Extreme weather and probabilistic forecast approaches

Petra Friederichs
Sabrina Bentzien, Andreas Hense

Meteorological Institute, University of Bonn

Statistical Methods for Meteorology and Climate Change
Montreal, 12 – 14 January 2011
Outline

Extreme weather and probabilistic prediction
  - Atmospheric scales and mesoscale atmospheric dynamics
  - High-impact weather
  - Ensemble prediction systems

Ensemble post-processing
  - Post-processing: Extract and calibrate information
  - Verification

Results
What are extremes?

► **Mathematically:**
Defined as block maxima or exceedances of large thresholds.
Events that lie in the tails of a distribution

► **Perception:**
Rare, exceptional, "large" and **high impact**

► **Problems:**
  ► 95% quantile of daily precipitation: $\approx 10 - 15 mm/d$
  ► $\approx 2$ years of data – only few extremes events for verification
Mesoscale Weather Prediction

- Strong and disastrous impact of many weather extremes calls for reliable forecasts
- “Although forecasters have traditionally viewed weather prediction as deterministic, a cultural change towards probabilistic forecasting is in progress.” (T N Palmer, 2002)
- Weather extremes do not come ”Out of the Blue”
- Numerical weather forecast models provide reliable forecasts of the atmospheric circulation prone to generate extremes
- Combination of dynamical and statistical analysis methods
Atmospheric scales and mesoscale dynamics

- Different scales exhibit different dominant force balances, different wave dynamics
- Mesoscale on horizontal scales 2km – 2000km
- Complex force balances

Steinhorst, Promet 35, 2010
Mesoscale weather extremes

- Heavy thunderstorms on July 14, 2010
- Strong horizontal gradients
- Strong vertical mixing
- Embedded in larger scale squall line – embedded in synoptic situation
Connection of Extremes on Different Scales

- Large vertical gradients of entropy
- Convective instability
- Deep convection lead to extremal vertical velocities
- Heavy precipitation and hailstones grow within this vertical circulation
Predictability

- Inherent limit of predictability
- Fastes error growth at smallest scales
- Predictability strongly depends on flow regime
- Moist convection is primary source of forecast-error growth
- Mesoscale forecasts are issued for $\leq 18h-24h$

E N Lorenz, Tellus 21, 19 (1969)
COSMO-DE Ensemble Prediction Prediction System (EPS)

- COSMO-DE: 2.8 km grid spacing, convection resolving NWP model
- Operational forecasts 0-21 hours – high-impact weather by DWD
- EPS with 20 (40) members
- Uncertainty due to initial conditions, boundary conditions, and model parameterisation errors
- First EPS with convection resolving limited area NWP model

Initial State | Boundary | Model
---|---|---

S. Theis, DWD (2010)
Probabilistic forecasting: Maximize sharpness of the predictive distribution subject to calibration

Calibration:

Raw ensemble data need adjustment: biased and underdispersive

(a) Raw Ensemble
(b) Bias-Corrected Ensemble
(c) EMOS Ensemble

Sharpness: Information of forecasts

from Hamill (2006)

Gneiting et al. (2005)
Conditional quantile function

**Semi-parametric**

- A-priori probability $\tau$, estimate conditional quantile $F_{Y|X}^{-1}(\tau|x) = \beta_T^T x$
- via (linear) quantile regression

**Parametric**

- A-priori assumption about parametric distribution $F_{Y|X}(y|x) = G(y; \Theta(x))$
- Estimate parameter function $\Theta(x)$
- Generalized linear model (GLM)
Quantile regression

\[ Q_{ZQR}(\tau|X) = \beta_T^T X, \quad \beta_T^T = (\beta_0, \ldots, \beta_K) \]

\[ \hat{\beta}_T = \arg \min_{\beta_T} \sum_{i=1}^{n} \rho_\tau \left( y_i - \beta_T^T x_i \right) \]

Censored quantile regression

\[ Q_{ZQR}(\tau|X) = \max(0, \beta_T^T X), \quad \beta_T^T = (\beta_0, \ldots, \beta_K) \]

\[ \hat{\beta}_T = \arg \min_{\beta_T} \sum_{i=1}^{n} \rho_\tau \left( y_i - \max(0, \beta_T^T x_i) \right) \]

with \( \rho_\tau(u) = \tau u \) for \( u \geq 0 \) and \( \rho_\tau(u) = (\tau - 1)u \) for \( u < 0 \)
Censoring

Equivariance with respect to non-decreasing function $h(\cdot)$

$$Q_{h(Y)}(\tau) = h(Q_Y(\tau))$$

Hidden process $Y^*$ observed through censored variable $Y$

$$Y = h(Y^*) = \max[0, Y^*]$$
### Generalized linear model – Mixture model

- **Probability of precipitation** \( (Y \geq 0.1 \text{mm}) \) – Logistic regression

\[
Pr(Y \geq 0.1 \mid x) = \pi(x)
\]

- **Distribution of precipitation** – Gamma GLM

\[
F(Y \mid x, Y \geq 0.1) = G_{\Gamma}(Y; \Theta(x))
\]

**Conditional mixture model for precipitation**

\[
F_{Y_{mix}}(y \mid x) = (1 - \pi) + \pi G_{\Gamma}(y; \Theta(x)) \ I_{y \geq 0.1}
\]
Conditional mixture model

Parametric – 'normal'

- A-priori assumption about parametric distribution for 'normal' part
  \[ F_{Y|X}(y|x) = G(y; \Theta(x)) \]
  Estimate parameter function \( \Theta(x) \)
  Generalized linear model (GLM)

Parametric: 'extreme'

- Above threshold/quantile: parametric distribution \( F_{Y|X}(y|x) = G(y; \Theta(x)) \) is of the family of max-stable distributions.
Extreme value theory  "Going beyond the range of the data"

- **Limit theorem** for sample maxima
  → asymptotic distribution for extremes

- **Condition of max-stability** (de Haan, 1984)
  → maxima follow a generalized extreme value distribution

- **Garantees universal behavior of extremes**
  → enables extrapolation!

In praxis: often not enough data to reach asymptotic limit
Extreme value distribution

Generalized extreme value distribution (GEV)

\[ G_\xi(y) = \begin{cases} 
\exp(- (1 + \xi \frac{y-\mu}{\sigma})^{-1/\xi}+), & \xi \neq 0 \\
\exp(- \exp(- \frac{y-\mu}{\sigma})), & \xi = 0 
\end{cases} \]
Generalized Pareto distribution

Threshold excesses $Z = Y - u$ follow a GPD

$$\text{Prob}(Z \leq y - u) = \begin{cases} 
1 - \left(1 + \xi \frac{y - u}{\sigma_u}\right)^{-1/\xi}, & \xi \neq 0 \\
1 - \exp\left(-\frac{y - u}{\sigma_u}\right), & \xi = 0
\end{cases},$$

for $y - u > 0$ and $(1 + \xi \frac{y - u}{\sigma_u}) > 0$
Mixture GLM including Extremes

- Conditional mixture model for precipitation

\[ F_{Y_{mix}}(y \mid x) = (1 - \pi) + \pi G_{\Gamma}(y; \Theta(x)) \mathbb{I}_{y \geq 0.1} \]

- GPD for 'extreme' precipitation – above \( u_\tau = F_{Y}^{-1}(\tau \mid x) \)

\[ F(Y \mid x, Y > u_\tau) = G_{GPD}(Y - u_\tau; \sigma(x)) \]

Conditional mixture model for precipitation with extremes

\[ F_{Y_{GPD}}(y \mid x) = (1 - \pi) + \pi G_{\Gamma}(y; \Theta(x)) \mathbb{I}_{Y \geq 0.1, Y \leq u_\tau} \]
\[ + \quad (1 - \tau)G_{GPD}(Y - u_\tau; \sigma(x)) \mathbb{I}_{Y > u_\tau} \]
Prediction and Verification

- Model parameter training
- Verification on independent data
Forecast verification by means of scores

- Cost functions or distance between forecast and data
- Utility measure in a Bayesian context

A score is proper iff

\[ E_{y \sim Q} [S(P, y)] \geq E_{y \sim Q} [S(Q, y)] \quad \forall \quad P \neq Q \]

\( S(P, y) \): score function
\( Q \) forecasters best guess
\( E_{y \sim Q} [S(., y)] \) expectation of \( S(., y) \) over \( y \sim Q \)
Verification: Goodness-of-fit criterion

\[
QVS(\tau) = \min_{\{\beta \in \mathbb{R}^q\}} \sum_i \rho_{\tau}(y_i - \beta^T x_i) 
\]
\[
QVS_{\text{ref}}(\tau) = \min_{\{\beta_0 \in \mathbb{R}\}} \sum_i \rho_{\tau}(y_i - \beta_0) 
\]

Quantile verification skill score

\[
QVSS(\tau) = 1 - \frac{QVS(\tau)}{QVS_{\text{ref}}(\tau)}
\]

Log-likelihood ratio test: asymmetric Laplacian regression

\[
f_{\tau}(u) = \frac{\tau(1-\tau)}{\sigma_L} \exp(-\rho_{\tau}(u)/\sigma_L).
\]

proportional to \(\log(QVS(\tau)/QVS_{\text{ref}}(\tau))\)
**SKeleton EPS Interim Solution – Neighborhood method**

- 'Time-lagged' ensemble of COSMO-DE
- Initialized every 3 hours, forecasts for 21 hours
- 1 July 2008 – 30 April 2010

- First guess probability (fgp)
- First guess 0.9-quantile (fgq9)
- 4 COSMO-DE forecasts and 5 × 5 neighborhood
12h accumulated precipitation between 12 and 00 UTC

- 83 Station in NRW
- Rain radar composite
Reliability

- Forecast probability, $y_i$
- Observed relative frequency, $o_i$

0.9 quantile

- Ensemble QR
- mix.mod transf.
- fgq9
Quantile forecasts - Skill Score

![Map of quantile forecasts with skill score](image-url)
Quantile forecasts - Skill Score

![Graph showing quantile forecasts and skill scores](image-url)
Quantile forecasts - Skill Score

![Graph showing quantile forecasts and skill score](attachment:image.png)

- QR
- MIX
- MIX.t
- GPD

0.99 quantile
Mesoscale Weather Prediction
Ensemble Post-Processing
Prediction and Verification
Results

Ensemble Post-Processing
Verification
Example
Conclusions and Challenges

Kleve

Breckerfeld–Weng (Ennepe–Ruhr–Kreis)

P.Friederichs
Extreme weather
Lagged ensemble forecasts and radar measurements
Conclusions

- Weather forecasts provide information that conditions occurrence of extremes
- Linear (non-linear) statistical modeling extracts information
- Extreme value theory provides distributions tailored for extremes
- Parametric method less uncertain than non-parametric method and non-linear dependency (shape parameter) is not parsimony
- High-impact weather: insufficient data available for training and for validation
Challenges

▶ Improve physical understanding of generation processes of extremes

▶ Application to multi-variable and spatio-temporal predictions
  ▶ Combine spatial statistics with model post-processing (Berrocal et al., 2007)
  ▶ Develop methods for multivariate post-processing
  ▶ Develop novel ensemble methods tailored to extremes (Bayesian model averaging)

▶ Verification tailored to extremes

▶ Verification for probabilistic multivariate and spatial forecasts
Reference


Special thanks to:
Susanne Theis, Martin Göber, Deutscher Wetterdienst, Offenbach

Thank You for Your Attention!