INSTITUTE OF ATMOSPHERIC AND CRYOSPHERIC SCIENCES

Spatial Post-Processing over Complex Terrain using Standardized Anomalies

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Wednesday Seminar 2016-06-01

Outline

- Introduction
- Motivation: Latest Forecast
- Methodology
- The SAMOS Approach
- Results

Introduction

Numerical Weather Prediction (NWP)

1. analysis: $\rightarrow$ current state
2. prognosis: $\rightarrow$ future state

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- observations
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- numerical approximation
- "unknown" atmospheric processes

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Ensemble Prediction Systems

- to quantify the uncertainty

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Ensemble Prediction Systems

- to quantify the uncertainty
- number of members restricted
- typically underdispersive

Introduction

Forecast Error

- *total error* = *noise* + *systematic errors*

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- *noise*: unexplainable (signal-free)
- *systematic errors*: correction possible

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Post-Processing

- correct bias
- correct uncertainty

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Forecast Error

- *total error = noise + systematic errors*
- *noise*: unexplainable (signal-free)
- *systematic errors*: correction possible

Post-Processing

- correct bias
- correct uncertainty
- discrete $\rightarrow$ full distribution
- probabilities, quantiles, extremes

Final Product

To motivate

Live beta – impression of the “outcome” of the approach.

Introduction to Methodology

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Methodology

Introduce you to . . .

Left-Censored Non-Homogeneous Generalized Spatio-Temporal Additive Regression Model for Daily Precipitation Sums Using High-Resolution Standardized Anomalies

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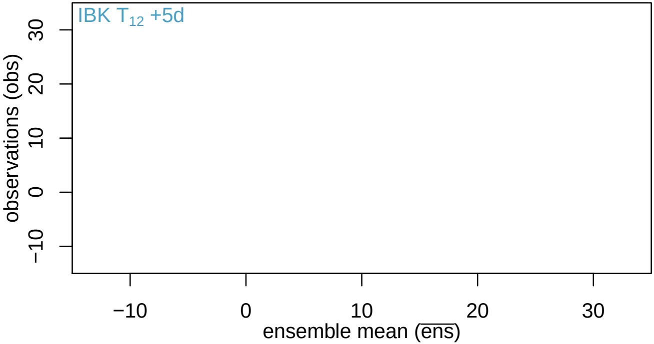
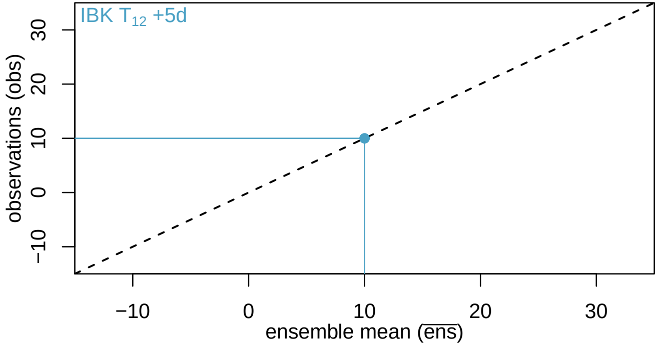
Left-Censored Non-Homogeneous Generalized Spatio-Temporal Additive Regression Model for Daily Precipitation Sums Using High-Resolution Standardized Anomalies

Methodology



Methodology



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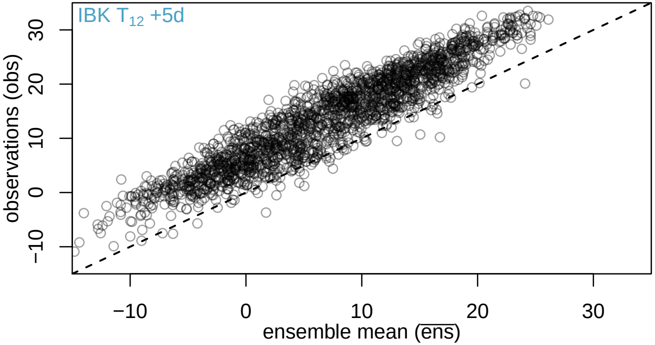

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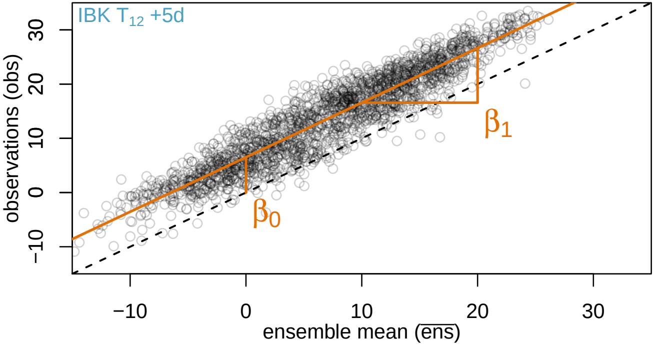
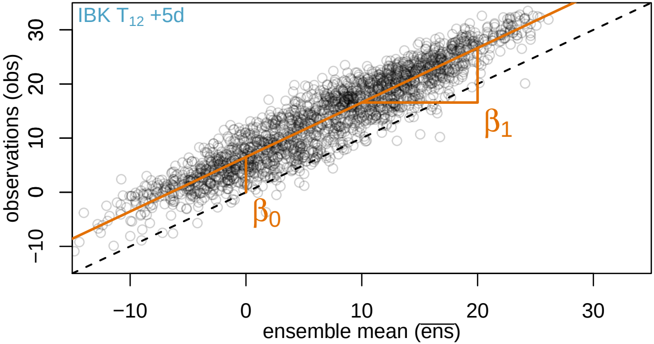


Gaussian Regression

$$\hat{obs} = \beta_0 + \beta_1 \cdot \overline{ens} \qquad (1)$$

Methodology



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$$obs \sim \mathcal{N}(\mu, \sigma)$$
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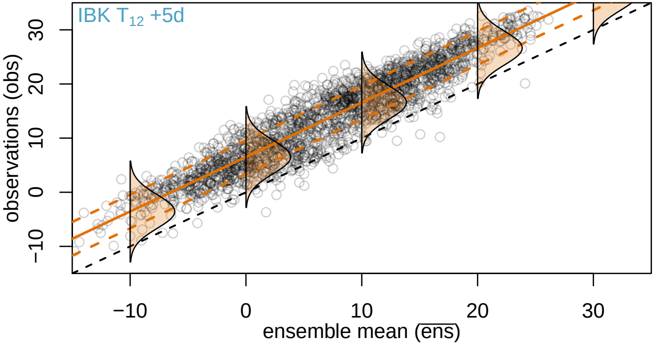
Methodology

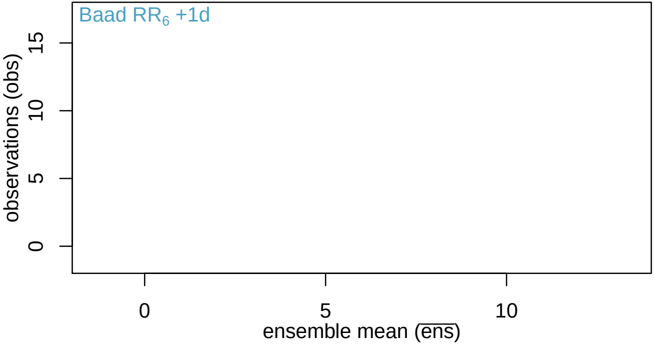


Gaussian Regression

$$\hat{obs} = \beta_0 + \beta_1 \cdot \overline{ens} \qquad (1)$$

$$\begin{aligned} obs &\sim \mathcal{N}(\mu, \sigma) \\ \mu &= \beta_0 + \beta_1 \cdot \overline{ens} \\ \sigma &= \gamma_0 \end{aligned} \qquad (2)$$

Methodology



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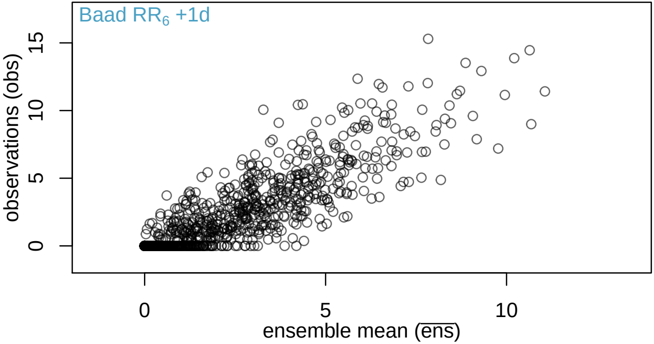

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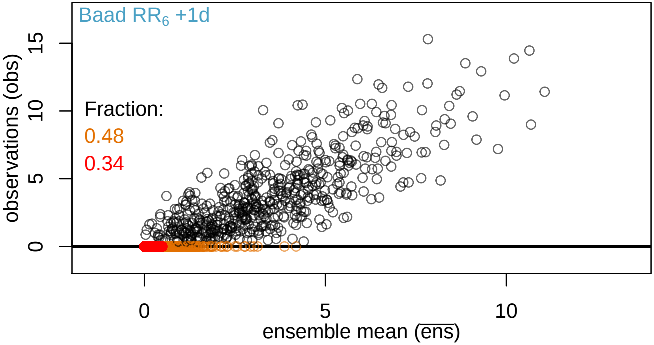

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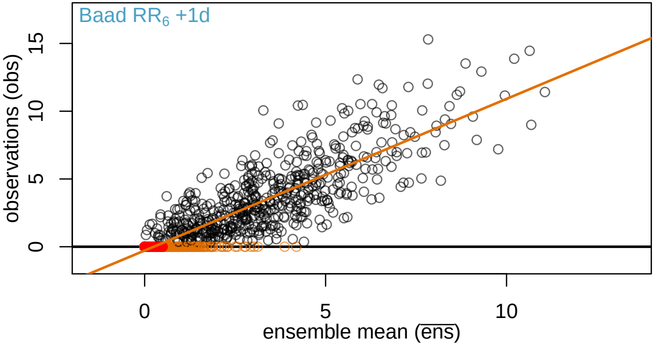
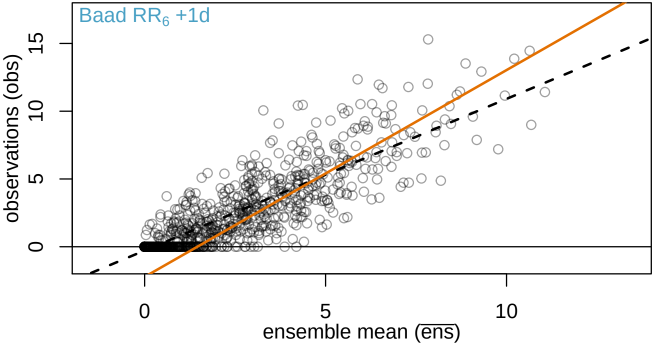


Gaussian Regression

$$\text{obs} \sim \mathcal{N}(\mu, \sigma)$$
$$\mu = \beta_0 + \beta_1 \cdot \overline{ens} \tag{3}$$
$$\sigma = \gamma_0$$

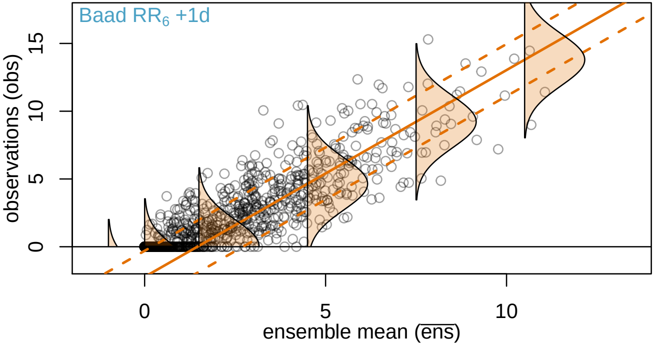
Methodology



Censored Gaussian Regression

$$\begin{aligned} obs = max(0, y) \quad & \textit{with} \quad y \sim \mathcal{N}(\mu, \sigma) \\ & \mu = \beta_0 + \beta_1 \cdot \overline{ens} \\ & \sigma = \gamma_0 \end{aligned} \tag{3}$$

Methodology



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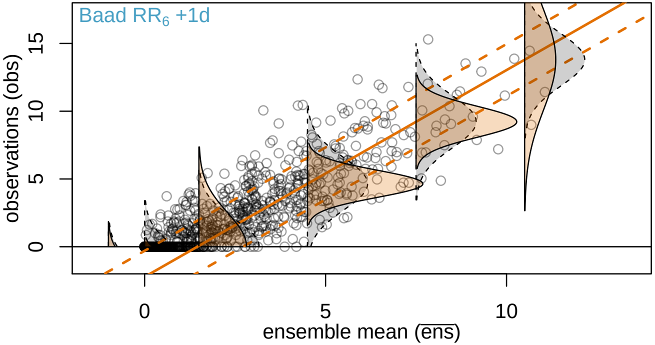

Censored Non-Homogeneous Gaussian Regression

$$\text{obs} = max(0, y) \quad with \quad y \sim \mathcal{N}(\mu, \sigma)$$
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$$\sigma = \gamma_0 + \gamma_1 \cdot \text{stdv}(\text{ens})$$

Methodology

Generalized Additive Model for Location, Shape, and Scale (GAMLSS)

$$\text{obs} = max(0, y) \;\; with \;\; y \sim \mathcal{N}(\mu, \sigma) \tag{4}$$

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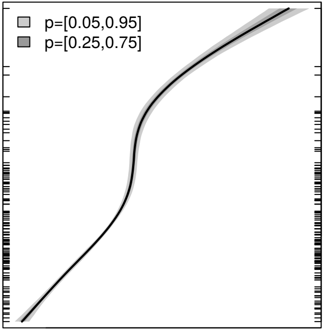

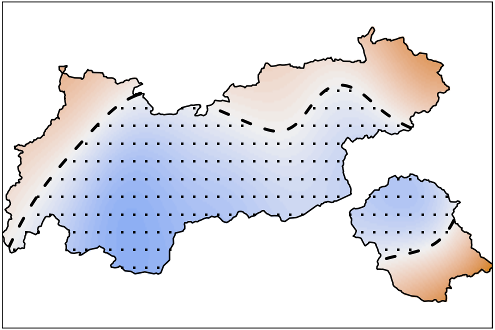

Generalized Additive Model for Location, Shape, and Scale (GAMLSS)

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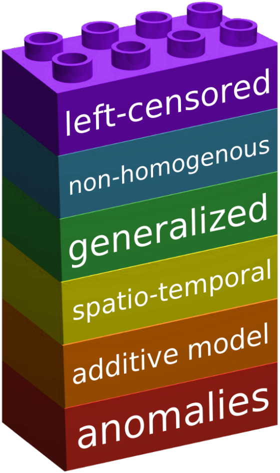
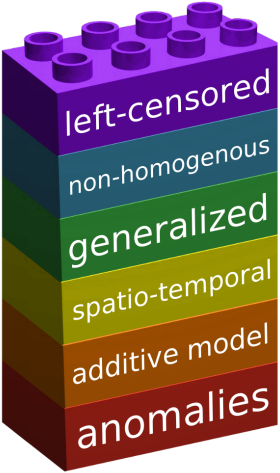


To Summarize

Methodology



To Summarize

- account for **physical limit** and large **fractions of** 0 observations

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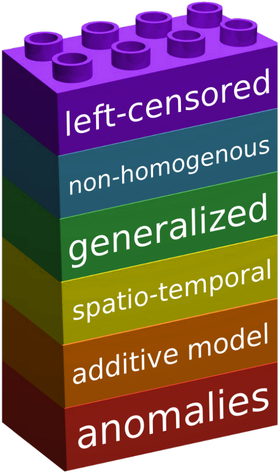

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- account for **physical limit** and large **fractions of** 0 observations
- **standard deviation** as a **function** of covariates

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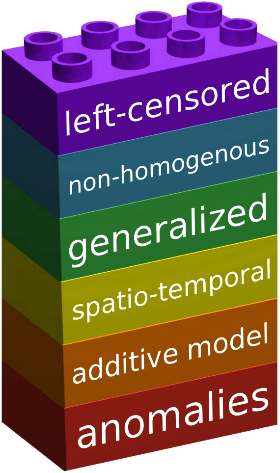

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- **including** all kind of **effects** (linear, multidim. splines, . . .)

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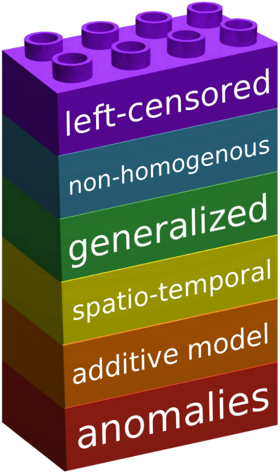

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- if **geographical & date/time covariates** included

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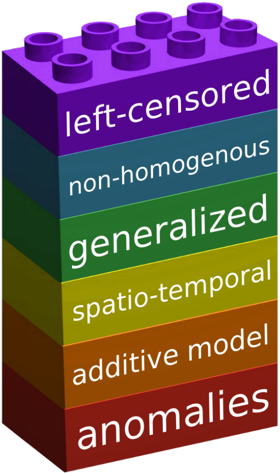

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- **simple** linear additive framework

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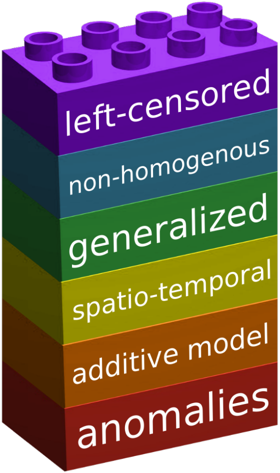

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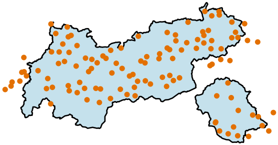
- **standard deviation** as a **function** of covariates
- **including** all kind of **effects** (linear, multidim. splines, ...)
- if **geographical & date/time covariates** included
- **simple** linear additive framework
- stay tuned for the anomalies!

Spatial Ensemble Post-Processing: The SAMOS Approach

Data

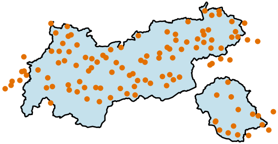
Observations



- 118 stations
- daily observations
- 1971 – 2012

Data

Observations



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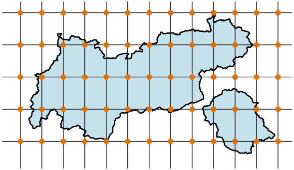
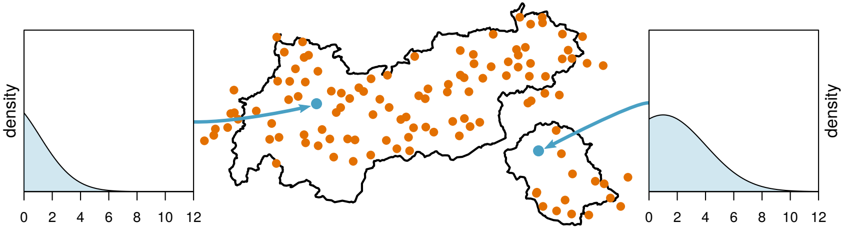
NWP Model



- ECMWF ENS
- ECMWF reforecasts
- February 2010–2012
- $\Delta x/\Delta y$: 25km

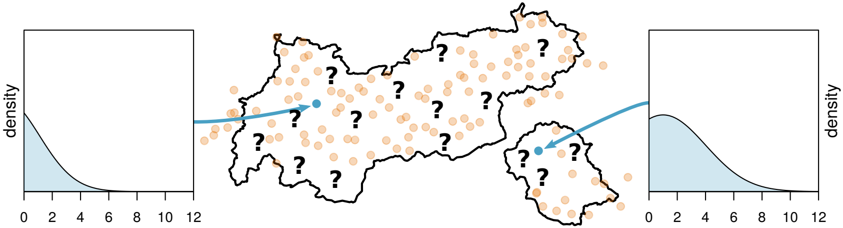
Pointwise Post-Processing



Single Station

- “relatively” simple
- interpolate ensemble
- apply censored non-homogeneous model
- **one model** for **each** station

Pointwise Post-Processing



Single Station

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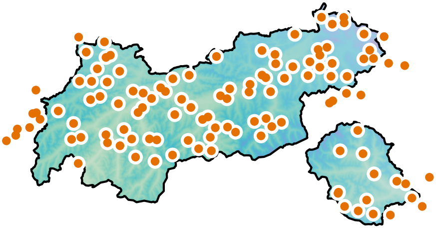
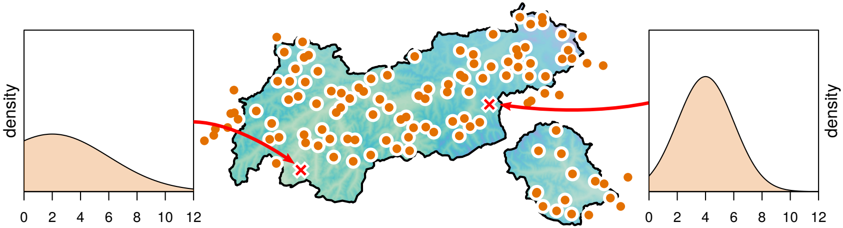
Spatial Post-Processing



Spatial Model

- **one model** for **all** stations
- model station independent
- full spatial prediction

Spatial Post-Processing



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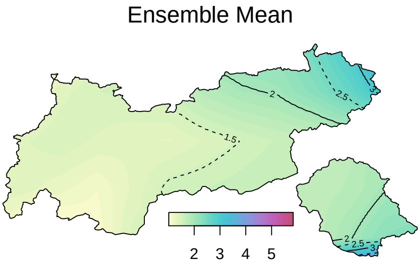

Spatial Model: Naive Assumption

$$
\begin{aligned}
\text{obs} = \mathit{max}(0, y) \ \ \mathit{with} \ \ y \sim \mathcal{N}(\mu, \sigma) \\
\mu = \beta_0 + \beta_1 \cdot \overline{\mathit{ens}} \\
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\end{aligned}
\tag{5}
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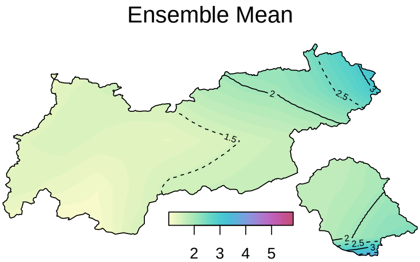
Spatial Post-Processing



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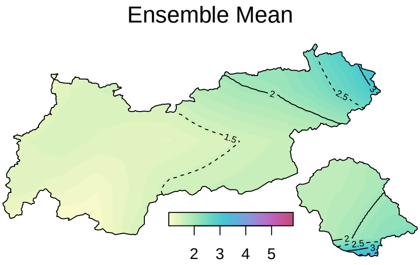

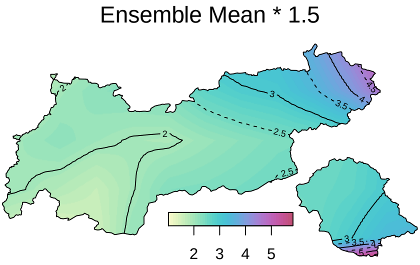

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Spatial Post-Processing: SAMOS

Naive Assumption

- not suitable
- local features can’t be depict

[1] Markus Dabernig: seminar in 3 weeks.

Spatial Post-Processing: SAMOS

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$\Rightarrow$ different approach required

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SAMOS: Post-Processing Using **Standardized Anomalies**[1]

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Spatial Post-Processing: SAMOS

Naive Assumption

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⇒ different approach required

SAMOS: Post-Processing Using **Standardized Anomalies**[1]

- climatology as **background knowledge**
- local variations described by climatology

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Spatial Post-Processing: SAMOS

Naive Assumption

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- local features can't be depict

⇒ different approach required

SAMOS: Post-Processing Using **Standardized Anomalies**[1]

- climatology as **background knowledge**
- local variations described by climatology
- climatology to **remove location-dependent features**
- bring stations to **compareable scale**

[1] Markus Dabernig: seminar in 3 weeks.

Spatial Post-Processing: SAMOS

Reminder: Naive Assumption

$$\begin{aligned} \text{obs} &= \mathit{max}(0, y) \;\; \mathit{with} \;\; y \sim \mathcal{N}(\mu, \sigma) \\ \mu &= \beta_0 + \beta_1 \cdot \overline{\mathit{ens}} \\ \sigma &= \gamma_0 + \gamma_1 \cdot \text{stdv}(\mathit{ens}) \end{aligned} \tag{6}$$

Spatial Post-Processing: SAMOS

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Spatial Post-Processing: SAMOS

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Standardized Anomaly Model Output Statistics (SAMOS)

$$\begin{aligned} \text{obs} &= \max(0, y) \;\; \text{with} \;\; \frac{y - obs_\mu}{obs_\sigma} \sim \mathcal{N}(\mu, \sigma) \\ \mu &= \beta_0 + \beta_1 \cdot \text{mean}\left(\frac{ens - ens_\mu}{ens_\sigma}\right) \\ \sigma &= \gamma_0 + \gamma_1 \cdot \text{stdv}\left(\frac{ens - ens_\mu}{ens_\sigma}\right) \end{aligned} \tag{7}$$

SAMOS Results

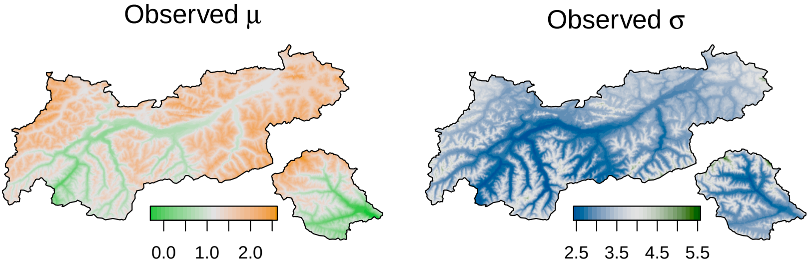

Figure: Climatology of observations: Stauffer et al. 2016.

Standardized Anomaly Model Output Statistics (SAMOS)

$$\text{obs} = \max(0, y) \;\; \text{with} \;\; \frac{y - obs_{\mu}}{obs_{\sigma}} \sim \mathcal{N}(\mu, \sigma)$$

$$\mu = \beta_0 + \beta_1 \cdot \text{mean}\left(\frac{ens - ens_{\mu}}{ens_{\sigma}}\right) \tag{8}$$

$$\sigma = \gamma_0 + \gamma_1 \cdot \text{stdv}\left(\frac{ens - ens_{\mu}}{ens_{\sigma}}\right)$$

SAMOS Results

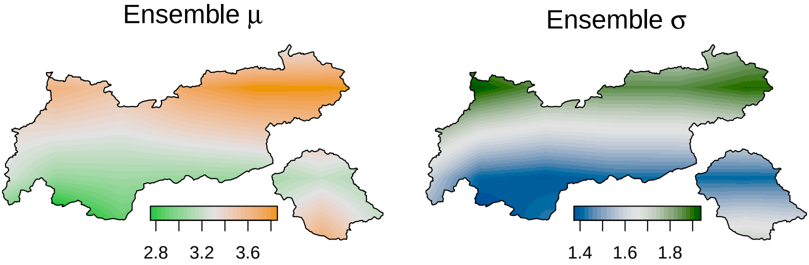

Figure: ECMWF ENS climatology: ECMWF reforecasts.

Standardized Anomaly Model Output Statistics (SAMOS)

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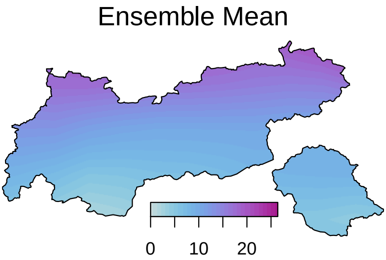
SAMOS Results



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SAMOS Results

Model Comparison

- **CRPS skill score**: full distribution
- **Mean Absolute Error**: deterministic score
- **Brier Score**: probability *obs* $> \tau$

SAMOS Results

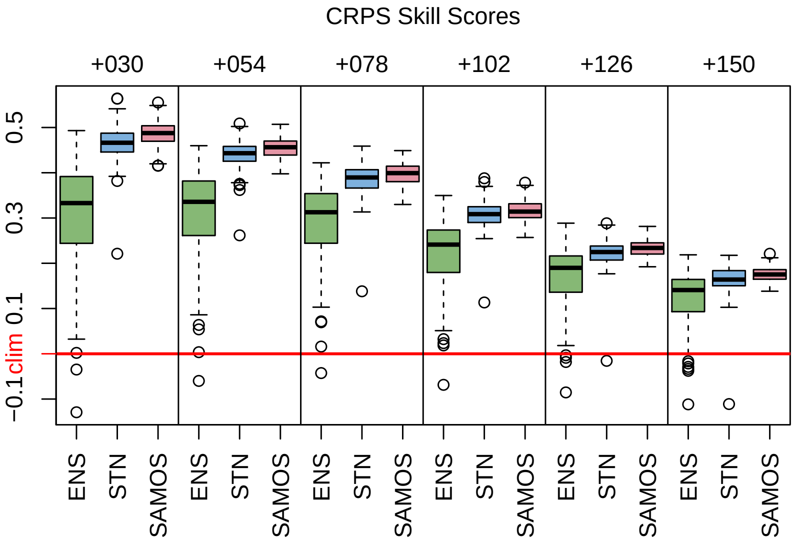
Model Comparison

- **CRPS skill score**: full distribution
- **Mean Absolute Error**: deterministic score
- **Brier Score**: probability *obs* $> \tau$

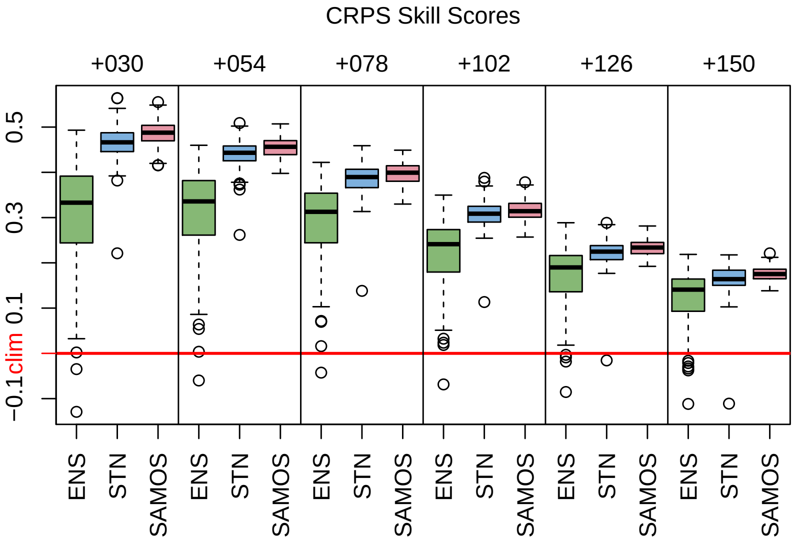
Reference Methods

- **ENS**: uncorrected ECMWF ENS
- **STN**: stationwise regression model
- **SAMOS**: spatial regression model (*loo*)
- **CLIM**: climatological estimates

SAMOS Results

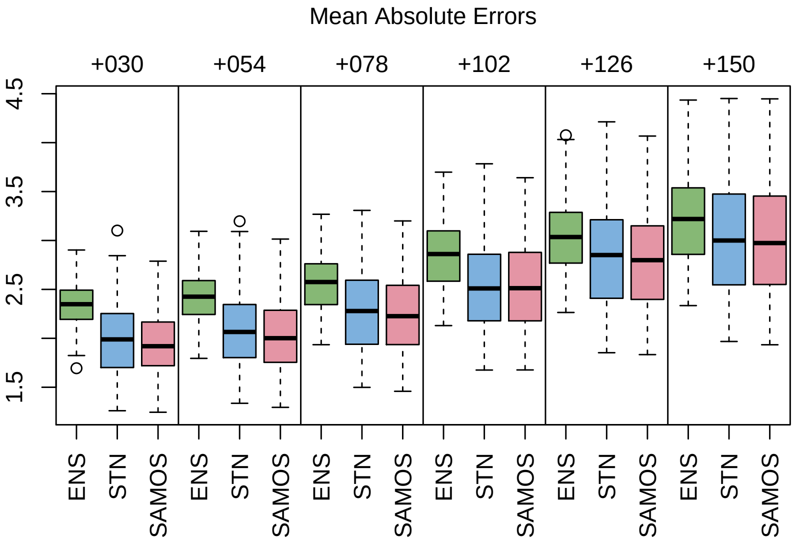


SAMOS Results

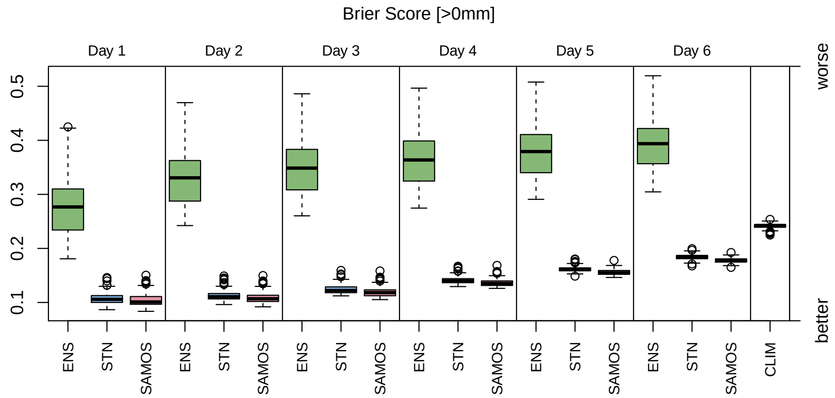


Note: ECEPS worse than the climatology in e.g., Axams, Hall, Imst, Oetz.

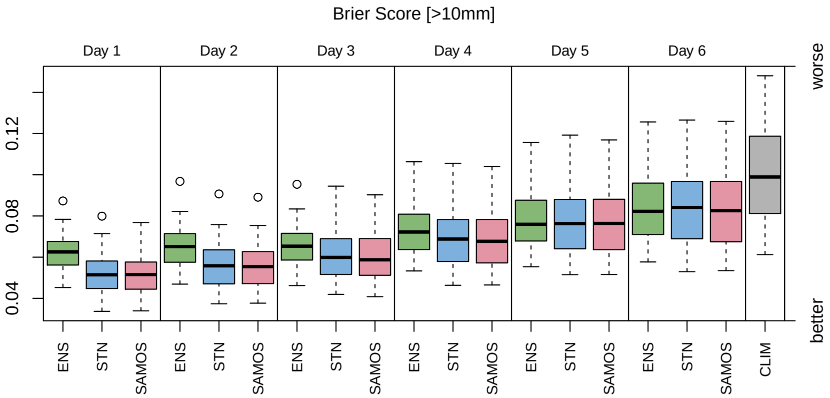
SAMOS Results



SAMOS Results



SAMOS Results



Summary & Outlook

SAMOS Approach

- **concept proofed** for daily precipitation
- **accurately** predicts **full distribution**
- **outperforms station-wise** estimates
- **all** historical observations included
- ECMWF reforecast: always on **latest** NWP **cycle**

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Outlook

- e.g. wind direction dependent climatologies
- include additional predictors
- precipitation $\Rightarrow$ new snow

Thank you for your attention!

Special thanks to the *SWAT*,
my collegues, and advisors!