Probabilistic Weather Forecasting via Bayesian Model Averaging

Adrian E. Raftery
University of Washington
raftery@u.washington.edu
www.stat.washington.edu/raftery

Joint work with Tilmann Gneiting
with contributions by Veronica Berrocal, Chris Fraley, Yulia Gel and McLean Sloughter
In collaboration with Cliff Mass, Susan Joslyn, and Jeff Baars
Supported by NSF and the ONR MURI Program

NWS Visit
University of Washington
May 27, 2009

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  - $\Longrightarrow$ the 4D probabilistic forecasting cube

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where $w_k \geq 0$ and $\sum_{k=1}^{K} w_k = 1$.

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- The model is estimated from a training set of recent data at stations by maximum likelihood using the EM algorithm.
- Good results with a 25-day "moving window" training period.

UW Ensemble Bayesian Model Averaging

User's Guide

Param: Max 2m Temp (24–48 hrs)

Valid for 24 hours ending at:

Wed May 27, 2009 5 PM

Jump to new date

Toggle Contour Lines OFF

Plot Size: Big Medium Small

Units: Celsius Fahrenheit

Grid Forecast:

Deterministic

Upper bound of interval .9

Lower bound of interval .1

Half-width of interval

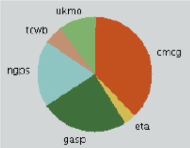
Prob. param exceeds threshold 0

Greater than Less than

Probability Distribution:

Latitude: 47.68049 Longitude: -122.2244

Retrieve Data



BMA Weights

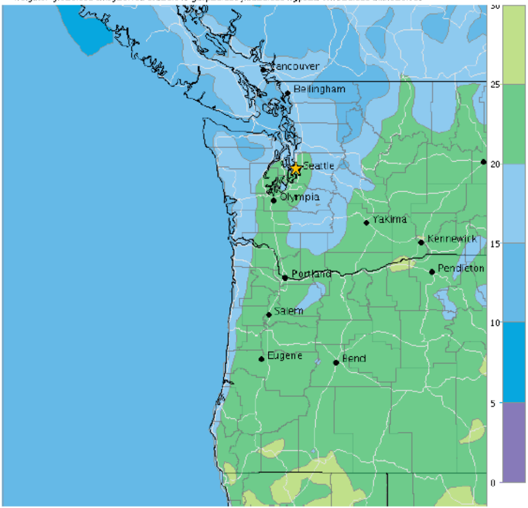
Forecasts Error: NORMAL: 2.16

BMA Forecast Verification

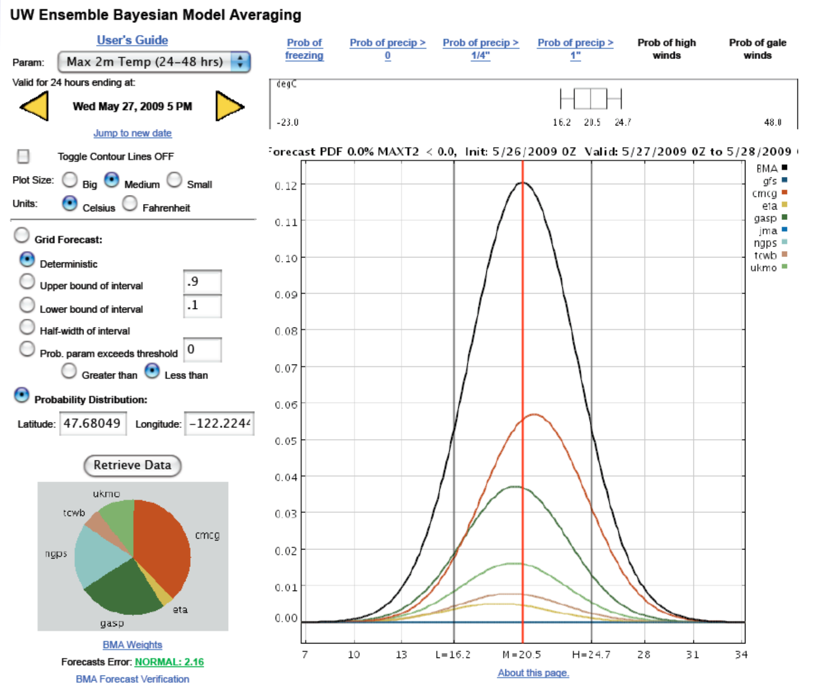
Prob of freezing | Prob of precip > 0 | Prob of precip > 1/4" | Prob of precip > 1" | Prob of high winds | Prob of gale winds

BMA MAXT2 Forecast Init: 5/26/09 12:00 AM UTC (5/25/09 5:00 PM) Valid: 5/26/09 5:00 PM to 5/27/09 5:00 PM PT

Weights: gfs=0.000 cmcg=0.462 eta=0.041 gasp=0.302 jma=0.000 ngps=[illegible] tcwb=0.063 ukmo=0.131



About this page.



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degC
-23.0
16.2 20.5 24.7
48.0
Forecast PDF 0.0% MAXT2 < 0.0, Init: 5/26/2009 0Z Valid: 5/27/2009 0Z to 5/28/2009
BMA
gfs
cmcg
eta
gasp
jma
ngps
tcwb
ukmo
0.12
0.11
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
7 10 13 L=16.2 M=20.5 H=24.7 28 31 34
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(24hr forecasts of 2m temperature at ASOS stations and buoys)

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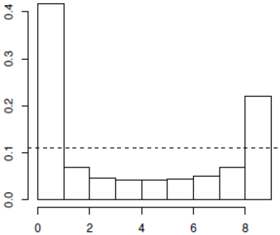

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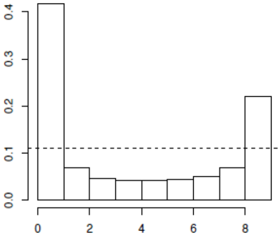

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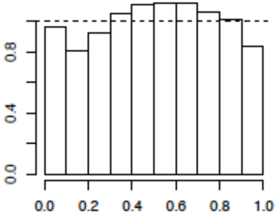

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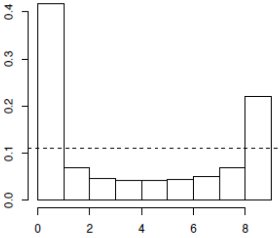

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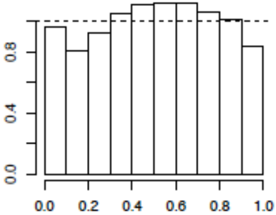

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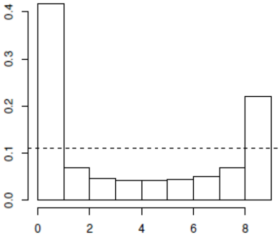

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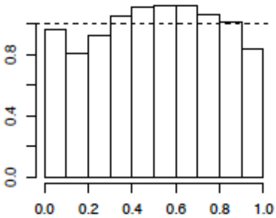

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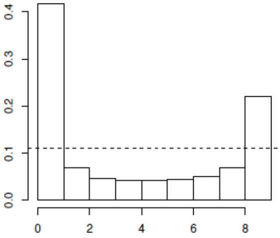

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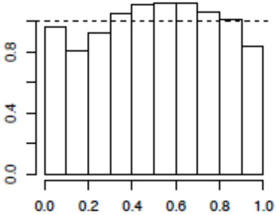

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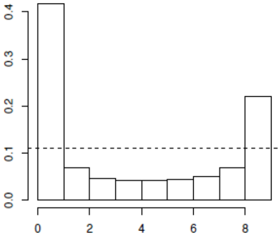

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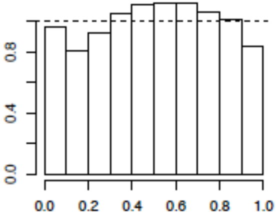

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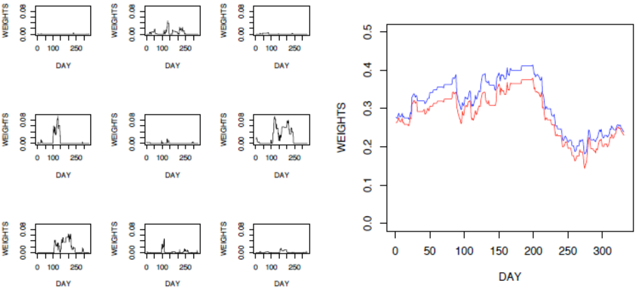

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Exchangeable BMA: Results for 2007

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BMA Predictive Distributions for Precipitation

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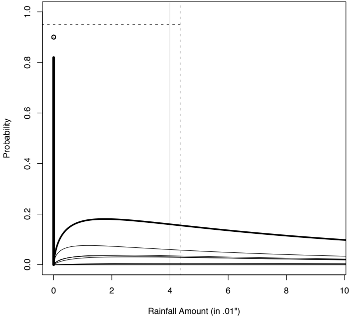

Renton, 19th May, 2003

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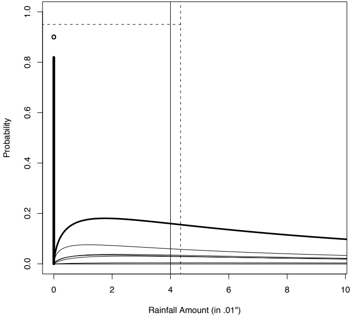

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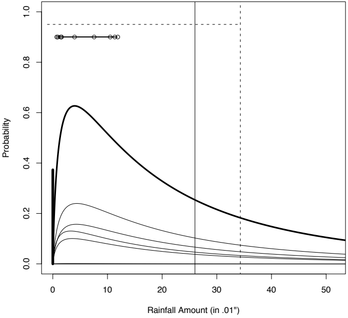

Station KPWT, 26th January, 2003

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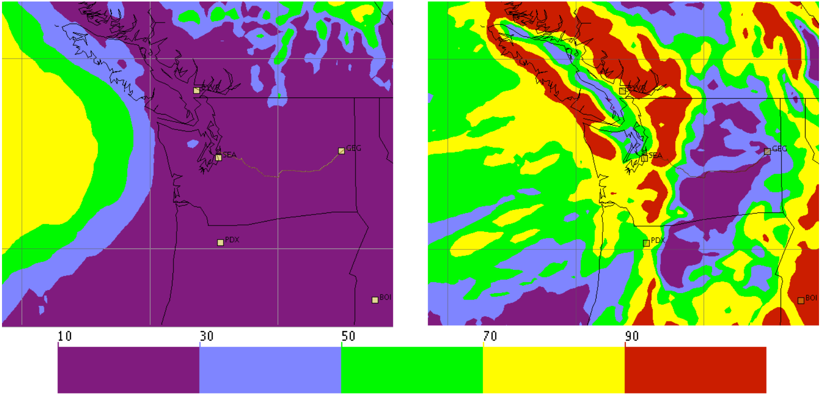

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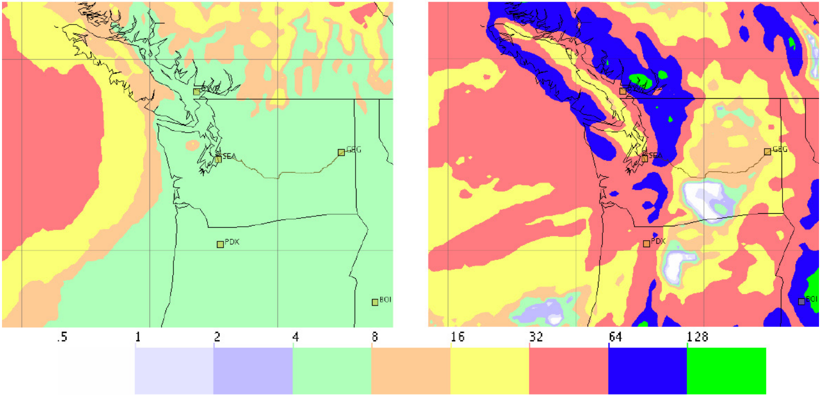

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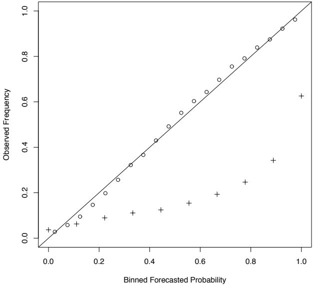

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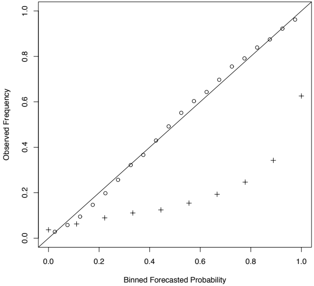

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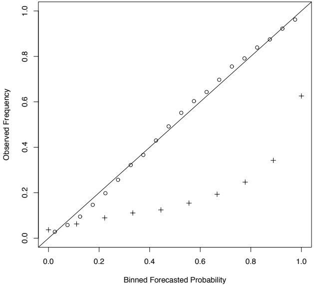

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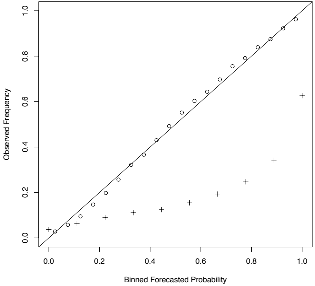

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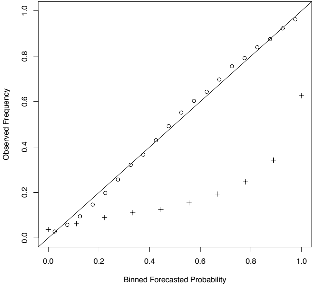

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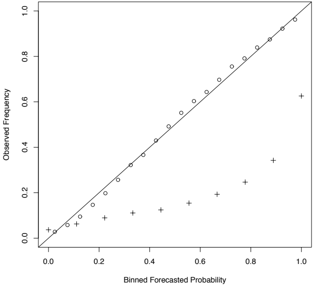

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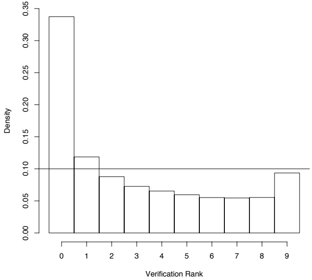

Verification rank histogram
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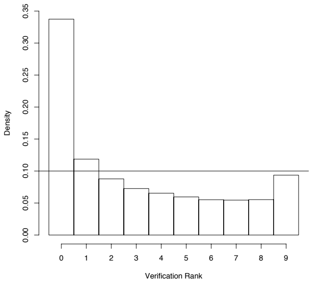

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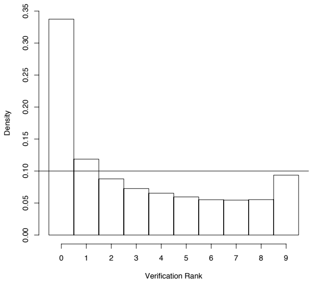

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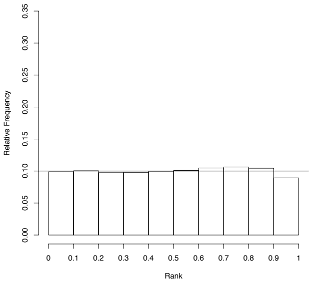

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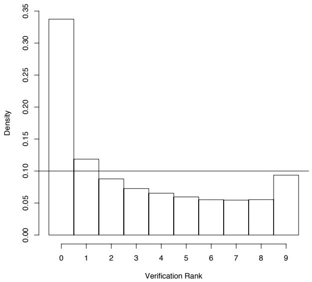

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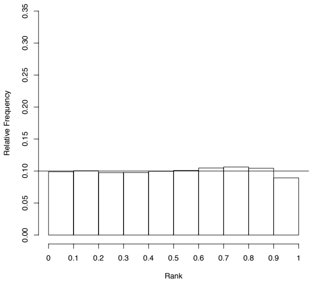

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- $\Longrightarrow$ feasible to use BMA for the nation

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Example

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Gridded Forecast for January 12, 2002

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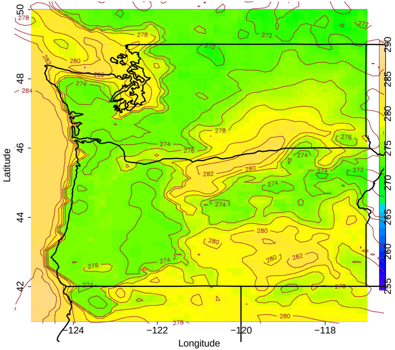

Gridded forecast

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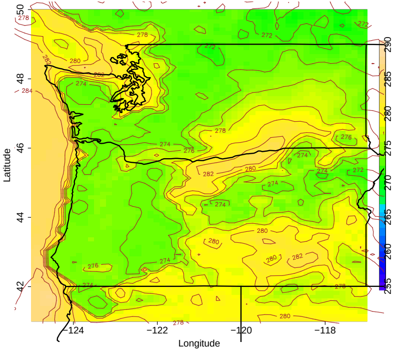

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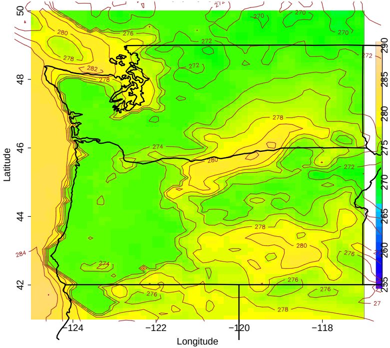

Bias-corrected

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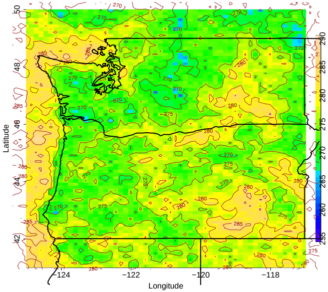

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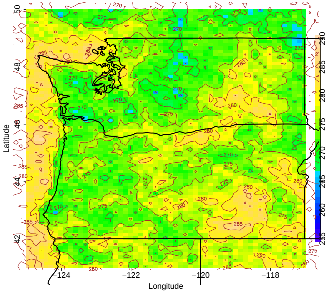

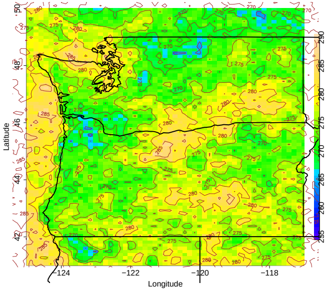

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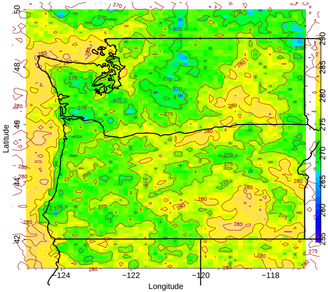

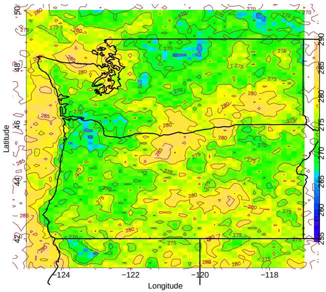

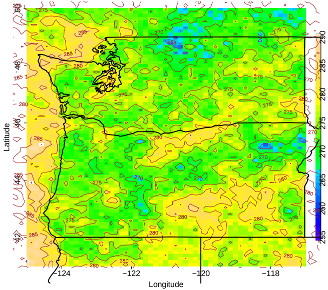

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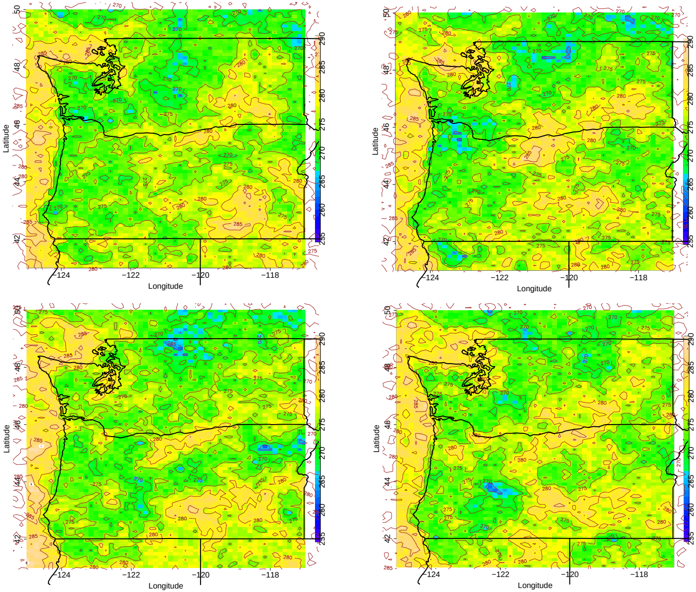

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