Mesoscale Predictability

Dale Durran[1], P. Alex Reinecke[2], James Doyle[2]

[1]University of Washington, Seattle, WA
[2]Naval Research Laboratory, Monterey, CA

July 13, 2011

Basics

Mesoscale: Pertaining to atmospheric phenomena having horizontal scales ranging from a few kilometers to several hundred kilometers.

- Thunderstorms, squall lines
- Fronts, precipitation bands in tropical and extratropical cyclones
- Mountain waves, downslope winds, sea breezes

Basics

Mesoscale: Pertaining to atmospheric phenomena having horizontal scales ranging from a few kilometers to several hundred kilometers.

- Thunderstorms, squall lines
- Fronts, precipitation bands in tropical and extratropical cyclones
- Mountain waves, downslope winds, sea breezes

Predictability: The extent to which future states of a system may be predicted based on knowledge of current and past states of the system.

The Issue

At UW we run 69-hour forecasts with the WRF model (initialized from GFS analyses) twice daily nested down to 4-km spatial resolution.

The Issue

At UW we run 69-hour forecasts with the WRF model (initialized from GFS analyses) twice daily nested down to 4-km spatial resolution.

Argue that it is ridiculous to expect forecast skill in features with scales of 16 km ($4\Delta x$) at hour 69.

The Issue

At UW we run 69-hour forecasts with the WRF model (initialized from GFS analyses) twice daily nested down to 4-km spatial resolution.

Argue that it is ridiculous to expect forecast skill in features with scales of 16 km ($4\Delta x$) at hour 69.

Argue that there is still hope for forecast skill at hour 69 in features with scales of 16 km.

The Issue

At UW we run 69-hour forecasts with the WRF model (initialized from GFS analyses) twice daily nested down to 4-km spatial resolution.

Argue that it is ridiculous to expect forecast skill in features with scales of 16 km ($4\Delta x$) at hour 69.

Argue that there is still hope for forecast skill at hour 69 in features with scales of 16 km.

Are there other reasons for using fine resolution besides trying to forecast small-scale features that actually verify?

The Lorenz Viewpoint

Errors migrate upscale in turbulent flows with a -5/3 energy spectrum.

The Lorenz Viewpoint

Errors migrate upscale in turbulent flows with a -5/3 energy spectrum.

- Predictability at a given scale decreases as the scale and the "eddy turnover time" decreases.

The Lorenz Viewpoint

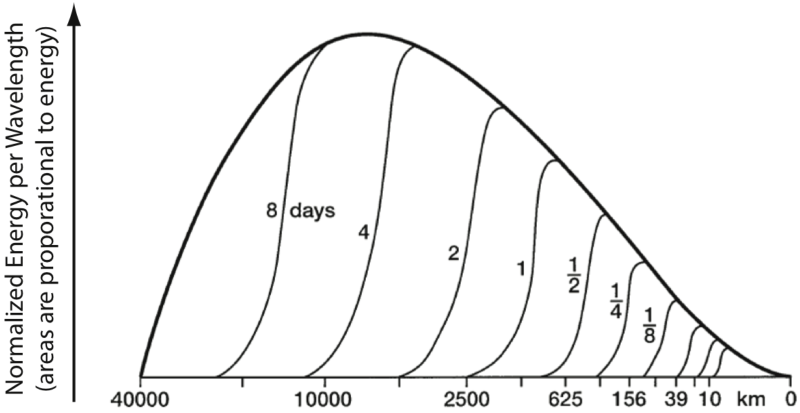
Errors migrate upscale in turbulent flows with a -5/3 energy spectrum.

- Predictability at a given scale decreases as the scale and the "eddy turnover time" decreases.
- Predictability times for motions with horizontal scale of 1,000 km estimated as 24 times that for motions with scales of 10 km

Lorenz, 1969: The predictability of a flow which possesses many scales of motion. *Tellus*, **21,** 289-307.

Time for Errors to Propagate Upscale

1 hour to 20 km, 1 day to 1,250 km



The Anthes Viewpoint

Estimates of mesoscale predictability from classical turbulence theory are too pessimistic.

The Anthes Viewpoint

Estimates of mesoscale predictability from classical turbulence theory are too pessimistic.

- Coherent structures in fluids may resist turbulent decay, e.g., supercell thunderstorms.

The Anthes Viewpoint

Estimates of mesoscale predictability from classical turbulence theory are too pessimistic.

- Coherent structures in fluids may resist turbulent decay, e.g., supercell thunderstorms.
- Physical forcing at the earth's surface, such as mountains, may contribute to extended predictability.

The Anthes Viewpoint

Estimates of mesoscale predictability from classical turbulence theory are too pessimistic.

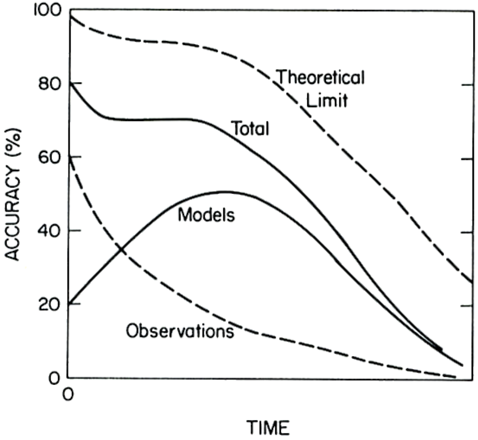
- Coherent structures in fluids may resist turbulent decay, e.g., supercell thunderstorms.
- Physical forcing at the earth's surface, such as mountains, may contribute to extended predictability.
- Mesoscale phenomena, such has fronts, can evolve from purely large-scale intial conditions.

Anthes, et al., 1985: Predictability of mesoscale atmospheric motions. *Adv. Geophysics,* **28B,** 159-202.

Anthes' Update

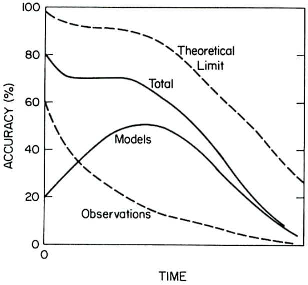
July 7, 2011 UCAR magazine

Mesoscale Magic



(Anthes 1984: Predictability of mesoscale meteorological phenomena. In *Predictabilty of Fluid Motions.*)

Influence of the Lateral Boundaries



Enhanced predictability in mesoscale forecast experiments arises because the same lateral boundary data were imposed in all simulations.

(Vukicevic and Errico 1990, *Mon. Wea. Rev.*)

Recent Evidence for the Lorenz Viewpoint

Rapid growth of precipitation errors in “surprise" snowstorm of 24-25 January 2000.

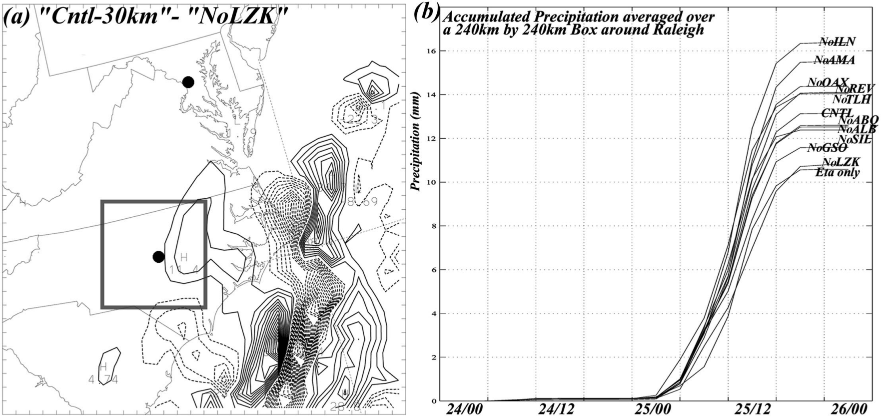


FIG. 15. (a) The 36-h accumulated precipitation difference (every 4 mm) between Cntl-30km and NoLZK. (b) Time evolution of the accumulated precipitation (mm) averaged over a 240-km × 240 km box around Raleigh, NC, from each individual sounding experiment, Cntl-30km and EtaOnly. The location of the box is shown in (a).

(Zhang et al., 2002: *Mon. Wea. Rev.*)

Effects of Moist Convection on Mesoscale Predictability

Zhang et al., 2003: *JAS*—on the lack of predictability of the 24-25 January 2000 snowstorm.

“The errors in the convective-scale motions subsequently influence the development of meso- and larger-scale forecast aspects such as the position of the surface low and the distribution of precipitation, thus providing evidence that growth of initial errors from convective scales places an intrinsic limit on the predictability of larger scales."

Roadmap

We will look at the sensitivity to initial conditions in two specific contexts:

- Downslope windstorms
- Distinguishing between rain and snow in the Puget-Sound lowlands

Roadmap

We will look at the sensitivity to initial conditions in two specific contexts:

- Downslope windstorms
- Distinguishing between rain and snow in the Puget-Sound lowlands

We will ignore:

- Other important phenomena (e.g., convection)
- Measures of forecast skill

Does Topography Help?

"Topographic forcing increases the predictability of atmospheric flows"
(Vukicevic and Errico 1990, *Mon. Wea. Rev.*)

Does Topography Help?

"Topographic forcing increases the predictability of atmospheric flows" (Vukicevic and Errico 1990, *Mon. Wea. Rev.*)

- "... *synoptic-scale* perturbations are most sensitive to the change of topography..."
- Cases involved lee-cyclongenesis
- Simulations used $\Delta x = 120$ km

Does Topography Help?

What happens at smaller scales?

Does Topography Help?

What happens at smaller scales?

> “Most of the region’s [Pacific NW] mesoscale circulations are created by the interaction of the synoptic-scale flow with the mesoscale terrain; thus, mesoscale predictability is substantially controlled by longer-lived synoptic predictability." (Mass et al., 2002. *BAMS*)

Does Topography Help?

What happens at smaller scales?

> "Most of the region's [Pacific NW] mesoscale circulations are created by the interaction of the synoptic-scale flow with the mesoscale terrain; thus, mesoscale predictability is substantially controlled by longer-lived synoptic predictability." (Mass et al., 2002. *BAMS*)

The large-scale gives the mesoscale extended predictability.

Downslope Wind Predictions–1975

Multi-layer linear mountain-wave model using coarse resolution large-scale forecasts.

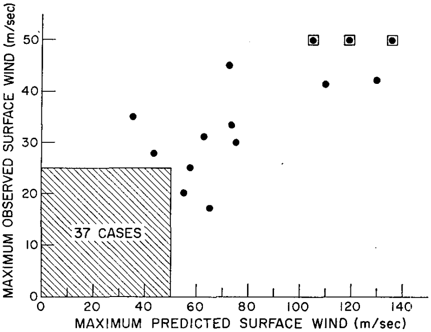
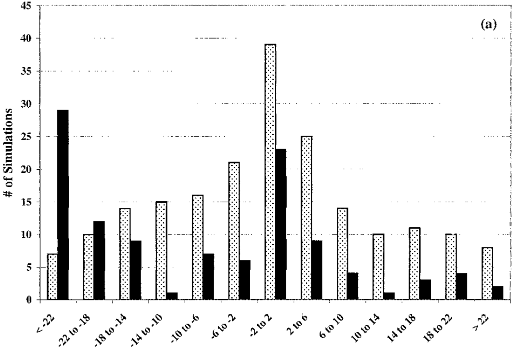


FIG. 16. Comparison of the maximum predicted surface winds with the maximum recorded by the Southern Hills anemometer in the interval 2–5 h after the soundings were taken. A box around a data point indicates that the recorder pegged at 100 mph.

(Klemp and Lilly, 1975: J. Atmos. Sci)

Downslope Wind Predictions–2000

Nonlinear 2D mountain-wave model using Eta-model forecasts.



Obs-Forecast: black/stippled bars for cases with/without mean-state critical level

(Nance and Colman, 1995: J. Atmos. Sci)

2D Sensitivity Study

- Ensemble of perturbed January 11, 1972 soundings, 20 members.
- Large spread near the regime boundary between mountain waves and wave breaking.

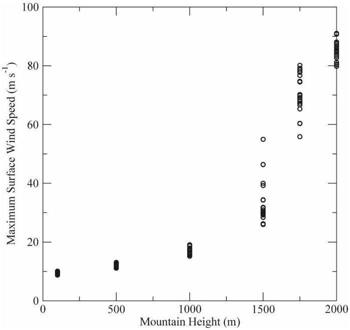


FIG. 5. Maximum leeside wind speed (m s^{-1}) at the lowest model level (100 m) for each ensemble member as a function of the mountain height (m) at the 4-h simulation time.

2D Sensitivity Study

- Ensemble of perturbed January 11, 1972 soundings, 20 members.
- Large spread near the regime boundary between mountain waves and wave breaking.

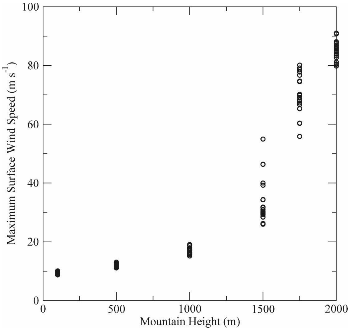


FIG. 5. Maximum leeside wind speed (m s^{-1}) at the lowest model level (100 m) for each ensemble member as a function of the mountain height (m) at the 4-h simulation time.

Doyle and Reynolds, 2008, *Mon. Wea. Rev.*

How predictable are downslope winds?

How predictable are downslope winds?

- Cases from T-REX in the Sierra Nevada.

How predictable are downslope winds?

- Cases from T-REX in the Sierra Nevada.
- 70-member ensemble forecasts using the COAMPS model

How predictable are downslope winds?

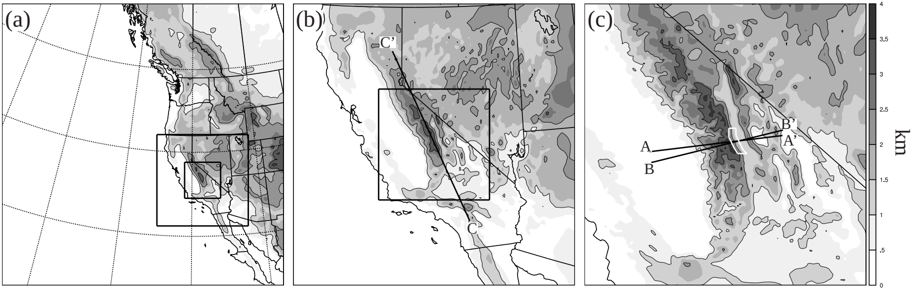
- Cases from T-REX in the Sierra Nevada.
- 70-member ensemble forecasts using the COAMPS model
- Ensemble members generated using a ensemble Kalman filter.

How predictable are downslope winds?

- Cases from T-REX in the Sierra Nevada.
- 70-member ensemble forecasts using the COAMPS model
- Ensemble members generated using a ensemble Kalman filter.
- Two types of downslope wind events considered
  - Induced by wave breaking
  - Induced by strong low-level static stability with weak stability aloft

Triply Nested Domain for COAMPS

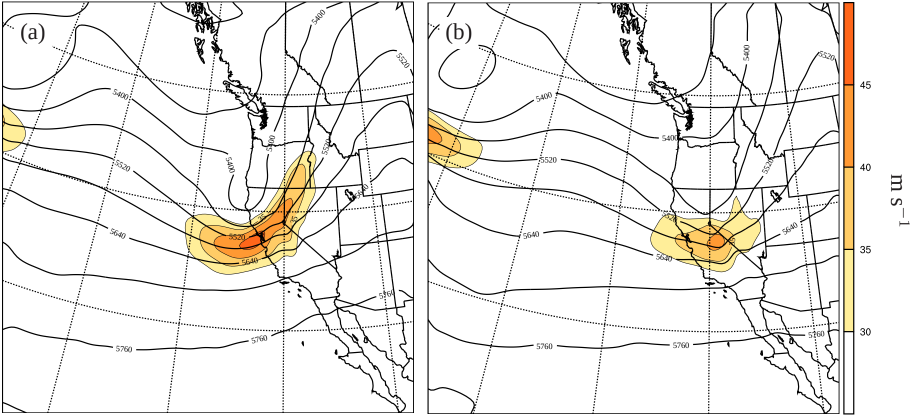
Owen's Valley lee-slope winds are averaged between 0 and 350 m AGL in the region outlined in white in panel c.



27 km / 9 km / 3 km

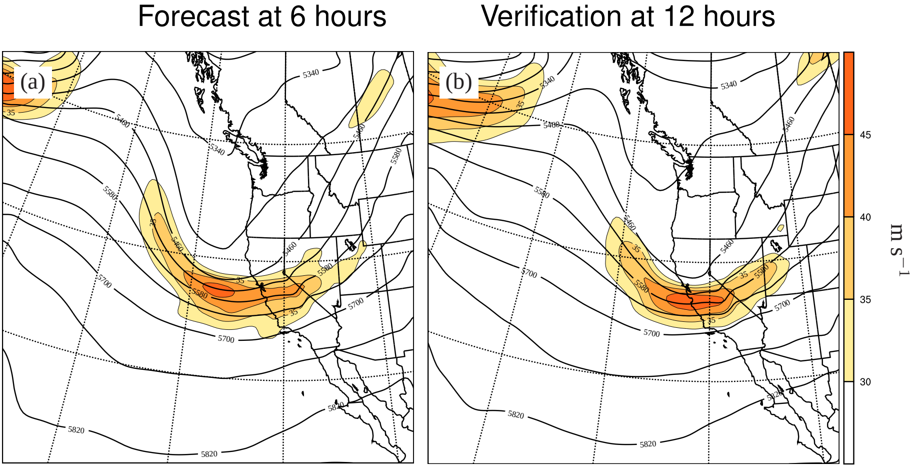
500-hPa Flow for the Wave-Breaking Case

Initialization   Verification 6 hours later



High winds at 00 UTC March 26, 2006 (IOP 6)

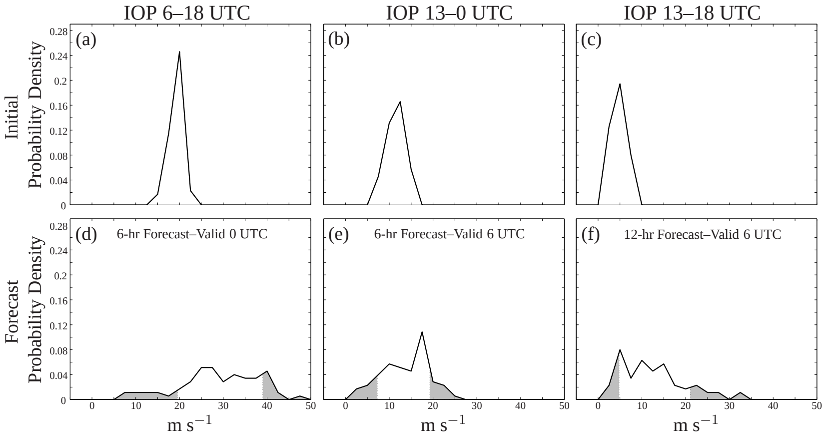
500-hPa Flow for the Case with Strong Low-Level Stability



High winds at 06 UTC April 17, 2006 (IOP 13)

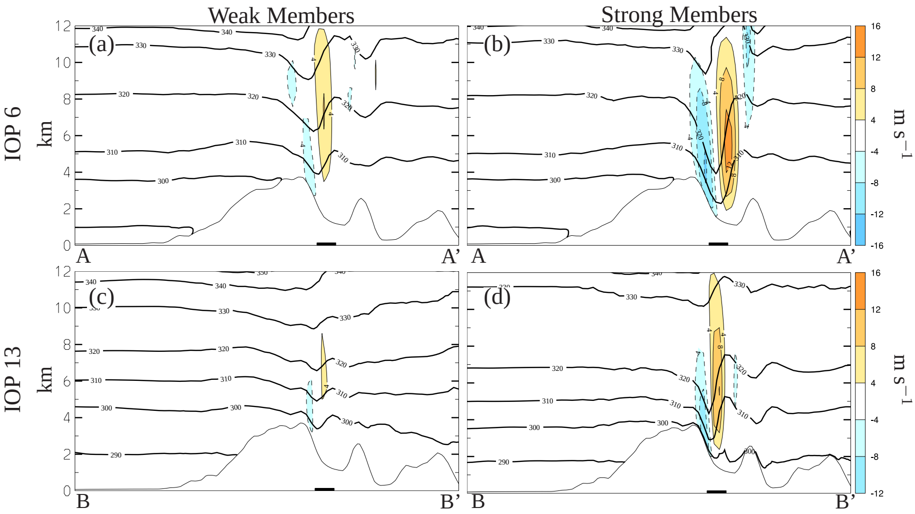
Ensemble Distributions of Owens-Valley Surface Winds

Breaking | Layered | Layered



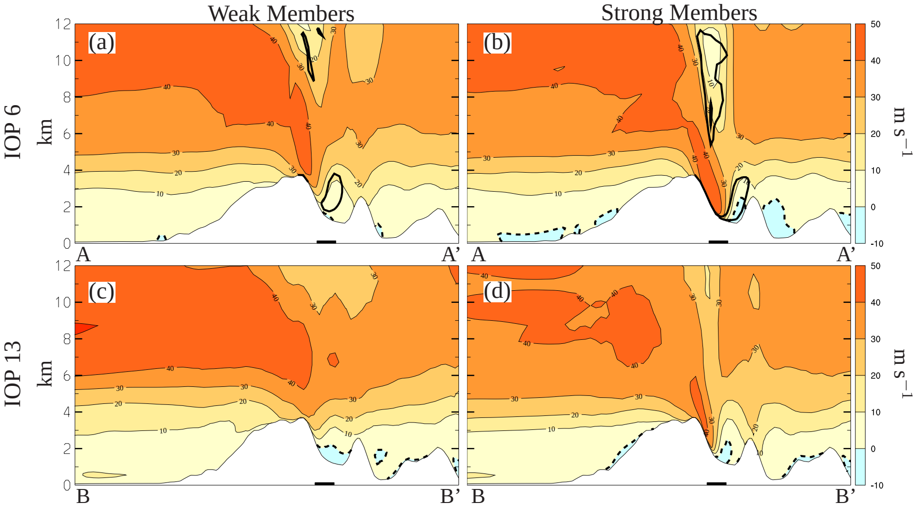
Shading shows the weakest and strongest 10-member subsets

Contrasting the Weakest and Strongest 10 Events



Vertical velocity (colors) and isentropes of potential temperature

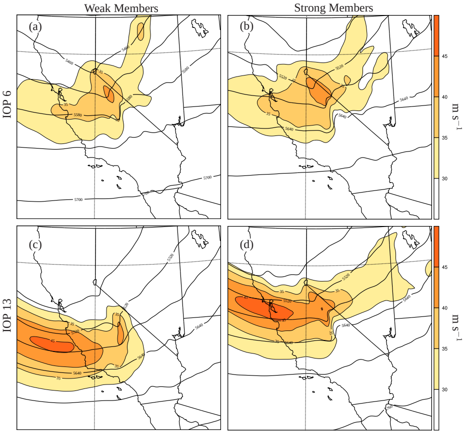
Contrasting the Weakest and Strongest 10 Events



Zonal velocity (colors) and turbulent kinetic energy (heavy contours)

Contrasts in the 500-hPa Flow

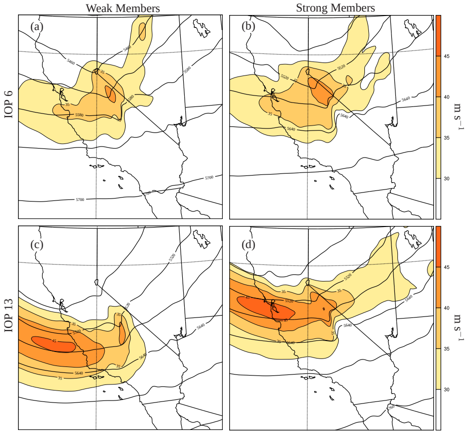
500 hPa wind speed (contoured) and geopotential heights



- At time of high winds

Contrasts in the 500-hPa Flow

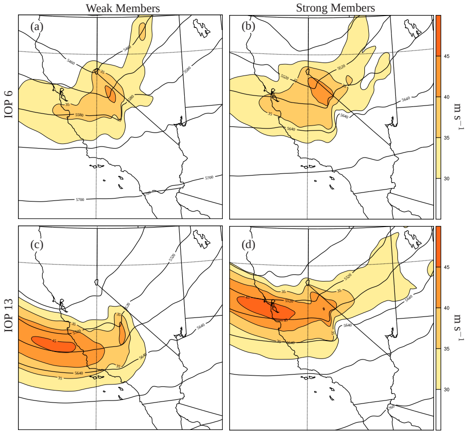
500 hPa wind speed (contoured) and geopotential heights



- At time of high winds
- Upper: IOP 6: almost no difference

Contrasts in the 500-hPa Flow

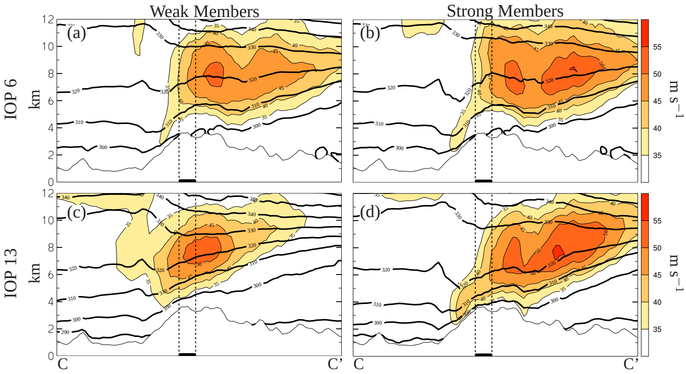
500 hPa wind speed (contoured) and geopotential heights



- At time of high winds
- Upper: IOP 6: almost no difference
- Lower: IOP 13: Jet axis is further south in the weak events

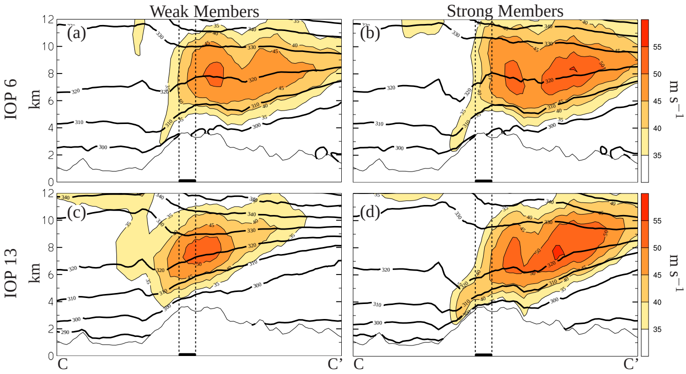
Contrasts in Vertical Section Above Ridge Crest

Total wind speed and isentropes looking west at time of maximum winds



Contrasts in Vertical Section Above Ridge Crest

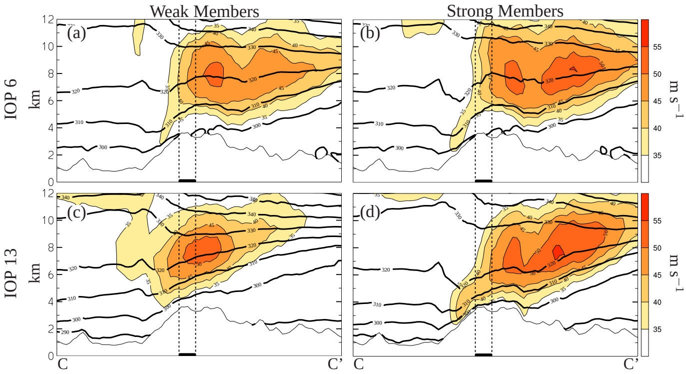
Total wind speed and isentropes looking west at time of maximum winds



- Upper: IOP 6: Little difference upstream of Owens Valley

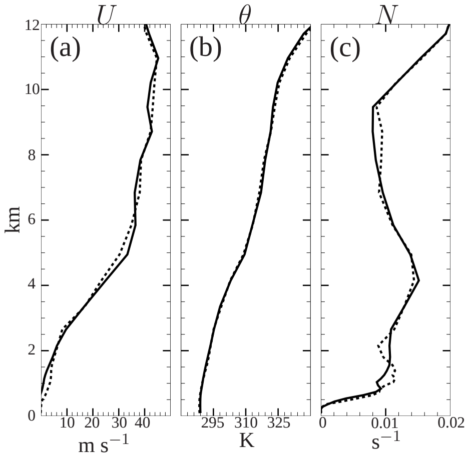
Contrasts in Vertical Section Above Ridge Crest

Total wind speed and isentropes looking west at time of maximum winds



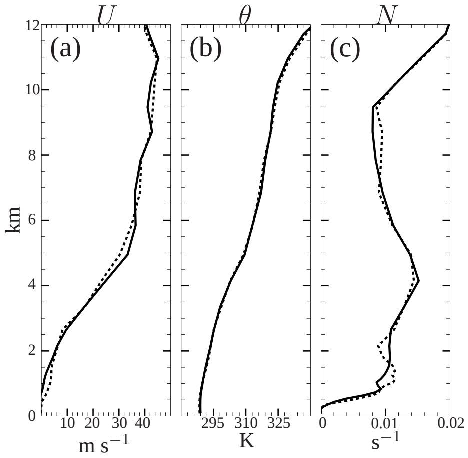
- Upper: IOP 6: Little difference upstream of Owens Valley
- Lower: IOP 13: Stronger subset has (1) stronger low-level stability, (2) weaker upper-level stability, (3) weaker winds

Breaking Case: Soundings 1-Hour Prior to Wind Max



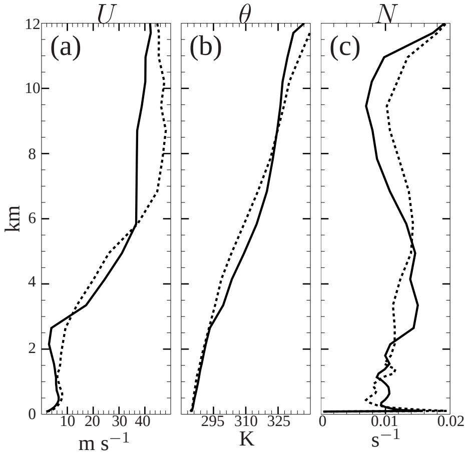
- At termination of a 1-hour mid-level back trajectory.
- Strongest subset (solid), weakest (dashed)

Breaking Case: Soundings 1-Hour Prior to Wind Max



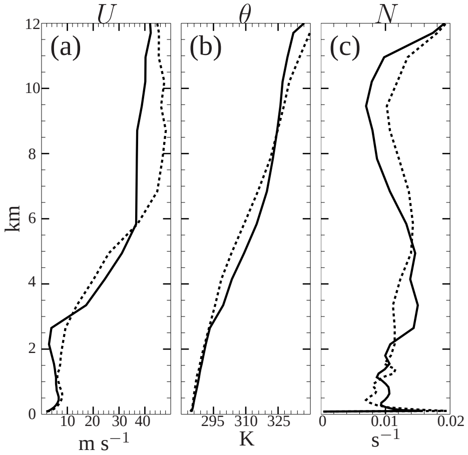
- At termination of a 1-hour mid-level back trajectory.
- Strongest subset (solid), weakest (dashed)
- Differences are less than typical errors in radiosonde data

Low-Level Stability: Soundings 1-Hour Prior to Wind Max



- At termination of a 1-hour mid-level back trajectory.
- Strongest subset (solid), weakest (dashed)

Low-Level Stability: Soundings 1-Hour Prior to Wind Max



- At termination of a 1-hour mid-level back trajectory.
- Strongest subset (solid), weakest (dashed)
- Significant differences in wind speed and stabilty.

Conclusions

Terrain induced downslope winds (and breaking mountain waves?) do not appear to be predictable at time scales longer than those suggested by Lorenz.

Conclusions

Terrain induced downslope winds (and breaking mountain waves?) do not appear to be predictable at time scales longer than those suggested by Lorenz.

- The IOP 6 wave breaking event and downslope windstorm probably could not be accurately predicted via a deterministic forecast that assimilated upstream data collected just one hour prior to the event

Conclusions

Terrain induced downslope winds (and breaking mountain waves?) do not appear to be predictable at time scales longer than those suggested by Lorenz.

- The IOP 6 wave breaking event and downslope windstorm probably could not be accurately predicted via a deterministic forecast that assimilated upstream data collected just one hour prior to the event
- Deterministic forecasts of the IOP 13 event have some skill using data 6 hours prior to the event, but little skill using data from 12 hours prior.

The Next Question

Beyond what lead time is deterministic forecasting of snow in the Puget-Sound lowlands crippled by initial condition uncertainty?

The Next Question

Beyond what lead time is deterministic forecasting of snow in the Puget-Sound lowlands crippled by initial condition uncertainty?

- Focus on the growth of initial perturbations.

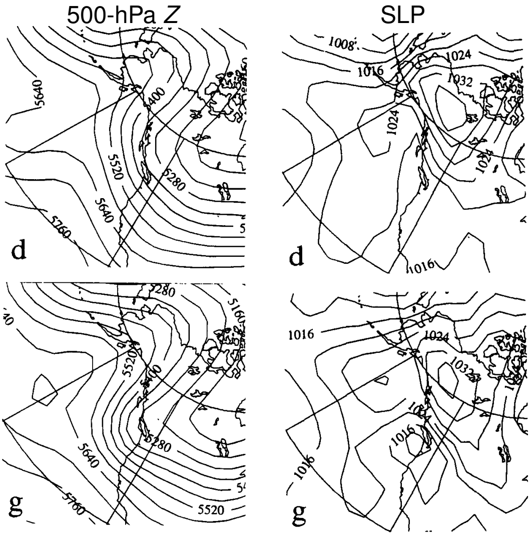
The Next Question

Beyond what lead time is deterministic forecasting of snow in the Puget-Sound lowlands crippled by initial condition uncertainty?

- Focus on the growth of initial perturbations.
- Ignore model errors

Prototypical PNW Snow Events

- Composite of 11 of 13 events producing more than 4" of snow at SEATAC over a 27-year period.
- Top: 24 hours prior
- Bottom: Onset time of the heavy snow



Ferber et. al. 1993

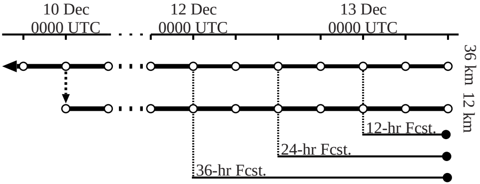
Ensemble Implementation

Two cases:

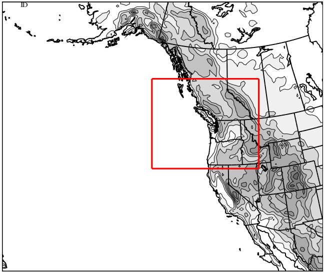
- 12-13 December 2008
- 17-18 December 2008

100-member ensemble:

- 6-hr EnKF DA cycle
- 12 UTC 05–18, December 2008

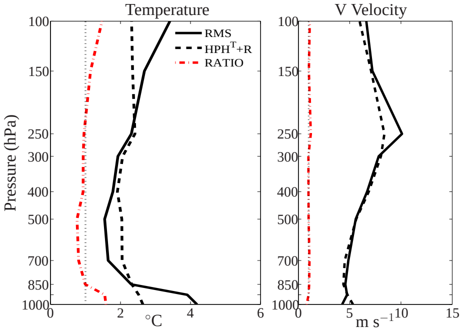


COAMPS (1-way nest)



Δx =36- and 12-km

Ensemble Performance (24 6-hr forecasts)



Forecast of 6-hour mean-square error in ensemble at radiosonde sites ≈ (forecast 6-hour ensemble variance + observational uncertainty) at same sites.

Avoiding Details of the Model Parameterizations

Characterize the likelihood of snow by the:

- Presence of precipitation.
- 850-mb temperature

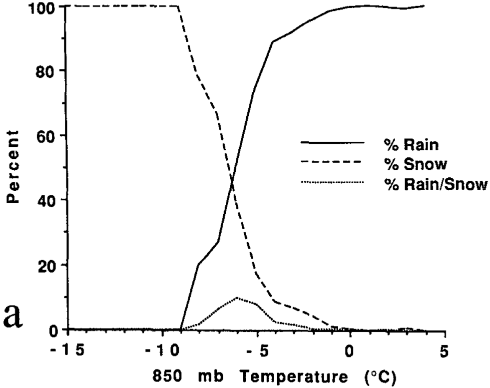
Avoiding Details of the Model Parameterizations

Characterize the likelihood of snow by the:

- Presence of precipitation.
- 850-mb temperature
- Sidestep sensitivities to
  - Ice microphysical parameterizations
  - Boundary layer parameterizations

Climatological Conditions for Snow at SEATAC

Precipitation type at SEATAC as a function of 850-mb temperature.

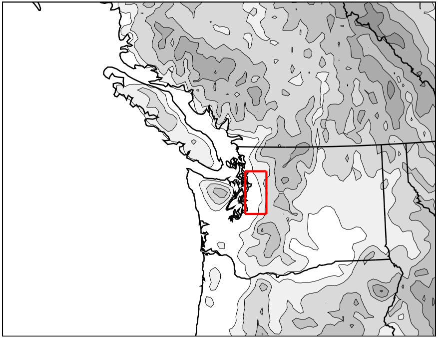


"Sharp rain-snow transition between about -4°and -8°C"

(Ferber et al., 1993: Snowstorms over the Puget Sound Low-Lands *Wea. Forecasting*)

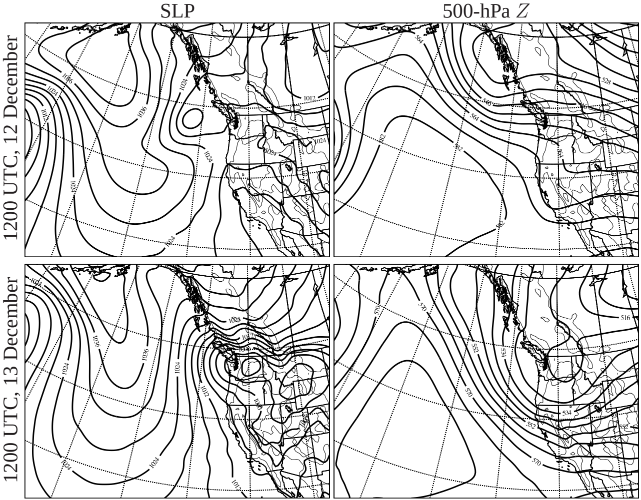
Ranking the Ensemble Members

850 hPa Temperature



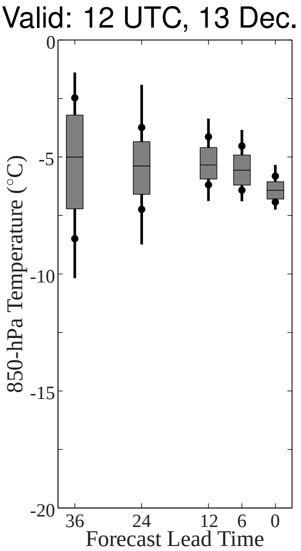
- Rank by average temperature over metric box
- 17 warmest and 17 coldest members at verification time

Ensemble Mean Analysis—Case 1

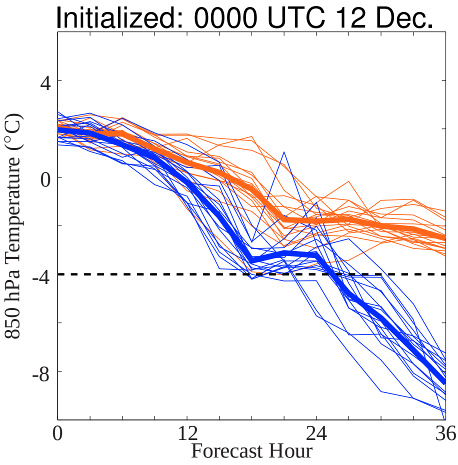


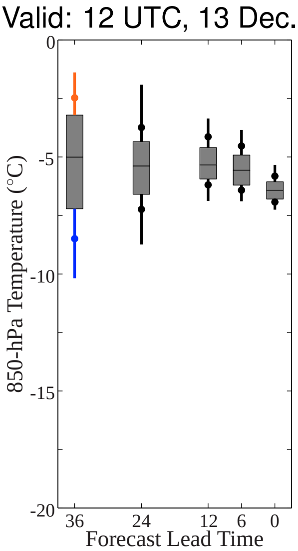
Spread of Metric at Various Lead Times

- Whiskers → outer sextiles.
- Increased uncertainty with longer lead times.

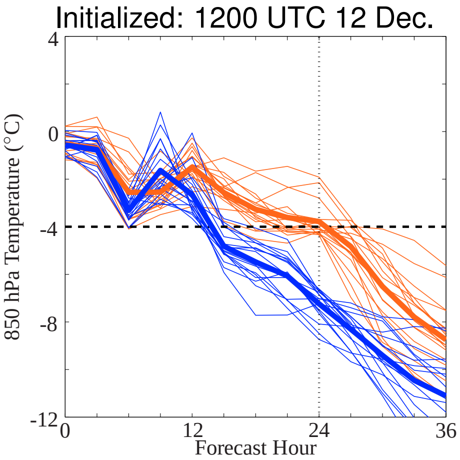


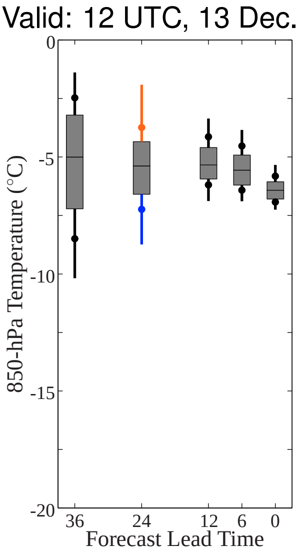
Spread of Metric at Various Lead Times





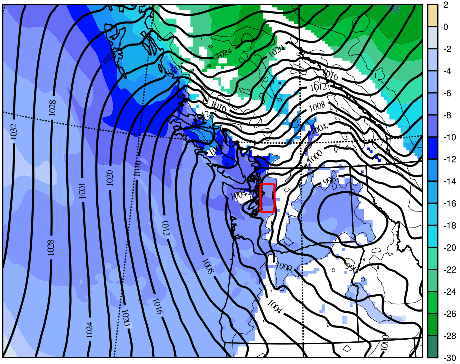
Spread of Metric at Various Lead Times



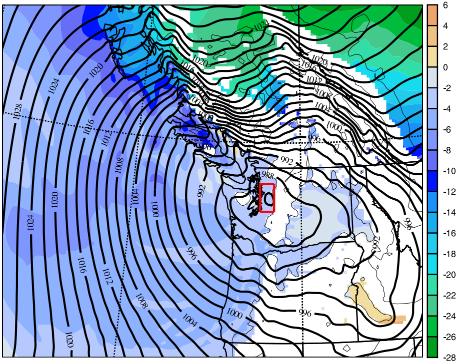


SLP and 850 hPa Temperature (36-hr Forecast)

Cold Subset

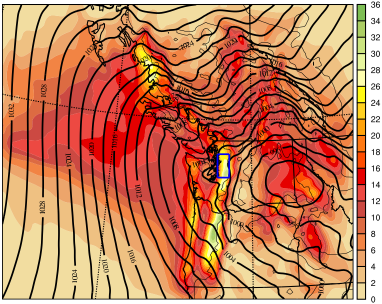


Warm Subset

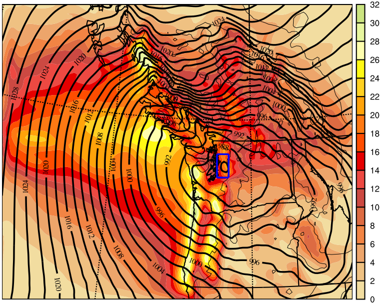


24-hr Accumulated Precipitation

Cold Subset



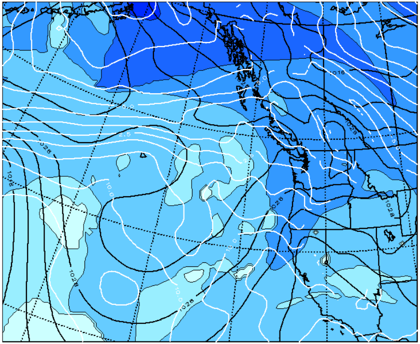
Warm Subset



- $>$10-mm difference in Puget Sound precipitation
- Cold Subset: 10 mm liquid equivalent fell when $T_{850hPa} < -4^{\circ}C$
- Warm Subset: All precipitation fell with $T_{850hPa} > -4^{\circ}C$

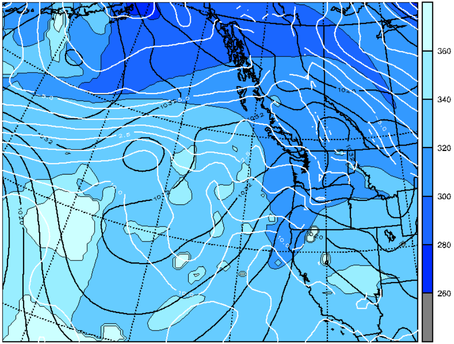
Contrast the Development

Cold Subset



T=0 hr

Warm Subset

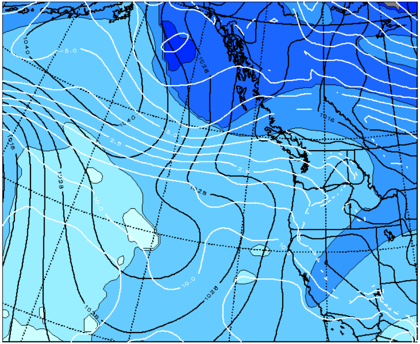


T=0 hr

Color Fill: θ on tropopause (2 PVU); Contours: 850 hPa temperature (White), SLP (Black)

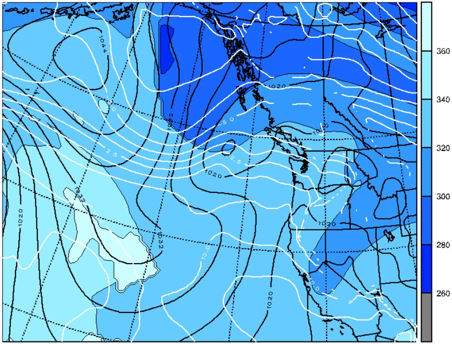
Contrast the Development

Cold Subset



T=12 hr

Warm Subset

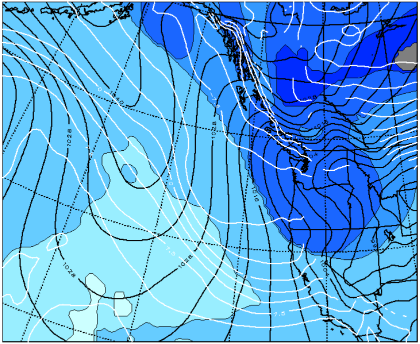


T=12 hr

Color Fill: θ on tropopause (2 PVU); Contours: 850 hPa temperature (White), SLP (Black)

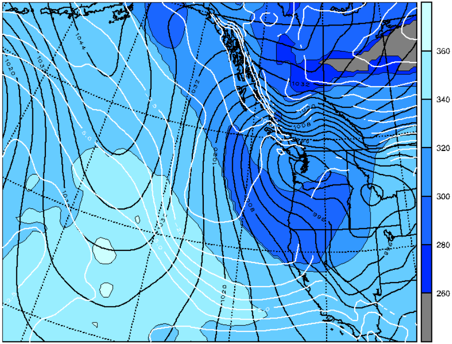
Contrast the Development

Cold Subset



T=36 hr

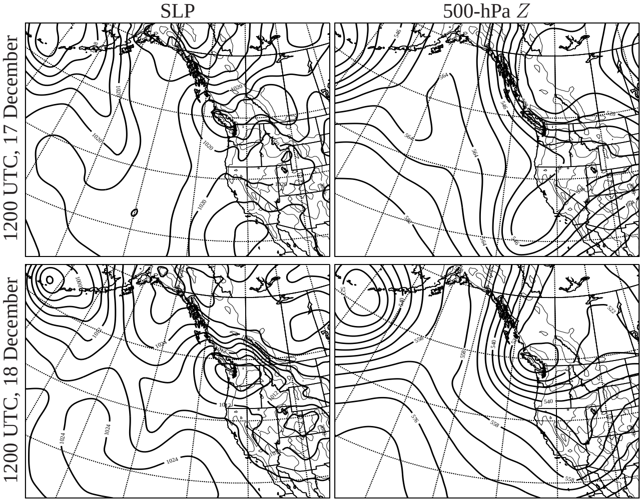
Warm Subset



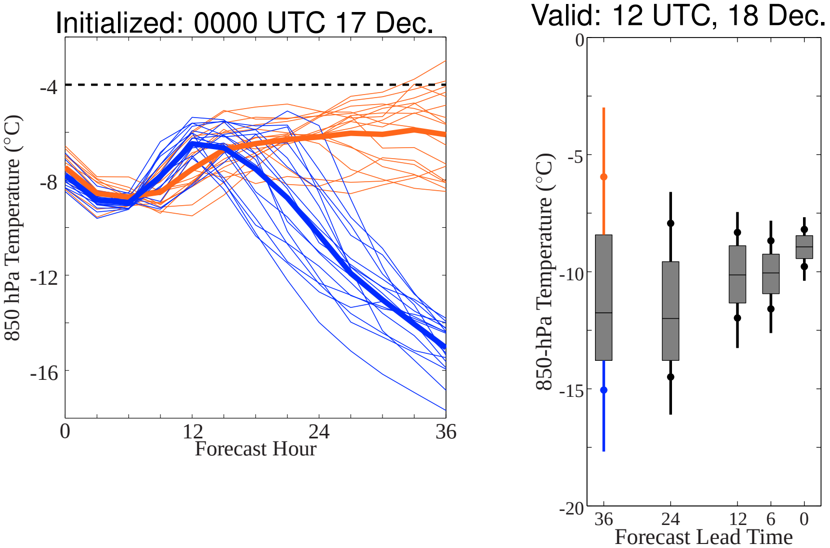
T=36 hr

Color Fill: θ on tropopause (2 PVU); Contours: 850 hPa temperature (White), SLP (Black)

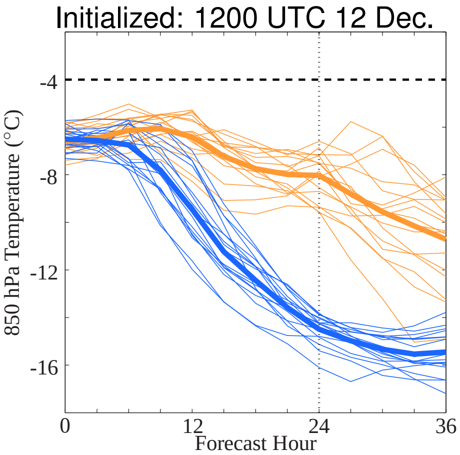
Case 2: Ensemble Mean Analysis

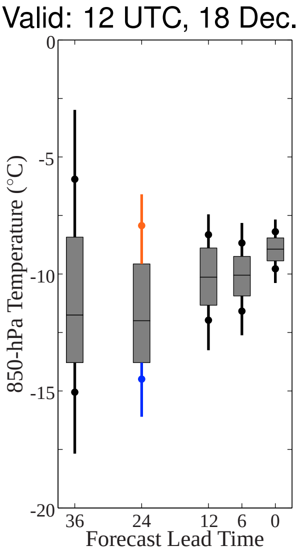


Spread of Metric at Various Lead Times



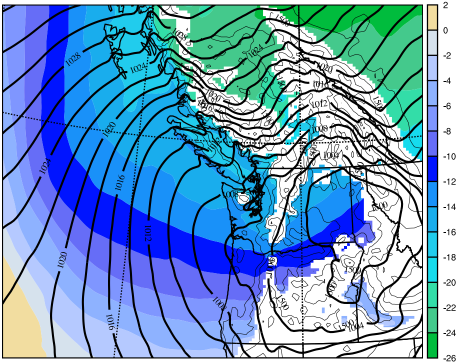
Spread of Metric at Various Lead Times



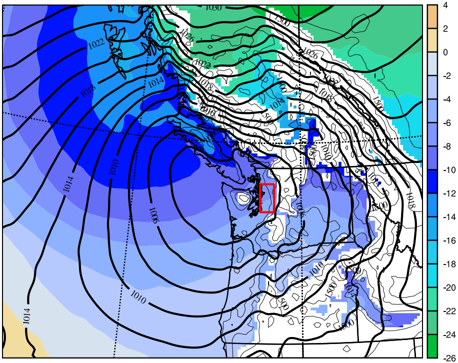


SLP and 850 hPa Temperature (36-hr Forecast)

Cold Subset

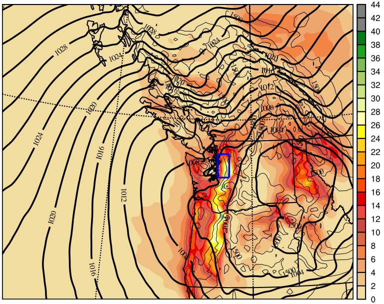


Warm Subset

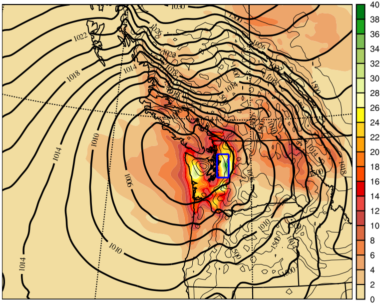


24-hr Accumulated Precipitation

Cold Subset



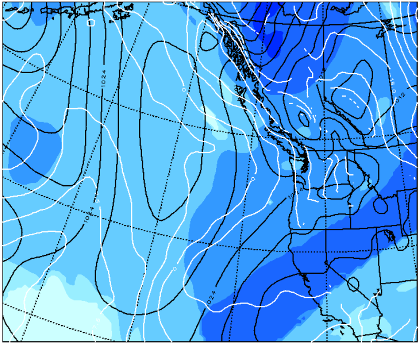
Warm Subset



- Cold Subset: 20.0 mm liquid equivalent total, all fell when $T_{850hPa} < -6^{\circ}C$
- Warm Subset: 25.7 mm liquid equivalent total, 3.6 mm fell with $T_{850hPa} > -6^{\circ}C$

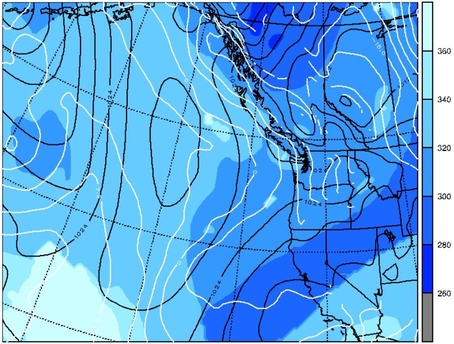
Initial Conditions

Cold Sextile Mean



T=0 hr

Warm Sextile Mean



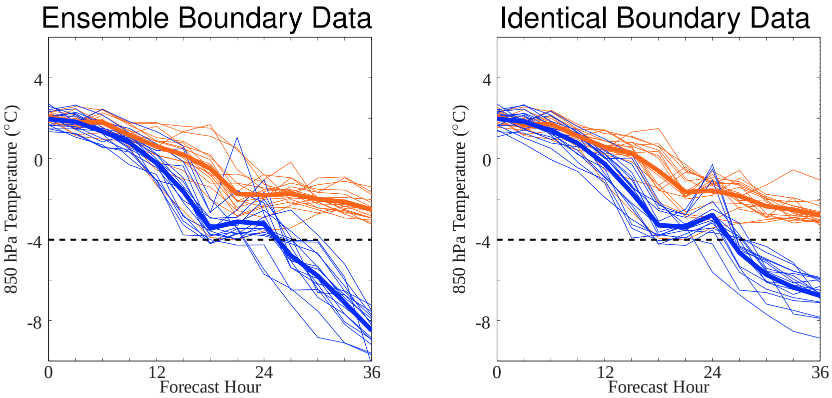
T=0 hr

Color Fill: θ on tropopause (2 PVU); Contours: 850 hPa temperature (White), SLP (Black)

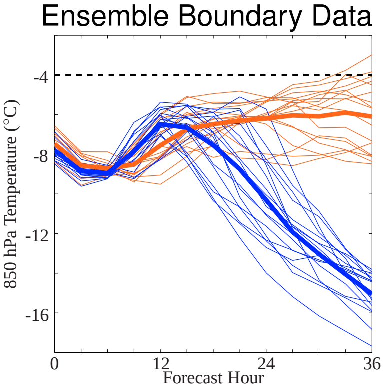
The Boundaries

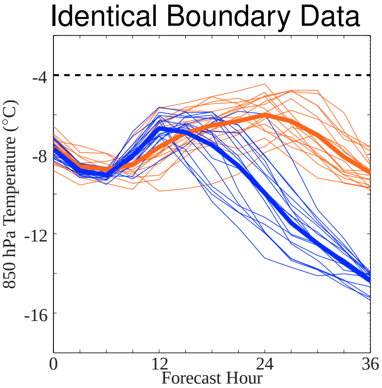
Is the sensitivity driven from the boundaries?

Case 1: 12–13 December



Case 2: 17–18 December





Summary

- Those ensemble members one-standard deviation away from the mean show large 850-mb temperature spread at it 36 hours
    - Climatological rain-snow transition over 4°C range.
    - Case 1: Range between cold and warm sextile means is 6°C.
    - Case 2: Range between cold and warm sextile means is 9°C.

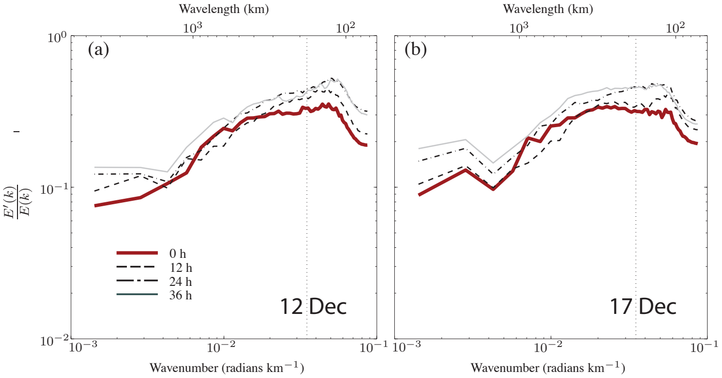
Summary

- Those ensemble members one-standard deviation away from the mean show large 850-mb temperature spread at it 36 hours
    - Climatological rain-snow transition over 4°C range.
    - Case 1: Range between cold and warm sextile means is 6°C.
    - Case 2: Range between cold and warm sextile means is 9°C.
- Substantial differences in synoptic-scale pattern at 36 hours
    - Case 1: Position of low centers differ by more than 400 km.
    - Case 2: Position of low centers differ by more than 800 km.

Summary

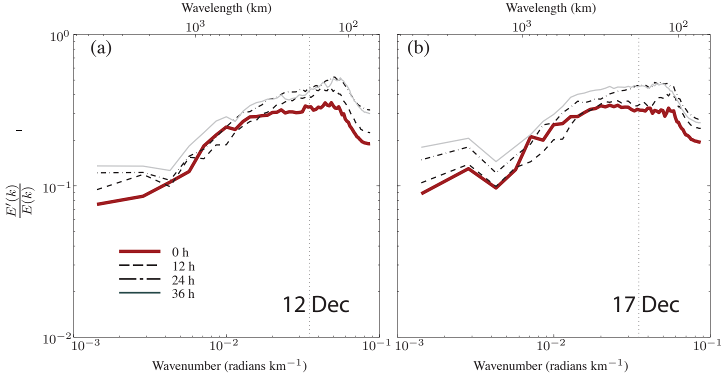
- Those ensemble members one-standard deviation away from the mean show large 850-mb temperature spread at it 36 hours
  - Climatological rain-snow transition over 4°C range.
  - Case 1: Range between cold and warm sextile means is 6°C.
  - Case 2: Range between cold and warm sextile means is 9°C.
- Substantial differences in synoptic-scale pattern at 36 hours
  - Case 1: Position of low centers differ by more than 400 km.
  - Case 2: Position of low centers differ by more than 800 km.
- More pessimistic than Zhang et al., 2002, 2003
  - Significant differences in surface pressure pattern at 36 hours.
  - Error growth likely not dependent on moist convection.

Why does the error grow so fast?



- Nontrivial initial errors at large scales.

Why does the error grow so fast?



- Nontrivial initial errors at large scales.
- Downscale error growth is very rapid†

†Rotunno and Snyder: A Generalization of Lorenz's Model for the Predictability of Flows with Many Scales of Motion, *JAS*, 2008

Tentative Conclusion

- A *theoretical* limit to atmospheric predictability arises due to the impossibility of correctly specifying all arbitrarily small-scale atmospheric circulations (Lorenz).

Tentative Conclusion

- A *theoretical* limit to atmospheric predictability arises due to the impossibility of correctly specifying all arbitrarily small-scale atmospheric circulations (Lorenz).
- The *practical* limit to mesoscale predictability can be imposed by unavoidable initial errors in the large scales.

Tentative Conclusion

- A *theoretical* limit to atmospheric predictability arises due to the impossibility of correctly specifying all arbitrarily small-scale atmospheric circulations (Lorenz).
- The *practical* limit to mesoscale predictability can be imposed by unavoidable initial errors in the large scales.

The large scale giveth and the large scale taketh away.

Reference

Reinecke, P.A., and D. R. Durran, 2009: Initial condition sensitivities and the predictability of downslope winds. *J. Atmos. Sci.,* **66,** 3401-3418