors in numerical models:

- More weight on numerical model parameterizations, and
- Less weight on observations.

Anomaly correlations greater that 0.9



From “Review of GFS forecast skills in 2014”, Fanglin Yang

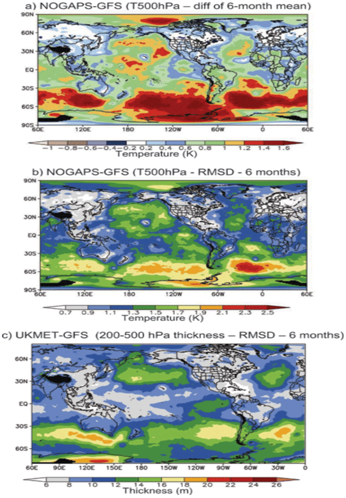
Antarctica: Why do we care?

Sparse population $\Rightarrow$ few permanent observation stations, relatively large errors in numerical models:

- More weight on numerical model parameterizations, and
- Less weight on observations.

Result: Atmospheric analyses exhibit high uncertainty $\Rightarrow$ very difficult to support scientific studies with:

- ➔ atmospheric reanalyses,
- ➔ numerical models of the atmosphere,
- ➔ coupled numerical models that depend on atmospheric forcings.



Langland et al. 2008

Atmospheric analyses

x^a	:	Model analysis
x^b	:	Background (short-term model forecasts)
x^o	:	Observations

$$x^a = x^b + K\left(x^o - \mathcal{H}(x^b)\right)$$

$$\underbrace{x^a - x^b}_{\text{Analysis increment}} = K\left(x^o - \mathcal{H}(x^b)\right)$$

where:

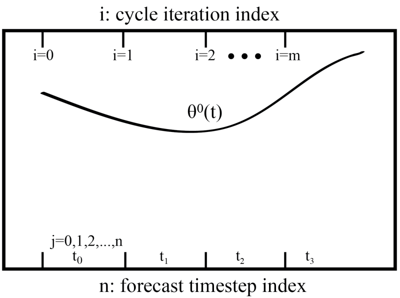
K	=	$BH^T\left[HBH^T + R\right]^{-1}$
$\mathcal{H}$	:	Function that maps state to observation space
B	:	Background error covariance
R	:	Observation error covariance
Analysis increment	:	The adjustment observations make to background model forecast; the impact of assimilating observations

Can we use data assimilation to diagnose the precise source of model error?

- Klinker and Sardeshmukh (1992) and Rodwell and Palmer (2007):
  - ➔ Mean analysis increment $\simeq$ - mean model forecast tendency when averaged over many data assimilation cycles.
  - ➔ For stationary systems, a non-zero analysis increment $\Rightarrow$ divergence of model state from observations via the model forecast tendencies.
  - ➔ Good initial analysis $\rightarrow$ model errors that develop in the early stages of a forecast simulation must be associated with errors in the model parameterizations of atmospheric processes (See also Wlliams and Brooks 2008; Xie et al. 2012; Williams et al. 2013).

Mean initial tendency and analysis (MITA) increment method

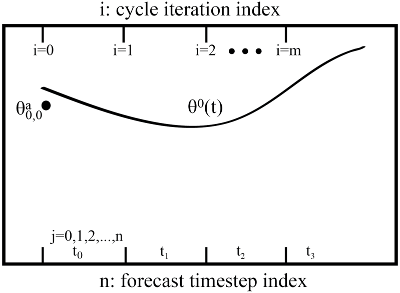
Schematic



$\theta^o(t)$: Observations of θ at time t

Mean initial tendency and analysis (MITA) increment method

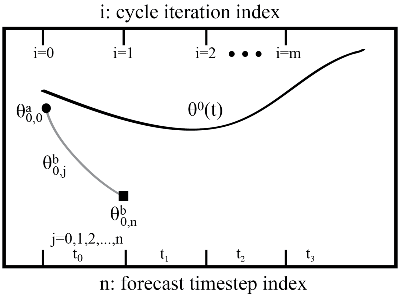
Schematic



$\theta^o(t)$:	Observations of θ at time t
$\theta^a_{0,0}$:	Analysis at forecast time step $j = 0$, data assim. (da) cycle $i = 0$

Mean initial tendency and analysis (MITA) increment method

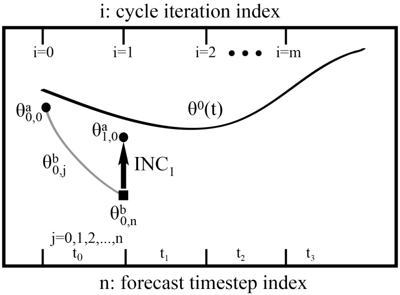
Schematic



$\theta^o(t)$:	Observations of θ at time t
$\theta^a_{0,0}$:	Analysis at forecast time step $j = 0$, data assim. (da) cycle $i = 0$
$\theta^b_{0,n}$:	Background forecast at forecast time step $j = n$, da cycle $i = 0$

Mean initial tendency and analysis (MITA) increment method

Schematic



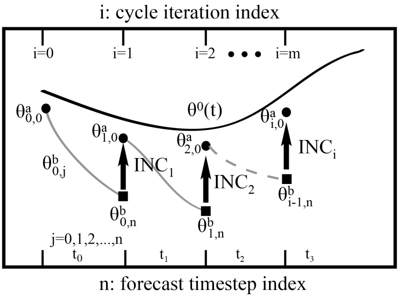
$\theta^{o}(t)$:	Observations of θ at time t
$\theta^{a}_{0,0}$:	Analysis at forecast time step $j = 0$, data assim. (da) cycle $i = 0$
$\theta^{b}_{0,n}$:	Background forecast at forecast time step $j = n$, da cycle $i = 0$

$$\theta^{a}_{1,0} = \theta^{b}_{0,n} + K\left(\theta^{o} - \mathcal{H}(\theta^{b}_{0,n})\right)$$

$$INC_1 = \theta^{a}_{1,0} - \theta^{b}_{0,n}$$

Mean initial tendency and analysis (MITA) increment method

Schematic



$\theta^o(t)$: Observations of x at time t

$\theta^a_{0,0}$: Analysis at forecast time step $j = 0$, da cycle $i = 0$

$\theta^b_{0,n}$: Background forecast at model time step $j = n$, da cycle $i = 0$

$$\boxed{INC_i = \theta^a_{i,0} - \theta^b_{i-1,n}} \qquad (1)$$

and the model forecast tendency can be written as:

$$\theta^b_{i,n} = \theta^a_{i,0} + \Delta t_i \frac{1}{n} \sum_{j=0}^{j=n} \dot{\theta}_{i,j}$$

$$\boxed{\Rightarrow \theta^b_{i,n} = \theta^a_{i,0} + \Delta t_i \left\langle \dot{\theta}_i \right\rangle} \qquad (2)$$

Mean initial tendency and analysis (MITA) increment method

Summing the analysis increment over m data assimilation cycles from (1):

$$\sum_{i=1}^{m} INC_i = \sum_{i=1}^{m-1} \left(\theta_{i,0}^{a} - \theta_{i-1,n}^{b} \right) + \theta_{m,0}^{a} - \theta_{m-1,n}^{b}. \tag{3}$$

Mean initial tendency and analysis (MITA) increment method

Summing the analysis increment over m data assimilation cycles from (1):

$$\sum_{i=1}^{m} INC_i = \sum_{i=1}^{m-1} \left(\theta^a_{i,0} - \theta^b_{i-1,n}\right) + \theta^a_{m,0} - \theta^b_{m-1,n}. \qquad (3)$$

After a little algebra, the above can be re-written as:

$$\sum_{i=1}^{m} INC_i = -\Delta t_i \sum_{i=1}^{m-1} \left\langle \dot{\theta}^b_i \right\rangle - \theta^b_{0,n} + \theta^a_{m,0}.$$

we can re-write in terms of just the analysis by substituting (2) into the above:

$$\theta^b_{0,n} = \theta^a_{0,0} + \Delta t_0 \left\langle \dot{\theta}^b_0 \right\rangle$$

to get

$$\sum_{i=1}^{m} INC_i = -\Delta t_i \sum_{i=1}^{m-1} \left\langle \dot{\theta}^b_i \right\rangle - \theta^a_{0,0} + \theta^a_{m,0} + \Delta t_0 \left\langle \dot{\theta}^b_0 \right\rangle$$

$$\boxed{\sum_{i=1}^{m} INC_i = -\Delta t \sum_{i=0}^{m-1} \left\langle \dot{\theta}^b_i \right\rangle + \theta^a_{m,0} - \theta^a_{0,0}.} \qquad (4)$$

Mean initial tendency and analysis (MITA) increment method

$$\boxed{\sum_{i=1}^{m} INC_i = -\Delta t \sum_{i=0}^{m-1} \left\langle \dot{\theta}_i^b \right\rangle + \theta_{m,0}^a - \theta_{0,0}^a .} \tag{5}$$

The last two terms of the R.H.S. of (5) is the ‘drift’ of the model’s climate state between the first and last data assimilation cycle.

Mean initial tendency and analysis (MITA) increment method

$$\boxed{\sum_{i=1}^{m} INC_i = -\Delta t \sum_{i=0}^{m-1} \left\langle \dot{\theta}_i^b \right\rangle + \theta_{m,0}^a - \theta_{0,0}^a.} \tag{5}$$

The last two terms of the R.H.S. of (5) is the 'drift' of the model's climate state between the first and last data assimilation cycle.

If the weather at the beginning and end of the data assimilation cycling is similar, then from (5):

$$\sum_{i=1}^{m} INC_i \simeq -\Delta t_i \sum_{i=0}^{m-1} \left\langle \dot{\theta}_i^b \right\rangle \tag{6}$$

$$\Rightarrow \overline{\mathrm{INC}} = -\Delta t_{da} \overline{\dot{\theta}_i^b} \tag{7}$$

when averaged over m data assimilation cycles where Δt_{da} is the time step between da cycles (usually 6 hours).

Other studies using the (MITA) method

- Kay et al. 2011: Diagnosed unrealistic cloud increases over the Arctic using Community Atmosphere Model (CAM).

Other studies using the (MITA) method

- Kay et al. 2011: Diagnosed unrealistic cloud increases over the Arctic using Community Atmosphere Model (CAM).
- Cloud-Associated Parameterizations Testbed: 'CAPT'
  - ➔ Deficiencies in climate models can not be identified simply by analyzing climate statistics (e.g. Phillips et al. 2004; Williamson et al. 2005; Williamson and Olson 2007; Hannay et al. 2009; Medeiros et al. 2012).
  - ➔ Must initialize forecasts from analyses produced with another model, and thus first few days of forecasts show inconsistencies between model and analysis instead of the true model bias.

Other studies using the (MITA) method

- Kay et al. 2011: Diagnosed unrealistic cloud increases over the Arctic using Community Atmosphere Model (CAM).
- Cloud-Associated Parameterizations Testbed: ‘CAPT’
  - ➔ Deficiencies in climate models can not be identified simply by analyzing climate statistics (e.g. Phillips et al. 2004; Williamson et al. 2005; Williamson and Olson 2007; Hannay et al. 2009; Medeiros et al. 2012).
  - ➔ Must initialize forecasts from analyses produced with another model, and thus first few days of forecasts show inconsistencies between model and analysis instead of the true model bias.
- Best when analysis used to initialize a forecast is produced by a data assimilation system using the **same model** (Rodwell and Palmer 2007)

Other studies using the (MITA) method

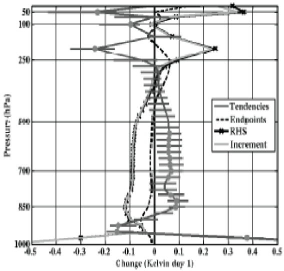
- Kay et al. 2011: Diagnosed unrealistic cloud increases over the Arctic using Community Atmosphere Model (CAM).
- Cloud-Associated Parameterizations Testbed: ‘CAPT’
  - ➔ Deficiencies in climate models can not be identified simply by analyzing climate statistics (e.g. Phillips et al. 2004; Williamson et al. 2005; Williamson and Olson 2007; Hannay et al. 2009; Medeiros et al. 2012).
  - ➔ Must initialize forecasts from analyses produced with another model, and thus first few days of forecasts show inconsistencies between model and analysis instead of the true model bias.
- Best when analysis used to initialize a forecast is produced by a data assimilation system using the **same model** (Rodwell and Palmer 2007)
- Although MITA has been applied in global models and by operational centers (i.e. ECMWF; Rodwell and Jung 2008) and Met Office Unified Model (Martin et al. 2010), it **has never been applied to a limited area model**.

Other studies using the (MITA) method

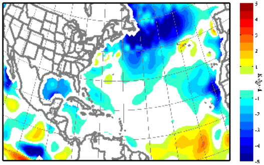
Cavallo, Berner, and Snyder (2016): Used EAKF with Advanced Hurricane WRF model for 2010 Atlantic hurricane season.

Warm surface bias found from large PBL heating, but was a result of erroneous SSTs.

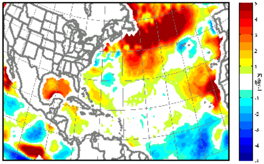
Warm mid-tropospheric bias found from deep convection in tropics.



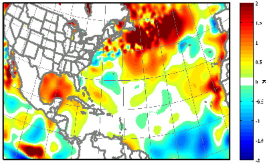
INC



$\overline{\dot{\theta}}$



Sea surface temp. (WRF - GFS)



Hypothesis

Hypothesis: The source(s) of model bias can be diagnosed to the precise physical parameterization and location(s) using the Weather Research and Forecasting (WRF) model forecast tendencies when using data assimilation.

Hypothesis

Hypothesis: The source(s) of model bias can be diagnosed to the precise physical parameterization and location(s) using the Weather Research and Forecasting (WRF) model forecast tendencies when using data assimilation.

- The analysis increment, alone, does not give the *exact source* of the model bias.
- Forecast tendencies ($\dot{\theta}$) are computed in the WRF integration:

$$\dot{\theta} = \dot{\theta}_{dynamics} + \dot{\theta}_{physics}$$

Hypothesis

Hypothesis: The source(s) of model bias can be diagnosed to the precise physical parameterization and location(s) using the Weather Research and Forecasting (WRF) model forecast tendencies when using data assimilation.

- The analysis increment, alone, does not give the *exact source* of the model bias.
- Forecast tendencies ($\dot{\theta}$) are computed in the WRF integration:

$$
\begin{aligned}
\dot{\theta} &= \dot{\theta}_{dynamics} + \dot{\theta}_{physics} \\
&= \dot{\theta}_{dynamics} + \left[\dot{\theta}_{radiation} + \dot{\theta}_{pbl} + \dot{\theta}_{cumulus} + \dot{\theta}_{microphysics}\right]
\end{aligned}
$$

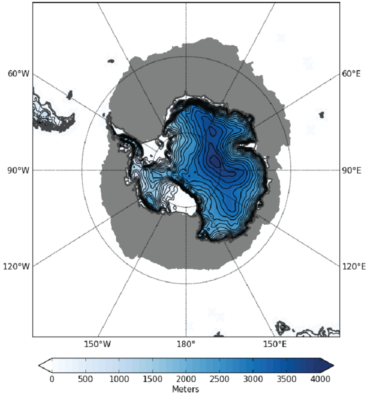
- The above budget can be **completely** closed using WRF
- If the largest adjustment is expected in the first few time steps, do we only need a fraction of the time steps to diagnose the model error?

Outline

Antarctic DART (A-DART)

- Model = Antarctic Mesoscale Prediction System (AMPS; Powers et al. 2012)

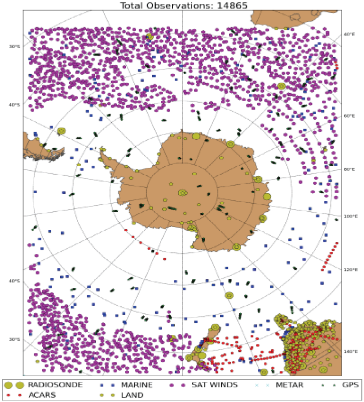
Domain and topography



Antarctic DART (A-DART)

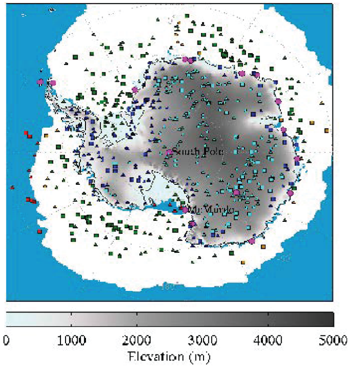
- Model = Antarctic Mesoscale Prediction System (AMPS; Powers et al. 2012)
- Data assimilation = Data Assimilation Research Testbed (DART; Anderson et al. 2001), Ensemble Kalman Filter (EnKF) using setup similar to Cavallo et al. 2012
- Assimilates surface and marine stations, radiosondes, ACARS, GPS, cloud-track wind.

"Conventional" observations assimilated



Antarctic DART (A-DART)

- Cycled continuously from 21 September 00 UTC - 21 October 2010
- Coincides with Concordiasi intensive observation period (IOP) (Rabier et al. 2010)
- One ensemble member selected for our analysis (here member 35)
- MITA evaluation period: 00 UTC 21 September - 18 UTC 30 September

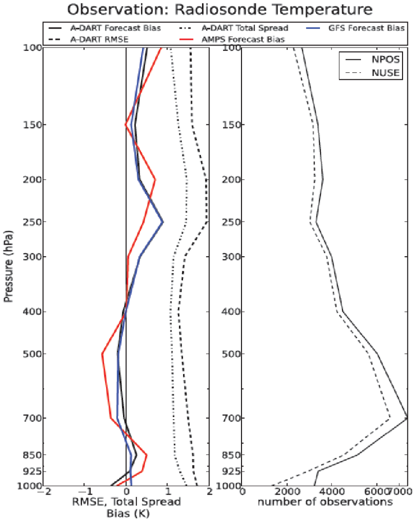


Terrain (grays), Oct. 2010 mean sea ice extent (white), radiosonde sites (pink), and Concordiasi dropsondes over the high plateau (cyan), continental low elevation (blue), total sea ice (green), partial sea ice (brown), and open water (red). Triangles (squares) are daytime (nighttime) soundings.

Summary of A-DART

	AMPS	A-DART
Dynamical core	WRF (ARW) v. 3.0.1.1 with polar modifications $\Delta t = 144$ s	
Grid(s)	$\Delta x = 45{,}15{,}5$ (x3),1.33 km $Nz = 44$	$\Delta x =$45 km $Nz = 44$
Init. times	00,12 UTC daily	00,06,12,18 UTC daily
Data assimilation	GFS “cold start”, then 3D-VAR Deterministic	EnKF “warm start” 96 ensemble members
	SST and sea ice updates, fractional sea ice	
Physics	Longwave: RRTM, Shortwave = Goddard PBL: Mellor-Yamada-Janjic Surface layer: Monin-Obukhov Land surface: NOAH Microphysics: WSM 5-class Cumulus: Kain-Fritsch	

Antarctic DART (A-DART)



Bias: Forecast - Observations (radiosonde)

Blue = GFS

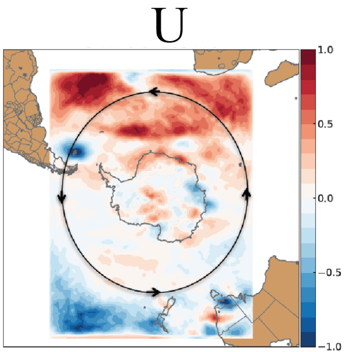
Red = AMPS

Black = A-DART

- Warm upper-level bias
- Cold mid-troposphere bias
- Warm boundary layer bias

Antarctic DART (A-DART)

200 hPa Analysis Increment

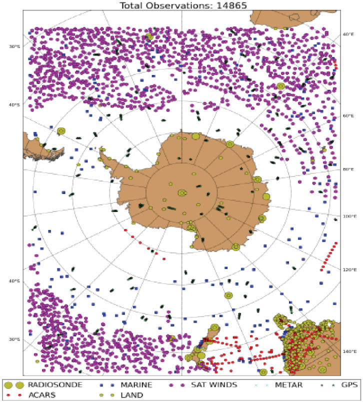


Observations are **increasing** the circumpolar flow.

⇒ The large-scale upper-level circulation in the **model** is **too weak**.

Immediate corrections in A-DART: Observations

Observations assimilated: “Conventional”

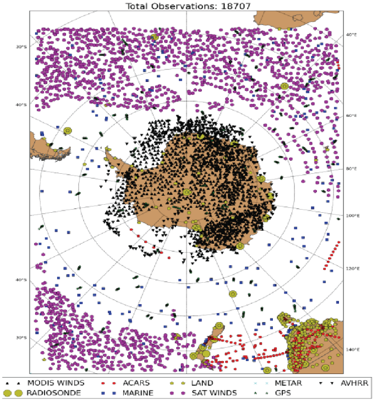


Warm upper-level bias ⇒ polar vortex too weak in A-DART

Too weak of an equator-to-pole temperature gradient.

Immediate corrections in A-DART: Observations

Observations assimilated: “Conventional” + MODIS polar orbiting atmospheric motion vectors

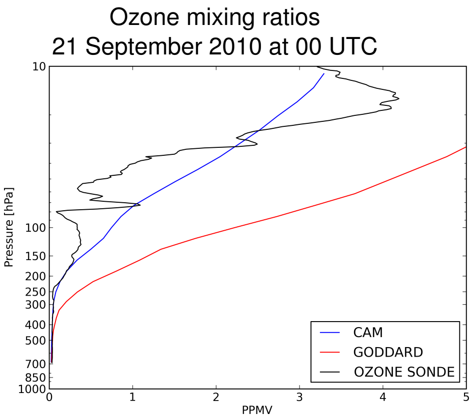


Warm upper-level bias ⇒ polar vortex too weak in A-DART

Too weak of an equator-to-pole temperature gradient.

Do polar orbiting data correct the temperature gradient?

Immediate corrections in A-DART: Physics



Warm upper-level bias ⇒ polar vortex too weak in A-DART

Too weak of an equator-to-pole temperature gradient.

Default ozone concentrations are too high in WRF?

⇒ Consistent with too much warming in stratosphere over pole.

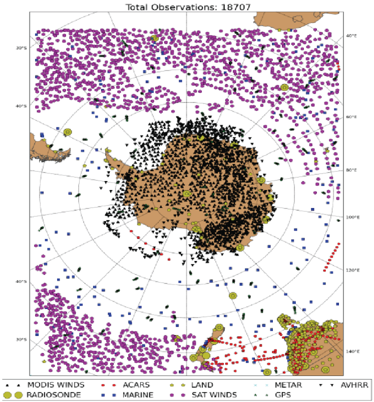
MITA experiments begin from here to determine exactly where the *remaining* model bias originates.

Experiments

Control configuration =
A-DART, conventional
observations

1. Control + polar orbiting wind obs. + CAM ozone
2. Control + AIRS retrievals

Observations assimilated

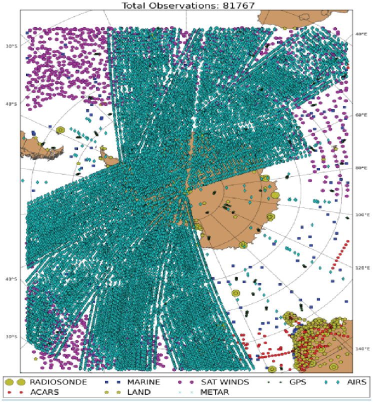


Experiments

Control configuration = A-DART, conventional observations

1. Control + polar orbiting wind obs. + CAM ozone
2. Control + AIRS retrievals

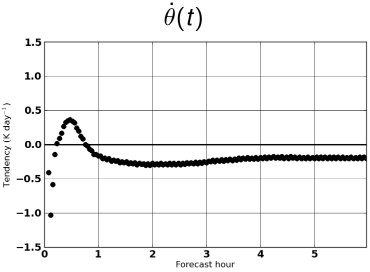
Observations assimilated

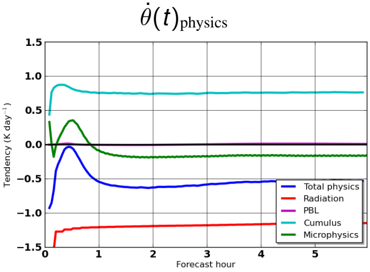


Outline

Analysis increment: What is an appropriate evaluation window?

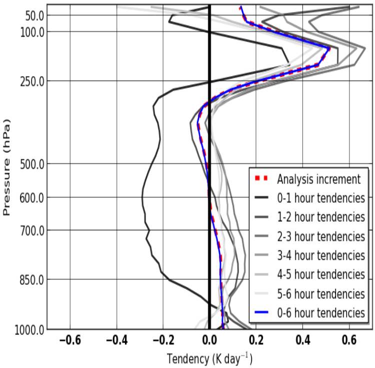
Forecast tendencies at 850 hPa for each Δt





Analysis increment: What is an appropriate evaluation window?

$$\sum_{i=1}^{m} INC_i = -\Delta t \sum_{i=0}^{m-1} \left\langle \dot{\theta}_i^b \right\rangle + \theta_{m,0}^a - \theta_{0,0}^a$$



Analysis increment reflects the mean forecast tendencies during the 6-h DA cycling period.

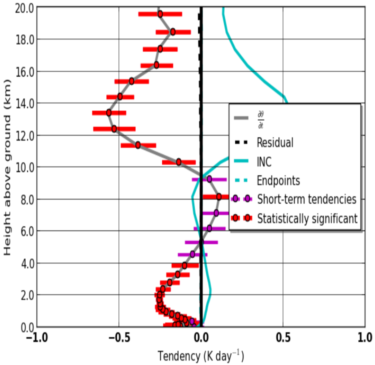
The forecast tendencies of the first hour **do not** represent the mean model bias of the 6-h DA cycling period.

If we would like to analyze the source of model bias during DA cycling, then any subset of the 1-h+ forecast tendencies are sufficient.

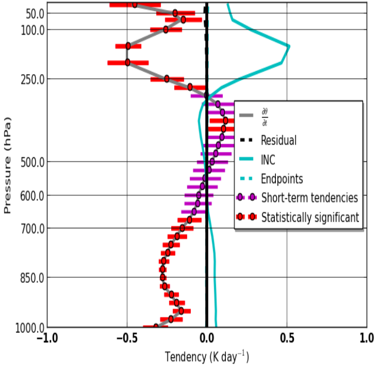
Tendency decomposition: Hours 1-2

$$\text{Model bias} = -\frac{\overline{\text{INC}}}{\Delta t_{da}} = \overline{\dot{\theta}} + \text{Endpoints} + \text{Residual}$$

Entire domain: vs. height AGL



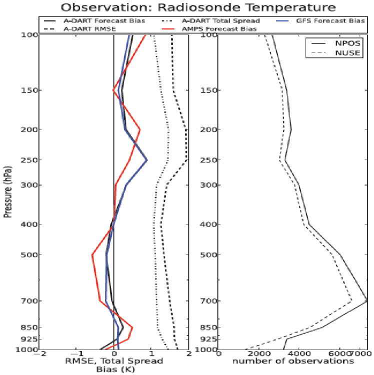
Entire domain: vs. pressure



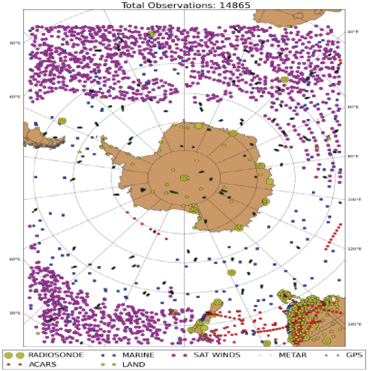
Why does this not match the expected bias?

Radiosondes are preferentially located $\sim 60^\circ$S latitude

Model bias
with respect to radiosondes

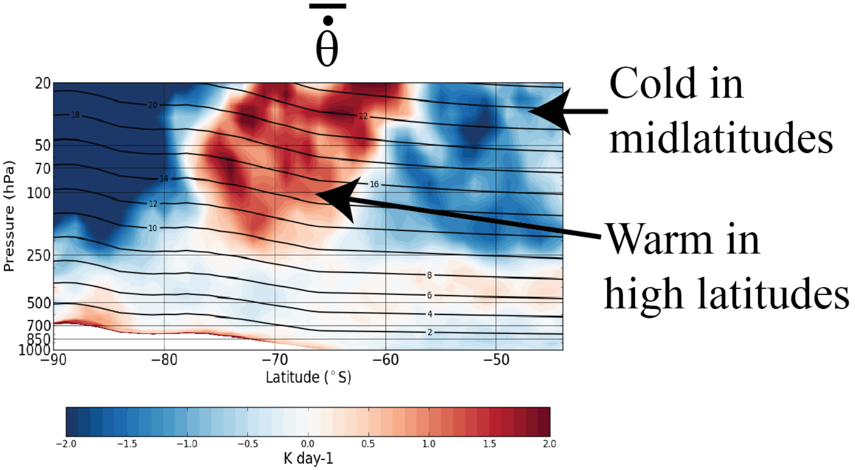


Thick yellow circles = radiosonde locations



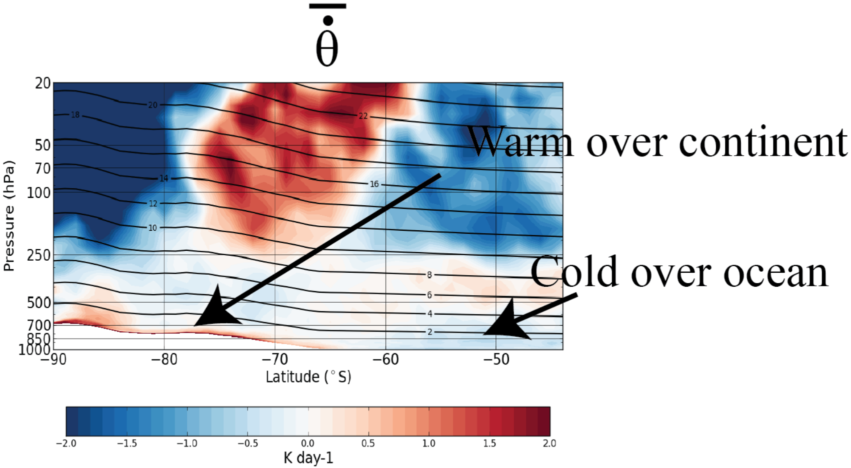
Why does this not match the expected bias?

Upper-level bias



Why does this not match the expected bias?

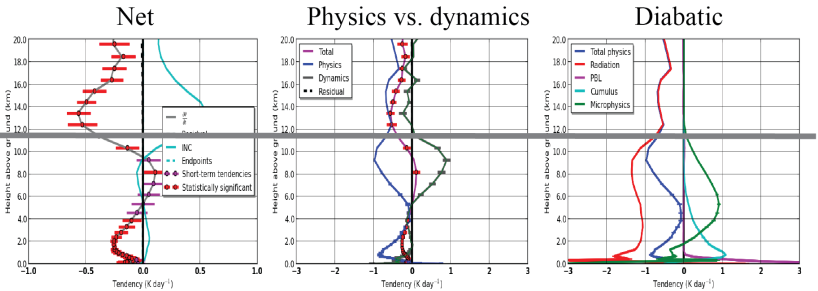
Boundary layer bias



Tendency decomposition

$$\dot{\theta} = \dot{\theta}_{\text{physics}} + \dot{\theta}_{\text{dynamics}} + \text{Residual}$$
$$\dot{\theta}_{\text{physics}} = \dot{\theta}_{\text{radiation}} + \dot{\theta}_{\text{microphysics}} + \dot{\theta}_{\text{cumulus}} + \dot{\theta}_{\text{PBL}}$$

Upper-level bias: 11.4 km above ground level



Tendency decomposition

In all horizontal slices to be shown subsequently, fields are masked to include only those grid points where:

- - sgn $\left(\overline{\mathrm{INC}}_{i,j}\right)$ = sgn($\bar{\dot{\theta}}$)

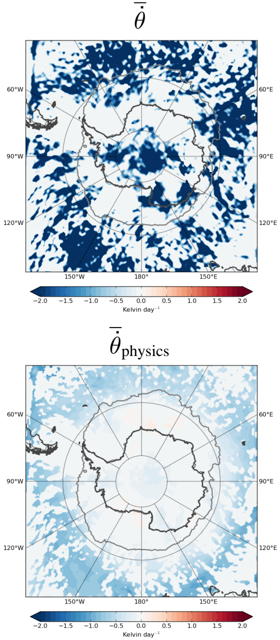
  ➔ Includes only locations where observations are pulling model state in opposite direction.

- $\bar{\dot{\theta}}_{i,j \text{ (any component)}} = \begin{cases} \bar{\dot{\theta}}_{i,j \text{ (any component)}} & \text{if } \operatorname{sgn}(\bar{\dot{\theta}}_{i,j}) = \operatorname{sgn}(\bar{\dot{\theta}}) \\ 0 & \text{otherwise} \end{cases}$

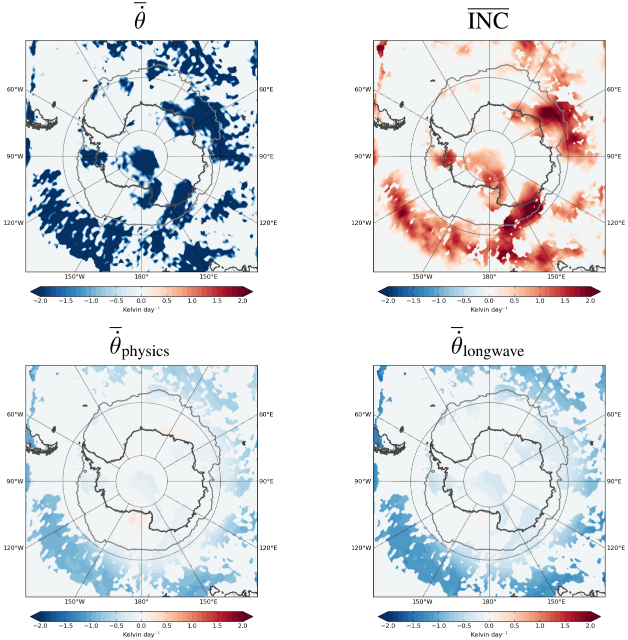
  ➔ If $\bar{\dot{\theta}} < 0$, all other components masked to exclude locations where $\bar{\dot{\theta}} > 0$

  ➔ **Includes only locations where the tendency component is pulling the model state in the same direction as the total model bias**.

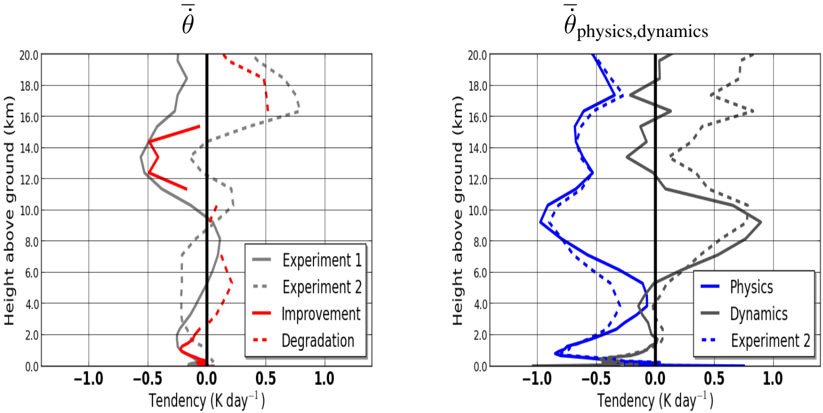
(Experiment 1) 11.4 km above ground level



(Experiment 2) 11.4 km above ground level



Experiment 1 vs. Experiment 2



Upper-level improvement from 11-15 km

Lower-level improvement from 0-2 km

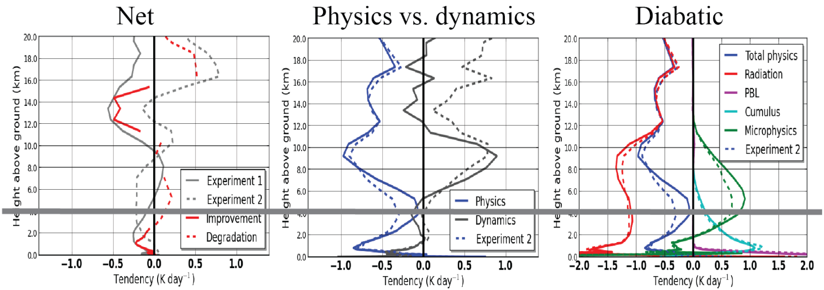
Degradation from 2-10 km. Why?

New mid-tropospheric bias?

Why is there a mid-tropospheric cold bias? Let's simplify by choosing a level in Experiment 2 where:

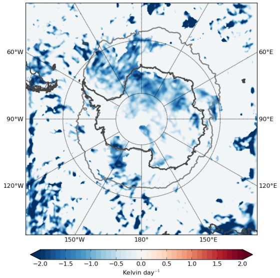
- Net tendencies are **strongly negative** and
- Mean dynamics tendencies ~ 0 K day^{-1}

$\Rightarrow$ 4-km above ground level

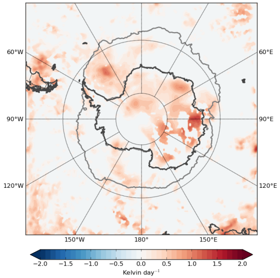


Experiment 2: 4-km above ground level

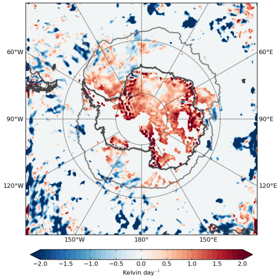
$\overline{\dot{\theta}}$



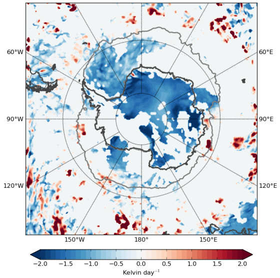
$\overline{\mathrm{INC}}$



$\overline{\dot{\theta}}_{\mathrm{dynamics}}$

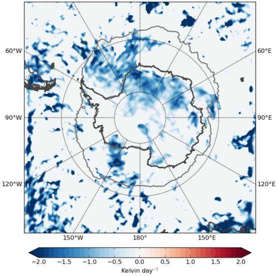


$\overline{\dot{\theta}}_{\mathrm{physics}}$

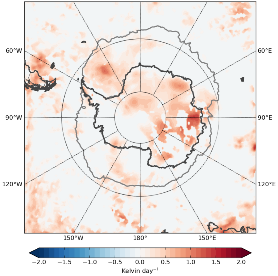


Experiment 2: 4-km above ground level

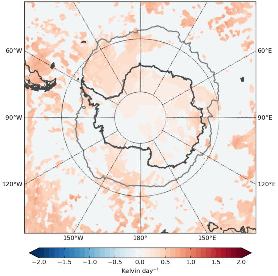
$\overline{\dot{\theta}}$



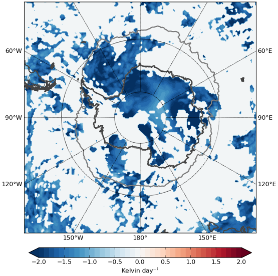
$\overline{\mathrm{INC}}$



$\overline{\dot{\theta}}_{\mathrm{shortwave}}$

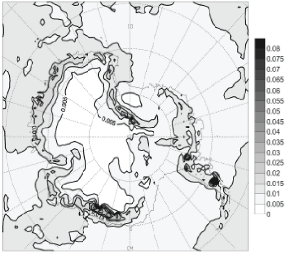


$\overline{\dot{\theta}}_{\mathrm{longwave}}$

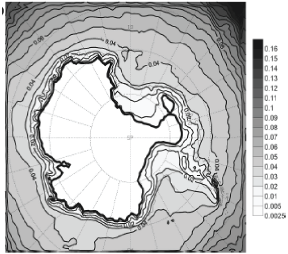


Cloud bias?

Cloud ice



Cloud liquid water



<u>Fogt and Bromwich (2008)</u>:

AMPS model

Vertically integrated q_c an q_i

6 months averages (DJF 2003-2004, 2004-2005)

"Deficiencies in capturing low-level cloudiness over cold ice surfaces primarily related to insufficient supercooled liquid water produced by the microphysics scheme"

Cloud bias?

- Observations show that clouds can maintain liquid water for temperatures $\rightarrow$ -34°C (e.g., Hobbs and Rango 1998; Intrieri et al. 2002; Shupe and Intrieri 2004; Zuidema et al. 2005)

- Cloud phase not represented well in NWP (e.g., Sandvik et al., 2007; Tjernström et al., 2008; Klein et al., 2009; Solomon et al. 2009; Karlsson and Svensson, 2011; Barton et al., 2012; Birch et al., 2012; de Boer et al., 2012)

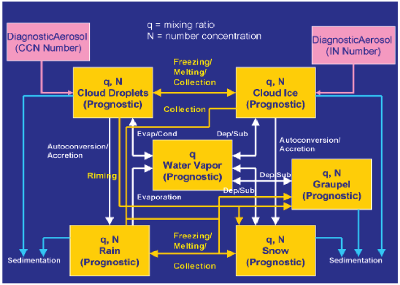
- High uncertainty in phase partitioning due to dependence on number, shape, and size of ice crystals (e.g., Chen and Lamb, 1994; Sheridan et al., 2009; Ervens et al., 2011; Hoose and Möhler, 2012)

- Particle size distributions are constant in *single-moment* microphysics, with specifications based on midlatitude weather systems (Morrison 2011).

New Experiment

Control configuration = A-DART, conventional observations

1. Control + polar orbiting wind obs. + CAM ozone
2. Control + AIRS retrievals
3. Control + AIRS retrievals + Double-moment microphysics



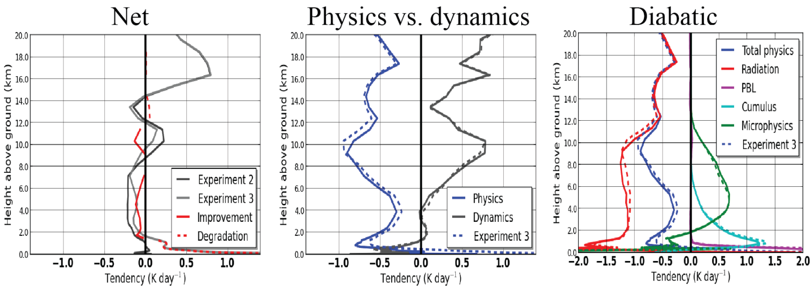
Prognostic equations for:

q_x = Mixing ratio of x

N = Number concentration

Experiment 2 vs. Experiment 3

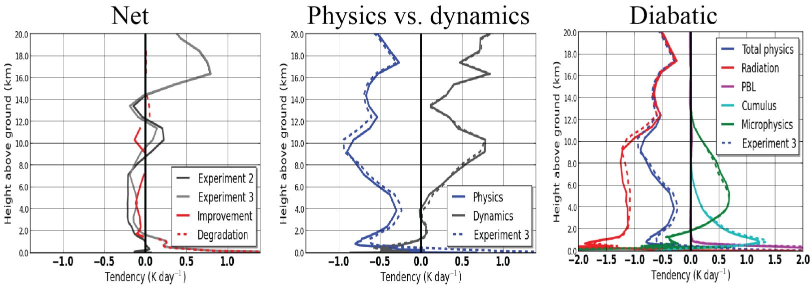
Cool bias in 2-8 km layer is alleviated (somewhat) with double moment microphysics. Where is this change occurring?



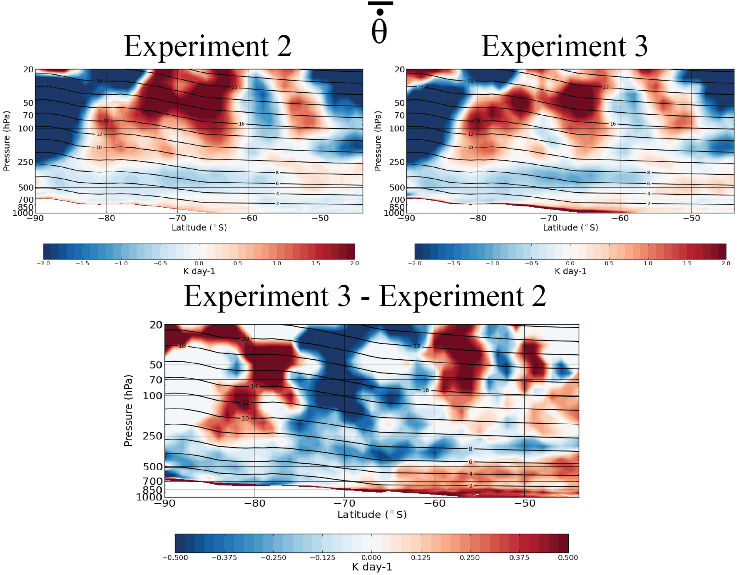
Experiment 2 vs. Experiment 3

Cool bias in 2-8 km layer is alleviated (somewhat) with double moment microphysics. Where is this change occurring?

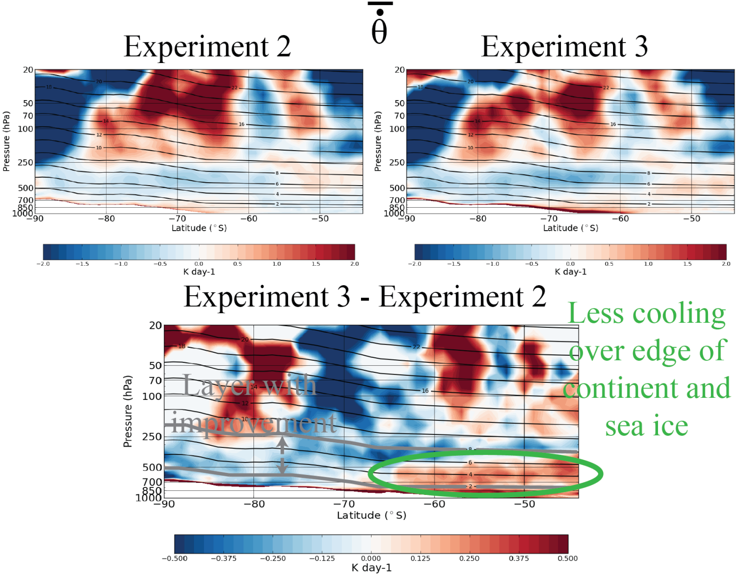
- Following plots are zonally averaged tendencies as a function of pressure and height above ground level (AGL)



Exp. 2 vs. Exp. 3: Zonal average cross sections

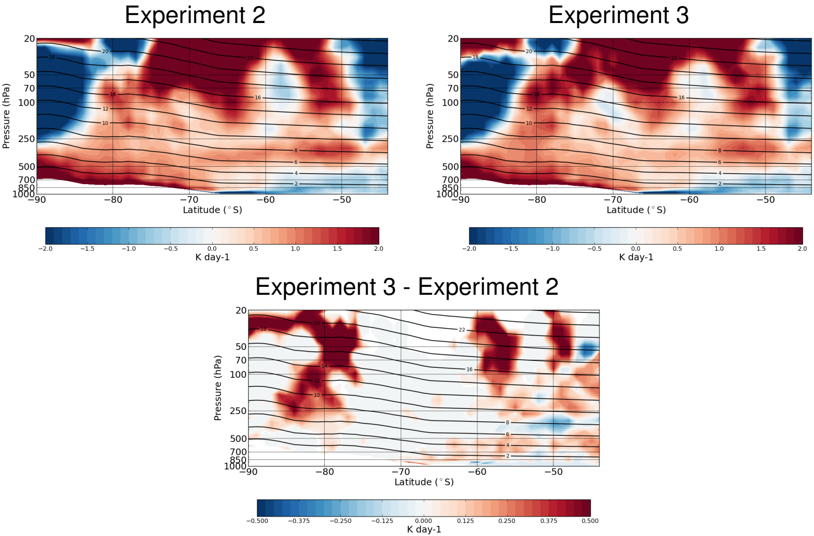


Exp. 2 vs. Exp. 3: Zonal average cross sections



Exp. 2 vs. Exp. 3: Zonal average cross sections

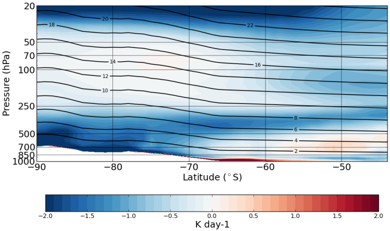
$$\overline{\dot{\theta}}_{\text{dynamics}}$$



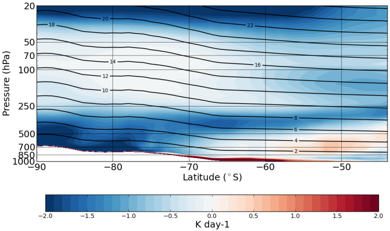
Exp. 2 vs. Exp. 3: Zonal average cross sections

$$\overline{\dot{\theta}}_{\text{physics}}$$

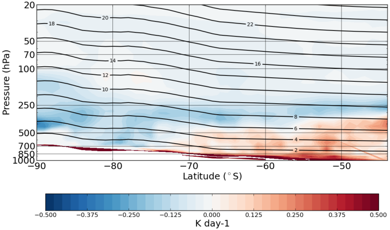
Experiment 2



Experiment 3



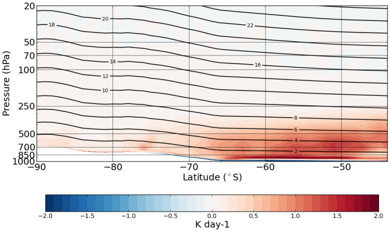
Experiment 3 - Experiment 2



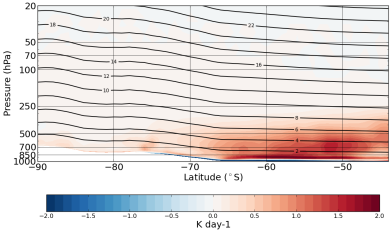
Exp. 2 vs. Exp. 3: Zonal average cross sections

$\overline{\dot{\theta}}_{\text{latent heating}}$

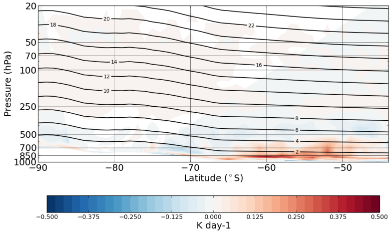
Experiment 2



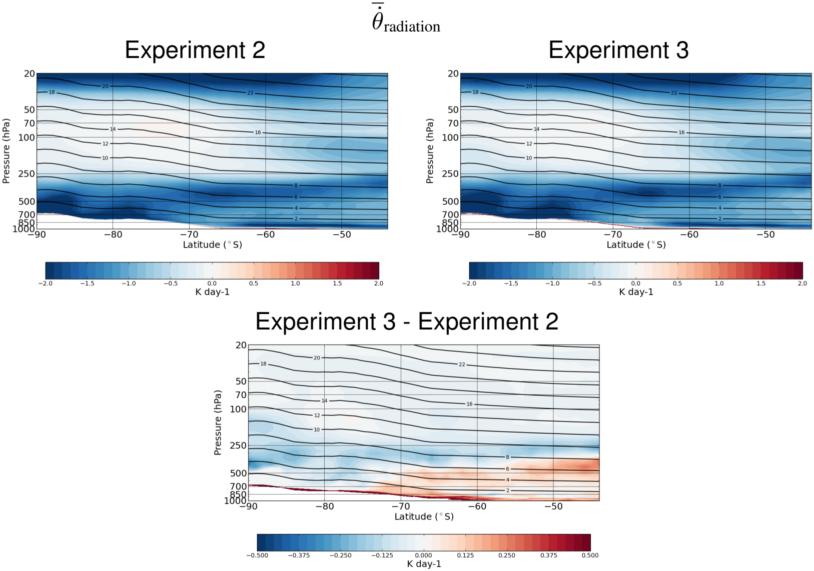
Experiment 3



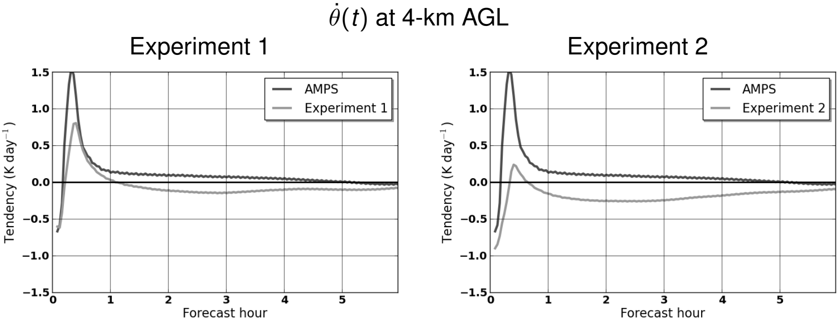
Experiment 3 - Experiment 2

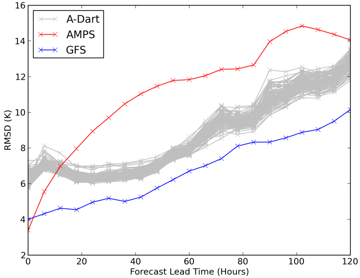


Exp. 2 vs. Exp. 3: Zonal average cross sections

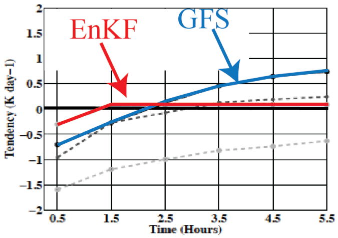


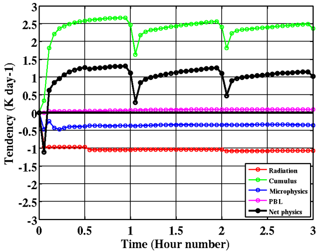
Adjustment from initial conditions





Adjustment from initial conditions





Cavallo, Berner, and Snyder (2016):

EAKF with Advanced Hurricane WRF (Cavallo et al. 2012)

EAKF warm starts: Adjustment ∼3-5 model time steps (less than 20 minutes)

GFS cold starts: Tendencies equilibrate at ∼ 3 days

The number of time steps before model error begins to dominate initial condition error may vary between modeling configurations

Outline

Mean initial tendency and analysis (MITA) increment method: Summary

- MITA increment method is:
  - ➔ a diagnostic using data assimilation to “narrow down” source of model bias to better direct hypothesis testing.
  - ➔ applied here with a limited area numerical weather model over the Antarctic region.
- Forecast tendencies converged to the bias reflected by analysis increment by $\sim$1 simulation hour.
  - ➔ Only a small subset of forecast tendencies are necessary to represent the systematic bias.
- Significant cold model bias in lower troposphere and lower stratosphere.
  - ➔ Upper-level large-scale circulation too weak in model.
  - ➔ Adding AIRS retrievals alleviated upper-level circulation bias.
  - ➔ Lower tropospheric cold bias sensitive to microphysics. Cloud phase?