Emerging methods for post-processing

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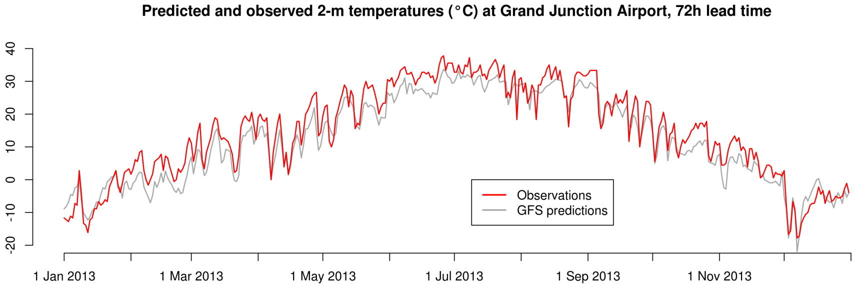
Why statistical post-processing?

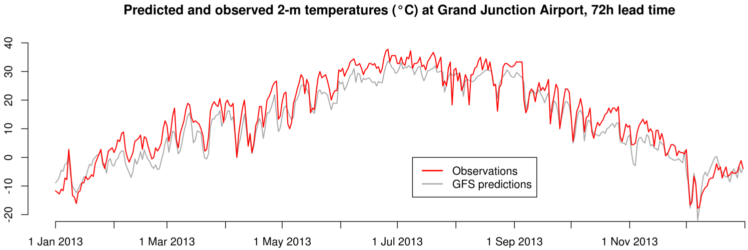
Despite continuous improvements to numerical weather prediction (NWP) systems, certain forecasts still suffer from systematic biases:

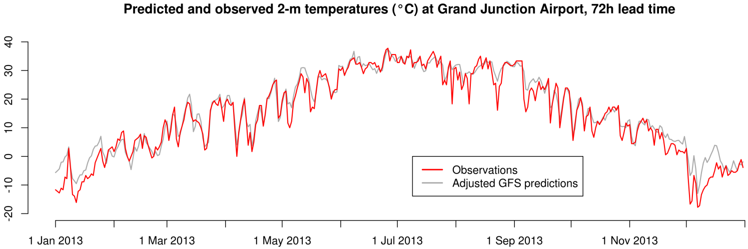
- insufficient model resolution
- less-than-optimal initial conditions
- etc.



Why statistical post-processing?

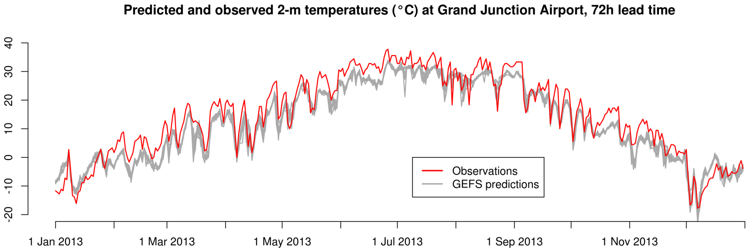
Statistical post-processing removes biases and improves forecast accuracy:

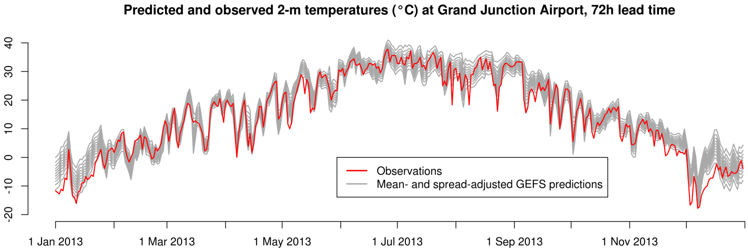




Why statistical post-processing?

For ensembles, the spread needs to be adjusted in addition to the mean:





Multivariate post-processing

In some applications, accounting for dependence between

- different variables
- different forecast lead times
- different locations

is crucial for the reliability of the quantity of interest.

Example:

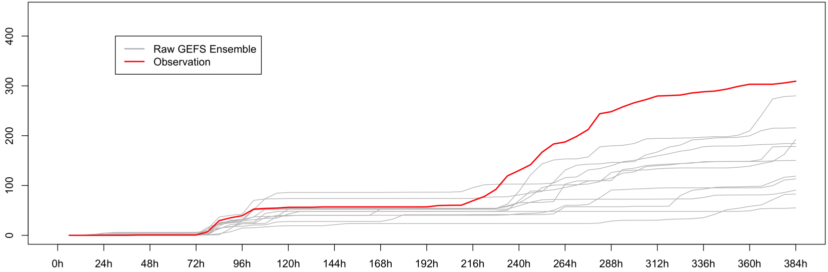
Average precipitation accumulations over seven stations in the Russian River basin.

We calibrate GEFS ensemble forecasts of 6-h precipitation accumulations up to day 15 and study the corresponding plume diagrams.

Example: Need for multivariate post-processing

Accumulated average precipitation over the Russian River basin, starting from 9 January 2010, 06 UTC.

a) Raw ensemble forecasts:

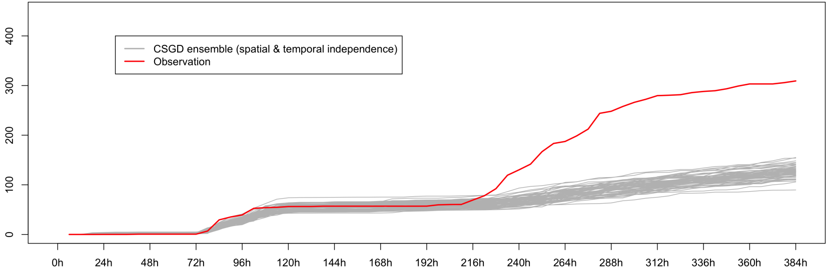


At longer lead times, the ensemble forecasts are overconfident; here, all members underestimate the precipitation amounts after day 9 and the observation plume lies way outside the ensemble range.

Example: Need for multivariate post-processing

Accumulated average precipitation over the Russian River basin, starting from 9 January 2010, 06 UTC.

b) CSGD method, no modelling of spatial and temporal dependence:

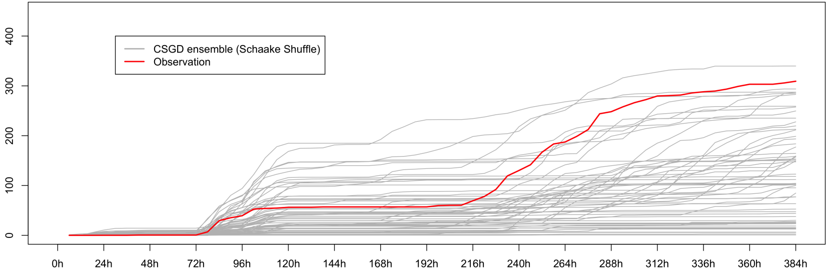


Even though the CSGD method yields reliable and sharp predictions *at every location* and *for every 6-h period individually*, the spatially averaged and temporally accumulated precipitation forecasts are underdispersive.

Example: Need for multivariate post-processing

Accumulated average precipitation over the Russian River basin, starting from 9 January 2010, 06 UTC.

c) CSGD method & Schaake Shuffle:

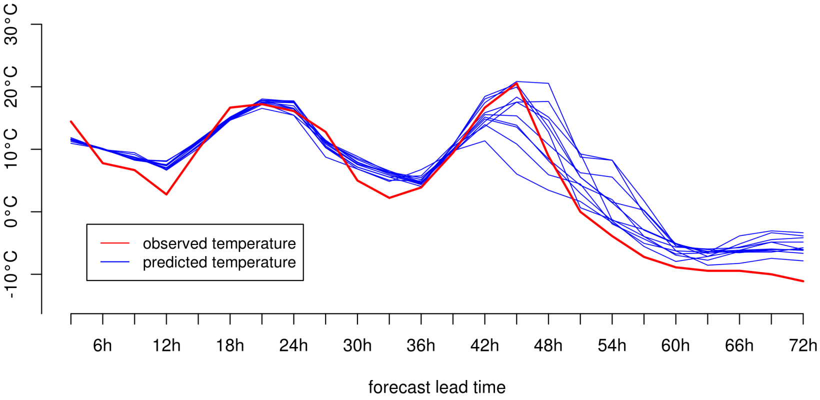


Performing an additional post-processing step to restore spatial and temporal dependence of forecast errors results in increased ensemble spread and thus in a better representation of forecast uncertainty.

Multivariate post-processing

Consider a probabilistic forecast of a multivariate quantity, where multivariate may refer to different variables, or the same variable at different time points and/or locations in space.

Example: Temperature forecasts at Denver for lead times up to 72-h



Multivariate post-processing

Applying the post-processing techniques discussed above yields calibrated forecasts at each lead time separately. How can we re-create forecast trajectories with adequate temporal correlations?

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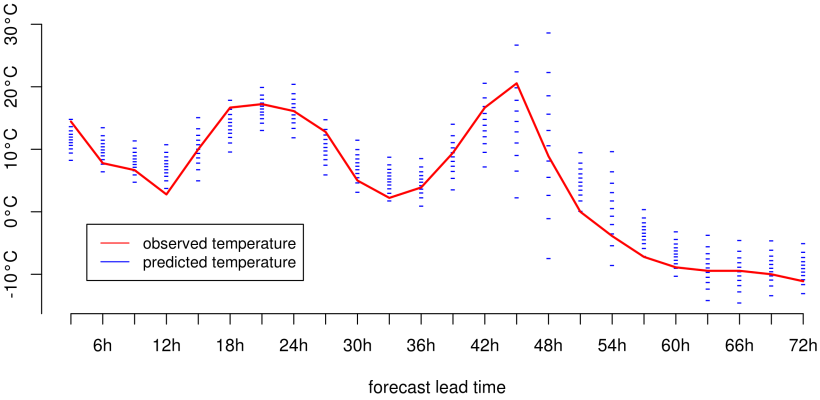

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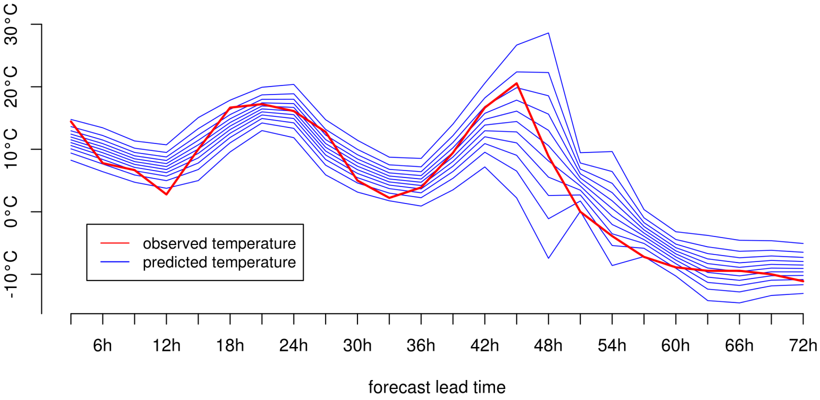

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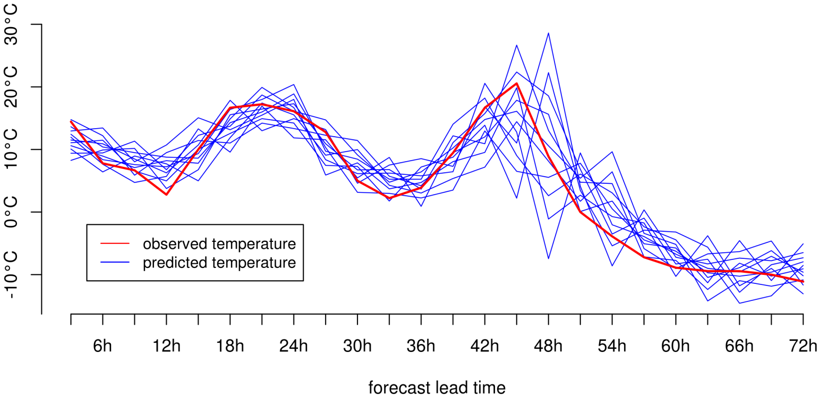

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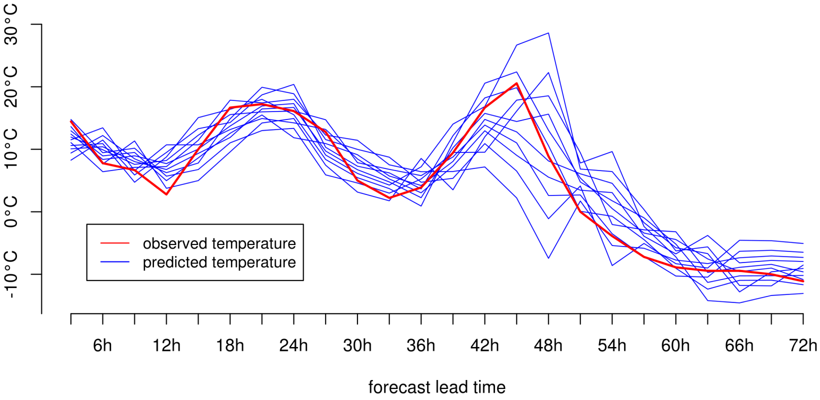
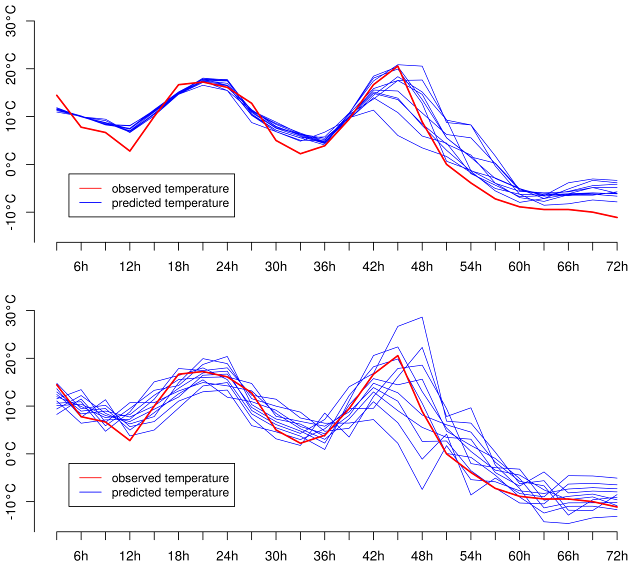


Using multivariate information from raw ensemble forecasts

Ensemble copula coupling (ECC):



Idea: retain the ordering (and thus the rank correlations) of the raw ensemble forecasts but replace their values by those derived from the calibrated marginal distributions.

Special case: member-by-member calibration

Using multivariate information from past observations

Schaake Shuffle:

Proceed as with ECC, but use the rank order of *past obervations at the same or similar days of the year* instead of the ranks of today's ensemble forecasts.

Similarity-based Schaake Shuffle:

Use again observation ranks but select the historic dates based on similarity of the respective forecasts.

Statistical dependence models:

Fit a statistical dependence model (Gaussian copulas, Gaussian random fields) using forecast error statistics at historic dates.

Two main approaches for multivariate post-processing

1. Use multivariate information from raw ensemble forecasts

+ flow-dependent, physics-based correlations
+ potentially different correlations for different forecast magnitudes

– spurious correlations in the raw ensemble may be amplified
– multivariate features that are not resolved by the NWP model are not accounted for
– ensemble size limits the representativeness of multivariate features

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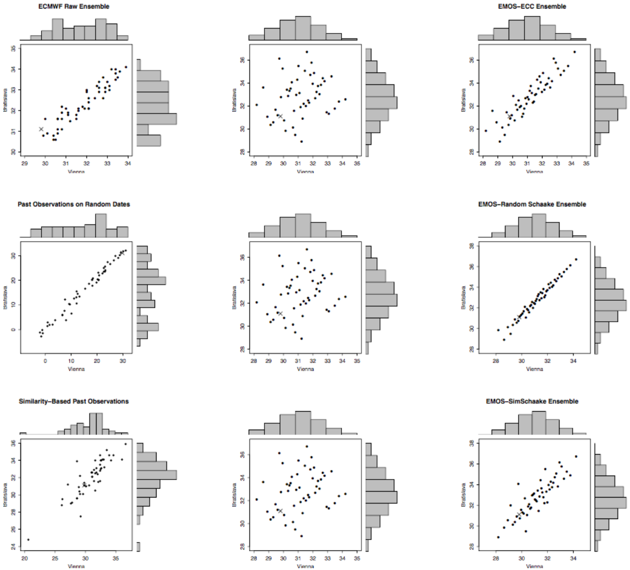
2. Use multivariate information from past observations

   + more realistic error structures
   + downscaling of dependence information

   – multivariate information is not flow-dependent
   – extra efforts are required to model correlations that depend on the forecast magnitude

Bivariate example: ECC vs. Schaake vs. SimSchaake



24 hour ahead EMOS-calibrated temperature forecasts (in °C) at Vienna and Bratislava valid on 9 July 2011, 1200 UTC.

Image courtesy of Roman Schefzik.

Probabilistic forecasts of rare events

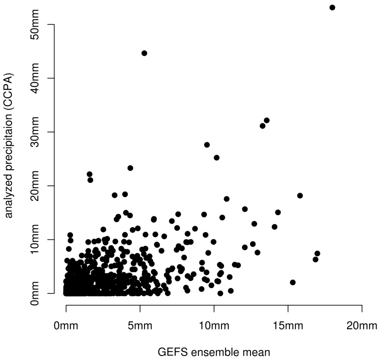
For some weather variables, we are often interested in particular events (e.g. "rainfall amounts exceed 10mm").

These event probabilities can be modeled directly, e.g. via logistic regression:

$$\mathrm{logit}\big(P(y > 10mm)\big) = \beta_0 + \beta_1 \cdot x$$

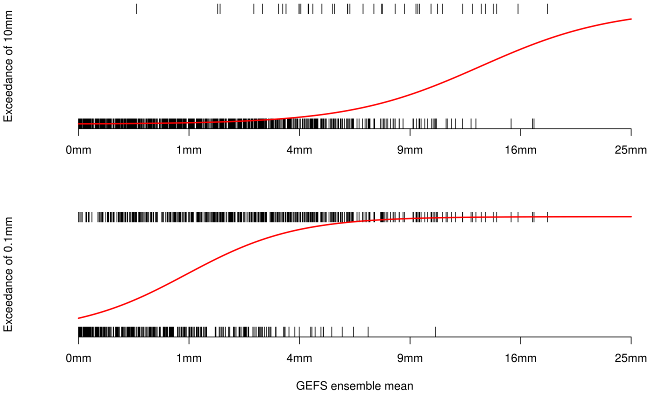
Example:

60 to 72-h Precipitation accumulations over Seattle during the winter season.



Probabilistic forecasts of rare events

Fitting a logistic regression model for high thresholds becomes increasingly difficult:



Parametric assumptions can mitigate the problems that come with modeling rare events, but limited training sample size remains a concern.

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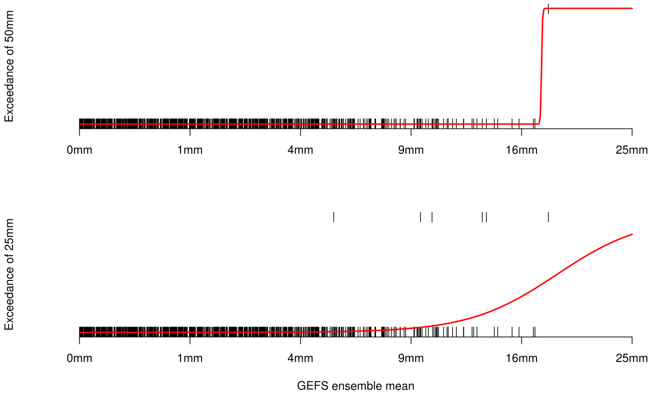

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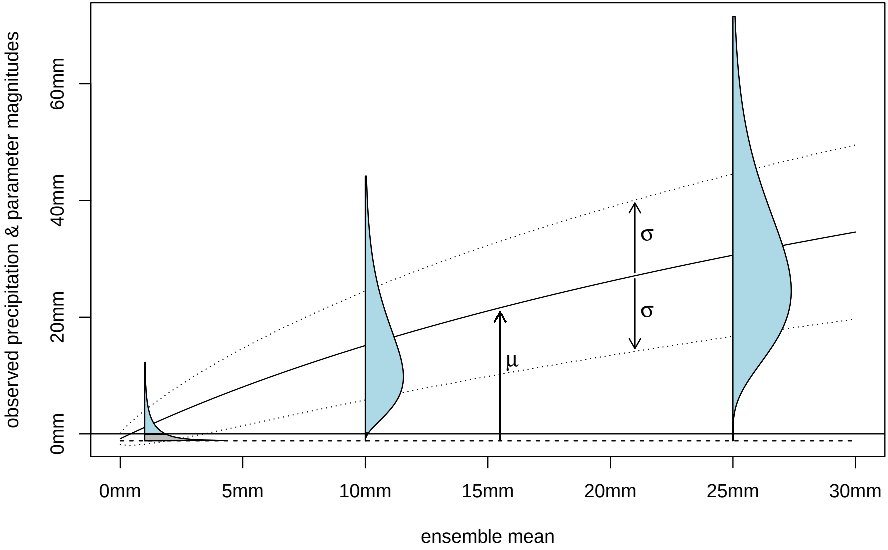
Example of the parametric CSGD model



Options for getting a sufficiently large training sample

1. Reforecasts!

   + no compromises, no biases
   + ideally cover several years, thus variations in climatology
   – expensive

2. Regional post-processing, supplemental locations, random field models that link locations statistically

   + can reduce the need for reforecasts
   – linking/combining less than perfectly similar locations entails biases

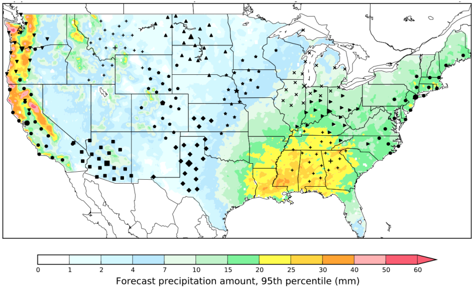
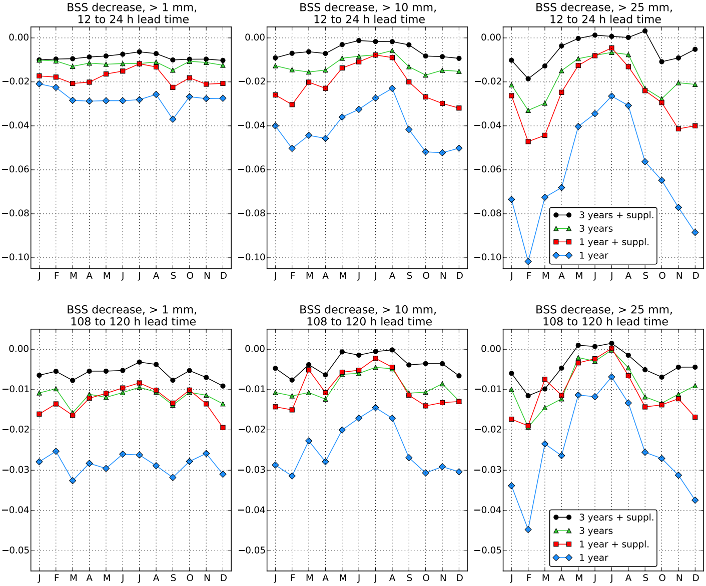


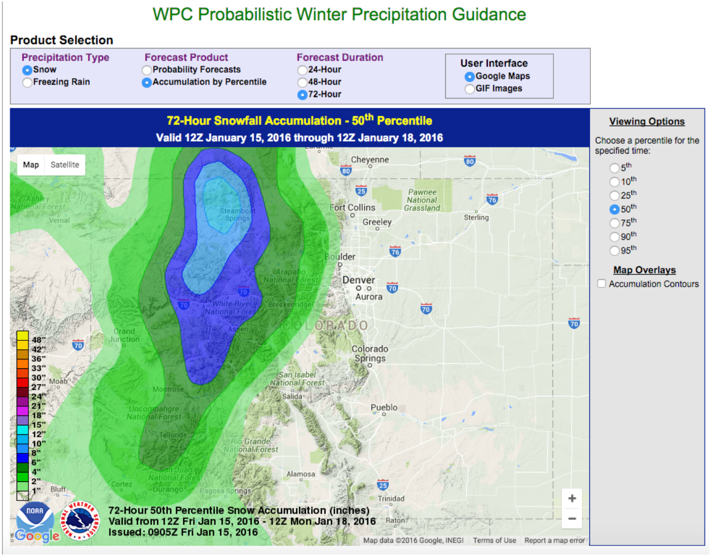
Image courtesy of Tom Hamill

Example: Loss of skill relative to a 11-year training sample



Brier skill scores for the CSGD post-processing method for precipitation amounts.

New variables/products: How far should NOAA go?



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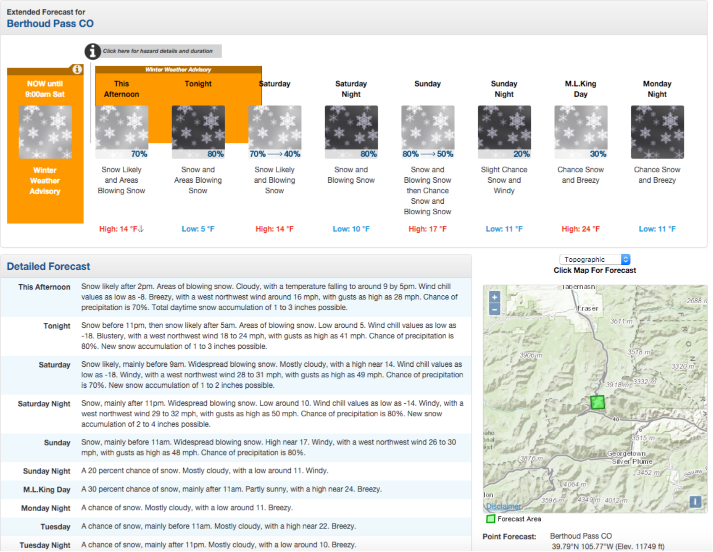


Extended Forecast for
Berthoud Pass CO

Click here for hazard details and duration

Winter Weather Advisory

NOW until 9:00am Sat	This Afternoon	Tonight	Saturday	Saturday Night	Sunday	Sunday Night	M.L.King Day	Monday Night
	70%	80%	70% ⟶ 40%	80%	80% ⟶ 50%	20%	30%	
Winter Weather Advisory	Snow Likely and Areas Blowing Snow	Snow and Areas Blowing Snow	Snow Likely and Blowing Snow	Snow and Blowing Snow	Snow and Blowing Snow then Chance Snow and Blowing Snow	Slight Chance Snow and Windy	Chance Snow and Breezy	Chance Snow and Breezy
	High: 14 °F↓	Low: 5 °F	High: 14 °F	Low: 10 °F	High: 17 °F	Low: 11 °F	High: 24 °F	Low: 11 °F

Detailed Forecast

This Afternoon	Snow likely after 2pm. Areas of blowing snow. Cloudy, with a temperature falling to around 9 by 5pm. Wind chill values as low as -8. Breezy, with a west northwest wind around 16 mph, with gusts as high as 28 mph. Chance of precipitation is 70%. Total daytime snow accumulation of 1 to 3 inches possible.
Tonight	Snow before 11pm, then snow likely after 5am. Areas of blowing snow. Low around 5. Wind chill values as low as -18. Blustery, with a west northwest wind 18 to 24 mph, with gusts as high as 41 mph. Chance of precipitation is 80%. New snow accumulation of 1 to 3 inches possible.
Saturday	Snow likely, mainly before 9am. Widespread blowing snow. Mostly cloudy, with a high near 14. Wind chill values as low as -18. Windy, with a west northwest wind 28 to 31 mph, with gusts as high as 49 mph. Chance of precipitation is 70%. New snow accumulation of 1 to 2 inches possible.
Saturday Night	Snow, mainly after 11pm. Widespread blowing snow. Low around 10. Wind chill values as low as -14. Windy, with a west northwest wind 29 to 32 mph, with gusts as high as 50 mph. Chance of precipitation is 80%. New snow accumulation of 2 to 4 inches possible.
Sunday	Snow, mainly before 11am. Widespread blowing snow. High near 17. Windy, with a west northwest wind 26 to 30 mph, with gusts as high as 48 mph. Chance of precipitation is 80%.
Sunday Night	A 20 percent chance of snow. Mostly cloudy, with a low around 11. Windy.
M.L.King Day	A 30 percent chance of snow, mainly after 11am. Partly sunny, with a high near 24. Breezy.
Monday Night	A chance of snow. Mostly cloudy, with a low around 11. Breezy.
Tuesday	A chance of snow, mainly before 11am. Mostly cloudy, with a high near 22. Breezy.
Tuesday Night	A chance of snow, mainly after 11pm. Mostly cloudy, with a low around 10. Breezy.

Topographic
Click Map For Forecast

Forecast Area

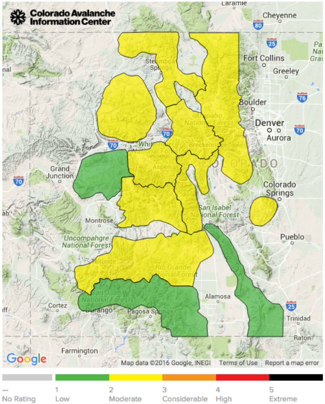
Point Forecast: Berthoud Pass CO
39.79°N 105.77°W (Elev. 11749 ft)

New variables/products: How far should NOAA go?

Avalanche danger is basically a function of

- snowfall
- temperatures
- wind speed and direction
- (air pollution)

over a series of several days.



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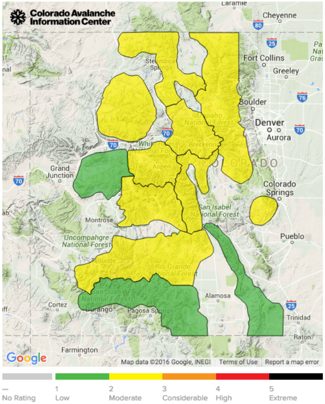

Could a machine learning method keep track of these variables and produce more highly resolved maps of avalache danger?

Could / should avalache danger be predicted with a lead time of several days to inform skiers / ski resort managers / rescuers?

Literature I

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