ACINN
INSTITUTE OF ATMOSPHERIC AND CRYOSPHERIC SCIENCES

Probabilistic Spatial Forecasting of Daily Precipitation Sums Over Complex Terrain

Supervised by: Georg J. Mayr & Achim Zeileis
Thesis Review: Daniel Wilks & Thomas Hamill

universität innsbruck

Ph.D. Defense Presentation 2016-11-14

The Project: SnowSafeFX

Project goals

- improve skill of **new snow amount** forecasts
- **spatial probabilistic** prediction, Tyrol

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Early remark: Our “snow” is still a bit liquid.

The Project: SnowSafeFX

Importance

- outdoor sportsmen:
  210 **avalanche events**,
  31 deaths (winter 14/15, A)[1]

[1] Winterbericht 2014/2015, Lawinenwarndienst Tirol.
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- public:
  safety of infrastructure and people,
  transport, . . .

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The Project: SnowSafeFX

Difficulties

- ensemble prediction system (EPS) **too coarse**
- **small-scale** features **not** well represented
- EPS often underdispersive[1]

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Approach to solution

- **down-scaling** (in general)
- statistical **post-processing** (MOS)

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The Project: SnowSafeFX

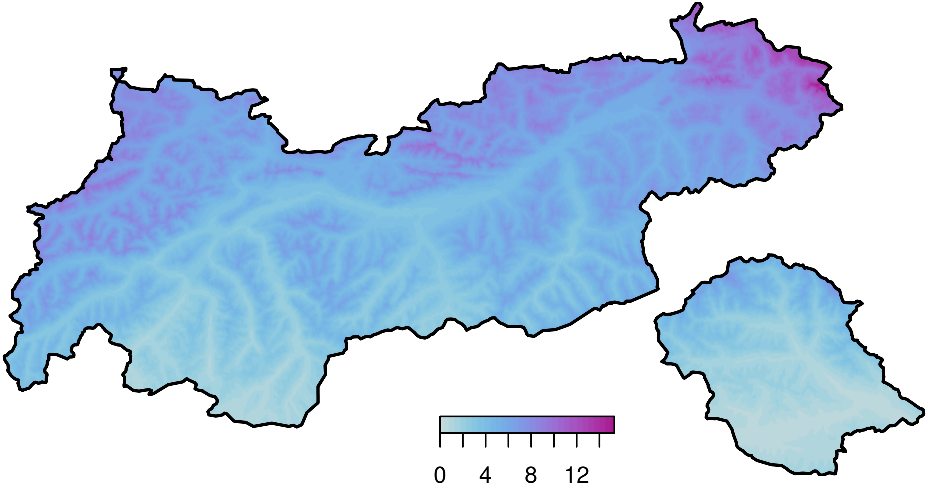

Figure 1: Precipitation forecast for North Tyrol [*mm day*$^{-1}$].

Publication I

Stauffer, R., G. J. Mayr, J. W. Messner, N. Umlauf, and A. Zeileis (2016): Spatio-Temporal Precipitation Climatology over Complex Terrain Using a Censored Additive Regression Model. *International Journal of Climatology*, doi: `10.1002/joc.4913`, in print.

Introduction

Research goals

- develop a **flexible** statistical model
- **spatio-temporal** climatology
- **daily** resolution
- **full** climatological **distribution**

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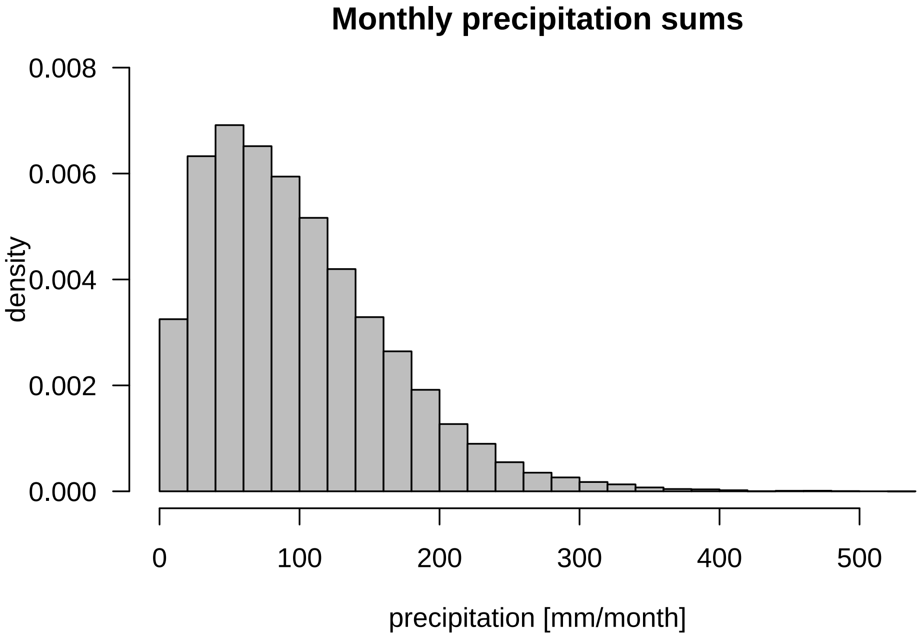
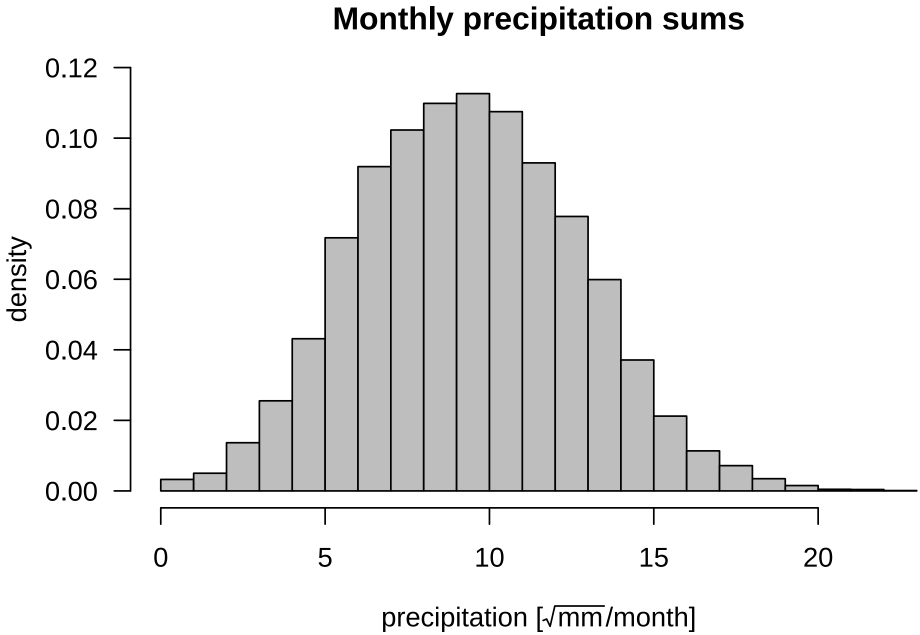
Challenges

- suitable **response distribution**
- **effects** to be considered

Response Distribution



Response Distribution



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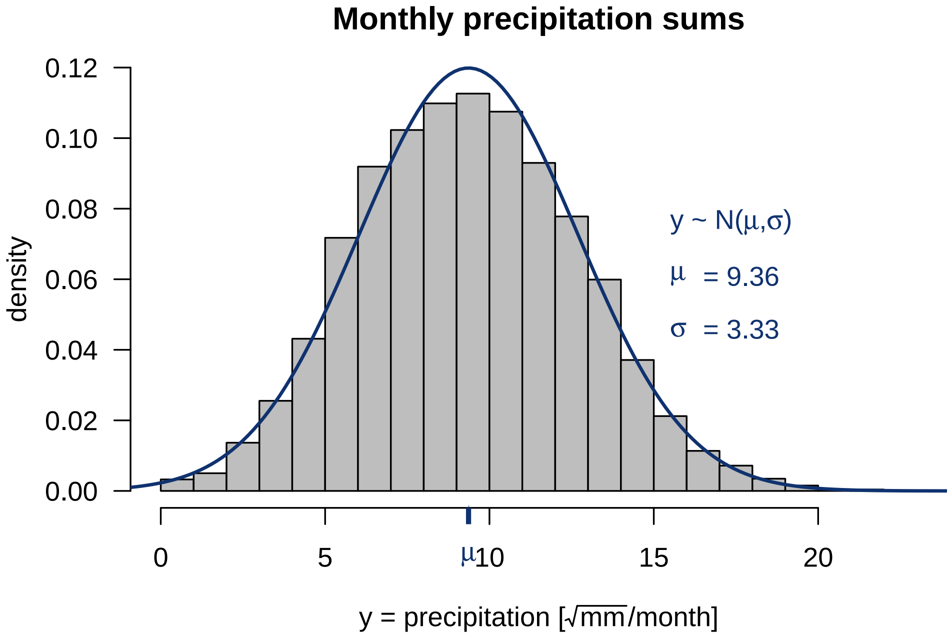

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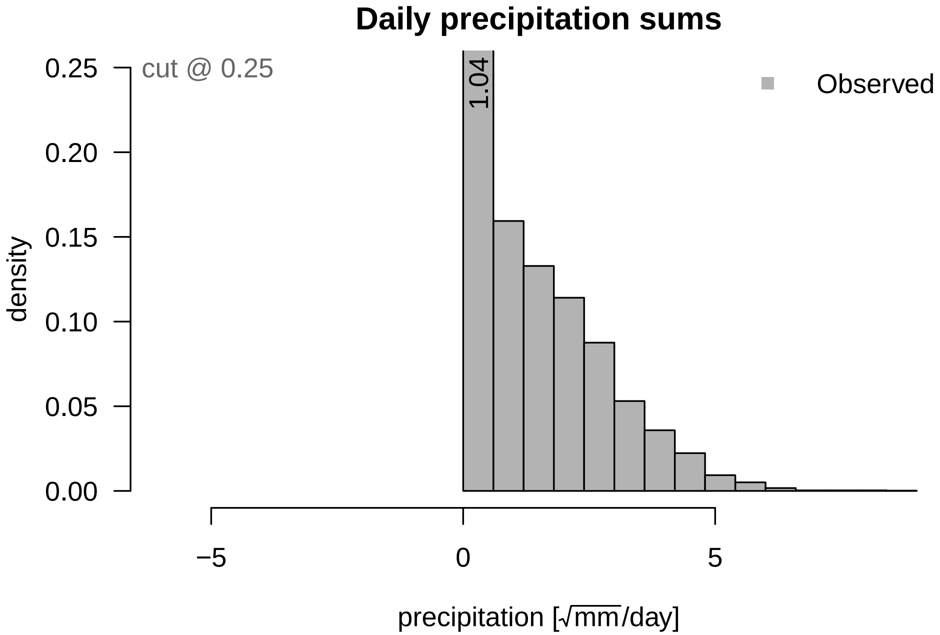

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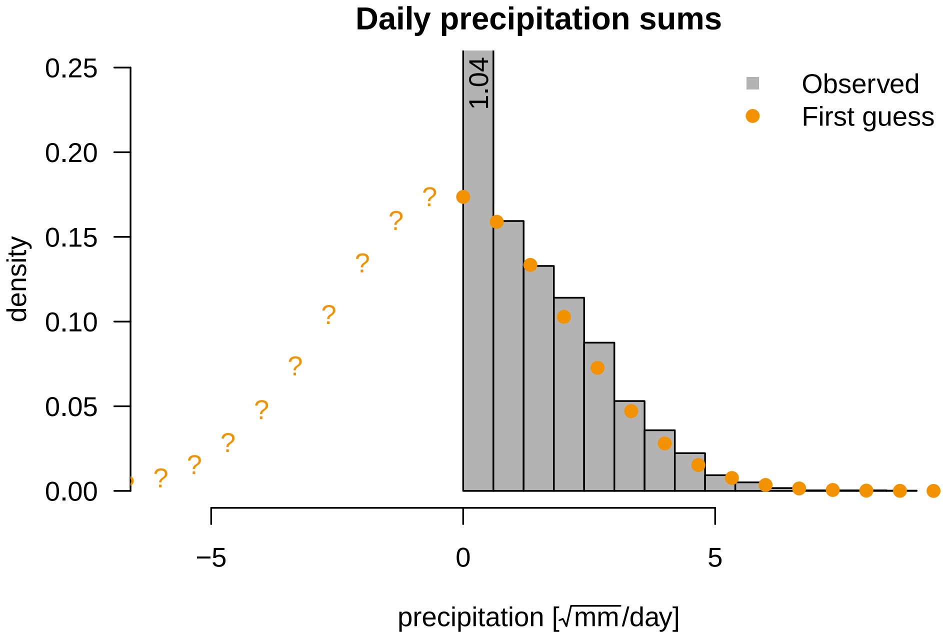

Censoring

Can be seen as censored if:

- **limited** to a threshold and . . .
- values exceeding threshold **cannot occur.**

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- survival in 5 *yr* clinical study: **right** $y_i \leqslant 5$
- hours worked this week: **two sided** $0 \leqslant y_i \leqslant 168$

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Model assumption

$$\underbrace{y \sim \mathcal{N}(\mu, \sigma)}_{\text{latent}}, \quad \underbrace{\text{precipitation} = \max(0, y)^p}_{} \tag{1}$$

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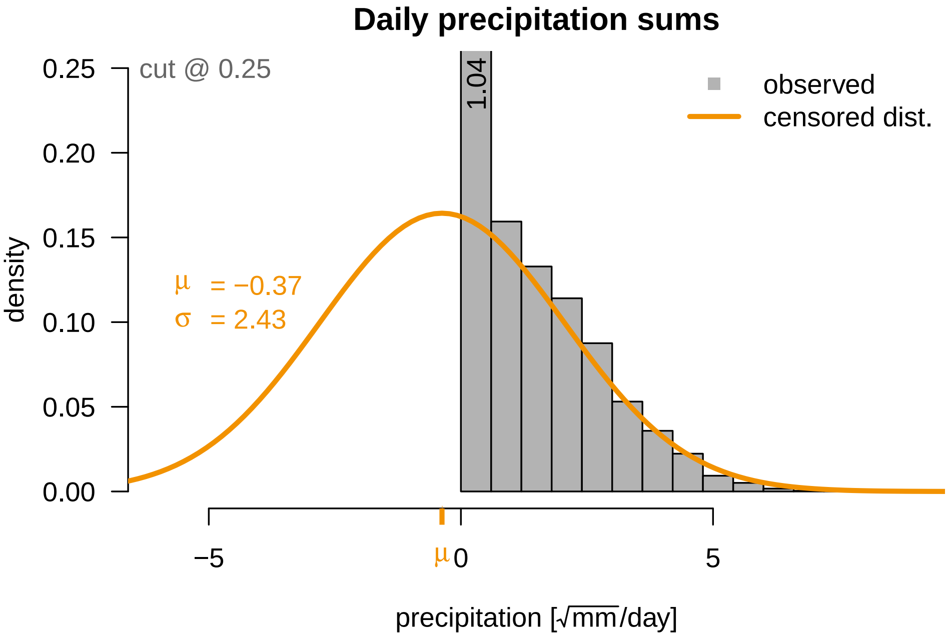
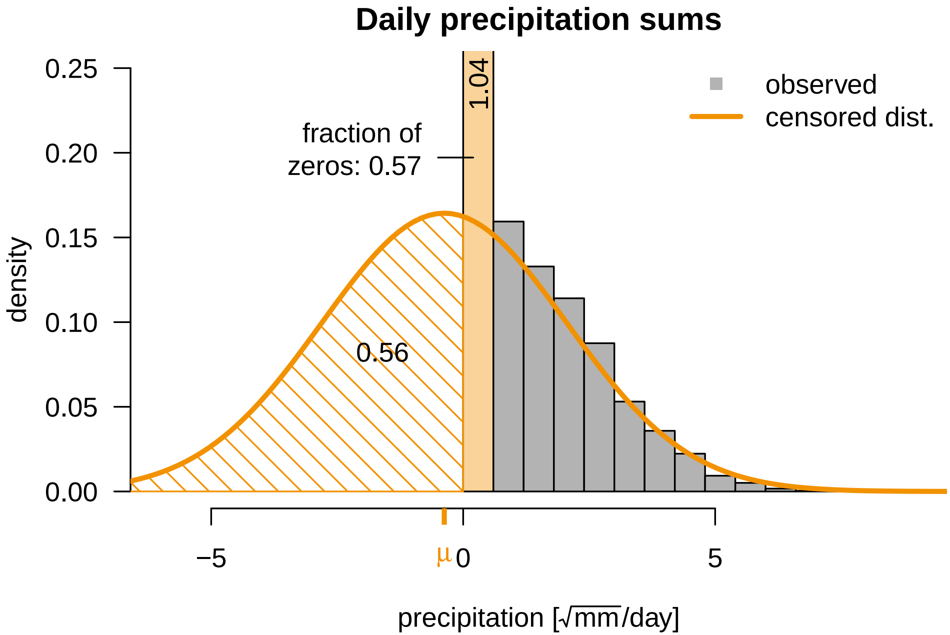
Censoring



Daily precipitation sums
cut @ 0.25
1.04
observed
censored dist.
μ = −0.37
σ = 2.43
density
0.25
0.20
0.15
0.10
0.05
0.00
−5
μ
0
5
precipitation [√mm/day]

Censoring


Daily precipitation sums
0.25
0.20
0.15
0.10
0.05
0.00
density
1.04
fraction of
zeros: 0.57
0.56
observed
censored dist.
−5
μ
0
5
precipitation [√mm/day]

Required Effects

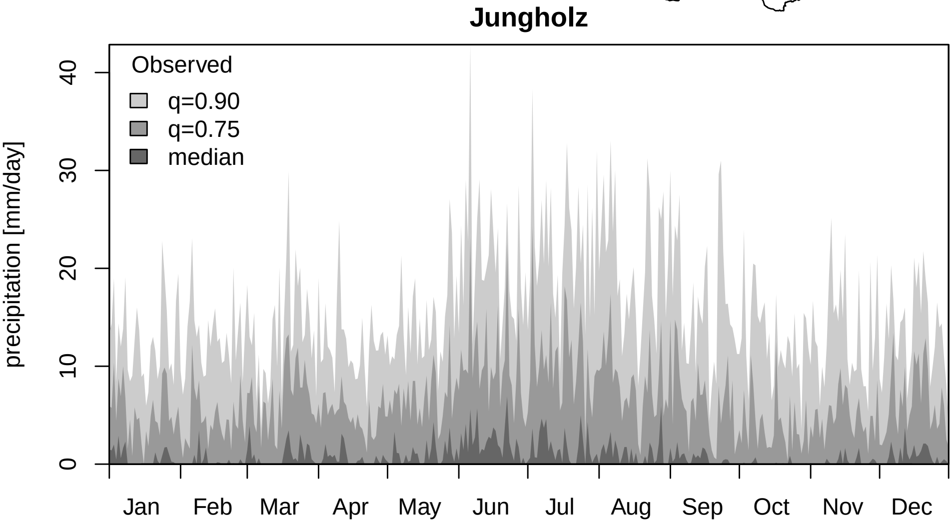
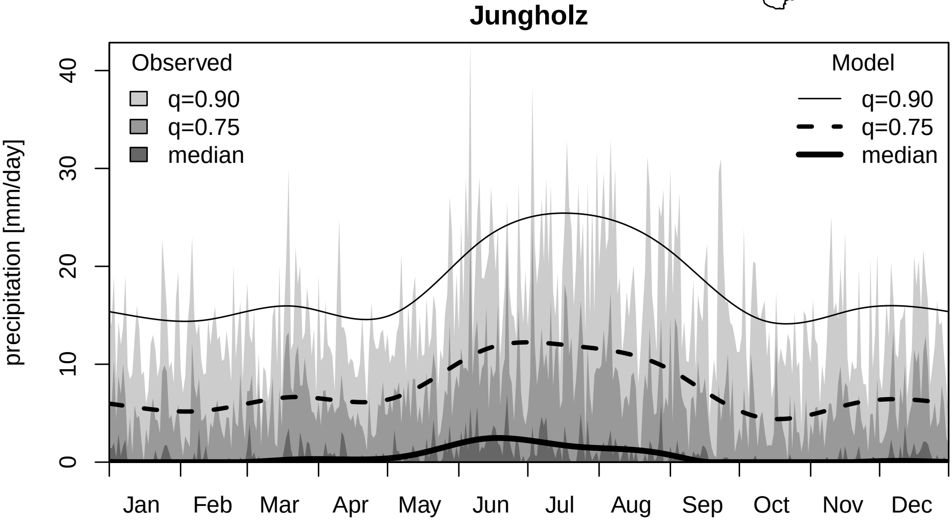


Figure 2: Empirical quantiles on a daily basis (1980-2012).

Required Effects



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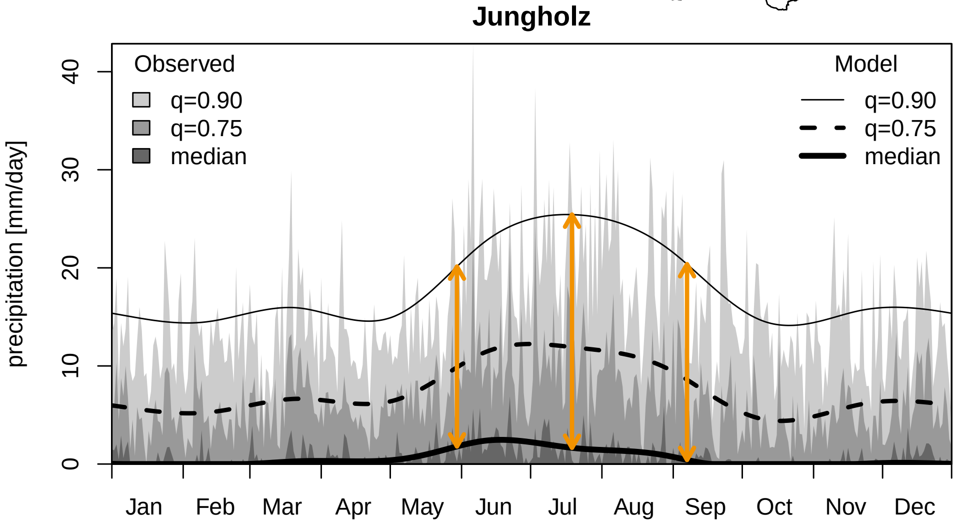

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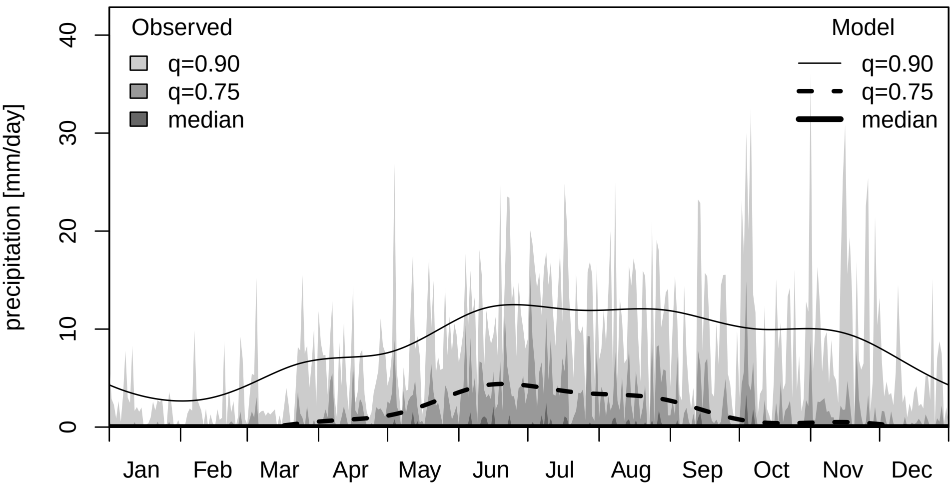

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Spatio-Temporal Model

Reminder

$$y \sim \mathcal{N}(\mu, \sigma), \quad \text{precipitation} = \max(0, y)^p \tag{2}$$

- y: latent response
- $\mathcal{N}(\ldots)$: Gaussian distribution
- μ,σ: latent location and scale
- p: power parameter

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Linear predictors

$$\mu = \beta_0 + s_1(\text{altitude}) + s_2(\text{season}) + s_3(\text{long,lat}) + s_4(\text{season,long,lat}) \tag{3}$$

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- β_0: global intercepts
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- s_2: cyclic seasonal effect
- s_3: spatial effect
- s_4: mixed effect

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Linear predictors

$$\begin{aligned} \mu &= \beta_0 + s_1(\text{altitude}) + s_2(\text{season}) + s_3(\text{long,lat}) + s_4(\text{season,long,lat}) \\ \sigma &= \gamma_0 + t_1(\text{altitude}) + t_2(\text{season}) + t_3(\text{long}, \text{lat}) + t_4(\text{season}, \text{long}, \text{lat}) \end{aligned} \tag{3}$$

- y: latent response
- $\mathcal{N}(\dots)$: Gaussian distribution
- μ,σ: latent location and scale
- p: power parameter
- β_0,γ_0: global intercepts
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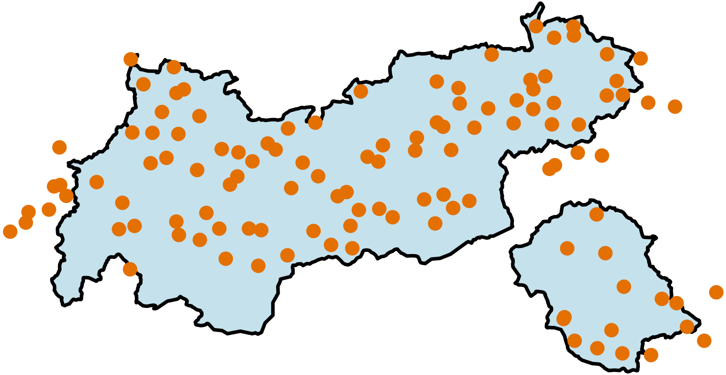
Data Set



- **118** stations[3]
- Tyrol and surrounding
- **daily** observations
- 1971 – 2012
- more than **1.5 million** unique observations

[3] Bundesministerium für Forstwirtschaft, Umwelt und Wasserwirtschaft, Abteilung IV/4 – Wasserhaushalt.
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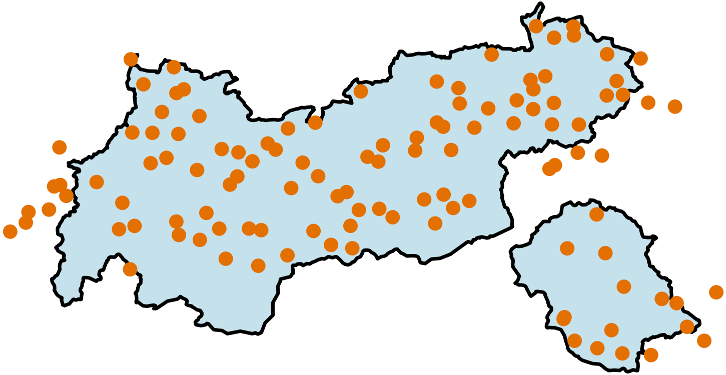

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Results

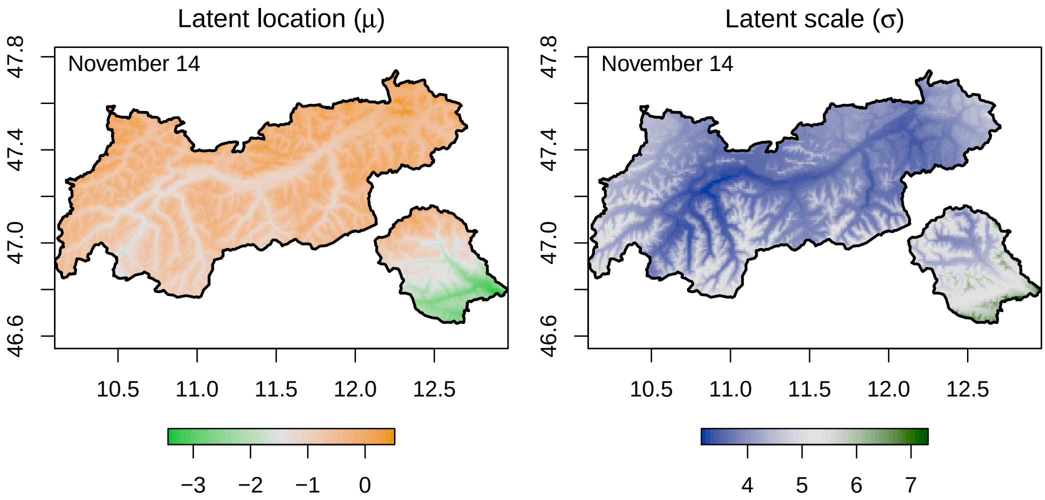

Figure 3: Climatological estimate. Location μ and scale σ on power-transformed latent scale.

Results

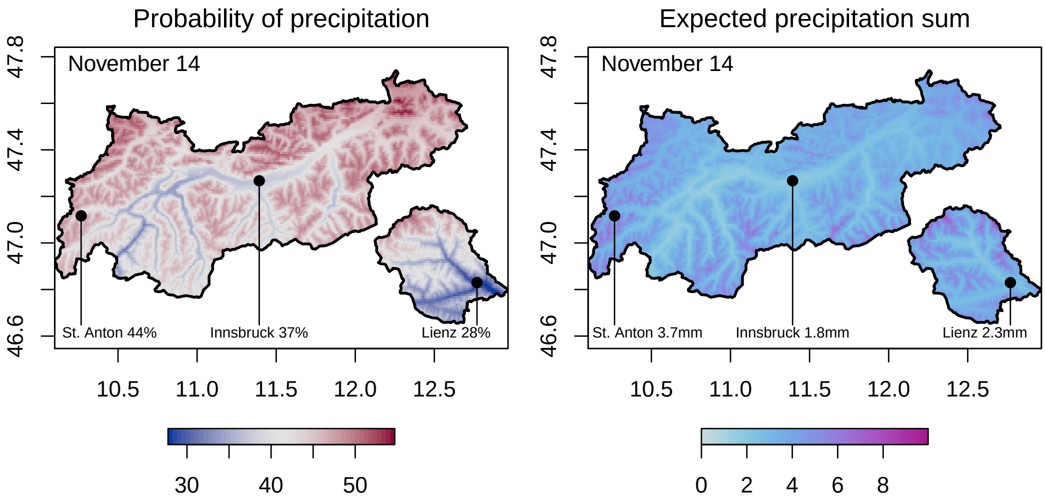

Figure 4: Climatological estimate. Probability of precipitation [%] and expectation [$mm\ day^{-1}$].

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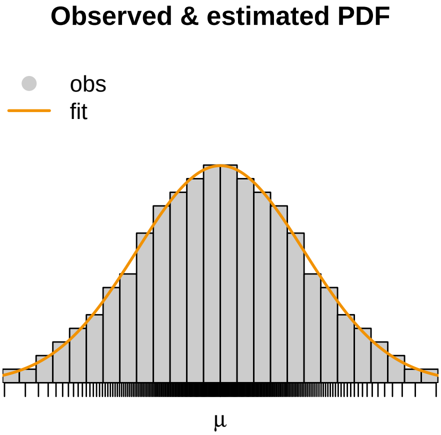

Figure 5: Probability integral transform (PIT; Gneiting et al. 2007) histogram.

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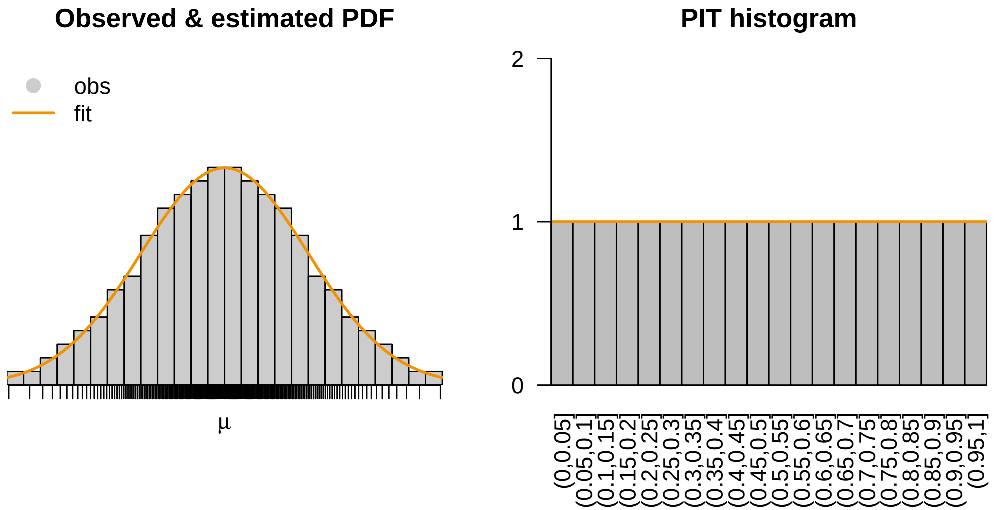

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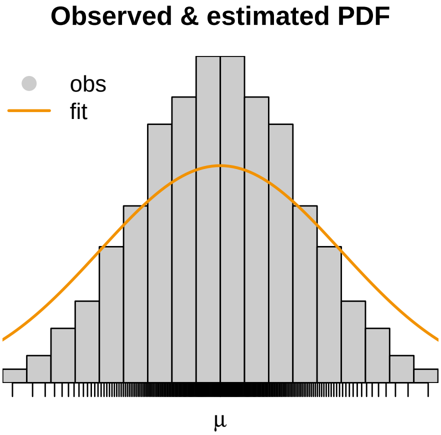

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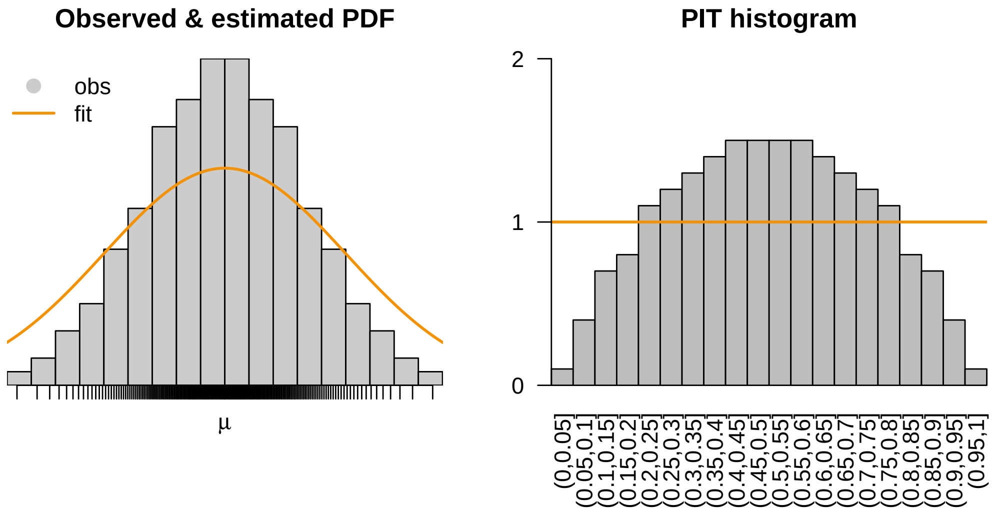

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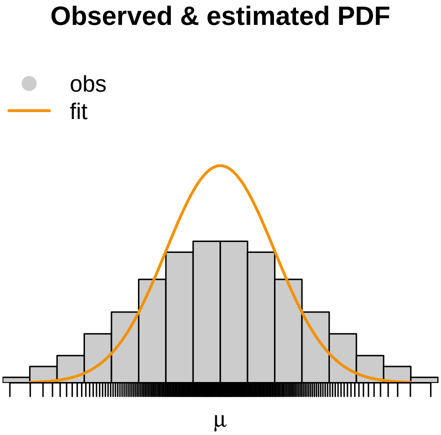

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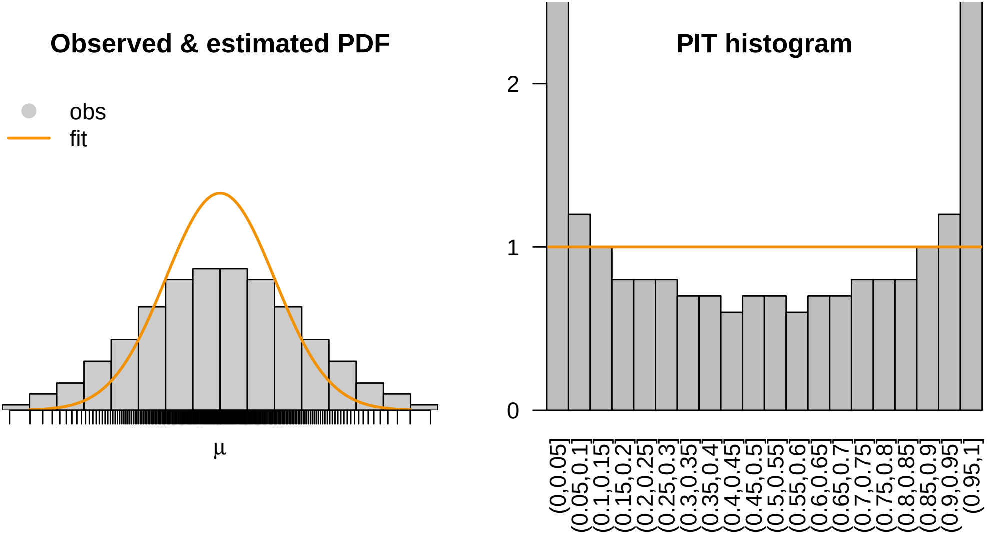

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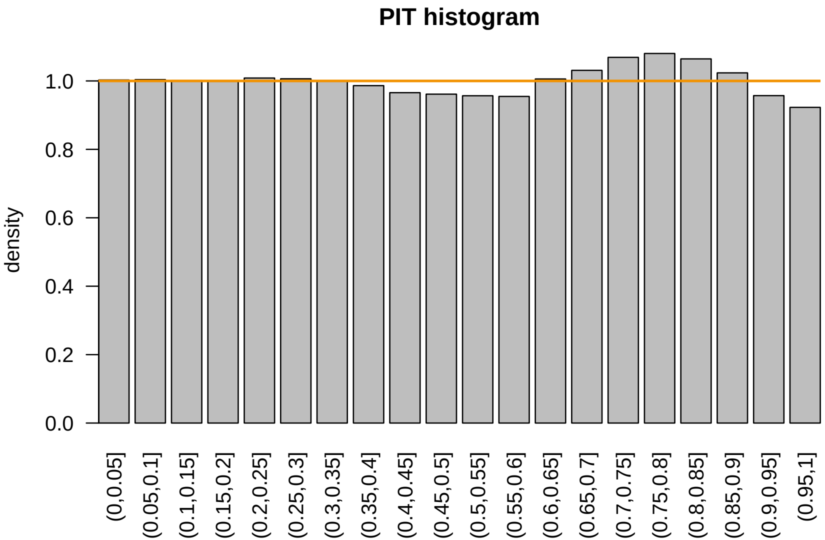
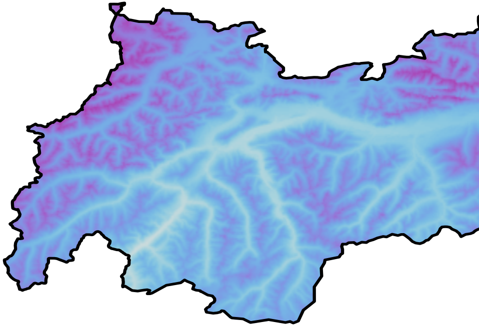

PIT histogram
density
1.0
0.8
0.6
0.4
0.2
0.0
(0,0.05]
(0.05,0.1]
(0.1,0.15]
(0.15,0.2]
(0.2,0.25]
(0.25,0.3]
(0.3,0.35]
(0.35,0.4]
(0.4,0.45]
(0.45,0.5]
(0.5,0.55]
(0.55,0.6]
(0.6,0.65]
(0.65,0.7]
(0.7,0.75]
(0.75,0.8]
(0.8,0.85]
(0.85,0.9]
(0.9,0.95]
(0.95,1]

Summary I

- **power transformation** to remove skewness
- censoring to handle **zero-observations**
- **full** climatological **distribution**



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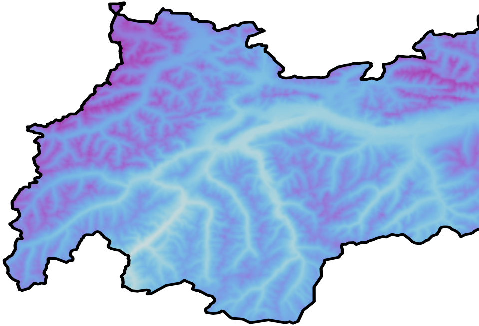
- **spatial/temporal** resolution arbitrary scalable
- accurate estimate at station level



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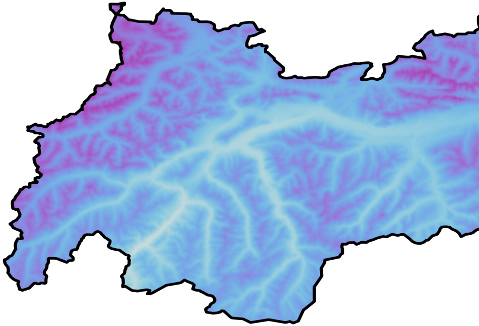
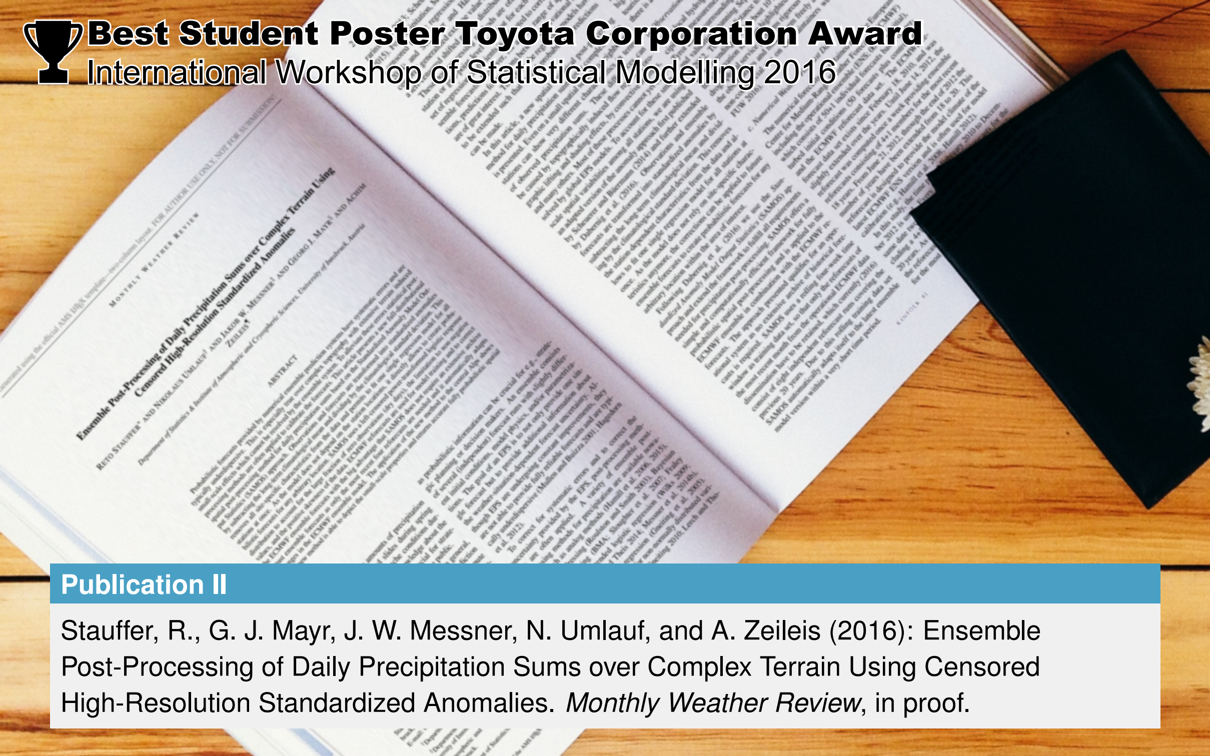
- **probabilistic** reference method
- **background information** for
  statistical post-processing methods





Best Student Poster Toyota Corporation Award

International Workshop of Statistical Modelling 2016

Publication II

Stauffer, R., G. J. Mayr, J. W. Messner, N. Umlauf, and A. Zeileis (2016): Ensemble Post-Processing of Daily Precipitation Sums over Complex Terrain Using Censored High-Resolution Standardized Anomalies. *Monthly Weather Review*, in proof.

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Numerical weather prediction (NWP)

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2. prognosis: $\rightarrow$ future state

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Ensemble prediction systems (EPS)

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

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Forecast error

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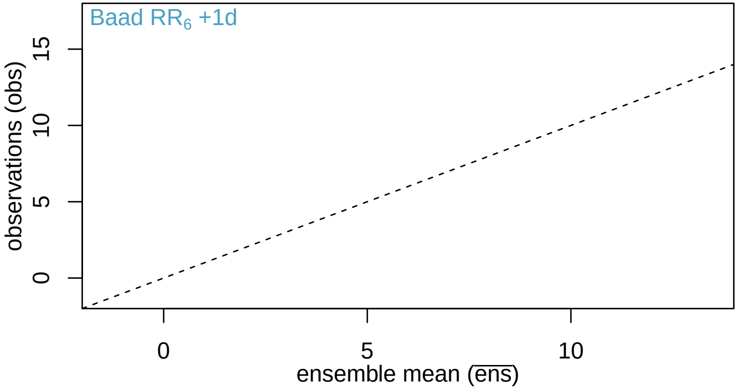
- correct **bias**
- correct **uncertainty**
- discrete $\rightarrow$ **full distribution**
- probabilities, quantiles, expectation

Methodology



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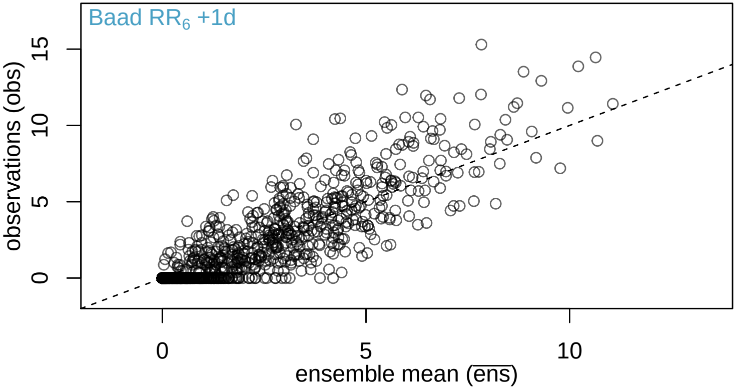

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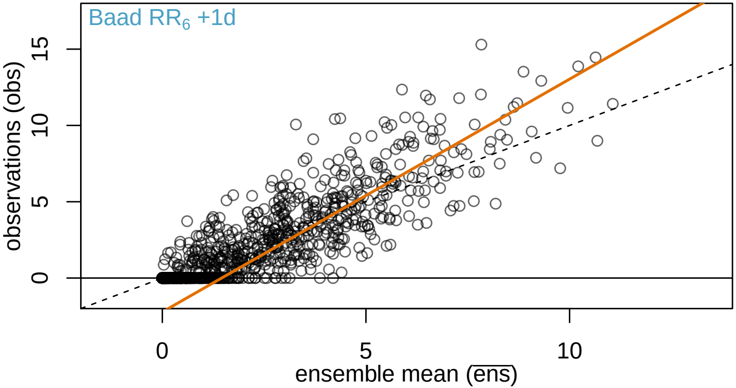
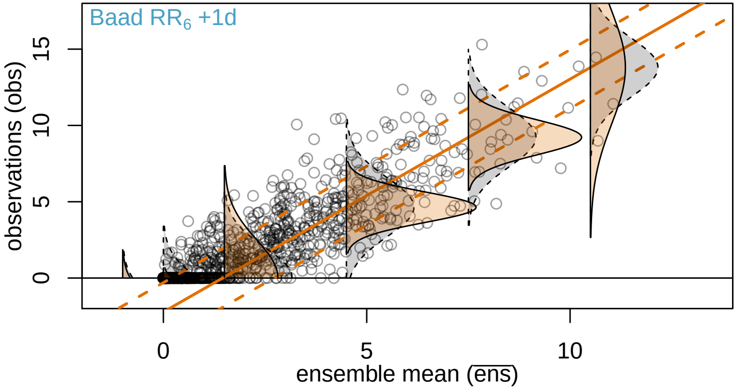


Censored logistic regression

$$\text{precipitation} = max(0, y)^p \quad with \quad y \sim \mathcal{L}(\mu, \sigma)$$
$$\mu = \beta_0 + \beta_1 \cdot \overline{ens} \tag{4}$$
$$\sigma = \gamma_0$$

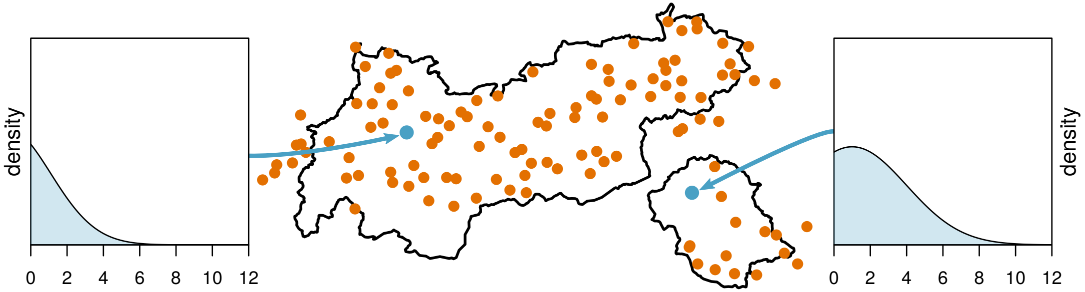
Methodology



Censored non-homogeneous logistic regression

$$\text{precipitation} = max(0, y)^p \quad with \quad y \sim \mathcal{L}(\mu, \sigma)$$
$$\mu = \beta_0 + \beta_1 \cdot \overline{ens} \tag{4}$$
$$\sigma = \gamma_0 + \gamma_1 \cdot \text{stdv}(\text{ens})$$

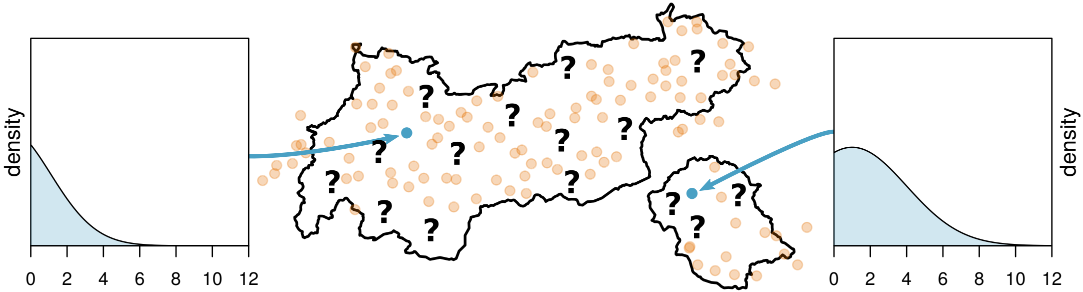
Pointwise Post-Processing



Pointwise models

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

Pointwise Post-Processing



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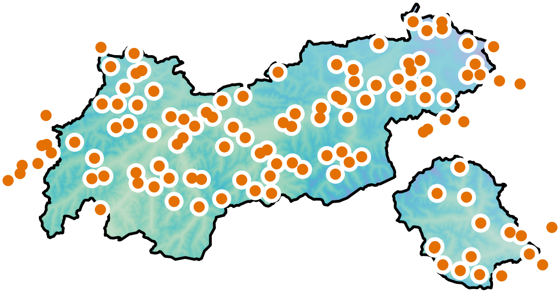
Spatial Post-Processing



Spatial model

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

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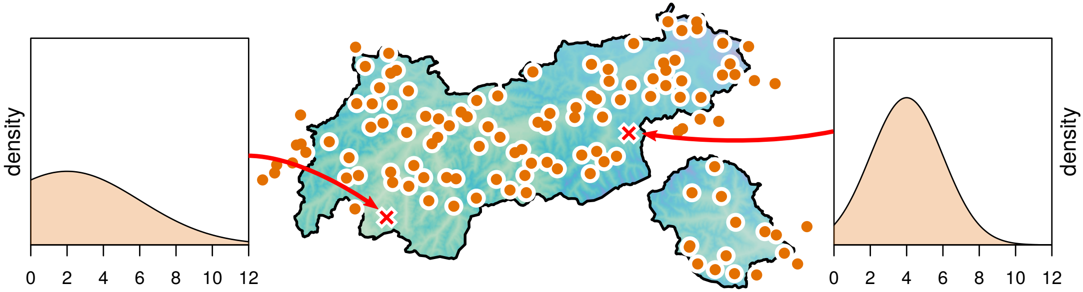

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Spatial Post-Processing

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Standardized Anomaly Model Output Statistics (SAMOS[5])

- Use climatology as **background information**
- . . . to **remove location-dependent features**
- . . . and to bring stations to a **comparable scale.**

[5] Dabernig et al. (2016): Spatial Ensemble Post-Processing with Standardized Anomalies.

Spatial Post-Processing

Standardized Anomaly Model Output Statistics (SAMOS)

$$\frac{y - obs_\mu}{obs_\sigma} \sim \mathcal{L}(\mu, \sigma) \tag{5}$$

- y: observations$^{1/p}$
- obs_μ,obs_σ: observed climatology
- $\mathcal{L}(\ldots)$: logistic distribution
- μ,σ: latent location and scale

Spatial Post-Processing

Standardized Anomaly Model Output Statistics (SAMOS)

$$\frac{y - obs_\mu}{obs_\sigma} \sim \mathcal{L}(\mu, \sigma)$$
$$\mu = \beta_0 + \beta_1 \cdot \text{mean}\left(\frac{ens - ens_\mu}{ens_\sigma}\right) \tag{5}$$

- y: observations$^{1/p}$
- obs_μ,obs_σ: observed climatology
- $\mathcal{L}(\ldots)$: logistic distribution
- μ,σ: latent location and scale
- ens: latest EPS forecast$^{1/p}$
- ens_μ,ens_σ: EPS climatology
- β_0: global intercept
- β_1: steepness coefficient

Spatial Post-Processing

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Spatial Post-Processing

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Spatial Post-Processing

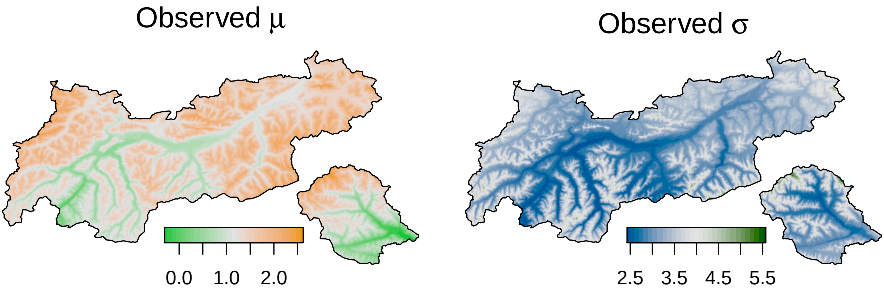

Figure 7: Spatio-Temporal Climatology, Stauffer et al. 2016.

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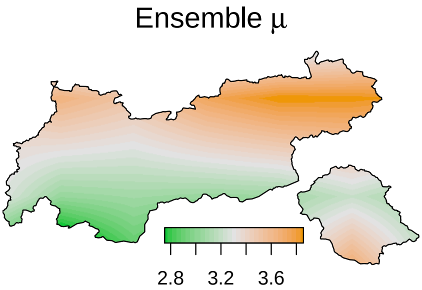
Spatial Post-Processing



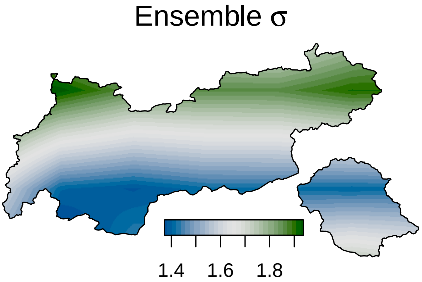


Figure 7: ECMWF ENS climatology: ECMWF reforecasts.

Standardized Anomaly Model Output Statistics (SAMOS)

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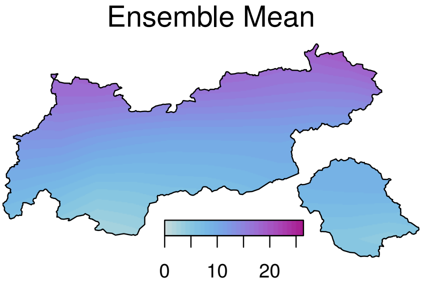
Spatial Post-Processing



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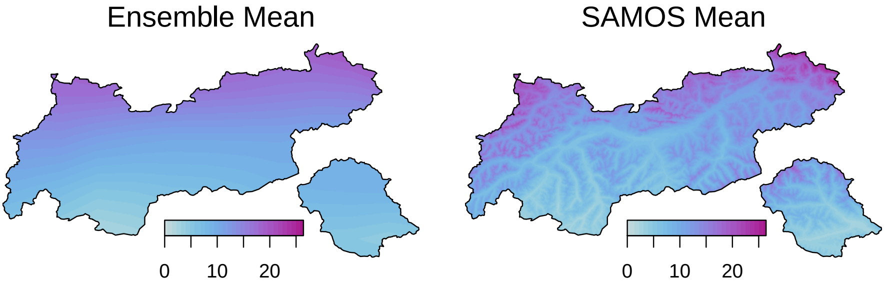

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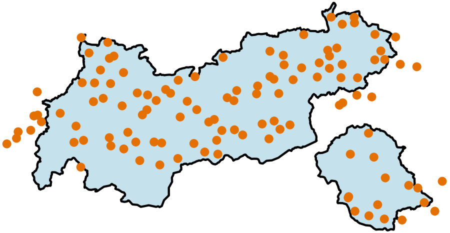
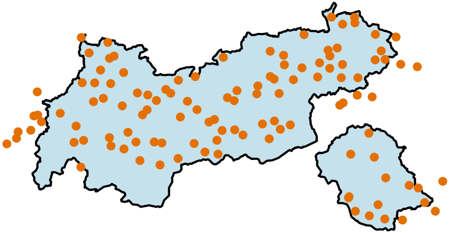
SAMOS Data & Results



Observations

- 118 stations
- daily observations
- 1971 – 2009; 2010 – 2012

SAMOS Data & Results



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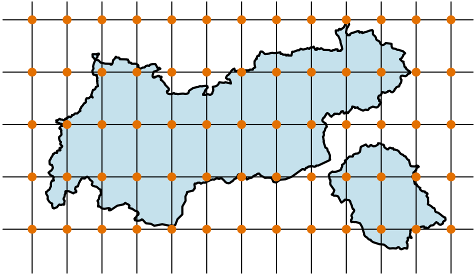
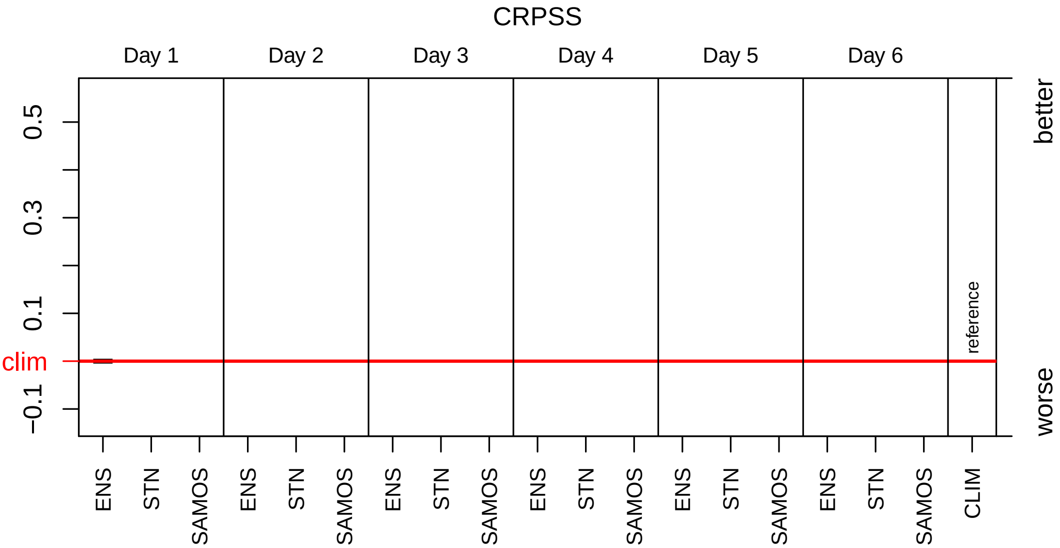


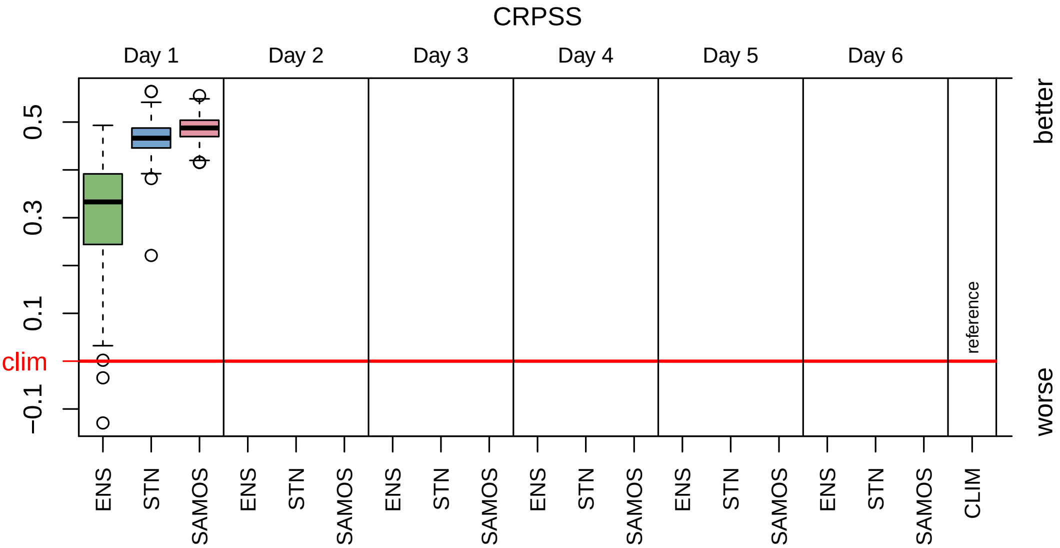
NWP data

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

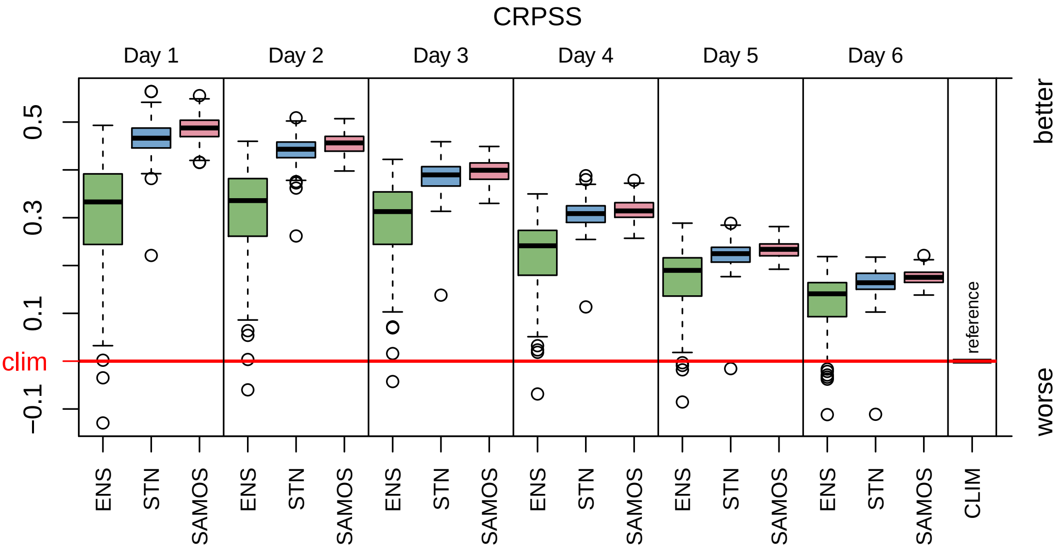
SAMOS Results: CRPSS



SAMOS Results: CRPSS



SAMOS Results: CRPSS



SAMOS Data & Results

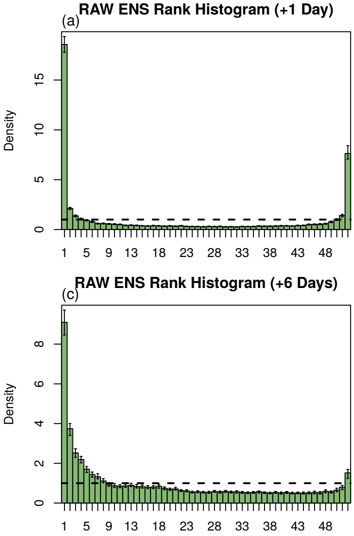


Figure 8: Rank histogram (left) and probability integral transform histograms (right) for one-day-ahead and six-day-ahead forecasts.

SAMOS Data & Results

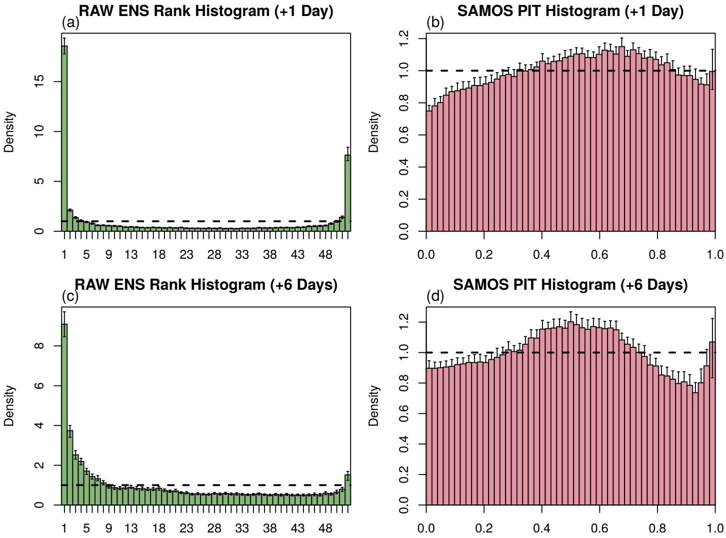
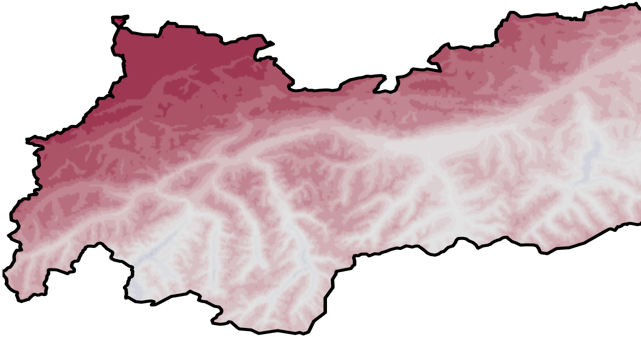


Figure 8: Rank histogram (left) and probability integral transform histograms (right) for one-day-ahead and six-day-ahead forecasts.

Summary II

- **concept proofed** for daily precipitation
- **accurately** predicts **full distribution**
- **outperforms station-wise** estimates



Best Student Paper Award 2015

Leopold-Franzens Universität

Publication III

Stauffer, R., G. J. Mayr, M. Dabernig, and A. Zeileis (2015): Somewhere Over the Rainbow: How to Make Effective Use of Colors in Meteorological Visualizations. *Bulletin of the American Meteorological Society*, **96**(2), 203–216.

Introduction

Color

- **integral element** in graphical displays
- **easily available** in most common software languages
- **omnipresent**: publications, presentation slides, . . .

Introduction

Color

- **integral element** in graphical displays
- **easily available** in most common software languages
- **omnipresent**: publications, presentation slides, . . .

The Problem: Only little guidance about “how to choose appropriate colors” for a particular task.

Introduction

Goal of our work

- **raise** the **awareness**
- introduce **Hue-Chroma-Luminance** (HCL) model
  - based on human perception
  - better control for choosing color palettes
- **provide information** on why and how to use
- **provide** convenient **software** for everyone

The RGB Color Space

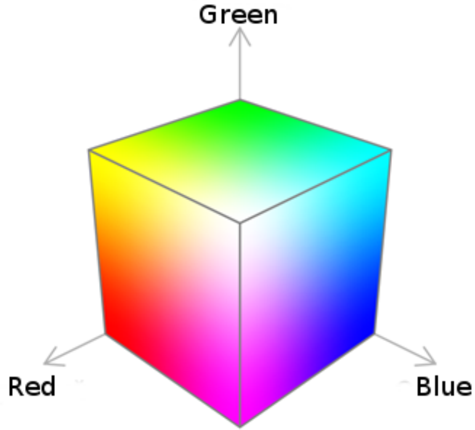


Figure 9: The Red-Green-Blue RGB color space.

The RGB Color Space

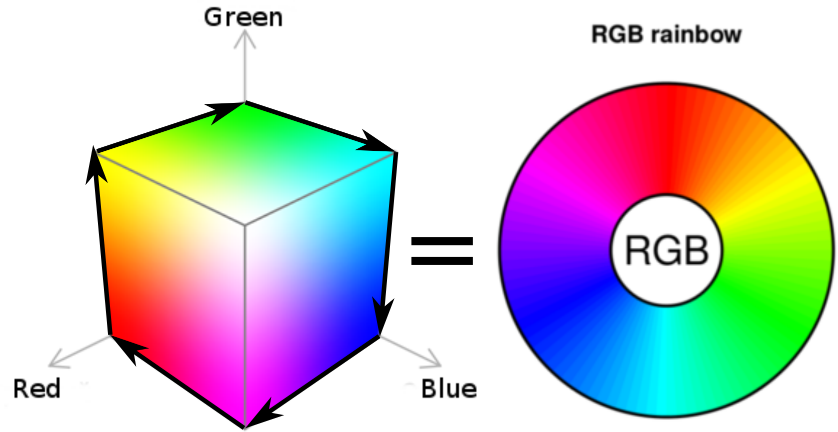
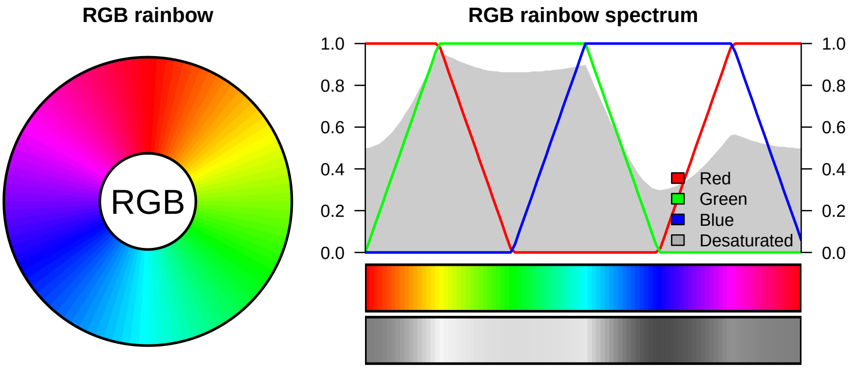
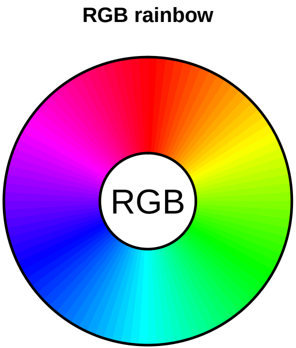


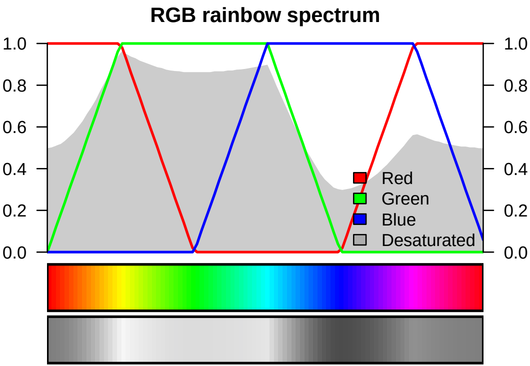
Figure 9: The (in)famous Red-Green-Blue RGB rainbow palette.

The RGB Color Space



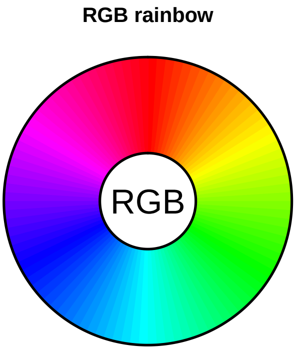
The RGB Color Space

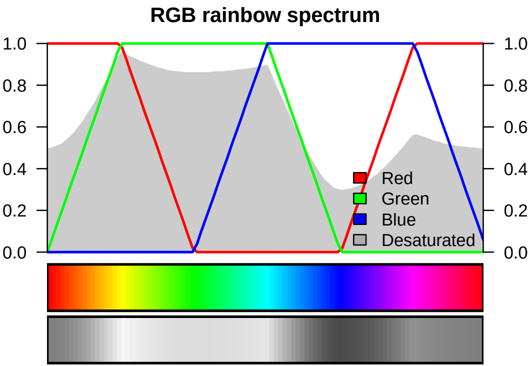




- **default color map** in many software packages
- **conveniently used** by many practitioners

The RGB Color Space





- **default color map** in many software packages
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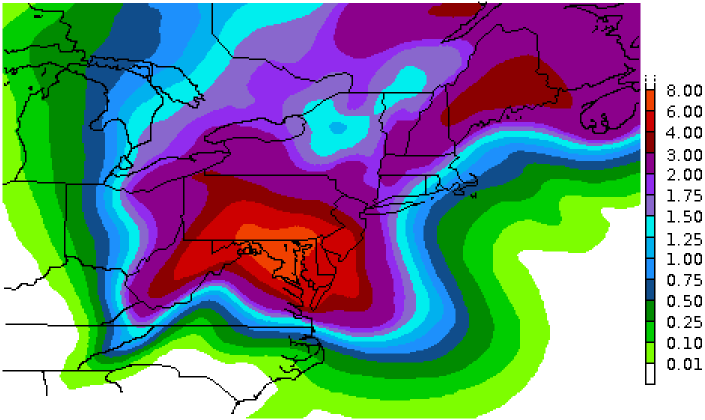
Question

Everybody does it – why should it be wrong?

What is Wrong?

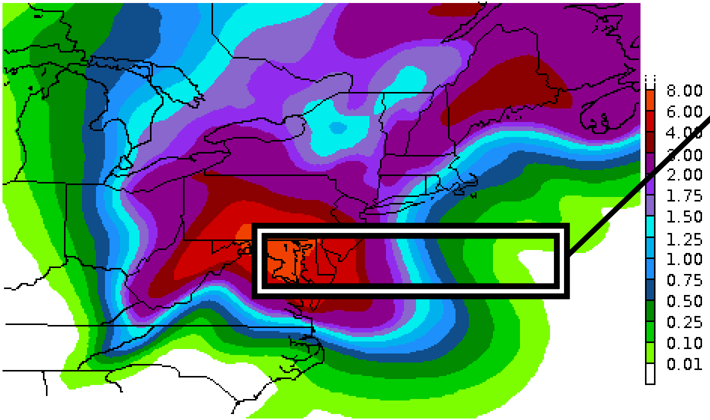


Hurricane Sandy
120-hour Day 1-5 Rainfall Forecast

Original figure as published by NOAA.

NOAA forecast, www.noaa.gov, 2012-10-27.

What is Wrong?



Gradients
very strong

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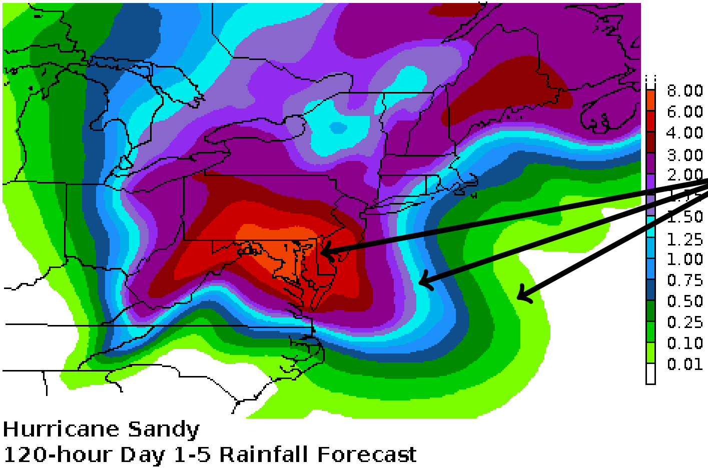

Gradients

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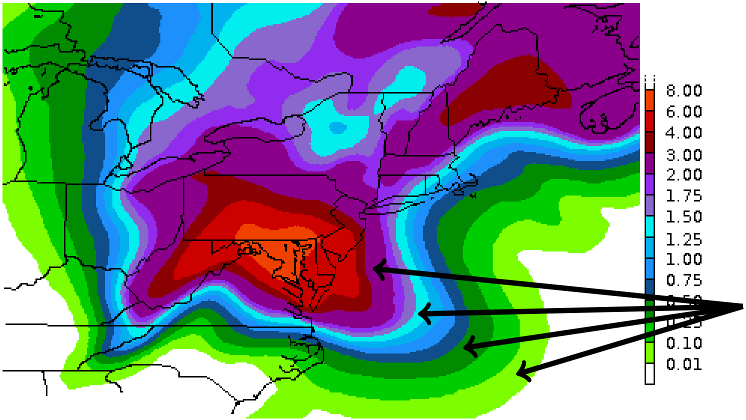
Saturation

highly-saturated colors

Original figure as published by NOAA.

What is Wrong?



Hurricane Sandy
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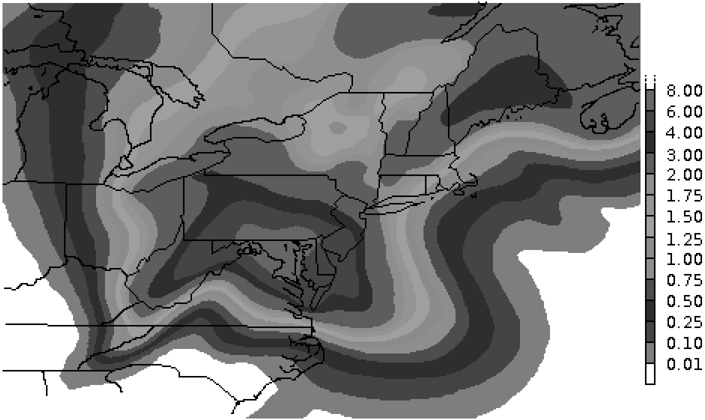
Original figure as published by NOAA.

Gradients
very strong

Saturation
highly-saturated colors

Discontinuous
bright, dark, bright, dark, ...

What is Wrong?



Hurricane Sandy
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Desaturated version of the original figure.

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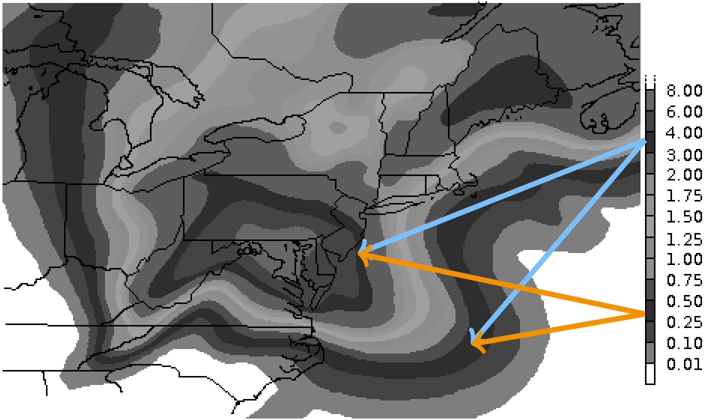
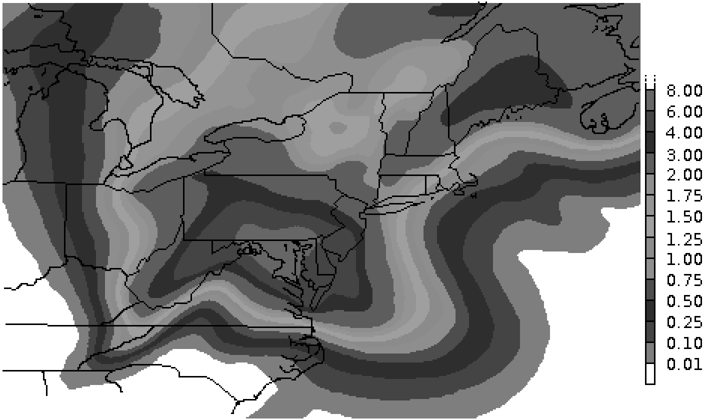


Desaturated version of the original figure.

Assignment

no longer unique

What is Wrong?



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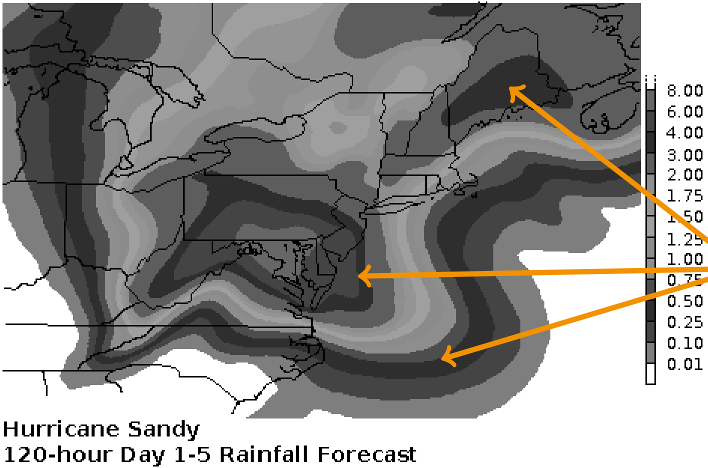
Interpretation
where is the maximum?

What is Wrong?



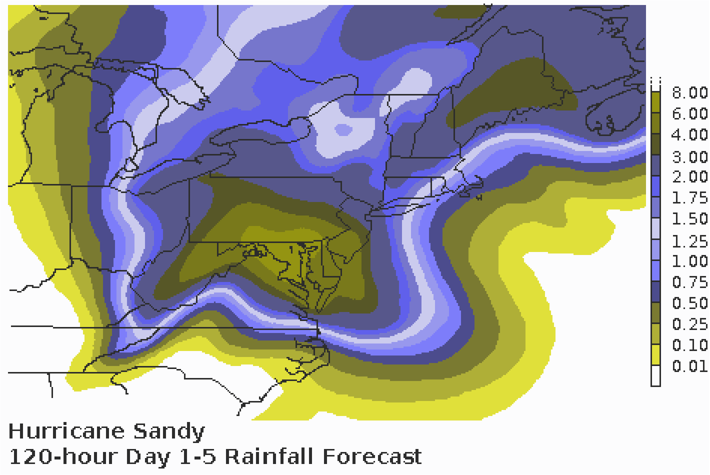
Desaturated version of the original figure.

Assignment
no longer unique

Interpretation
where is the maximum?

Focus
on dark artifacts

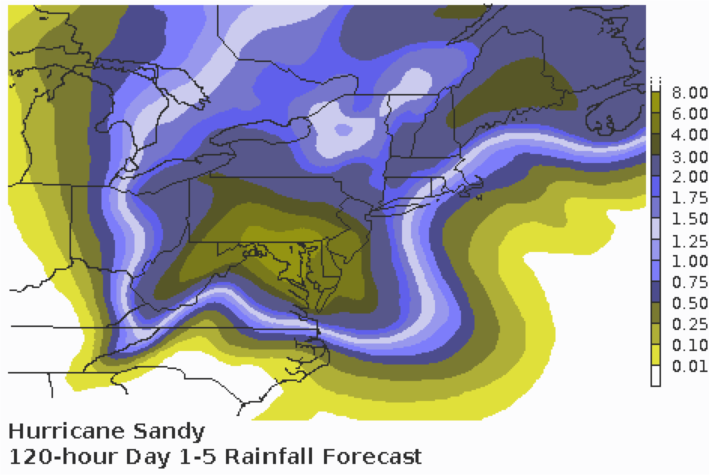
What's wrong?



Protanope sight (red-green weakness).

About 5% of all Europeans are affected.

What’s wrong?



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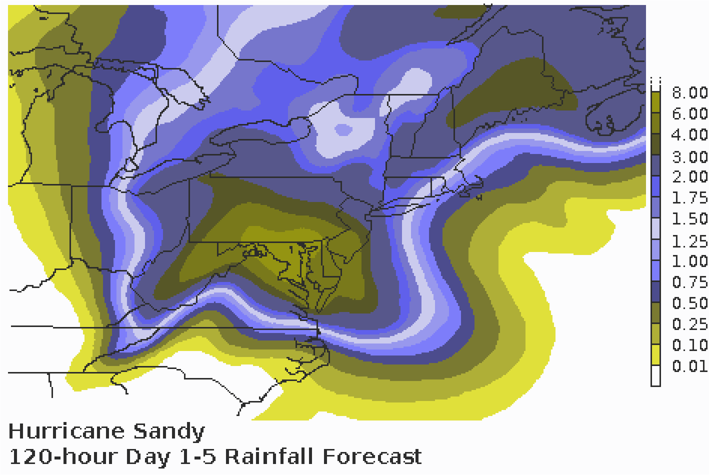
End-user

who is it?

What's wrong?



Protanope sight (red-green weakness).

About 5% of all Europeans are affected.

End-user

who is it?

To regard

visual constraints?

Challenges

Summary: Colors in a palette should . . .

- be **simple** and **natural**,
- not be un**appealing**,
- **highlight** the **important** information,
- **not mislead** the reader,
- **work everywhere** and for everyone.

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- People often **do not think** about it at all
- . . . and simply **use default** colors.

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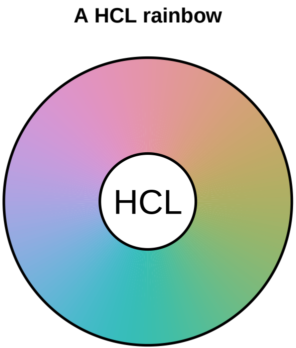
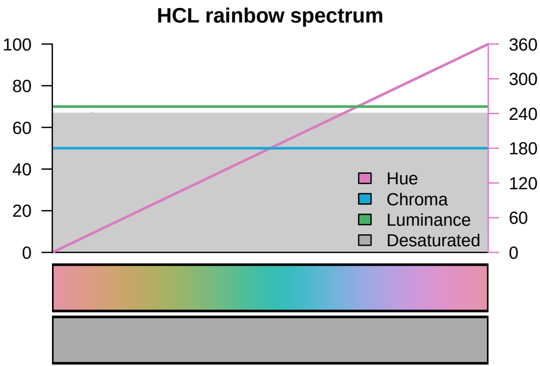
Potential problems

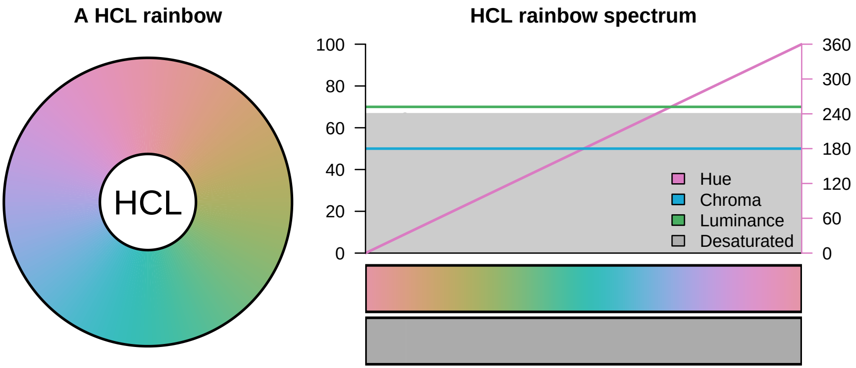
- for end-users – reviewer, supervisor, colleague, customer
- for your own day-to-day work

Perception-Based Way: HCL





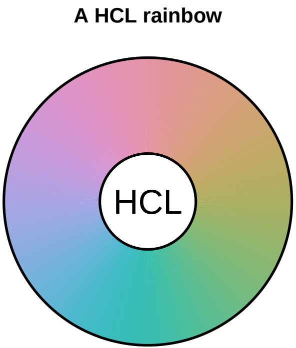
Perception-Based Way: HCL

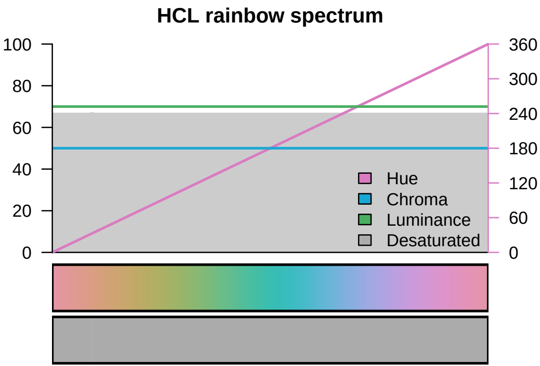


Triplet of:

- **H**ue (*defines the color*)

Perception-Based Way: HCL

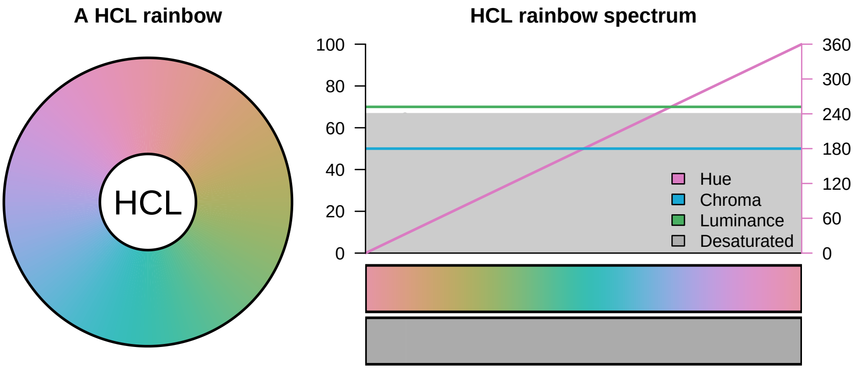




Triplet of:

- **H**ue (*defines the color*)
- **C**hroma (*defines the colorness*) and

Perception-Based Way: HCL



Triplet of:

- **H**ue (*defines the color*)
- **C**hroma (*defines the colorness*) and
- **L**uminance (*defines the brightness*)

Perception-Based Way: HCL

Advantages

- based on **human perception**

Perception-Based Way: HCL

Advantages

- based on **human perception**
- easy to control

Perception-Based Way: HCL

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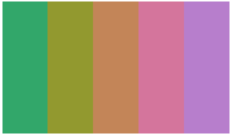
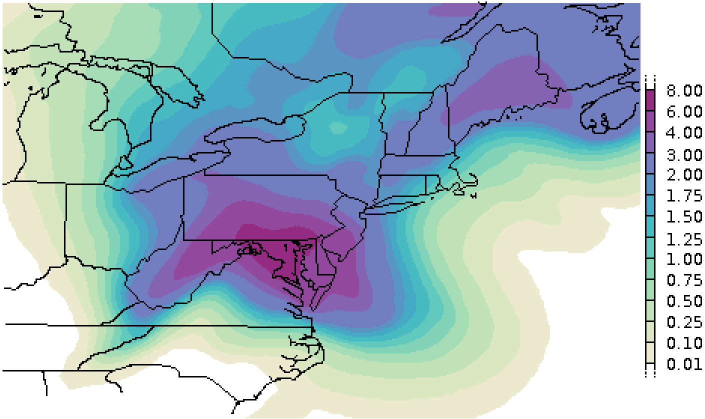
Hue



Chroma

Luminance

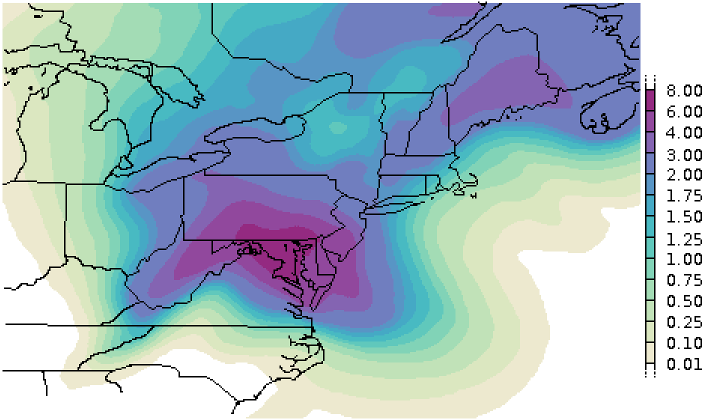
HCL Version



Hurricane Sandy
120-hour Day 1-5 Rainfall Forecast

Same information, changed color scheme.

HCL Version



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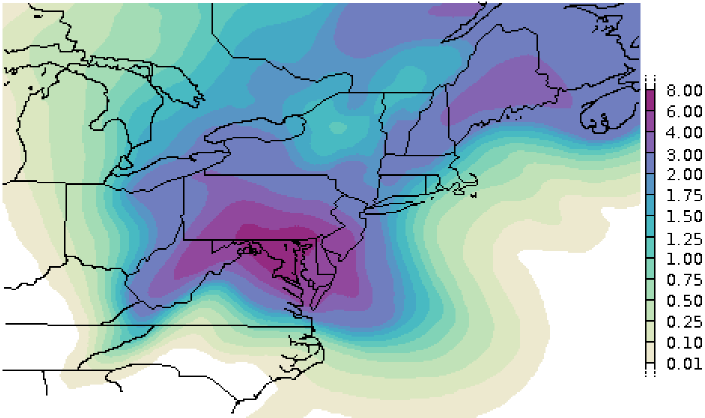
Same information, changed color scheme.

Colors

only two colors;

no irritating gradients

HCL Version



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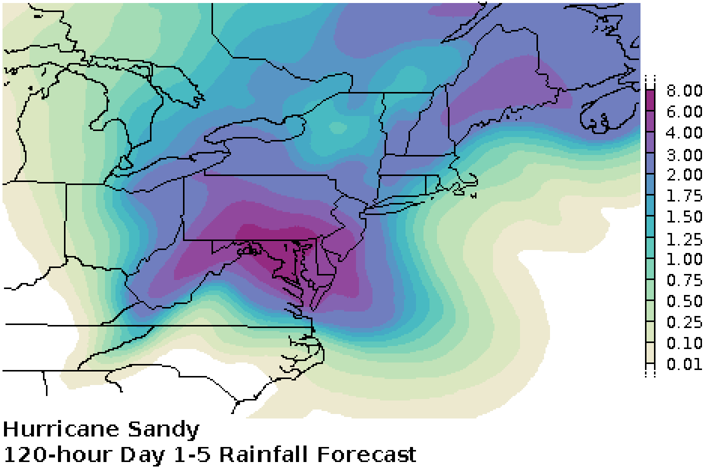
Information

guiding; no hidden information

HCL Version



Same information, changed color scheme.

Colors

only two colors;
no irritating gradients

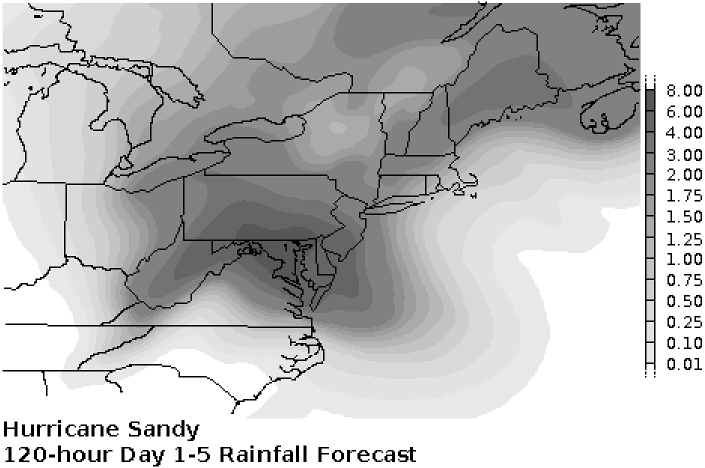
Information

guiding; no hidden information

Works

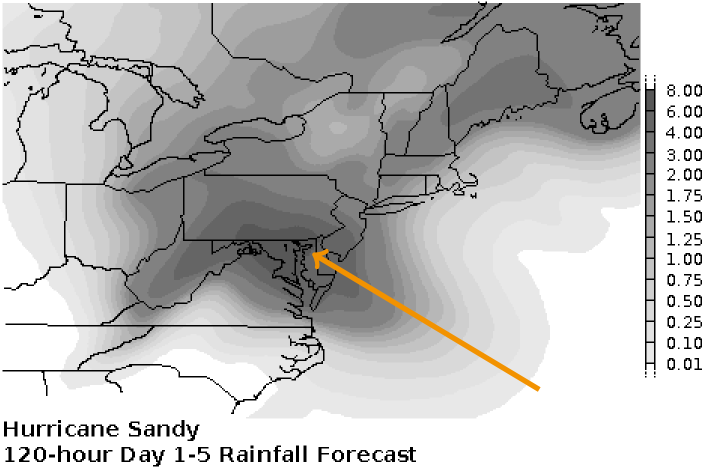
screen; projector; gray-scale device

HCL Version



Desaturated sight of the HCL-version.

HCL Version



Desaturated sight of the HCL-version.

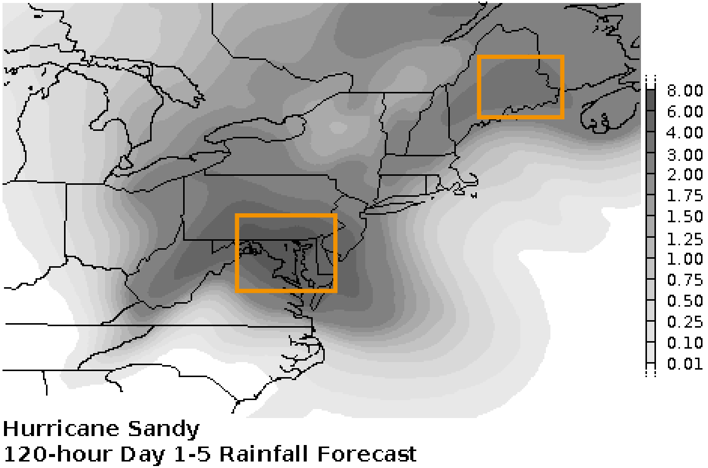
Assignment

higher values

(more precipitation)

$\rightarrow$ lower luminance

HCL Version



Desaturated sight of the HCL-version.

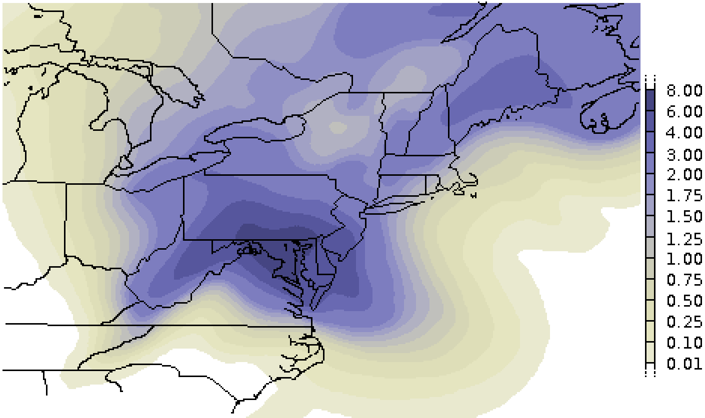
Assignment

higher values
(more precipitation)
$\rightarrow$ lower luminance

Focus

leads readers to most important areas

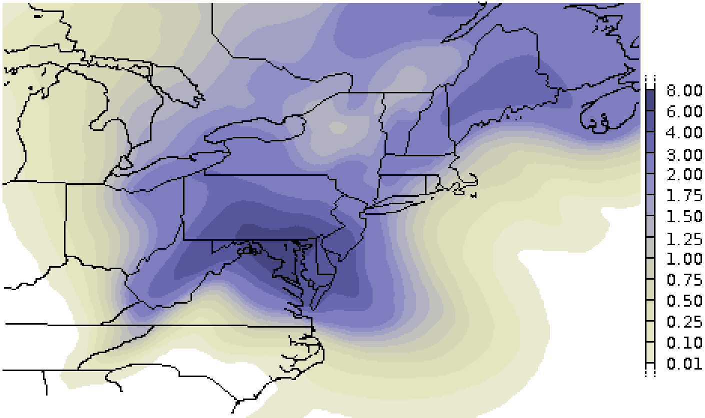
HCL Version



Hurricane Sandy
120-hour Day 1-5 Rainfall Forecast

Protanope sight of the HCL-version.

HCL Version

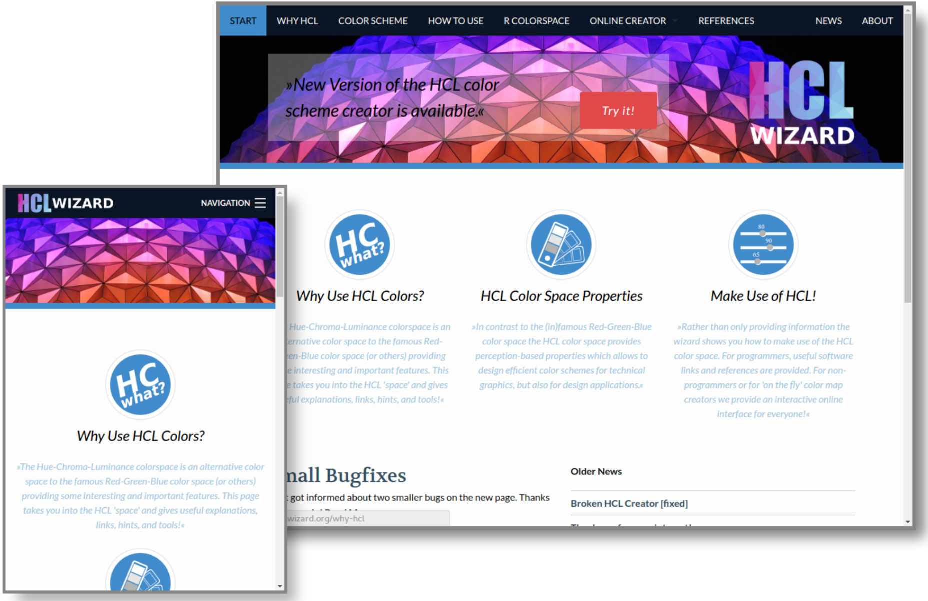


Hurricane Sandy
120-hour Day 1-5 Rainfall Forecast

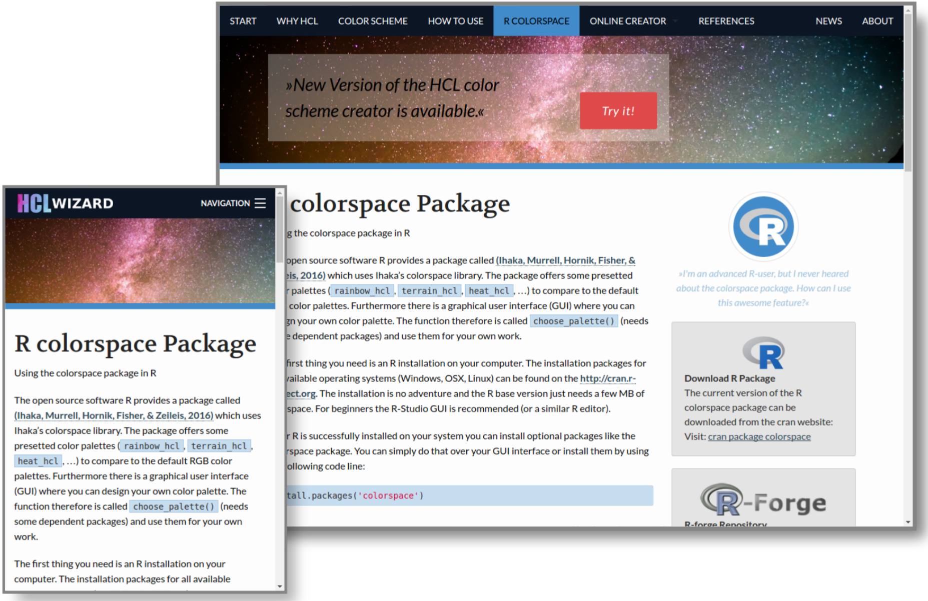
Summary

Solved a lot of problems by changing the color palette.

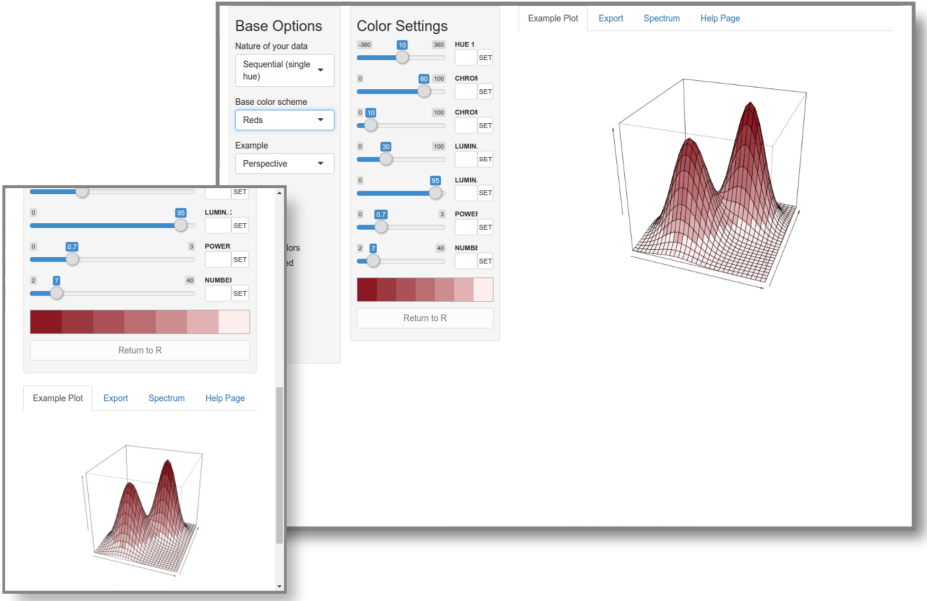
https://hclwizard.org



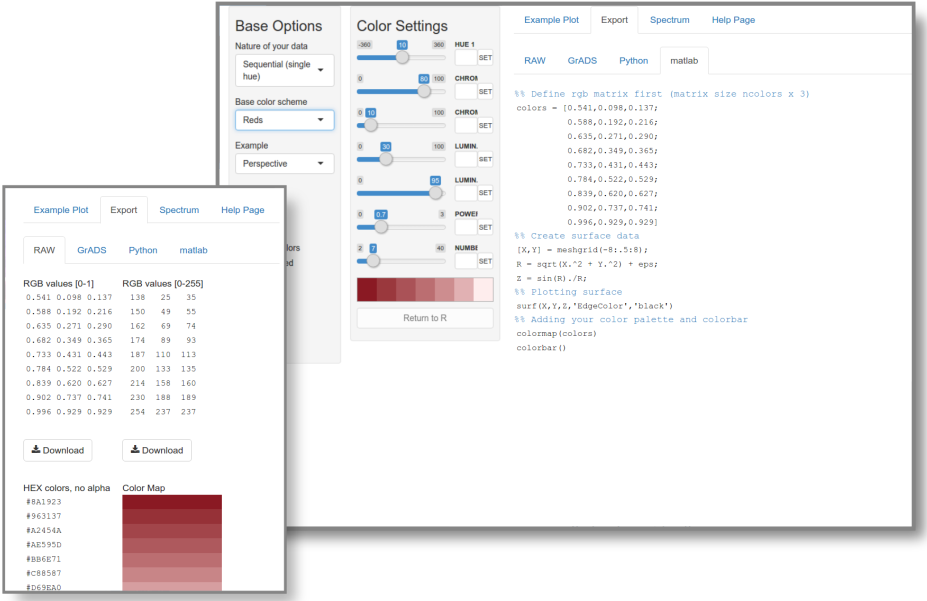
https://hclwizard.org



https://hclwizard.org



https://hclwizard.org



Summary III

Choice of colors

- **use** color **with care**, do not underestimate power of color
- think about **who** the reader/users are
- avoid large areas of **flashy**, **highly-saturated** colors
- employ **monotonic luminance scale** for continuous data

Summary III

Choice of colors

- **use** color **with care**, do not underestimate power of color
- think about **who** the reader/users are
- avoid large areas of **flashy**, **highly-saturated** colors
- employ **monotonic luminance scale** for continuous data

Try it yourself

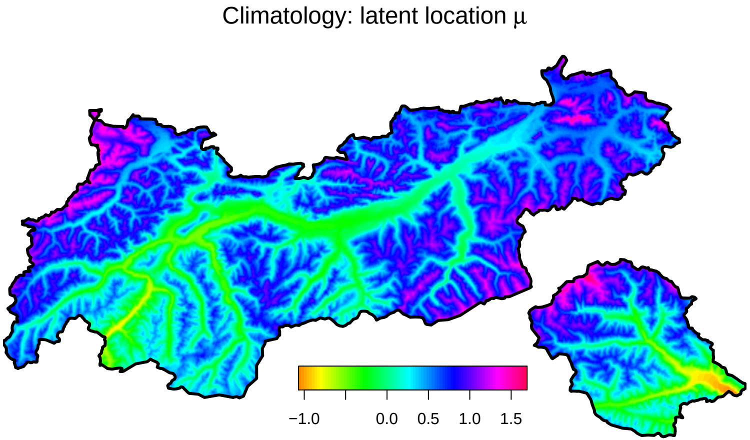
- `https://hclwizard.org`
  - interactive
  - several export options
  - information and guidance
- *colorspace* in *R*

INSTITUTE OF **ATMOSPHERIC** AND **CRYOSPHERIC** SCIENCES

To Recapitulate

Ph.D. Defense Presentation 2016-11-14

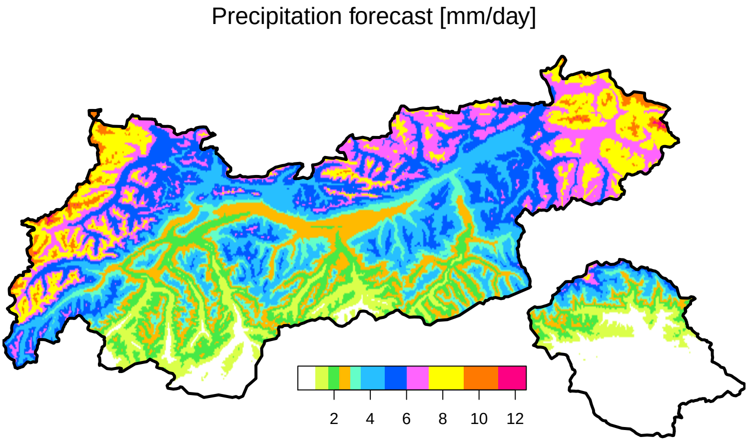
To Recapitulate



Part I

Spatio-Temporal Precipitation Climatology over Complex Terrain Using a Censored Additive Regression Model.

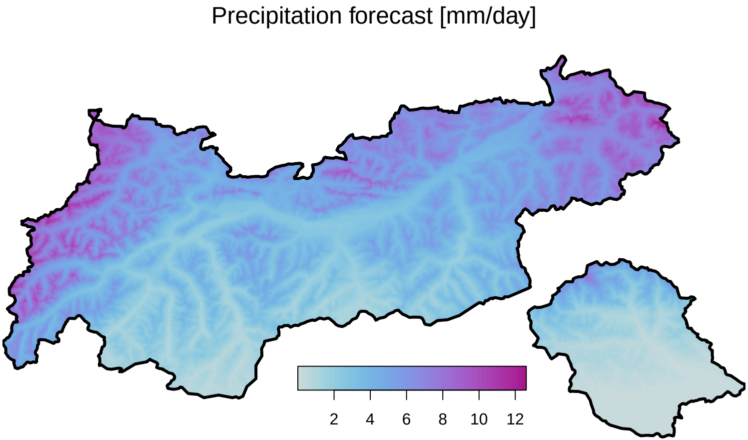
To Recapitulate



Part II

Ensemble Post-Processing of Daily Precipitation Sums over Complex Terrain Using Censored High-Resolution Standardized Anomalies.

To Recapitulate



Part III

Somewhere Over the Rainbow: How to Make Effective Use of Colors in Meteorological Visualizations.

Thank you for your attention!

Special thanks to the *SWAT*, my colleagues and advisors, my family and the FWF which made this possible!

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