



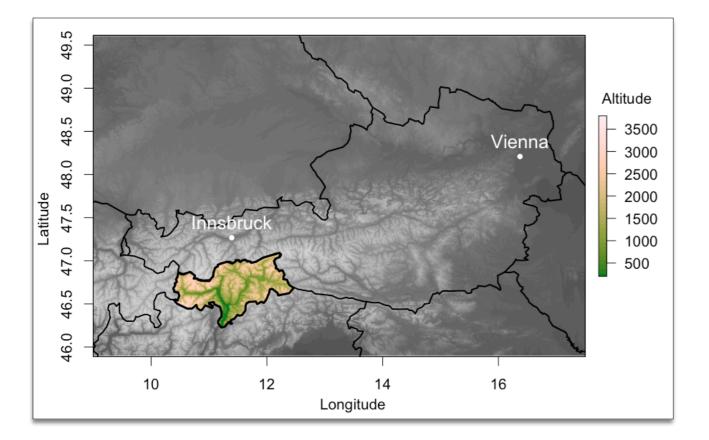
# Spatial Ensemble Post-Processing with Standardized Anomalies

Markus Dabernig, Georg J. Mayr, Jakob W. Messner and Achim Zeileis

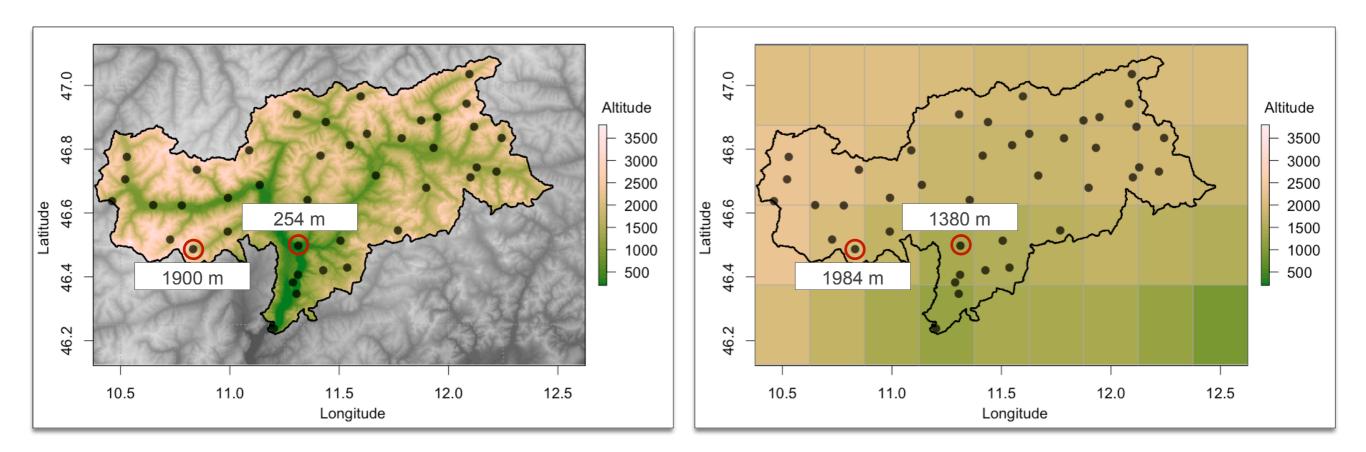




### **Motivation**



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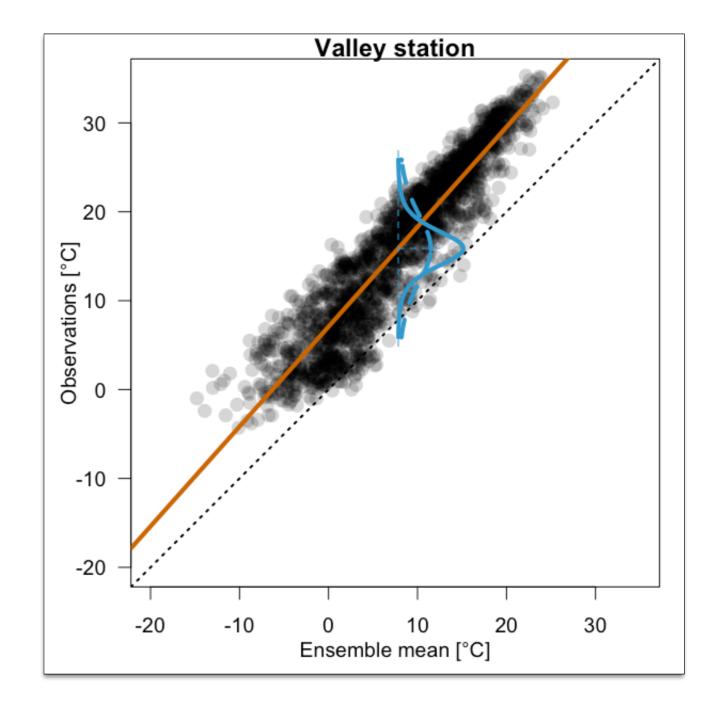
Topography

ECMWF ensemble topography (0.25°)

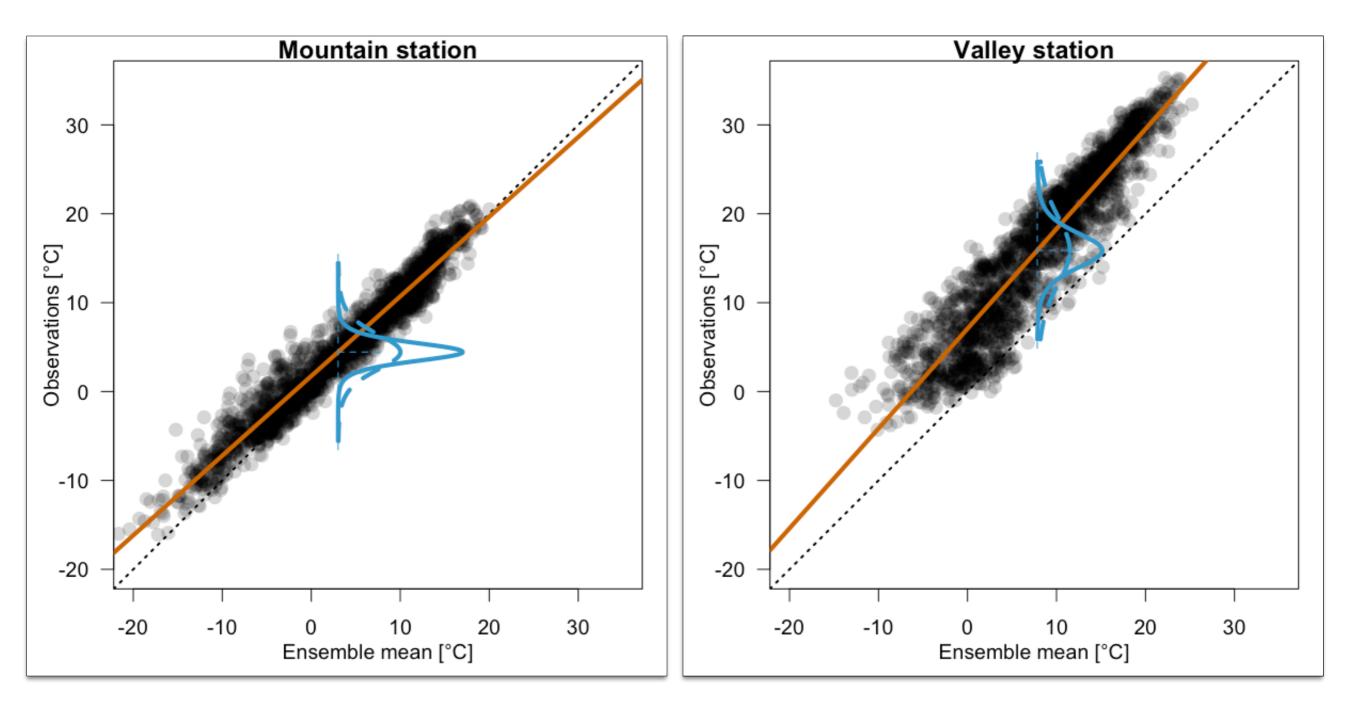
- 18 UTC temperature measurements from automatic weather stations
- + 18 h ECMWF ensemble temperature forecasts, 00 UTC run

### **Ensemble Model Output Statistics (EMOS)**

$$y \sim N(\mu, \sigma)$$
  
 $\mu = b_0 + b_1 m$   
 $\log(\sigma) = c_0 + c_1 \log(s)$   
 $y...Observations$   
 $m...Ensemble mean$   
 $s...Ensemble spread$ 



### **Ensemble Model Output Statistics (EMOS)**



$$\frac{y - \mu_y}{\sigma_y} \sim N(\mu, \sigma)$$

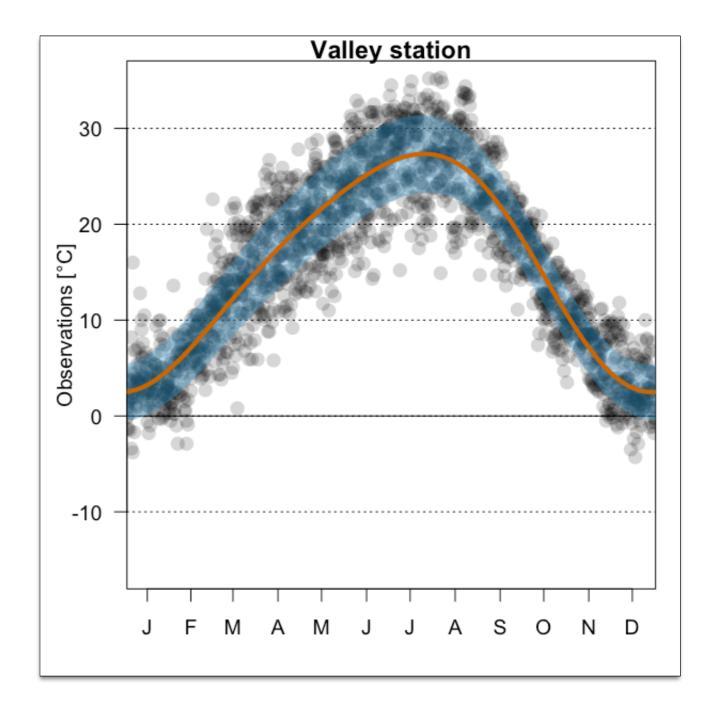
$$\mu = b_0 + b_1 \frac{m - \mu_m}{\sigma_m}$$

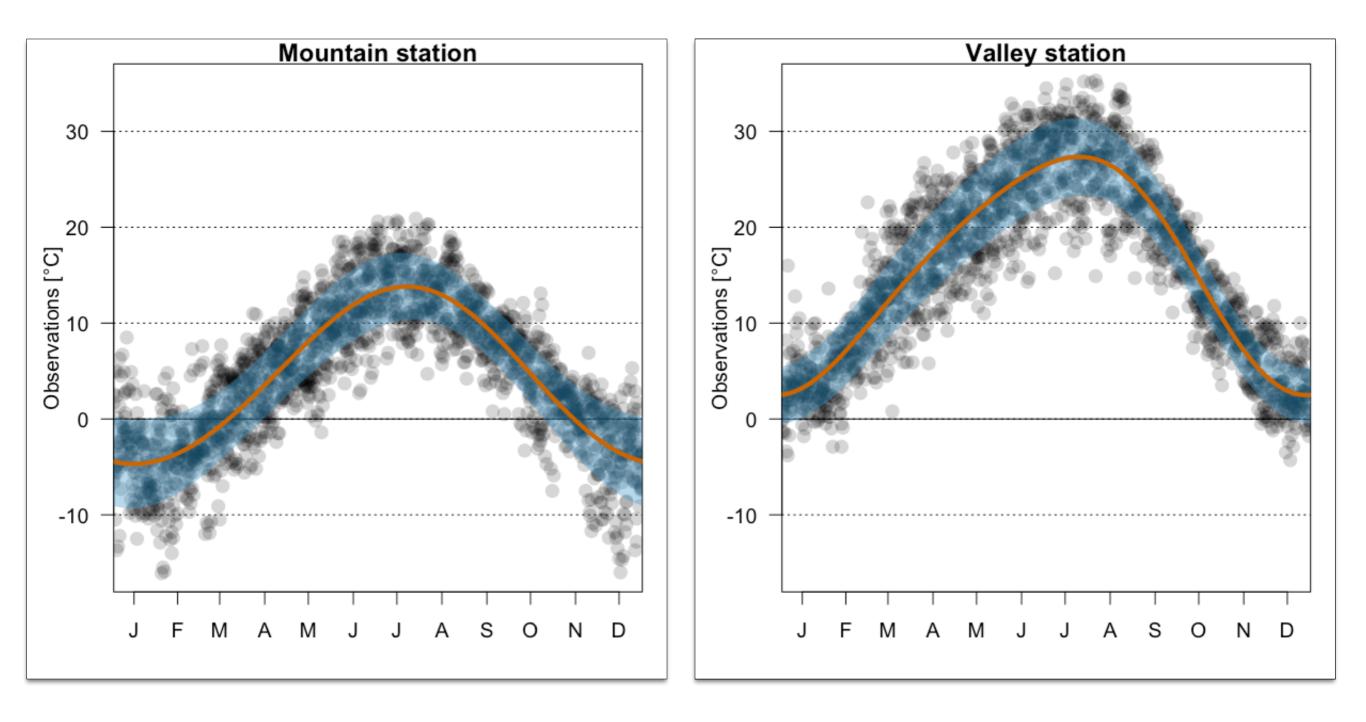
$$\log(\sigma) = c_0 + c_1 \frac{\log(s) - \mu_{\log(s)}}{\sigma_{\log(s)}}$$

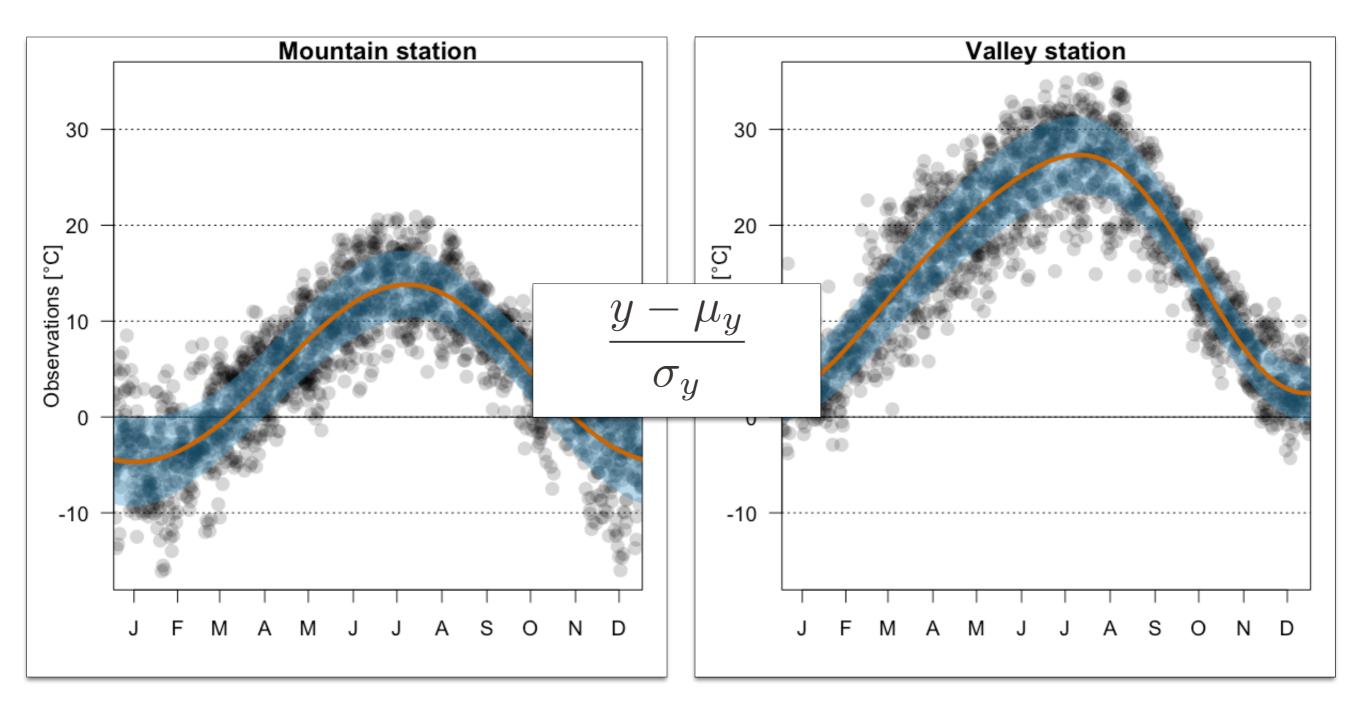
 $\mu_{y,m,\log(s)}$ ...Climatological mean  $\sigma_{y,m,\log(s)}$ ...Climatological standard deviation

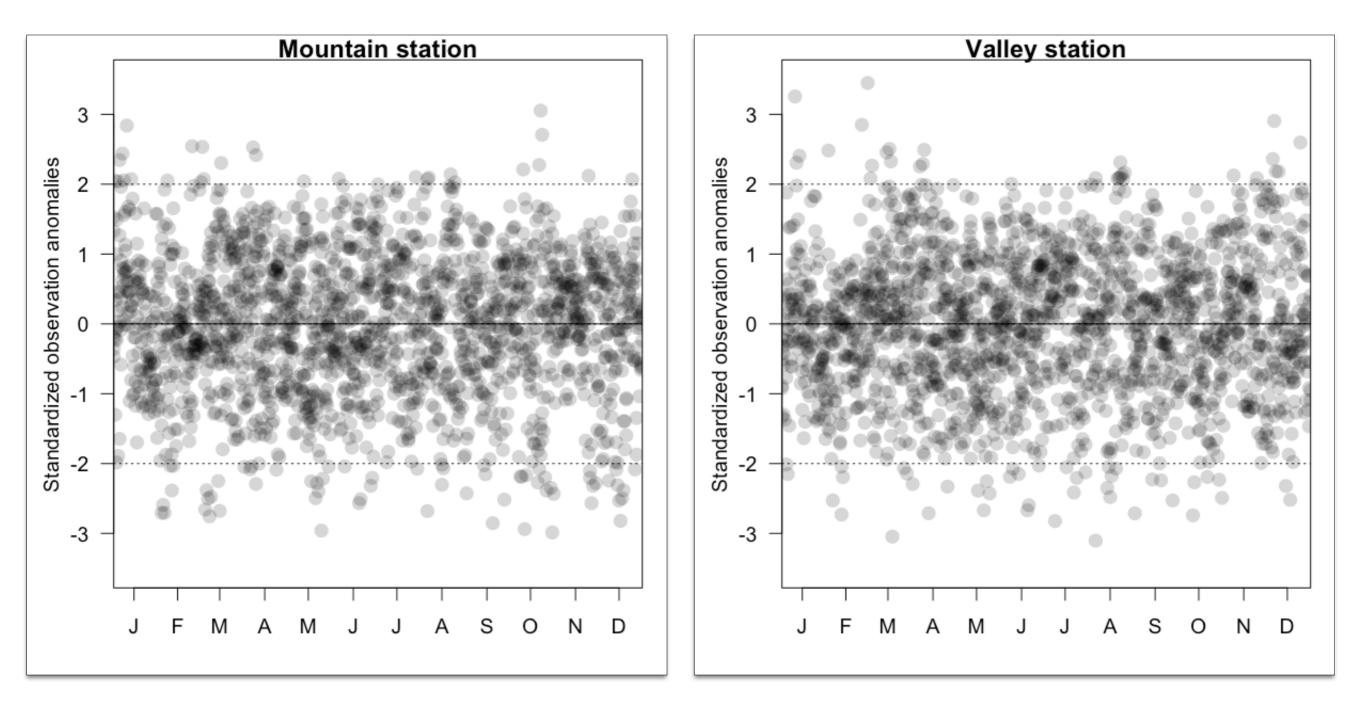
 $\frac{\text{Generalized Additive Model for}}{\text{Location, Scale and Shape:}}$  $y \sim N(\mu_y, \sigma_y)$  $\mu_y = \beta_0 + f(\text{Season})$  $\log(\sigma_y) = \gamma_0 + g(\text{Season})$ 

f, g...non linear function

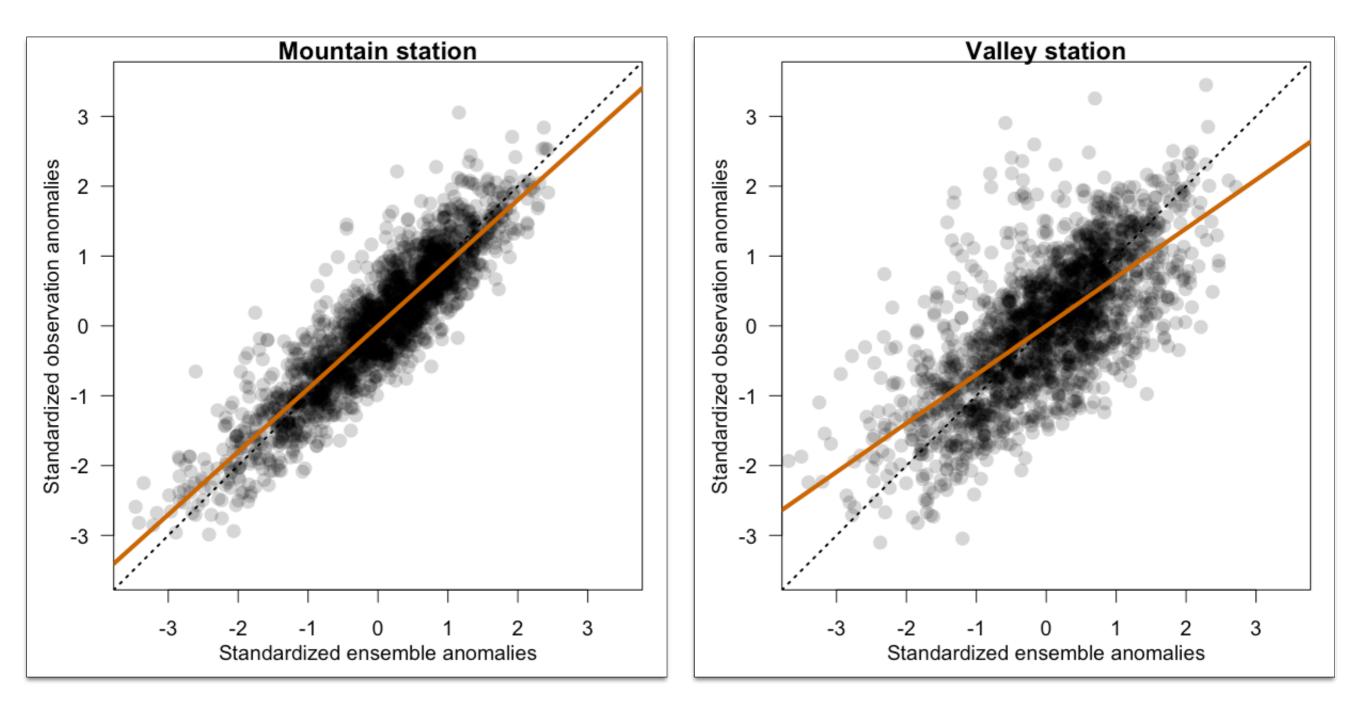


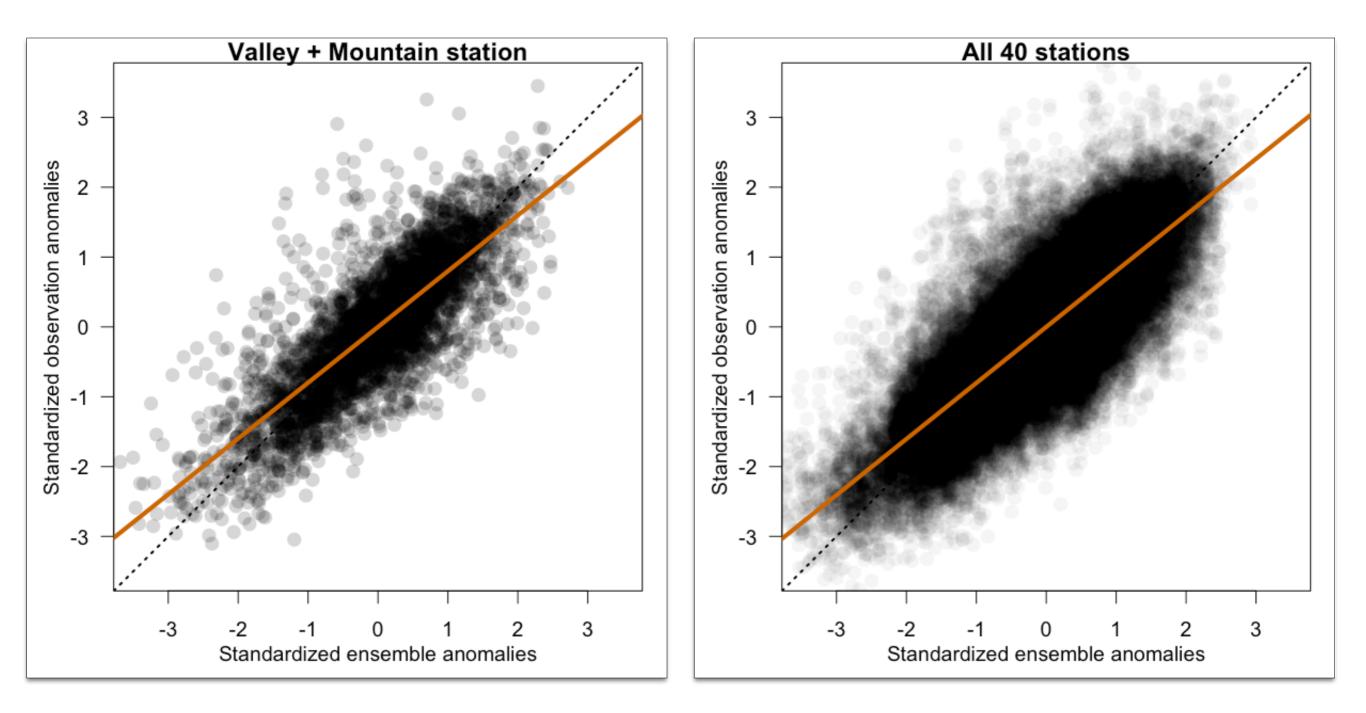






season- and site-specific characteristics are removed





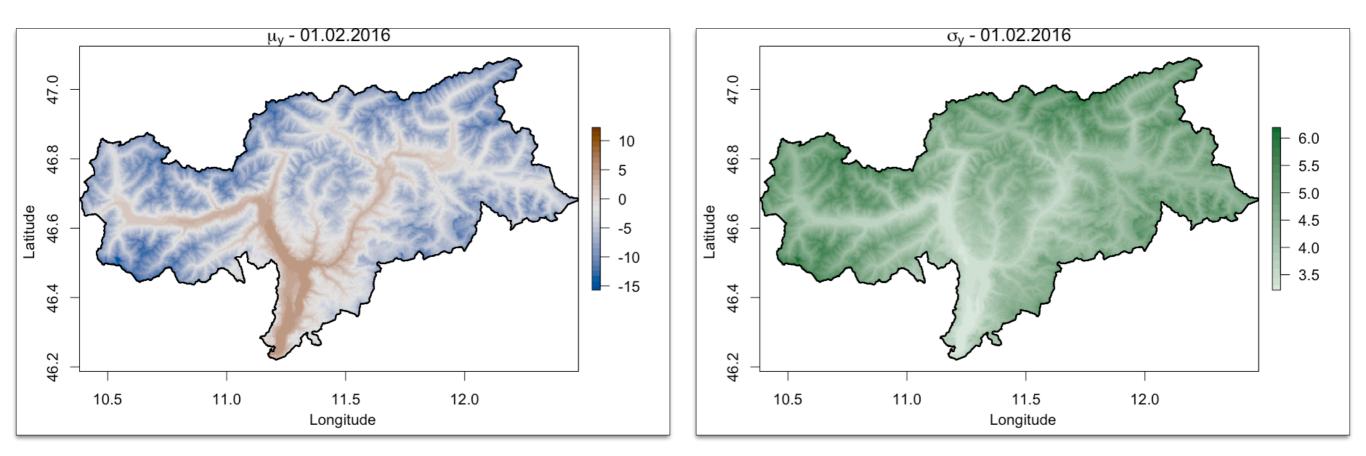
$$\frac{y - \mu_y}{\sigma_y} \sim N(\mu, \sigma)$$
$$\mu = b_0 + b_1 \frac{m - \mu_m}{\sigma_m}$$
$$\log(s) - \log(s) - \log(s)$$

$$\log(\sigma) = c_0 + c_1 \frac{\log(s) - \mu_{\log(s)}}{\sigma_{\log(s)}}$$

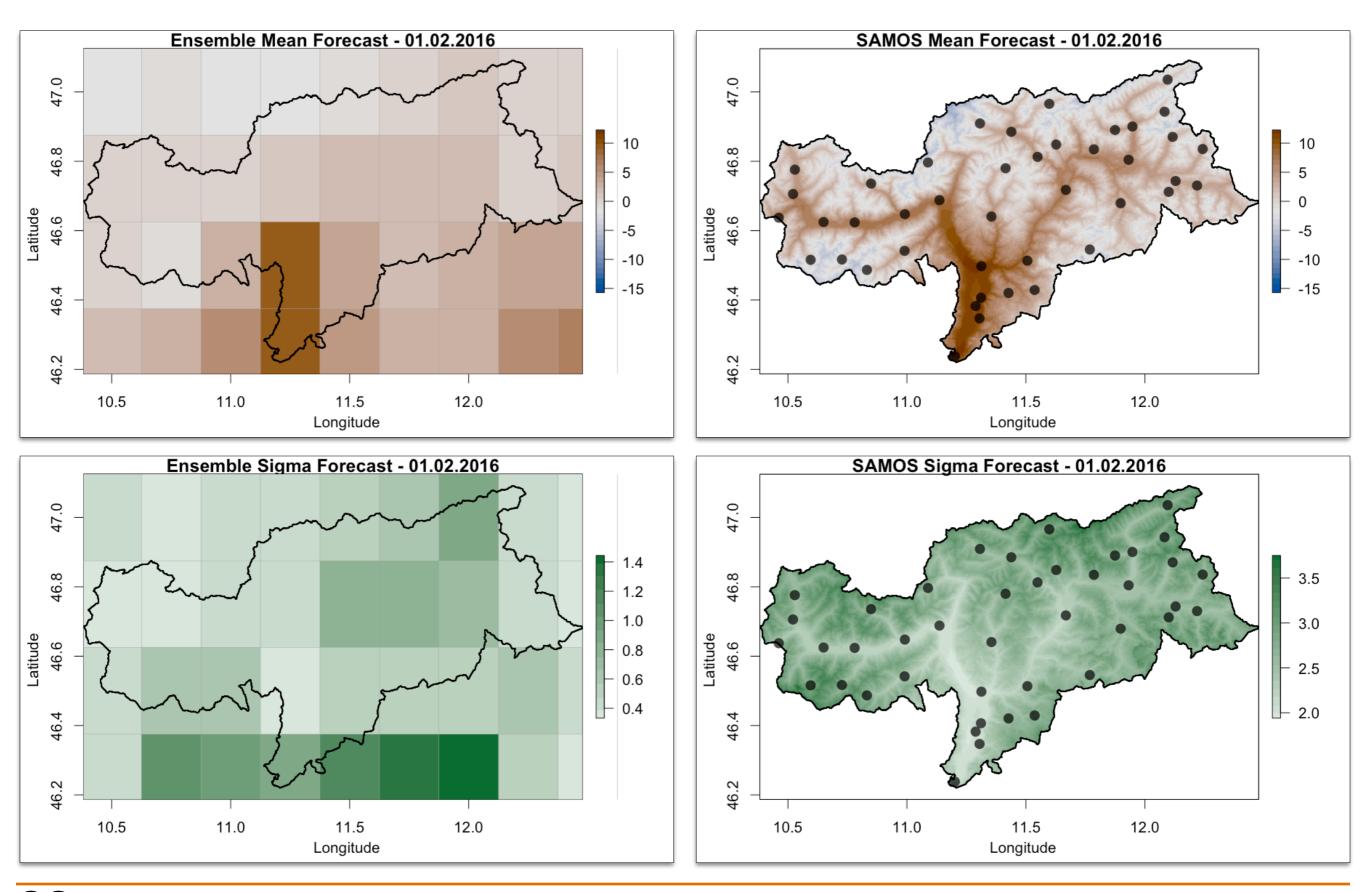
 $\mu_{y,m,\log(s)}$ ...Climatological mean  $\sigma_{y,m,\log(s)}$ ...Climatological standard deviation

### **Spatial Climatology**

 $\mu_y = \beta_0 + f_1(\text{Season}) + f_2(\text{Altitude}) + f_3(\text{Spatial}) + f_4(\text{Season} \cdot \text{Altitude})$  $\log(\sigma_y) = \gamma_0 + g_1(\text{Season}) + g_2(\text{Altitude}) + g_3(\text{Spatial}) + g_4(\text{Season} \cdot \text{Altitude})$ 



#### **Forecast Example**



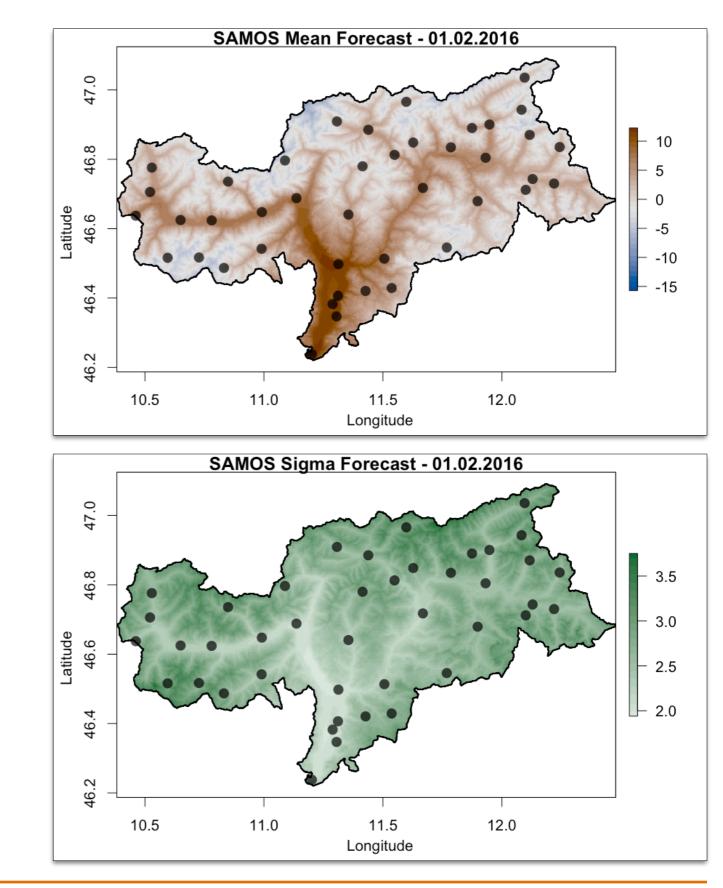
## **Forecast Example**

EMOS:

**temporal:** trained on last 30 days **spatial:** on every station individually

SAMOS same stations: temporal: full dataset spatial: tested on the same stations as fitted

SAMOS new stations: temporal: full dataset spatial: tested on new stations that are not in the training data ("Leave-One-Out")



## **Results**

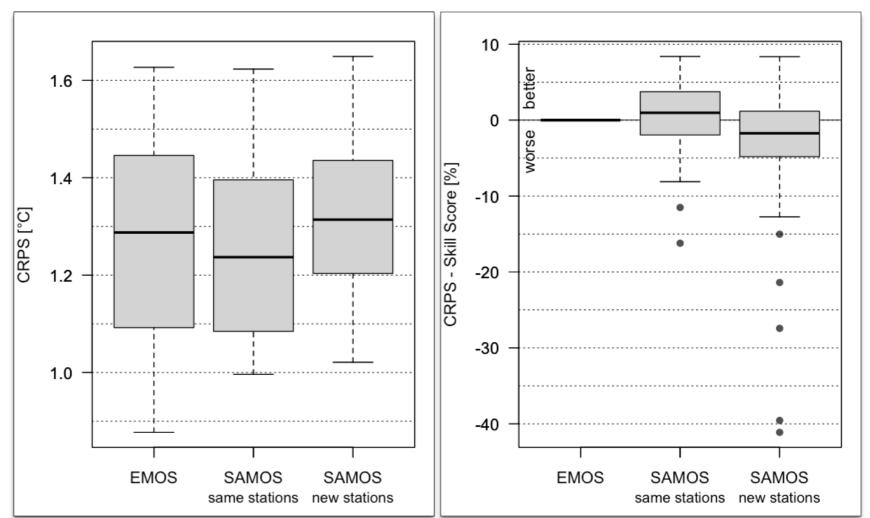
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temporal: trained on last

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#### Conclusion

#### **Standardized Anomalies:**

- are without *season-specific* characteristic:
  - all training data can be used
- are without **site-specific** characteristics:
  - all stations can be forecasted simultaneously
  - every point in between can be forecasted
- forecasts are comparable to stationwise EMOS forecasts

**Dabernig M, Mayr GJ, Messner JW, Zeileis A. 2016:** Spatial Ensemble Post-Processing with Standardized Anomalies. Working papers, Faculty of Economics and Statistics, University of Innsbruck, URL http://EconPapers.repec.org/RePEc:inn:wpaper:2016-08