Probabilistic Precipitation Forecasts from Deterministic Forecast Models

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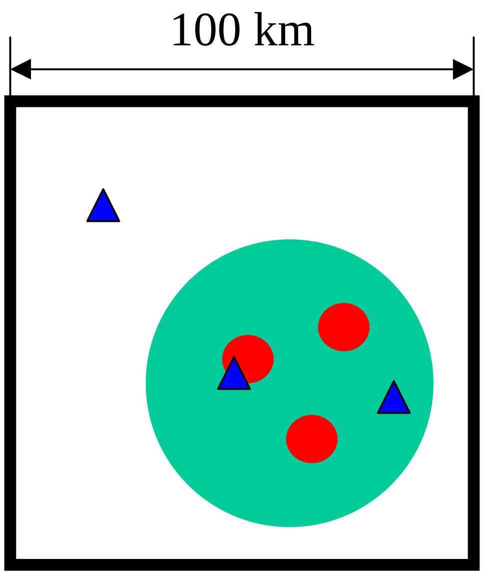
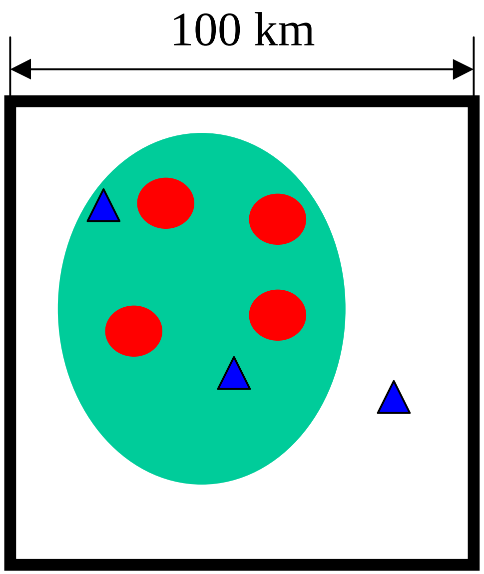
- Motivation
- Probabilistic upscaling of high-resolution model results
- Comparison to purely deterministic forecasts
- Dependence of forecast quality on region/season, size, intensity, etc.
- Conclusions

Motivation

For example:



"True" precipitation

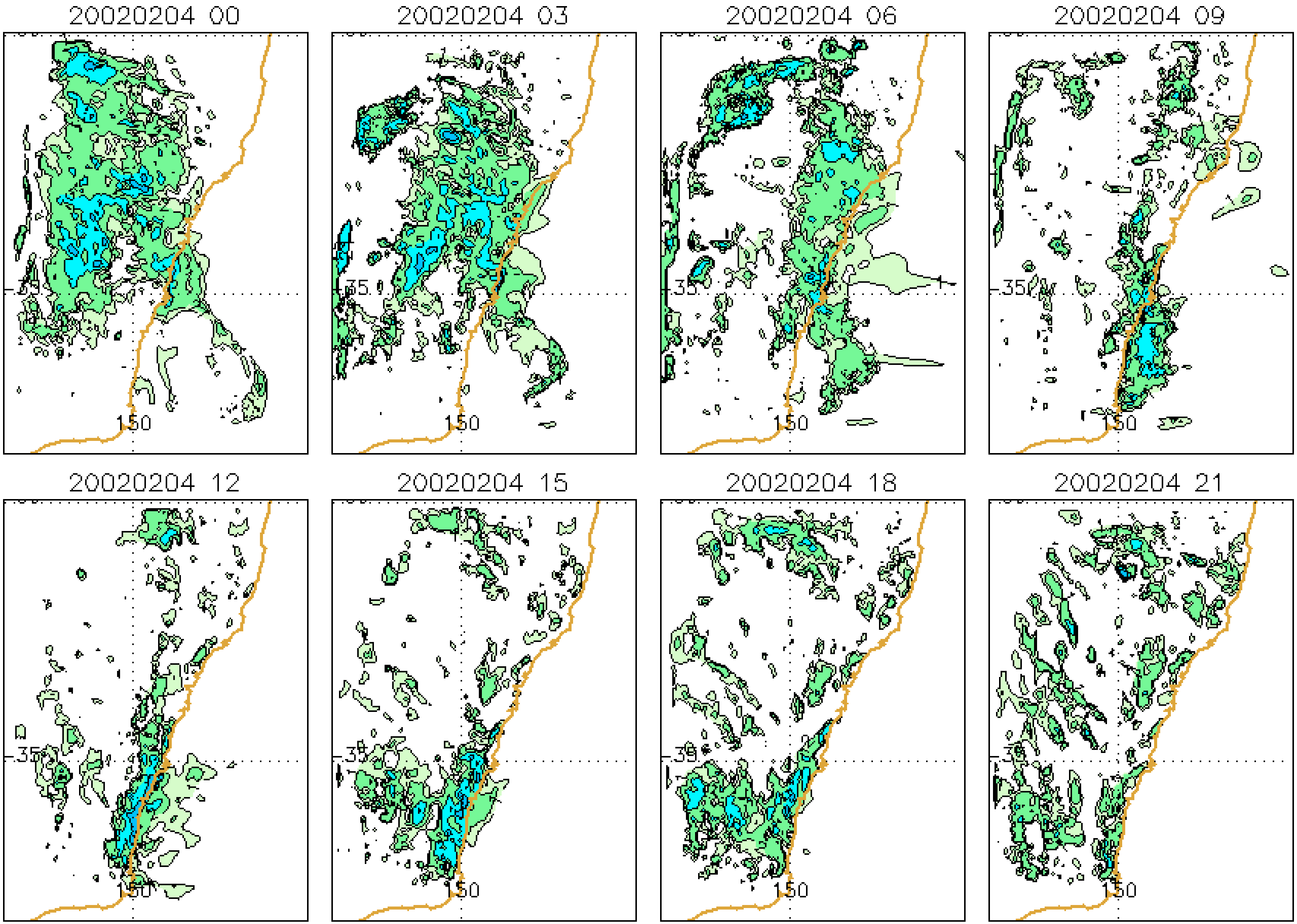


High resolution model forecast

Precipitation is in wrong place

At *face value*, this forecast is not very useful

Example: LAPS05 hourly rainfall forecasts

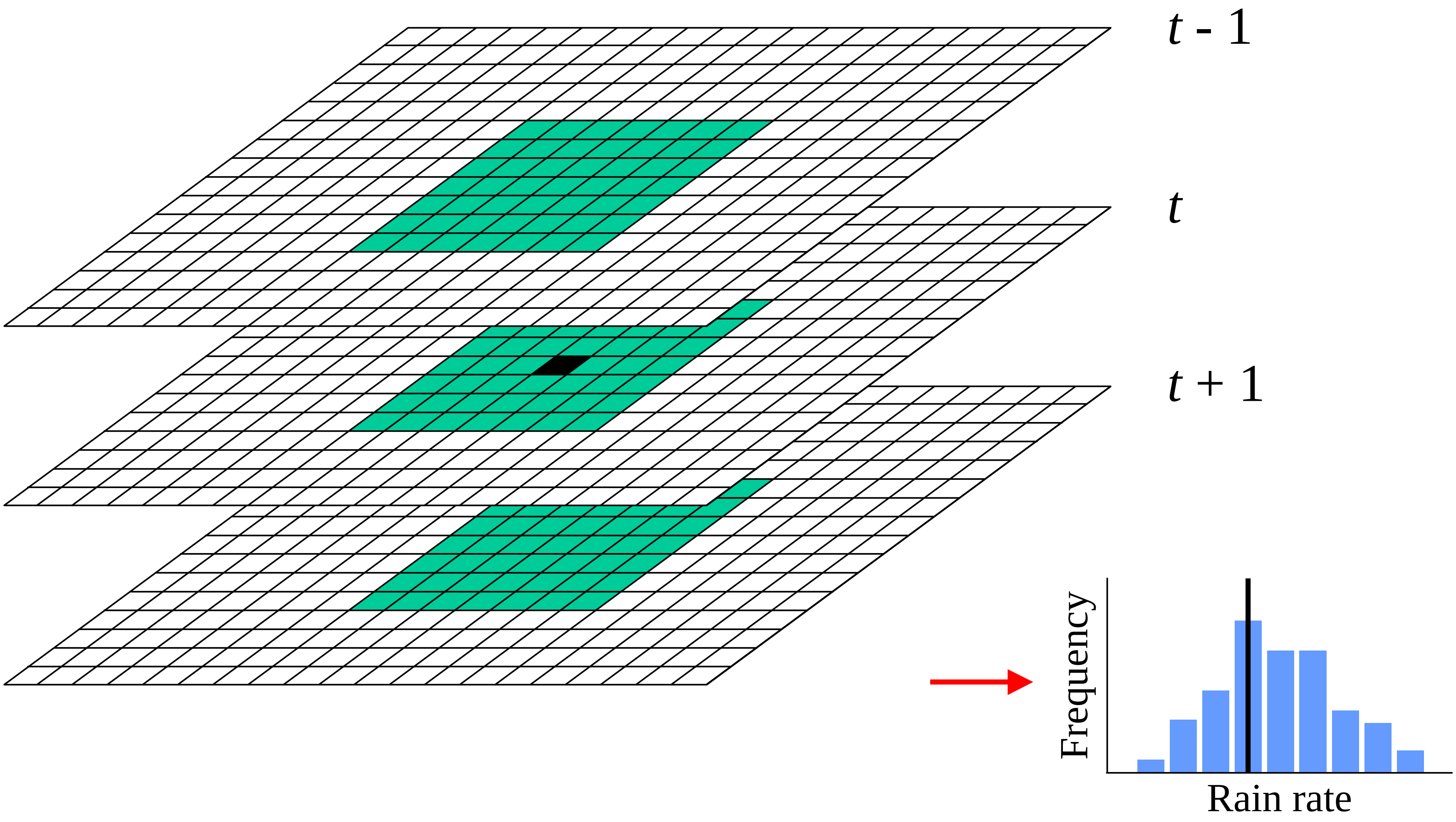


Probabilistic upscaling

- We don't take high-resolution mesoscale forecasts of rain at face value
- Rather, we take it as an indication of what may happen around that general region and time

--> Use the neighbourhood in space and time to derive a probability distribution at each point

Space-time neighbourhood



Daily rainfall

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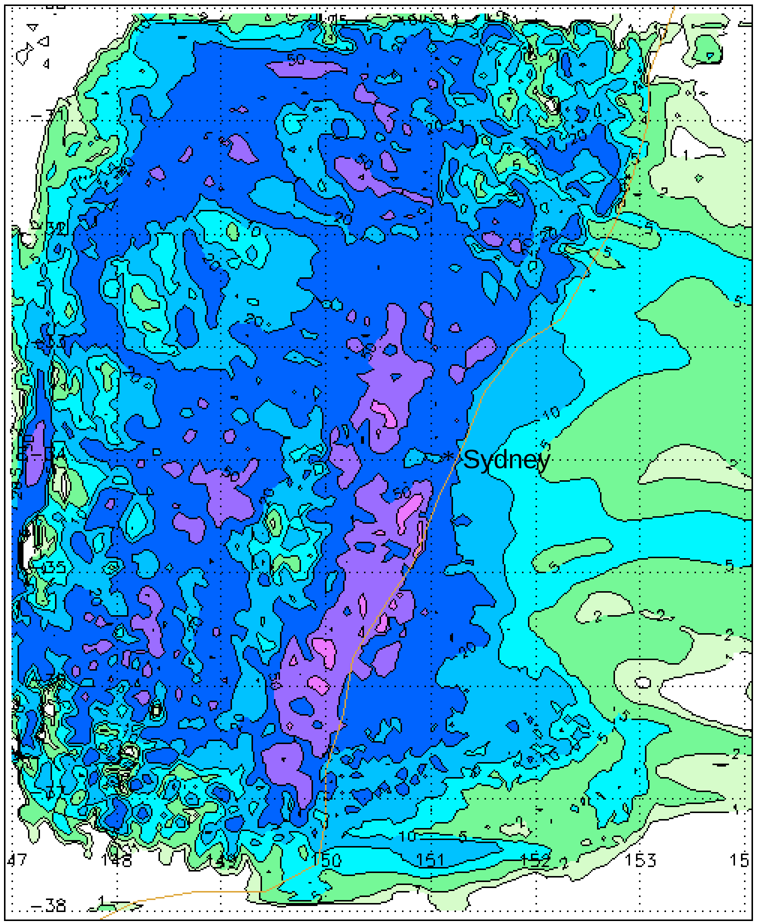
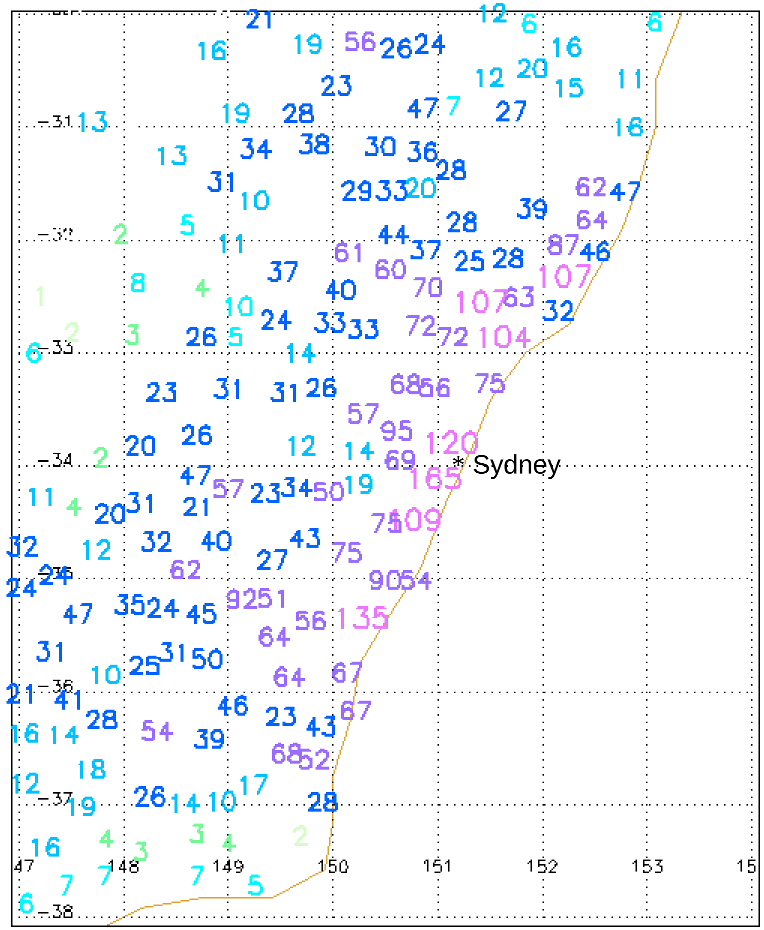
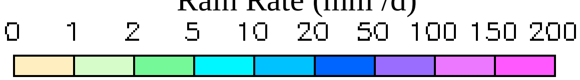
Deterministic forecast of daily rainfall
MesoLAPS.05 36 hr



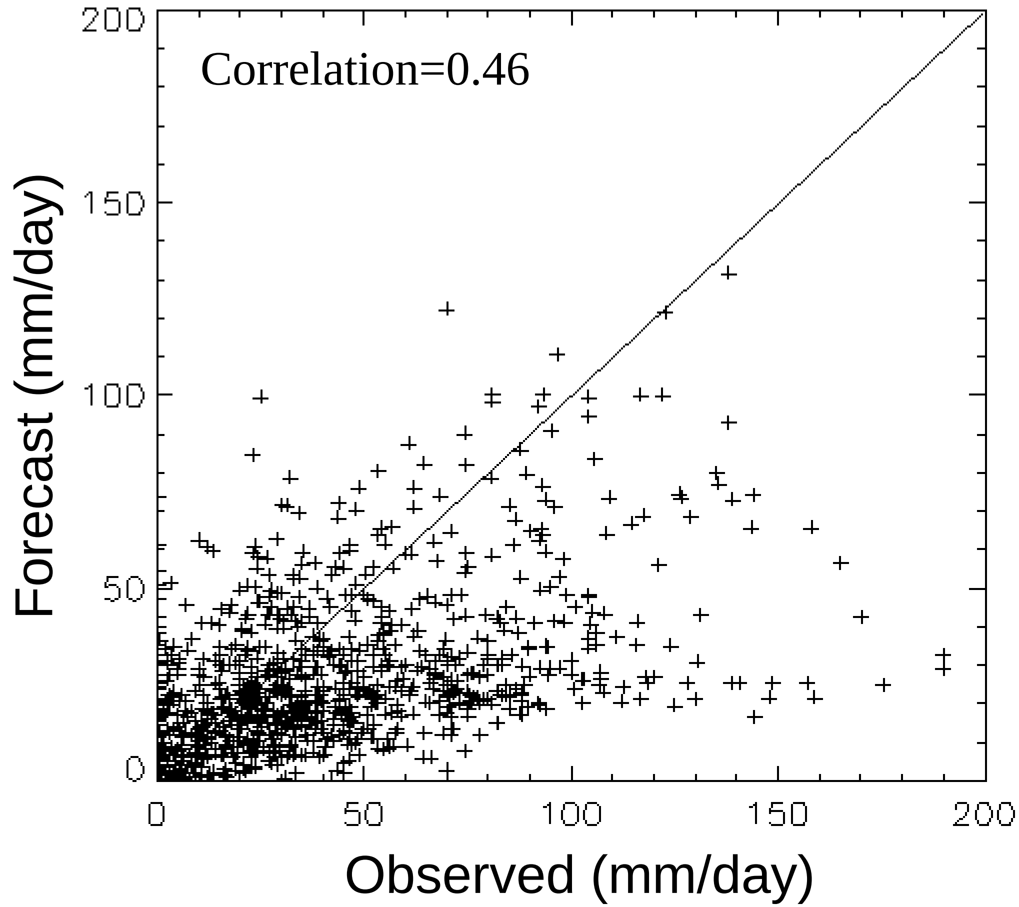
Observations of daily rainfall
valid 00 UTC 4 Feb 2002



Rain Rate (mm /d)

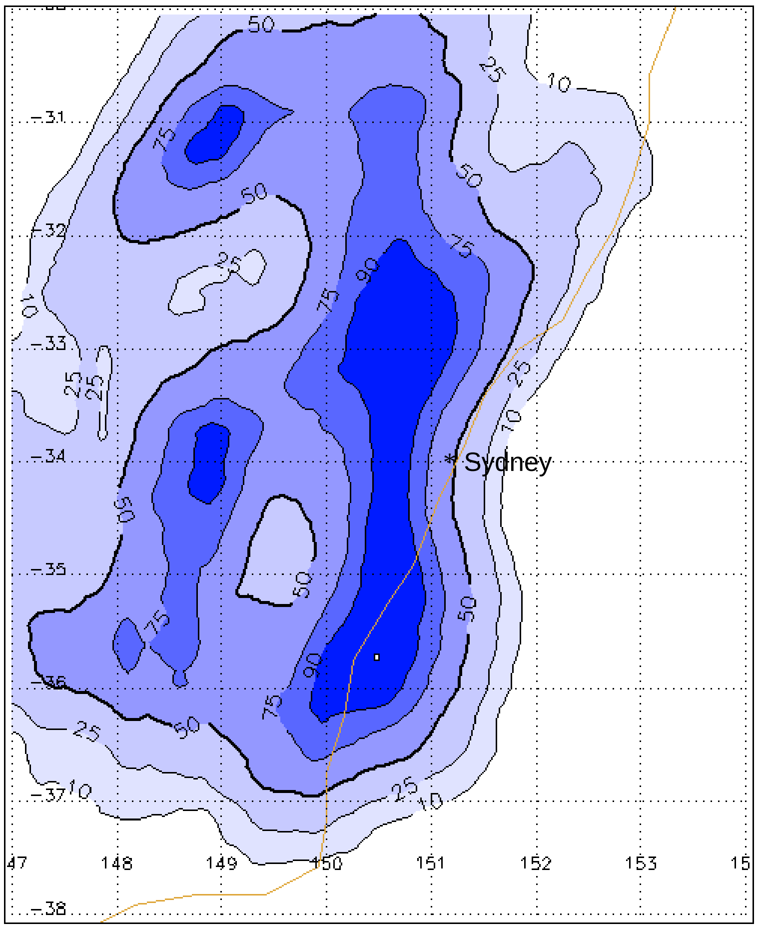


Comparison of direct model output with observations



Daily rainfall probability

Probabilistic forecast of rain ≥ 20 mm/d
Spatial window=105 km, time window=0 hrs



Observations of daily rainfall
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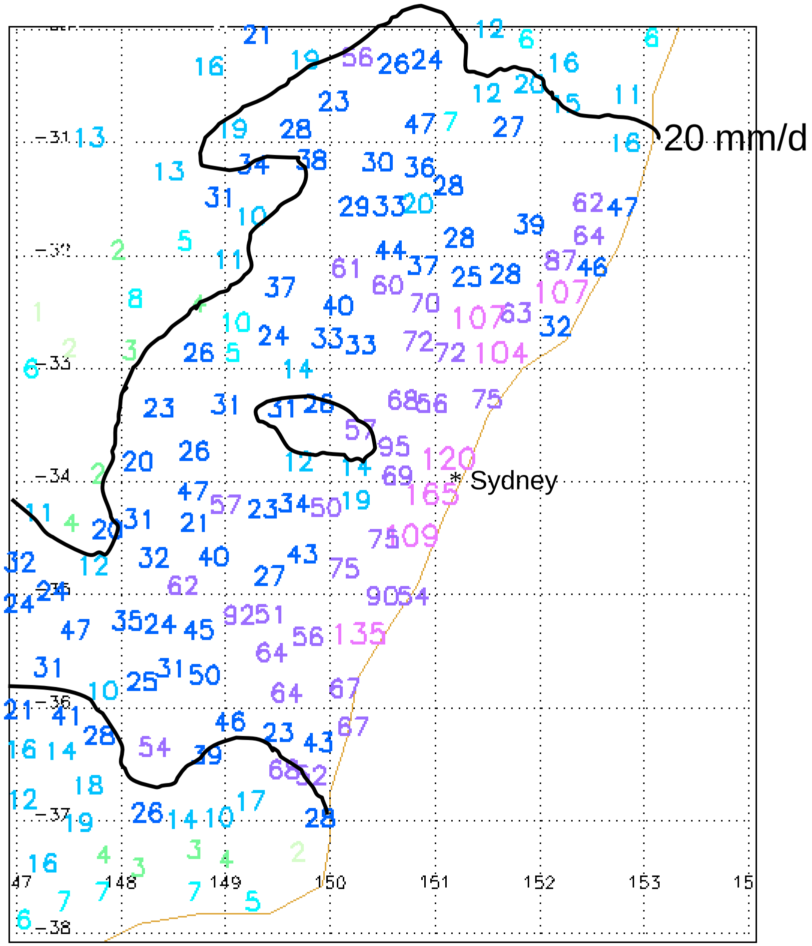
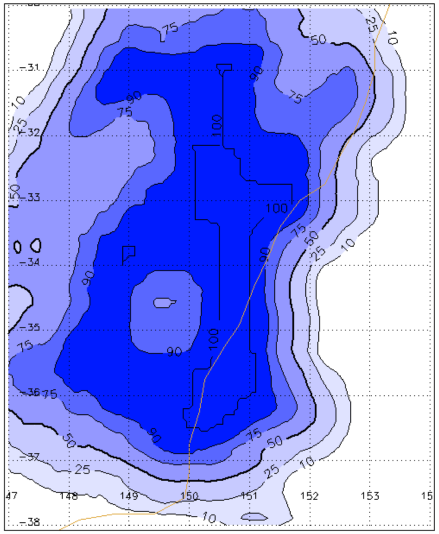
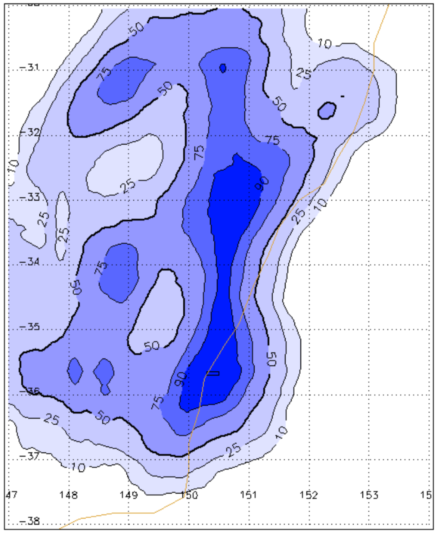


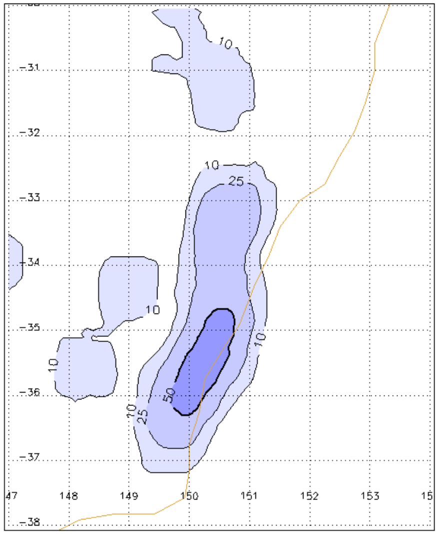
Probability maps



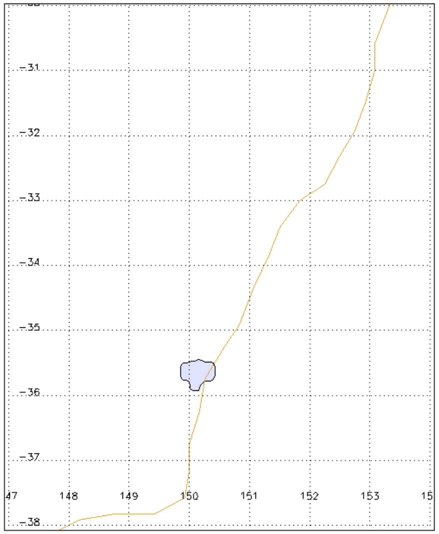
P (rain>10 mm/d)



P (rain>20 mm/d)

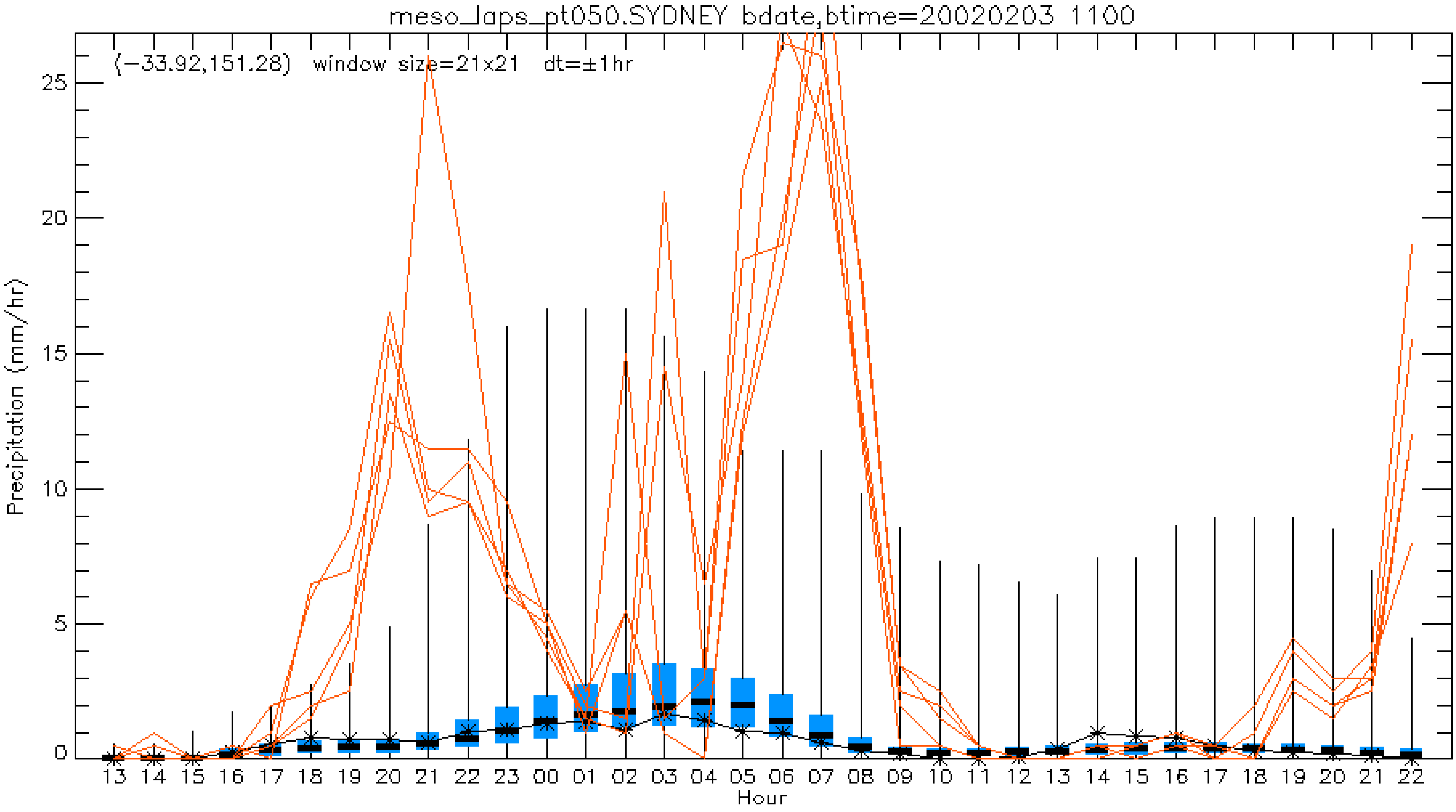


P (rain>50 mm/d)



P (rain>100 mm/d)

Time series


meso_laps_pt050.SYDNEY bdate,btime=20020203 1100
(−33.92,151.28) window size=21x21 dt=±1hr
Precipitation (mm/hr)
Hour
0
5
10
15
20
25
13 14 15 16 17 18 19 20 21 22 23 00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22

Evaluation of probabilistic forecasts

Brier score - Mean squared probability error

$$BS = \frac{1}{N}\sum_{i=1}^{N}(p_i - o_i)^2$$

where p_i is the forecast probability, and o_i is the observation (0=no, 1=yes).

Perfect score = 0.

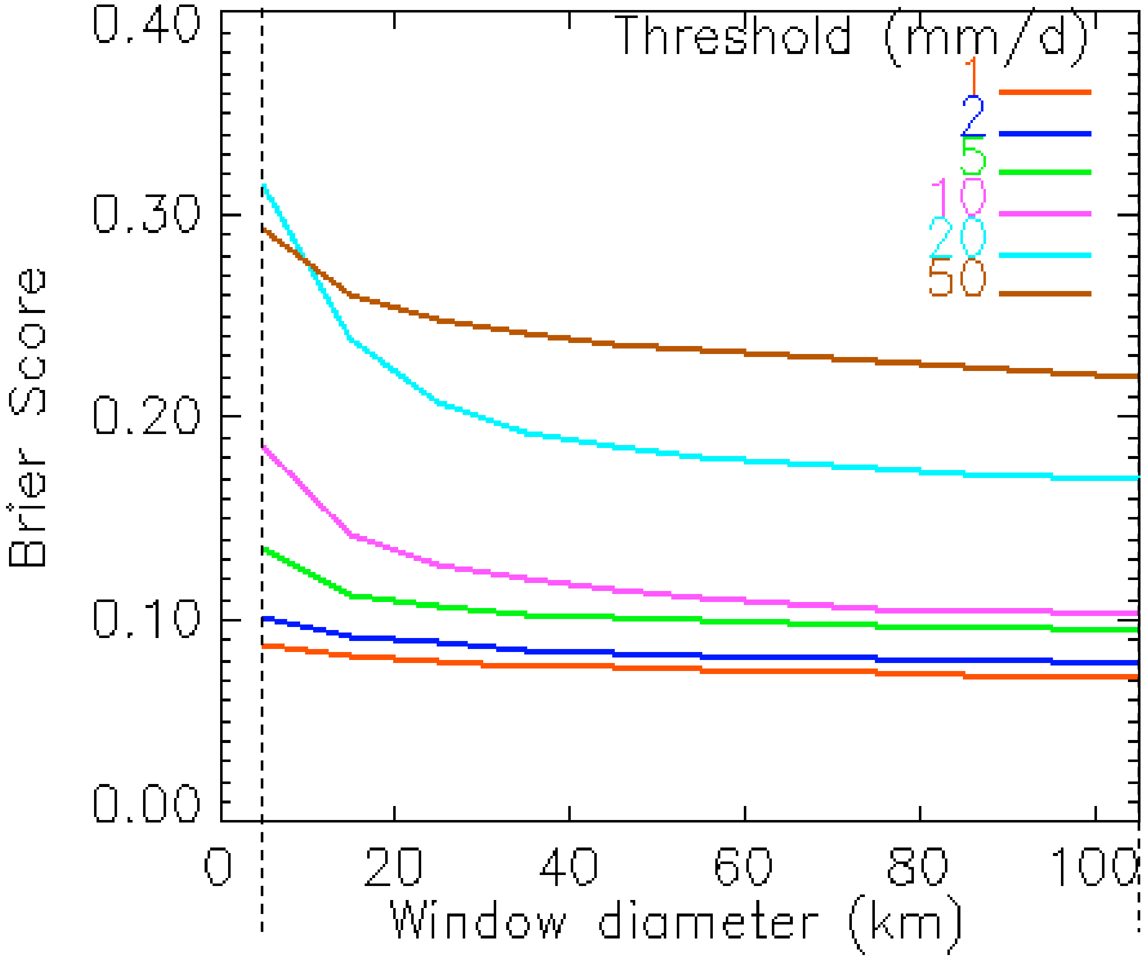
(Deterministic forecast: $p_i = \begin{cases} 0 & \text{no rain} \\ 1 & \text{rain} \end{cases}$)

Brier skill score w.r.t. forecast - Relative improvement over deterministic forecast

$$BSS_f = \frac{BS - BS_{forecast}}{0 - BS_{forecast}}$$

Perfect score = 1,   no improvement = 0

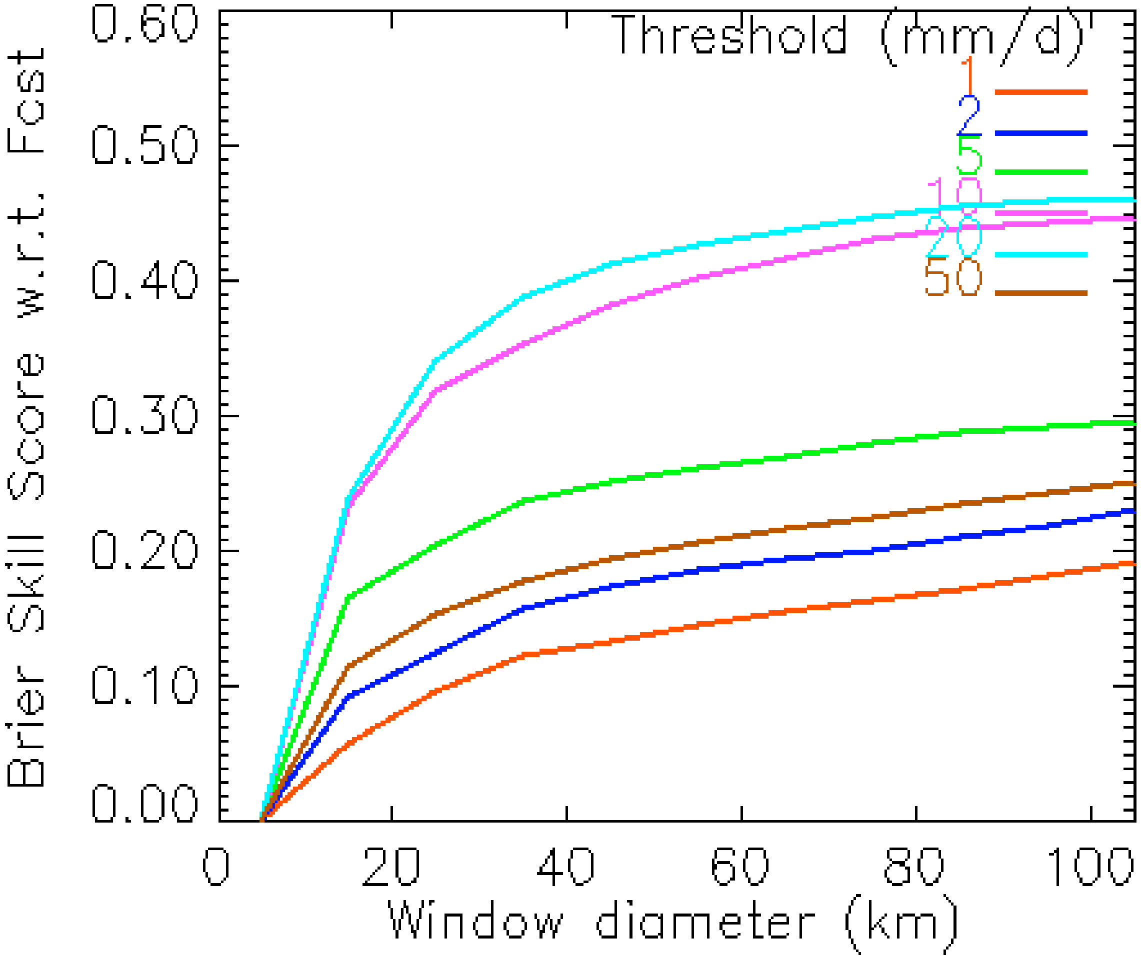
Comparison with deterministic forecast



Deterministic forecast
window = 1 gridpoint

Probabilistic forecast
window = 21 gridpoints

Comparison with deterministic forecast



Issues

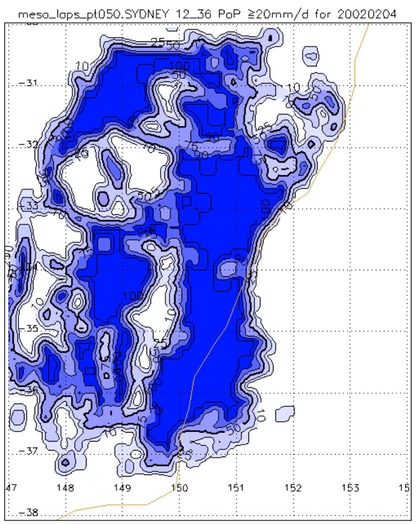
- How does the probablistic forecast depend on the space and time windows?
- Where/when does this approach give the greatest forecast improvement over direct model output?
- How does the **optimum** space/time window depend on:
  - attributes of the weather system
  - accuracy of the model forecast
  - rain accumulation period

--> Is there a way to dynamically optimise the window to give the best probabilistic forecasts?

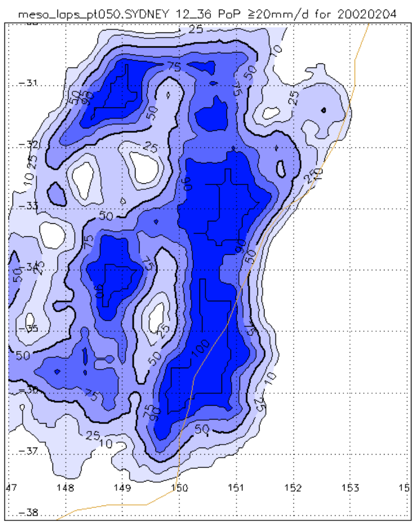
- How do the neighbourhood median and mean forecasts compare to the original forecast?
- Does probabilistic upscaling also work with coarse resolution forecasts such as global models?

Dependence on spatial window

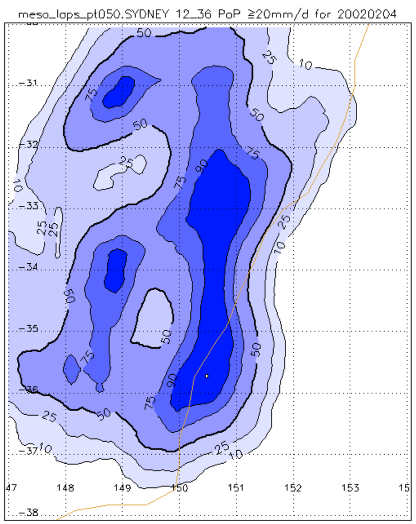
Probabilistic forecast of daily rain ≥ 20 mm/d
Time window = 0 hrs



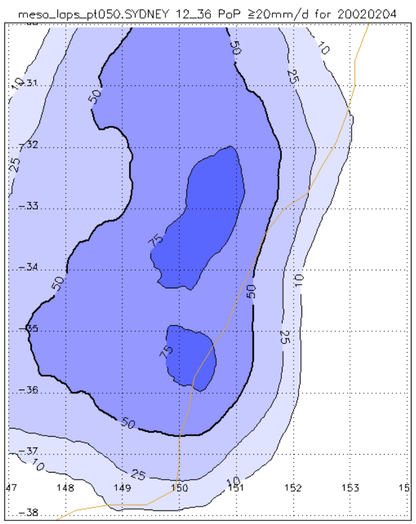
Window = 15 km
BS = 0.24
ROCarea = 0.79



Window = 55 km
BS = 0.18
ROCarea = 0.88



Window = 105 km
BS = 0.17
ROCarea = 0.92



Window = 205 km
BS = 0.18
ROCarea = 0.80

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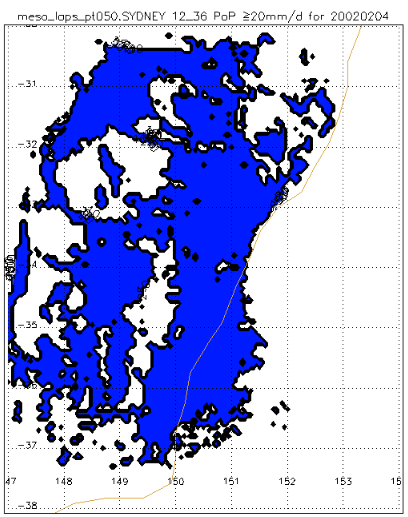
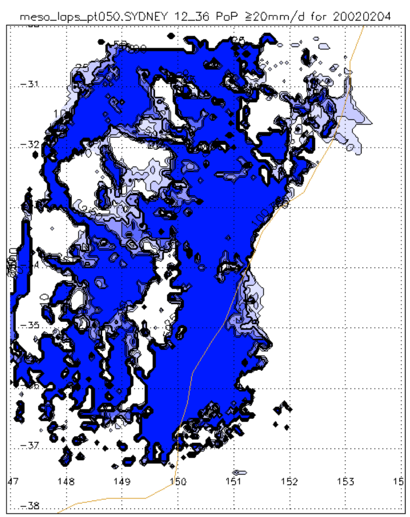
Dependence on time window

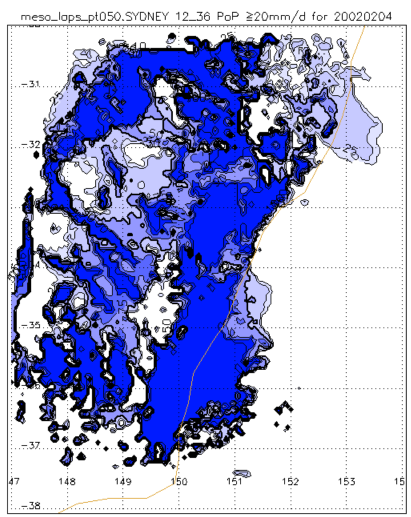
Probabilistic forecast of daily rain ≥ 20 mm/d
Spatial window = 5 km (single gridpoint)



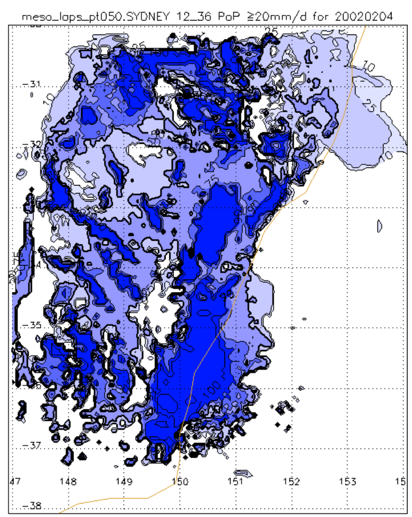
Window = ±0 hrs
BS = 0.32
ROCarea = 0.57



Window = ±2 hr
BS = 0.28
ROCarea = 0.59



Window = ±5 hrs
BS = 0.27
ROCarea = 0.61



Window = ±10 hrs
BS = 0.27
ROCarea = 0.66

Experiment

Model: MesoLAPS 0.125º resolution model

Forecast: 36 h forecasts of daily rainfall

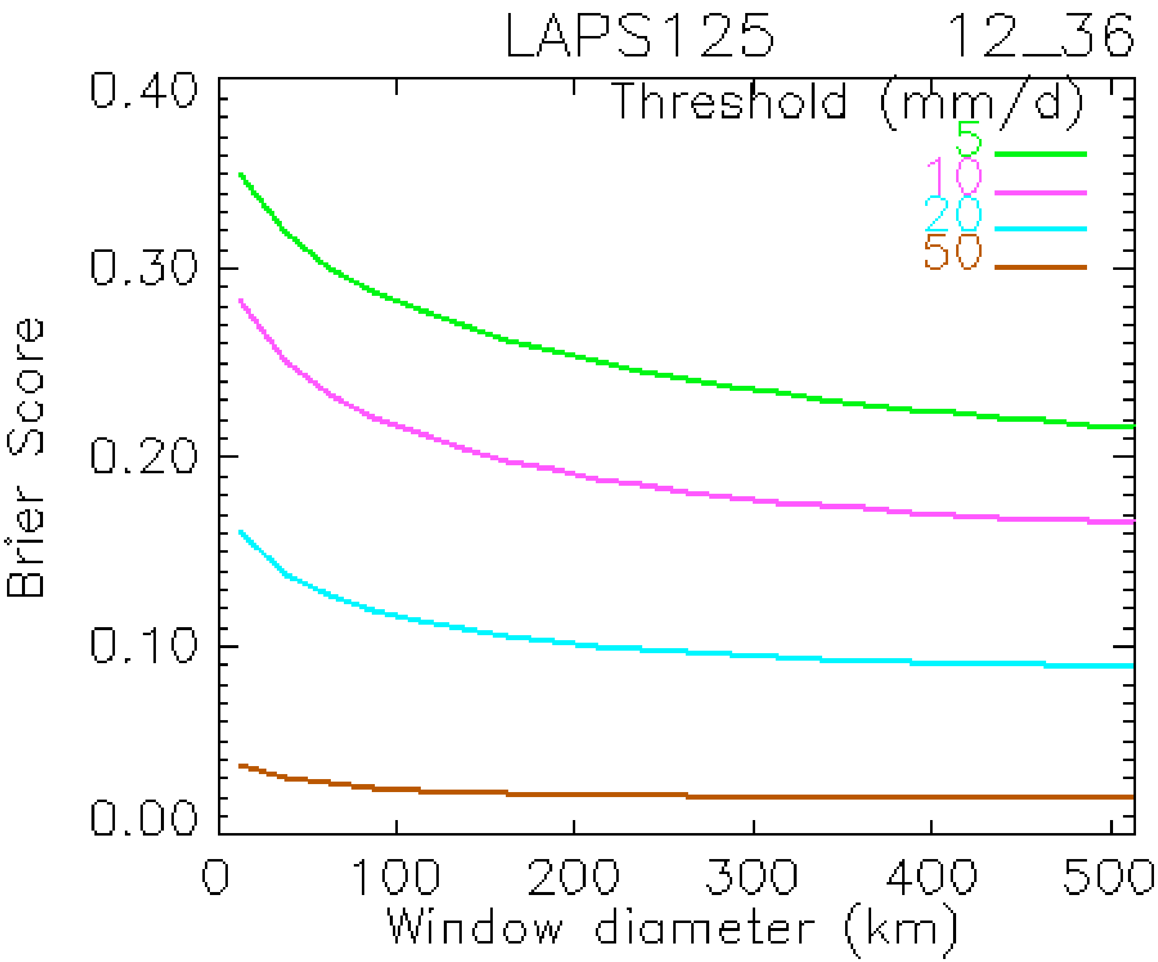
Domain: Draw a rectangular box around each rain system (defined by 5 mm/day isohyet) in the forecast and/or observations

Evaluation period: November 2000 - October 2002

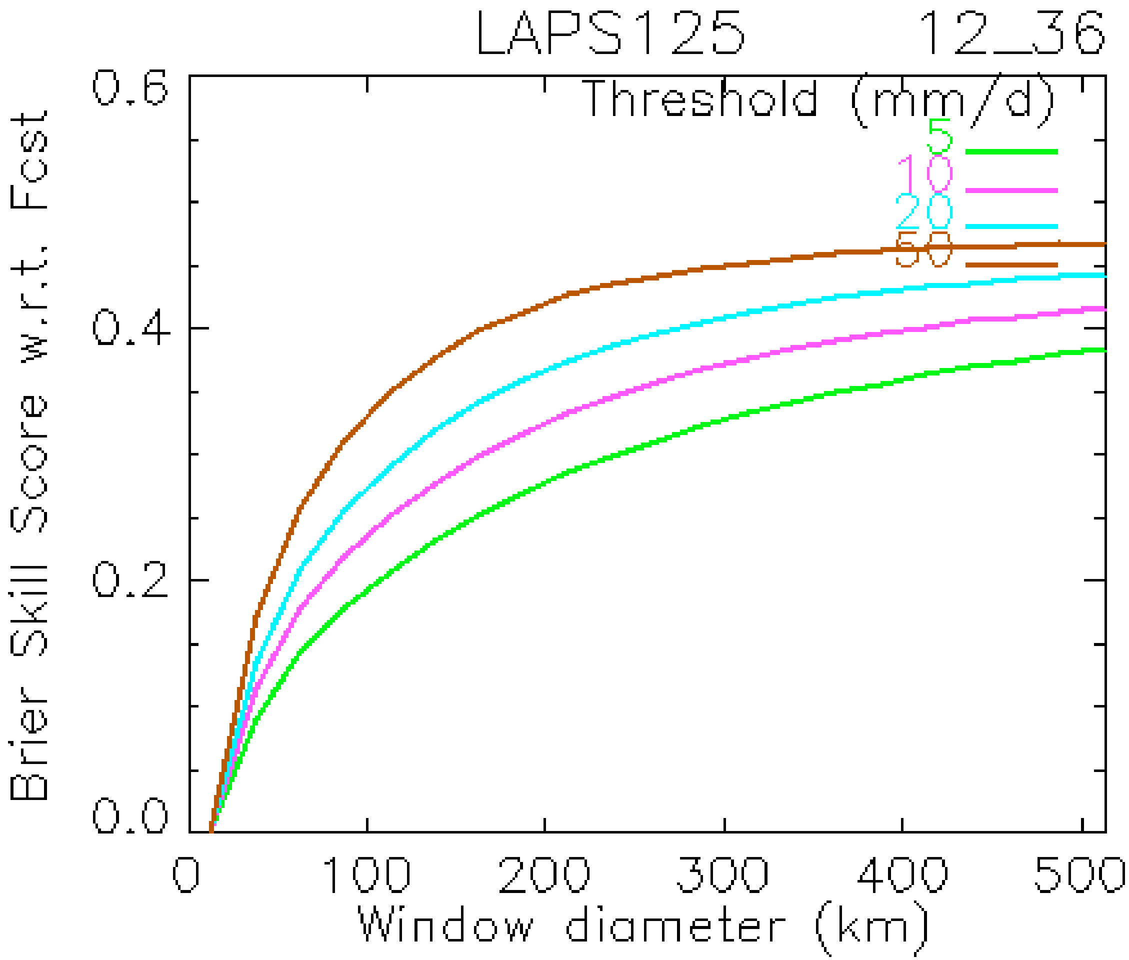
Verification data: ~5000 gauge observations each day

Regions: tropics - centre of box lies north of 25ºS
mid-latitudes - centre of box lies south of 25ºS

Overall performance - *BS*



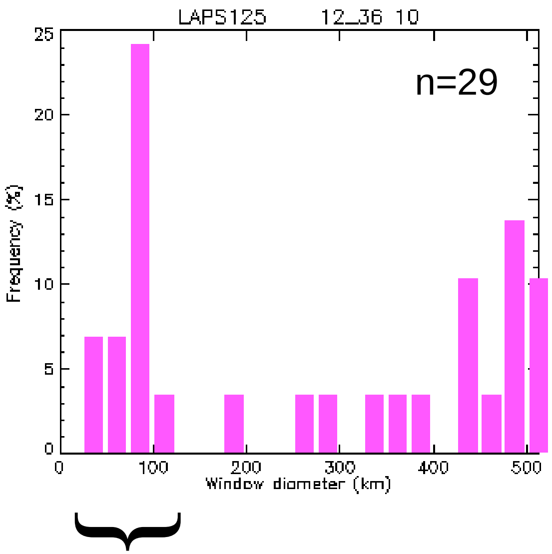
Overall performance - BSS_f

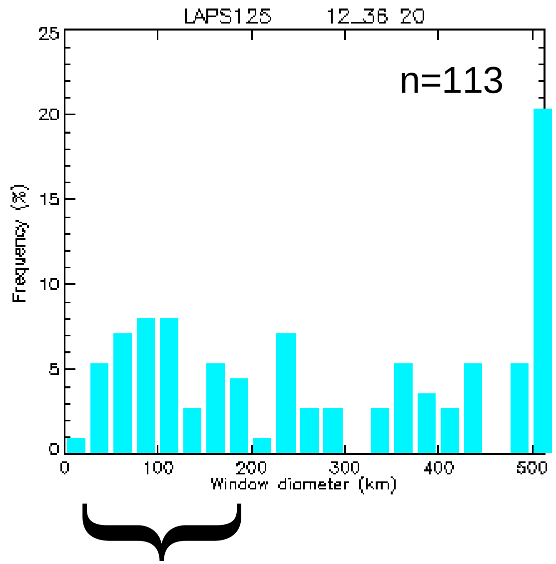


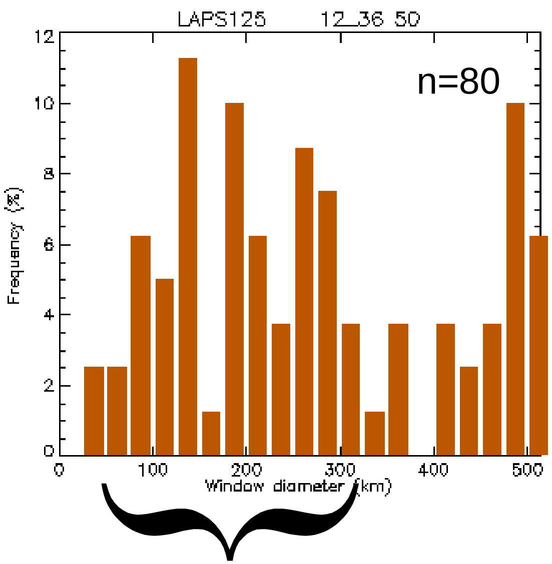
Regional/seasonal performance

- Probabilistic rain forecasts are more skillful in mid-latitudes than in tropics
- Probabilistic rain forecasts are more skillful in winter than in summer
- Relative improvement over deterministic forecasts is greater in summer than in winter
- Improvement over deterministic forecasts increases more quickly with window size in mid-latitudes than in tropics
- For larger window sizes the relative improvement is greater in tropics than in mid-latitudes

Optimum window size - relative frequency







Forecast max 10-20 mm/d (weak systems)	Forecast max 20-50 mm/d (moderate systems)	Forecast max > 50 mm/d (strong systems)
threshold=10 mm/d	threshold=20 mm/d	threshold=50 mm/d

Conclusions

Advantages:

- Probabilistic forecasts provide an estimate of uncertainty that may be very useful to forecasters and clients
- Probabilistic forecasts based on local space/time neighbourhood have greater skill than simple deterministic forecasts from high resolution models, as measured by the Brier Score

Disadvantages:

- Use of spatial neighbourhood may be inappropriate for some topographically forced weather
- Many users are not yet comfortable with probabilistic forecasts

Conclusions

This approach is complementary to ensemble prediction since it addresses a different aspect of the problem:

EPS: Will there be convection/fronts in the general area?

Probabilistic upscaling: If there is convection/fronts, what will the peak precipitation be and where is it most likely to be located?

Probabilistic upscaling can be applied to other quantities as well, not just rainfall!

"It is far better to foresee even without certainty than not to foresee at all. "

-- Henri Poincaré in *The Foundations of Science*

Extra slides...

Motivation

- Precipitation fields, even when accumulated in time, have high spatial variability.
- Many of the phenomena leading to precipitation (convection, rainbands in frontal systems, etc.) are not easily predicted on the time-scales of interest.
- Severe weather is often associated with smaller scales, which are not resolved in low-resolution models and extremely difficult to predict with high-resolution models.
- The most common, but also most expensive solution is Ensemble Prediction.

Can we make better use of the information provided by deterministic model simulations?

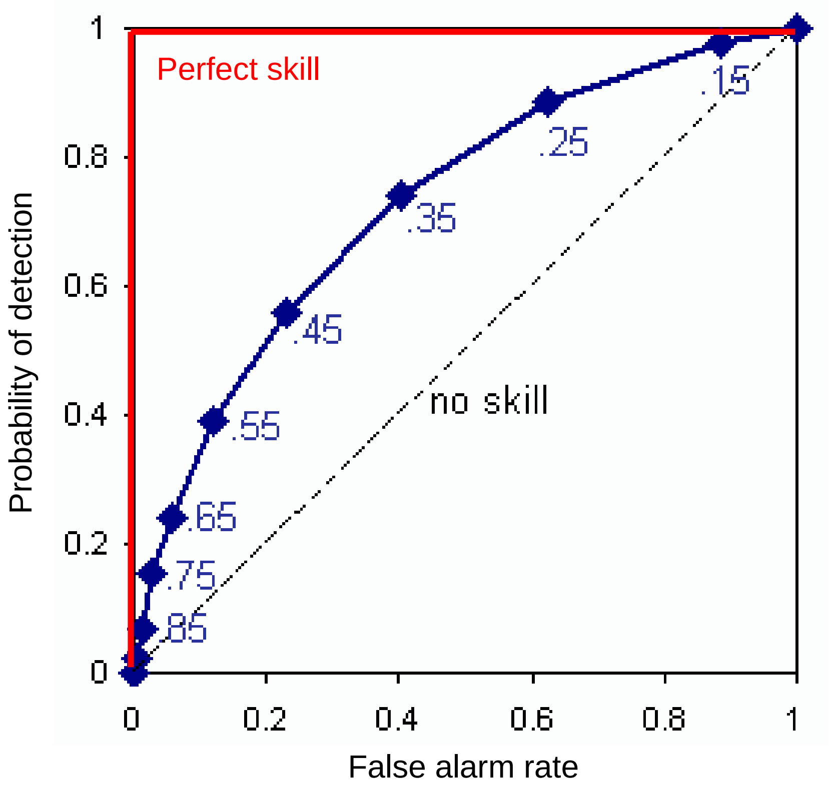
Evaluation (continued)

Relative Operating Characteristic (ROC) -

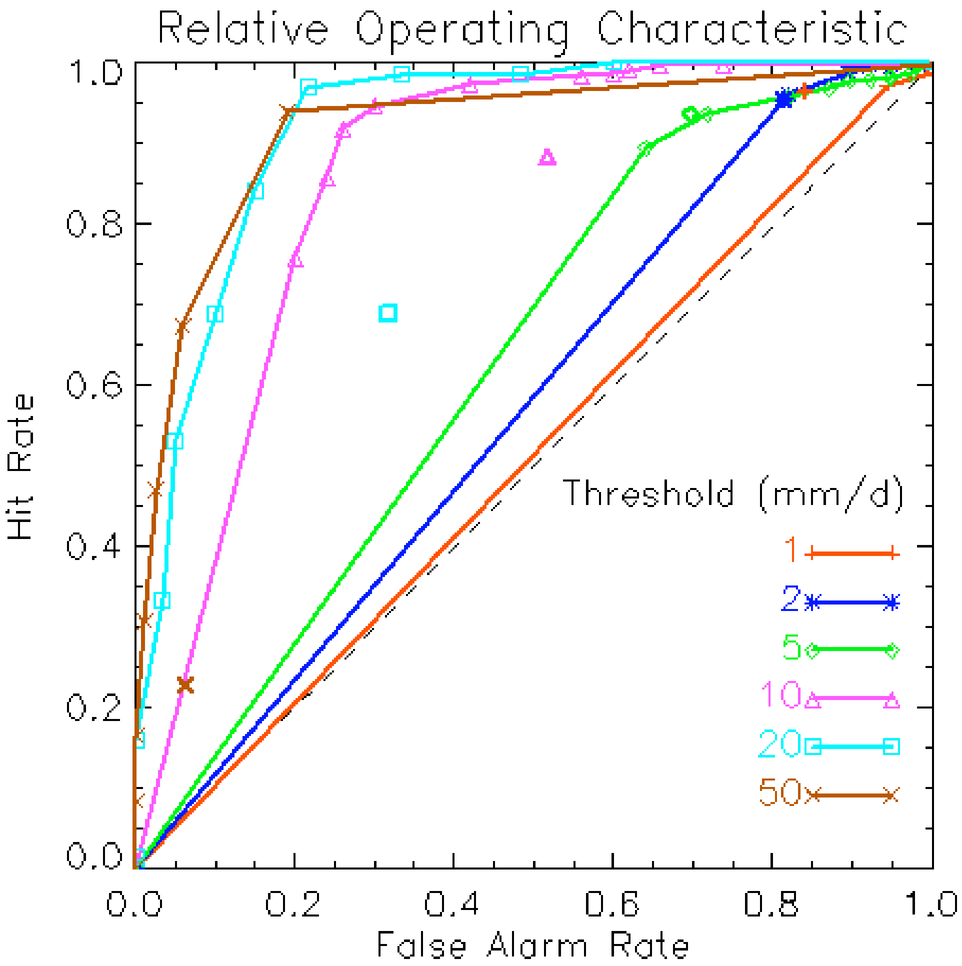
Hit rate vs. false alarm rate while varying the yes/no decision threshold from p_i=0 to p_i =1.

Area under curve is used as a score.

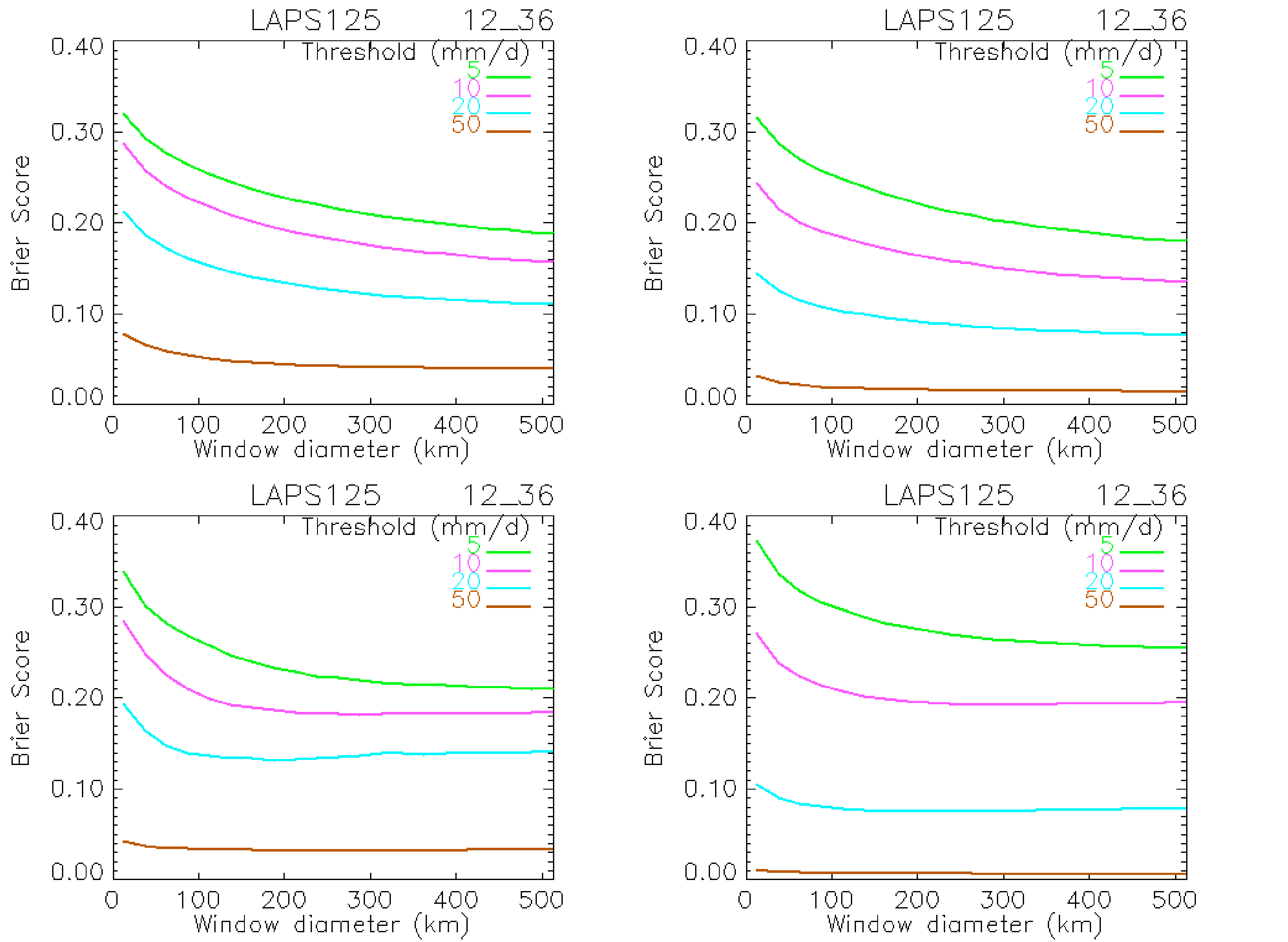
Perfect score = 1.



Comparison with deterministic forecast



Regional/seasonal performance - *BS*



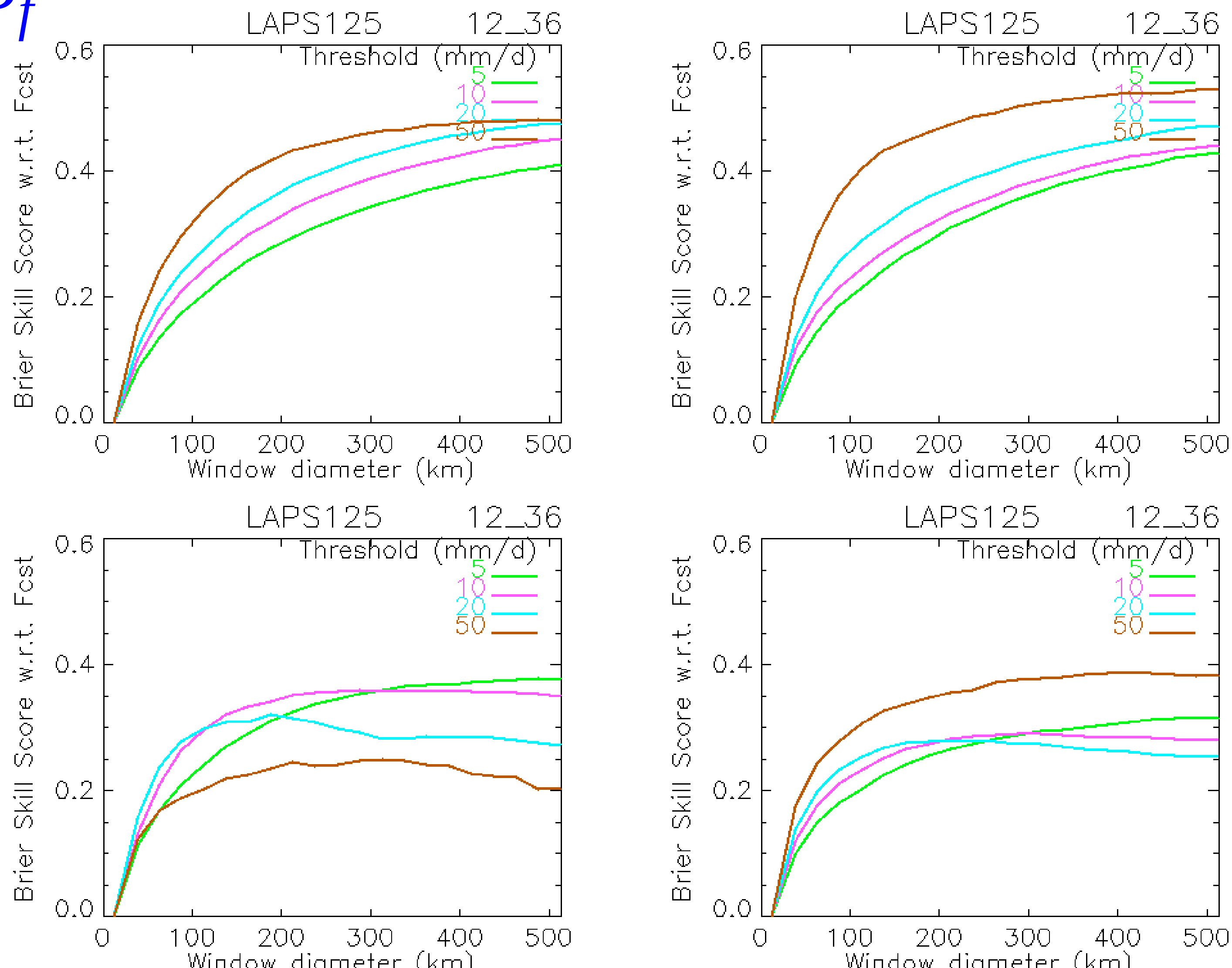
summer

winter

tropics

midlatitudes

Regional/seasonal performance - BSS_f



summer

winter

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midlatitudes