Statistical deep learning for modelling environmental extremes

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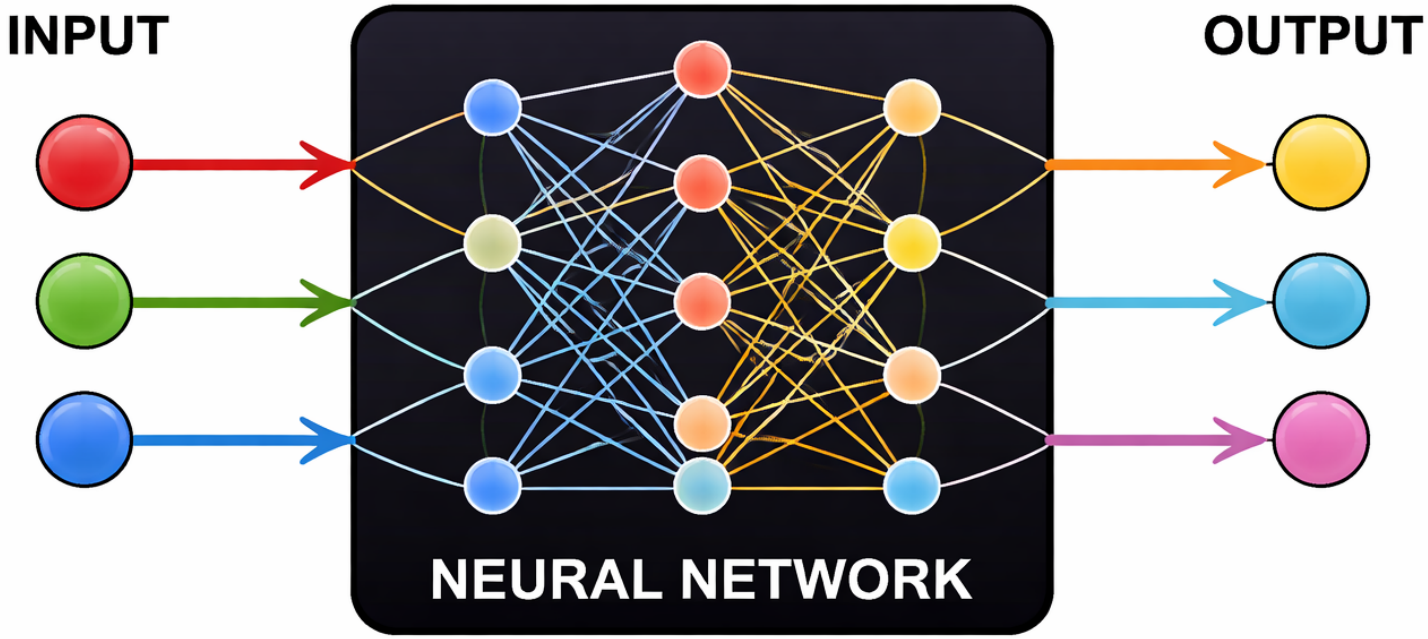
Statistical Deep Learning of Environmental Extremes

Using **explainable** deep learning models for flexible and fast statistical modelling of environmental extremes

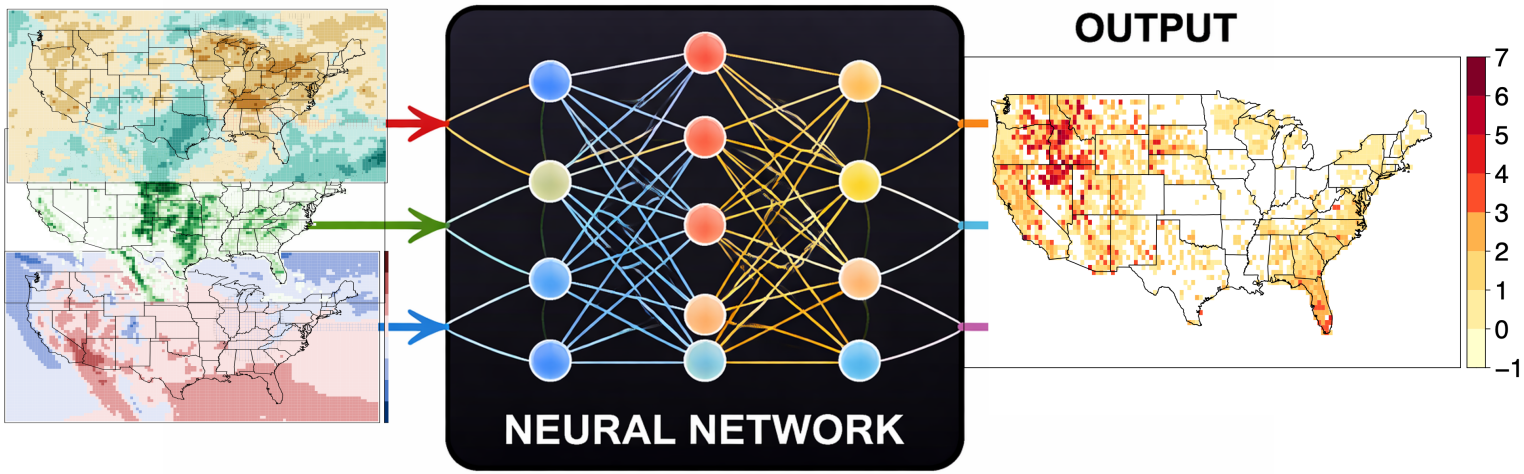
Deep learning 101 (Generated using ChatGPT)



Key ingredients:

- Some input data $\{\mathbf{x}_i\}_{i=1}^n$;
- A black-box mapping $\Rightarrow \mathcal{M} : \mathbf{x}_i \mapsto \hat{y}_i$;
- Loss function $\mathcal{L}(\mathbf{y}, \hat{\mathbf{y}})$ - determines stats. properties of the output;

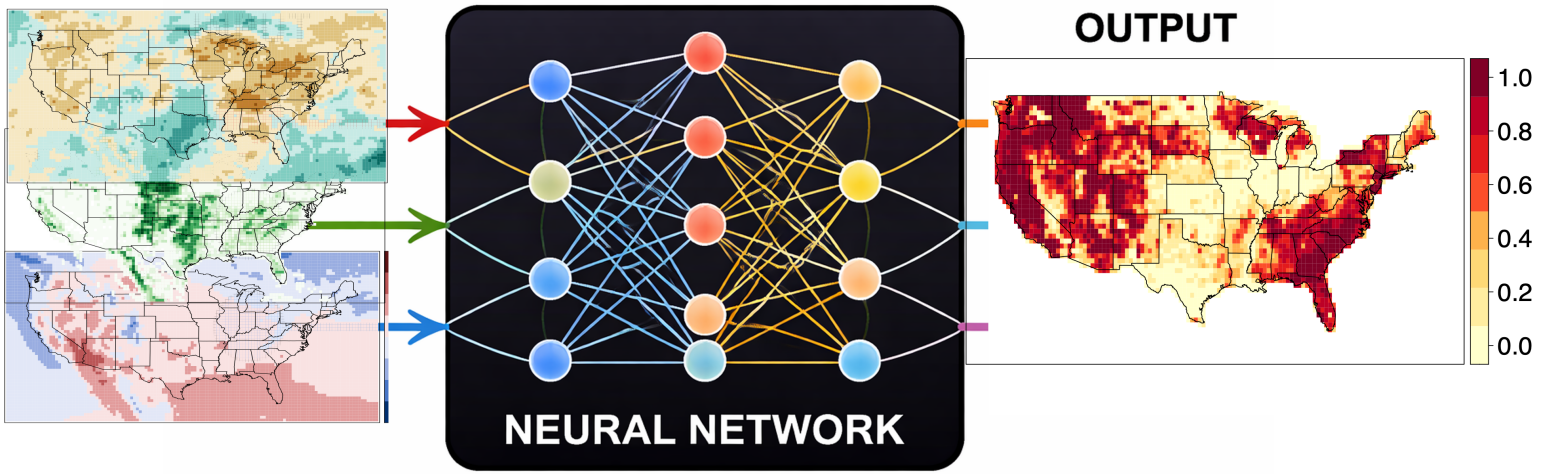
Environmental Deep learning



Key ingredients:

- $\mathbf{x}_i$: Spatial maps;
- A black-box mapping $\Rightarrow \mathcal{M} : \mathbf{x}_i \mapsto \hat{y}_i$;
- Least squares loss $\mathcal{L}(\mathbf{y}, \hat{\mathbf{y}}) = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \Rightarrow \hat{y}_i$ targets conditional expectation $\mathbb{E}[Y_i \mid \mathbf{X}_i = \mathbf{x}_i]$.

Environmental Deep learning



Key ingredients:

- $\mathbf{x}_i$: Spatial maps;
- A black-box mapping $\Rightarrow \mathcal{M} : \mathbf{x}_i \mapsto \hat{y}_i$;
- Binary cross-entropy $\mathcal{L}(\mathbf{y}, \hat{\mathbf{y}}) = -\log\left(\prod_{i=1}^{n} \hat{y}_i^{y_i}(1-\hat{y}_i)^{1-y_i}\right)$
  $\Rightarrow \hat{y}_i$ targets conditional probabilities $\Pr[Y_i = 1 \mid \mathbf{X}_i = \mathbf{x}_i]$.

Deep Extremal Regression

Deep Extremal Regression Models

Use **EVT-compliant** loss functions so neural net targets useful risk metrics

- Risk metrics, i.e., **return levels**/quantiles/expectiles* (using asymmetric least squares loss)
- Extreme return levels and joint probabilities (using likelihood-based losses from, e.g., GPD/GEV models)

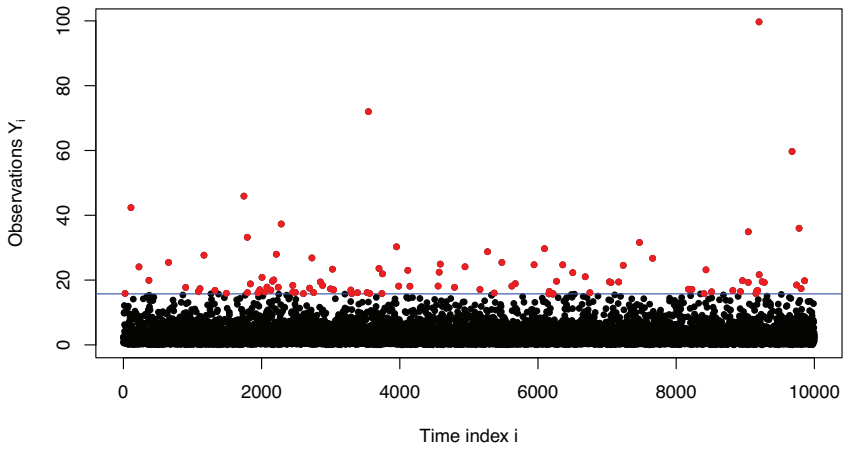
$$\mathcal{L}(\mathbf{y}, \hat{\mathbf{y}}) = -\log\left(\prod_{i=1}^{n} f_{Y|\mathbf{X}=\mathbf{x}}(y_i|\hat{\mathbf{y}}_i)\right),$$

where $f_{Y|\mathbf{X}=\mathbf{x}}$ is the density of $Y \mid \mathbf{X}$ and $\hat{\mathbf{y}}_i := \hat{\mathbf{y}}_i(\mathbf{x}_i)$ is a parameter.

*Daouia, Girard, Richards. (2026+) Deep tail expectile regression neural networks.

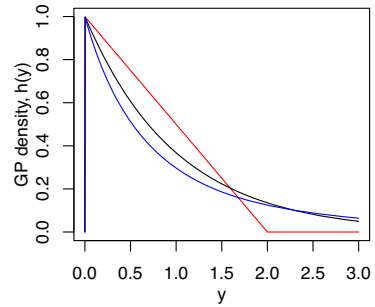
Deep Extremal Regression - Example

Threshold exceedance approach $Z_1, Z_2, \ldots, \overset{\text{iid}}{\sim} F$



Pickands–de Haan–Balkema Theorem: *For a broad range of distributions F, we have the following large-u approximation*

$$Y_i := Z_i - u \mid Z_i > u \sim \text{GPD}(\sigma, \xi).$$



Deep Extremal Regression - Example

Deep Extremal Regression Models

Use **EVT-compliant** loss functions so neural net targets useful risk metrics

- Using likelihood-based losses:

$$\mathcal{L}(\mathbf{y}, \hat{\mathbf{y}}) = -\log\left(\prod_{i=1}^{n} f_{Y|\mathbf{X}=\mathbf{x}}(y_i|\hat{\mathbf{y}}_i)\right),$$

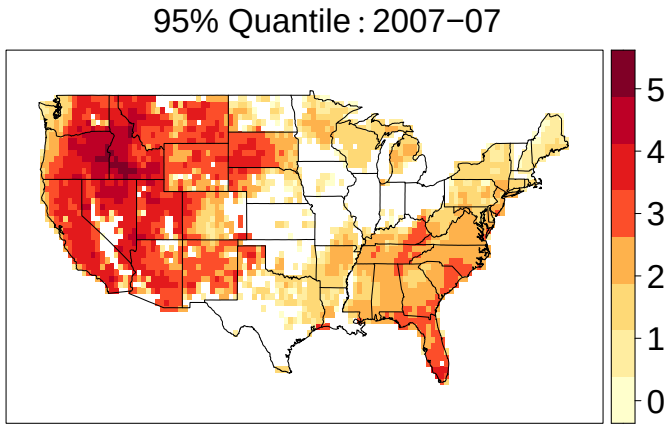
  where $f_{Y|\mathbf{X}=\mathbf{x}}$ is the density of $Y \mid \mathbf{X}$ and $\hat{\mathbf{y}}_i := \hat{\mathbf{y}}_i(\mathbf{x}_i)$ is a parameter.
- In a regression setting:

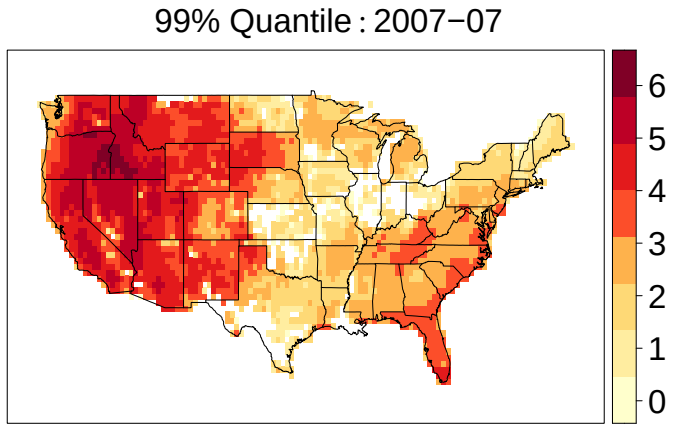
$$Y_i \mid (Y_i > 0, \mathbf{X}_i = \mathbf{x}_i) \sim \mathrm{GPD}(\sigma(\mathbf{x}_\mathrm{i}), \xi(\mathbf{x}_\mathrm{i})),$$

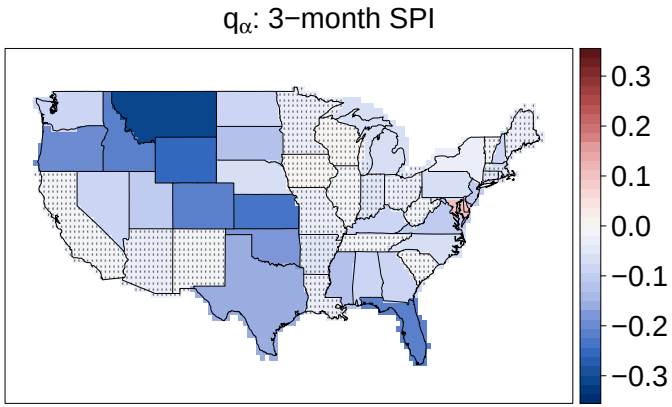
  and so $\hat{\mathbf{y}}_i := (\sigma(\mathbf{x}_i), \xi(\mathbf{x}_i))$ and $f_{Y|\mathbf{X}=\mathbf{x}}$ is the GPD density.
- Not new - just ask the experts (Carreau and Bengio, 2007)!

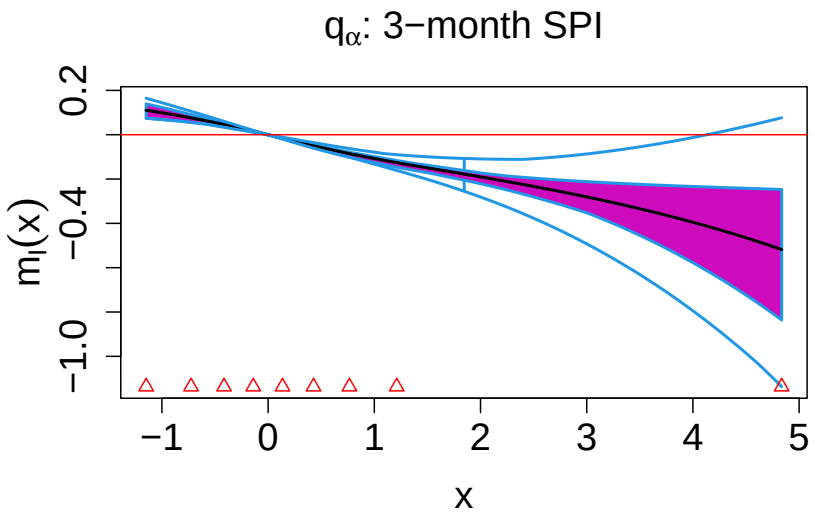
Carreau, Julie and Bengio, Yoshua. (2007) A Hybrid Pareto Model for Conditional Density Estimation of Asymmetric Fat-Tail Data. AIaS.

Extreme Wildfires - US (Richards and Huser, 2026b)



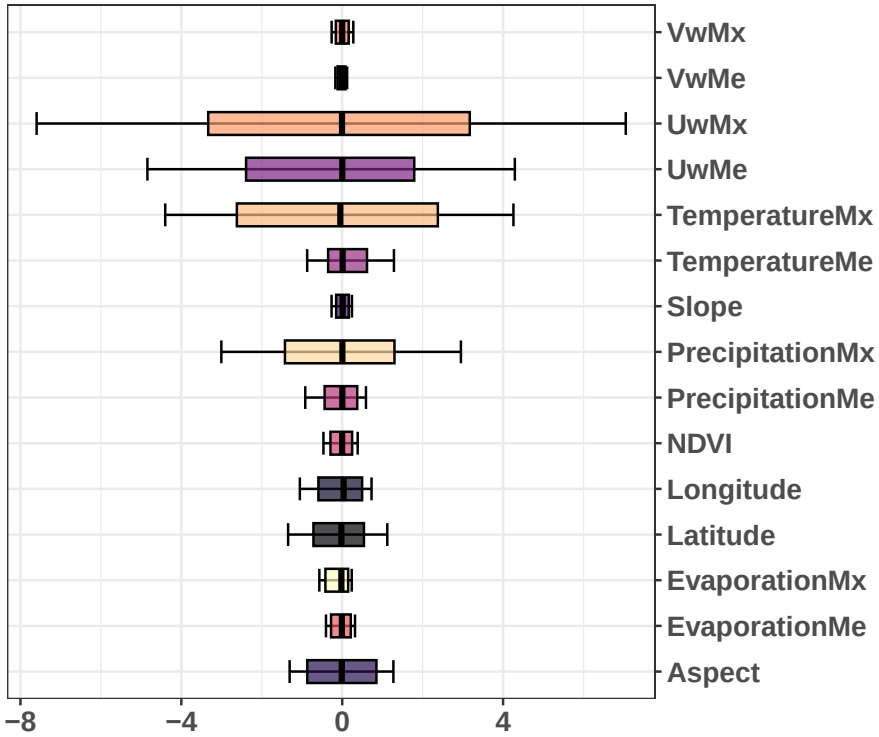






Richards, Huser (2026). Regression modelling of spatiotemporal extreme US wildfires via partially-interpretable neural networks. JCGS.

Wildfire Extremes - Australia (Cisneros et al., 2024)



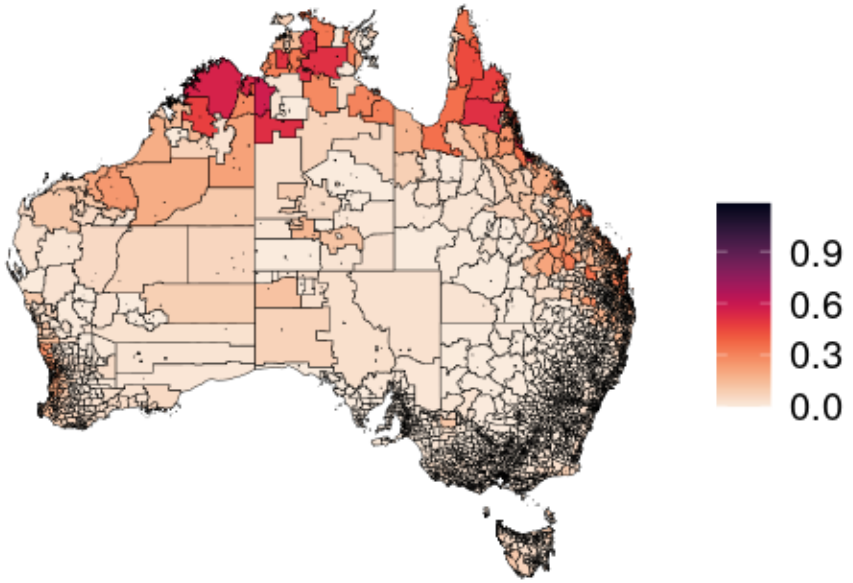


Figure: Left: boxplot of Shapley values. Right: return levels for wildfire risk.

Cisneros, Richards, Dahal, Lombardo, Huser (2024). Deep graphical regression for jointly moderate and extreme Australian wildfire. Spatial Statistics.

Wildfire Extremes - Mediterranean (Richards et al., 2023)

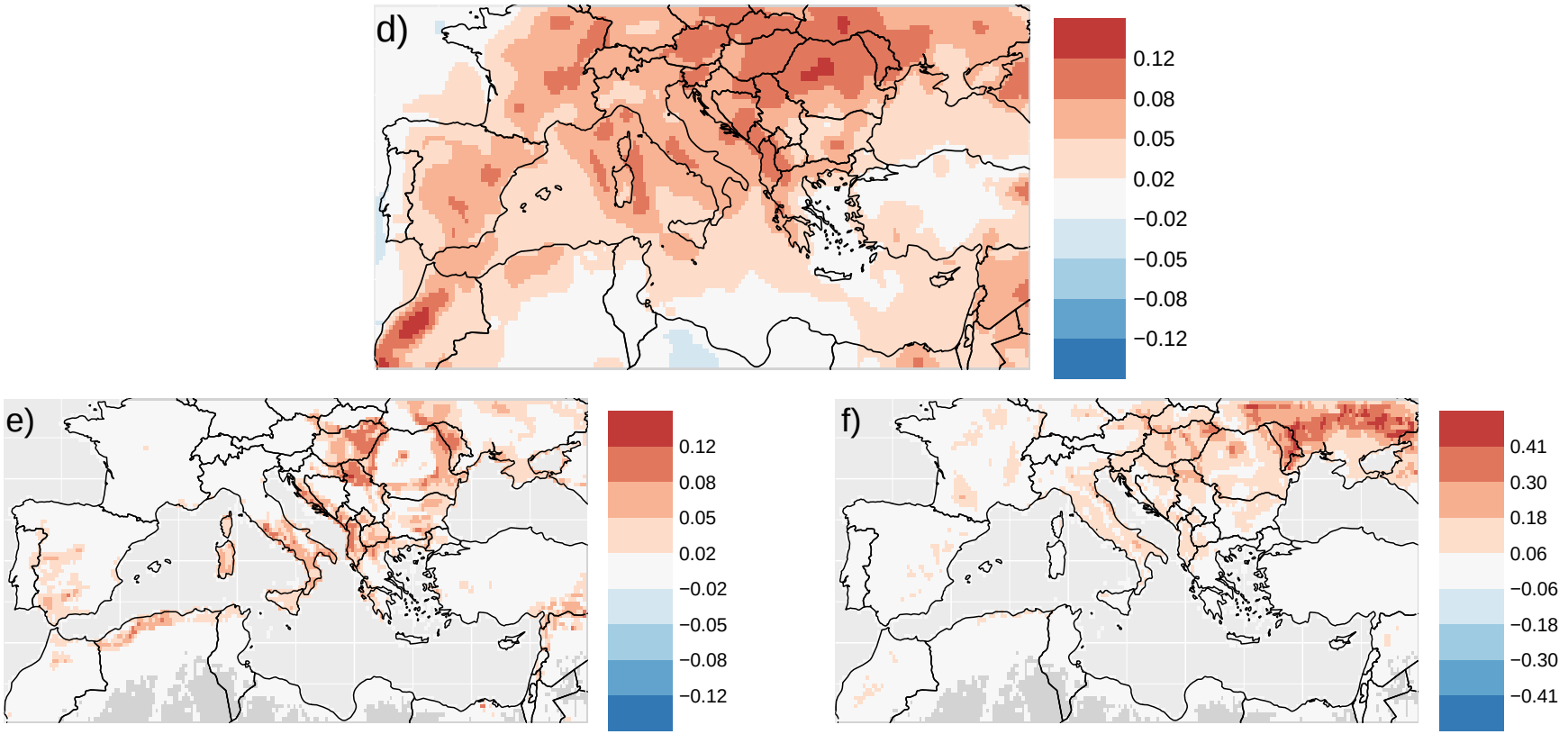


Figure: Trends in 2m air temperature [K]. Maps of changes in occurrence probability $p_0(s, t)$ and wildfire intensity for August 2001.

Richards, Huser, Bevacqua, Zscheischler, (2023). Insights into the drivers and spatio-temporal trends of extreme Mediterranean wildfires with statistical deep-learning. AIES.

Extreme UK Rainfall

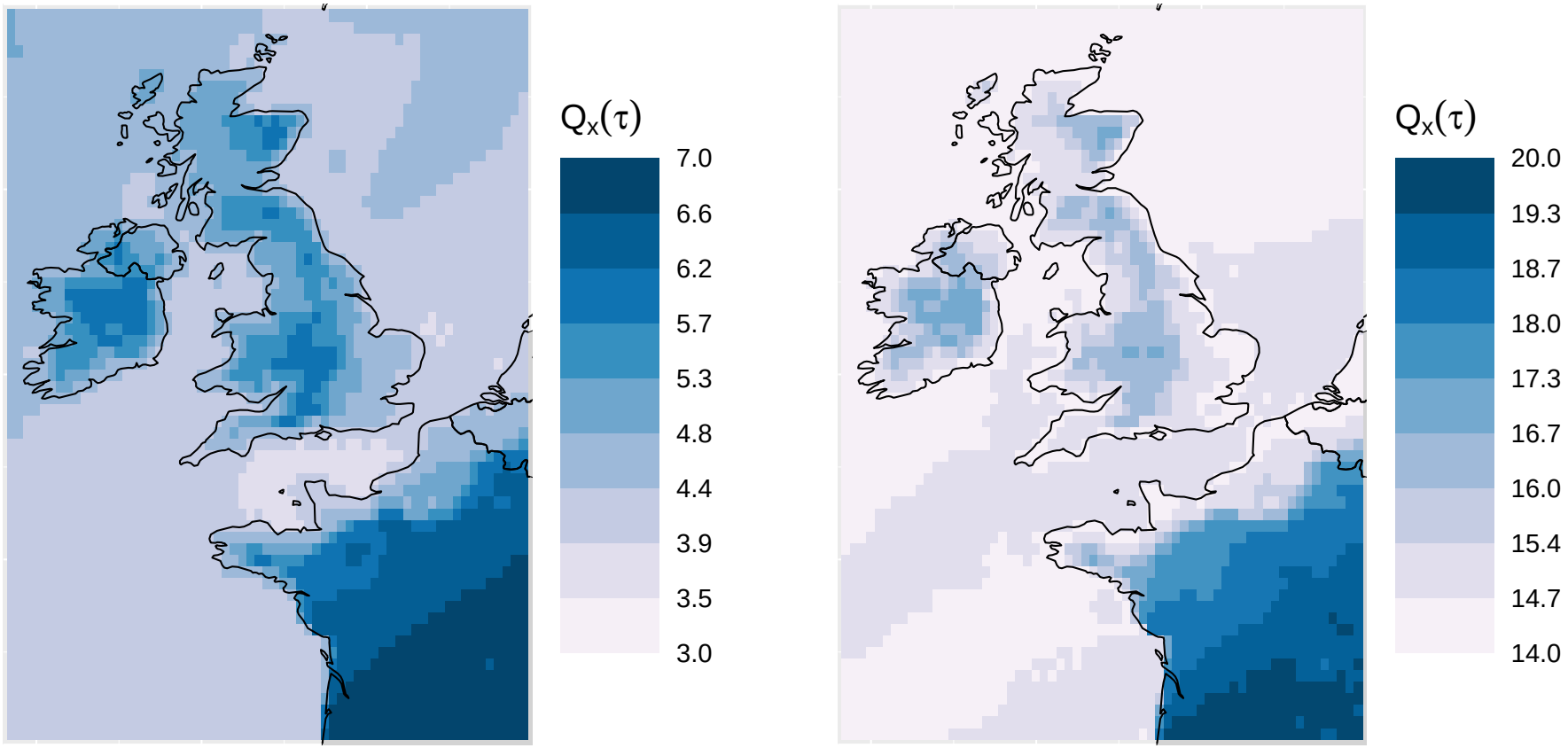
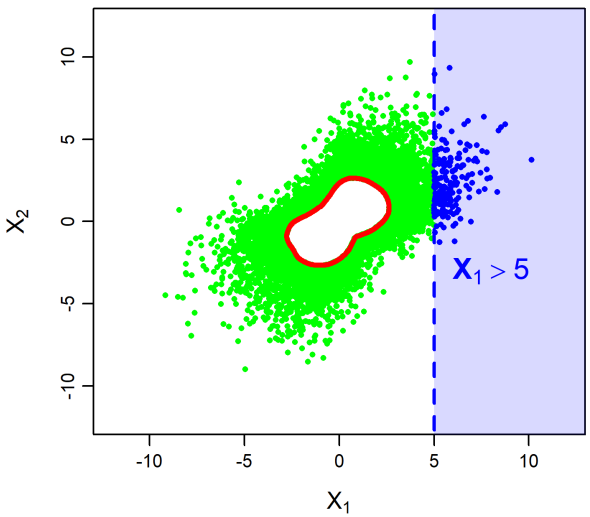
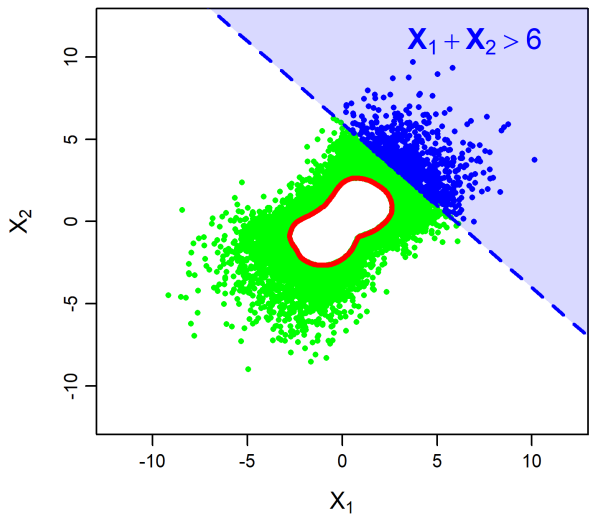


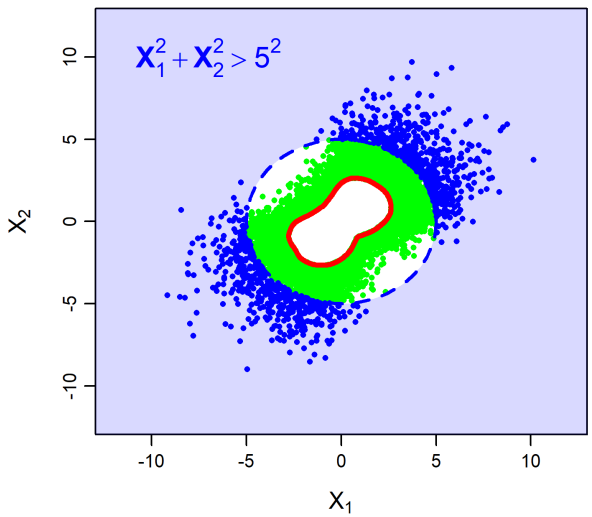
Figure: Maps of extreme conditional τ-quantiles, $Q_{\mathbf{x}}(\tau)$, of maximum hourly rainfall (mm) for July 2013, with $\tau = 0.9$ (left) and $\tau = 0.9999$ (right).

Richards, Huser (2026). Extreme Quantile Regression with Deep Learning. In Chapman and Hall/CRC Handbook on Statistics of Extremes.

Compound and multivariate extremes

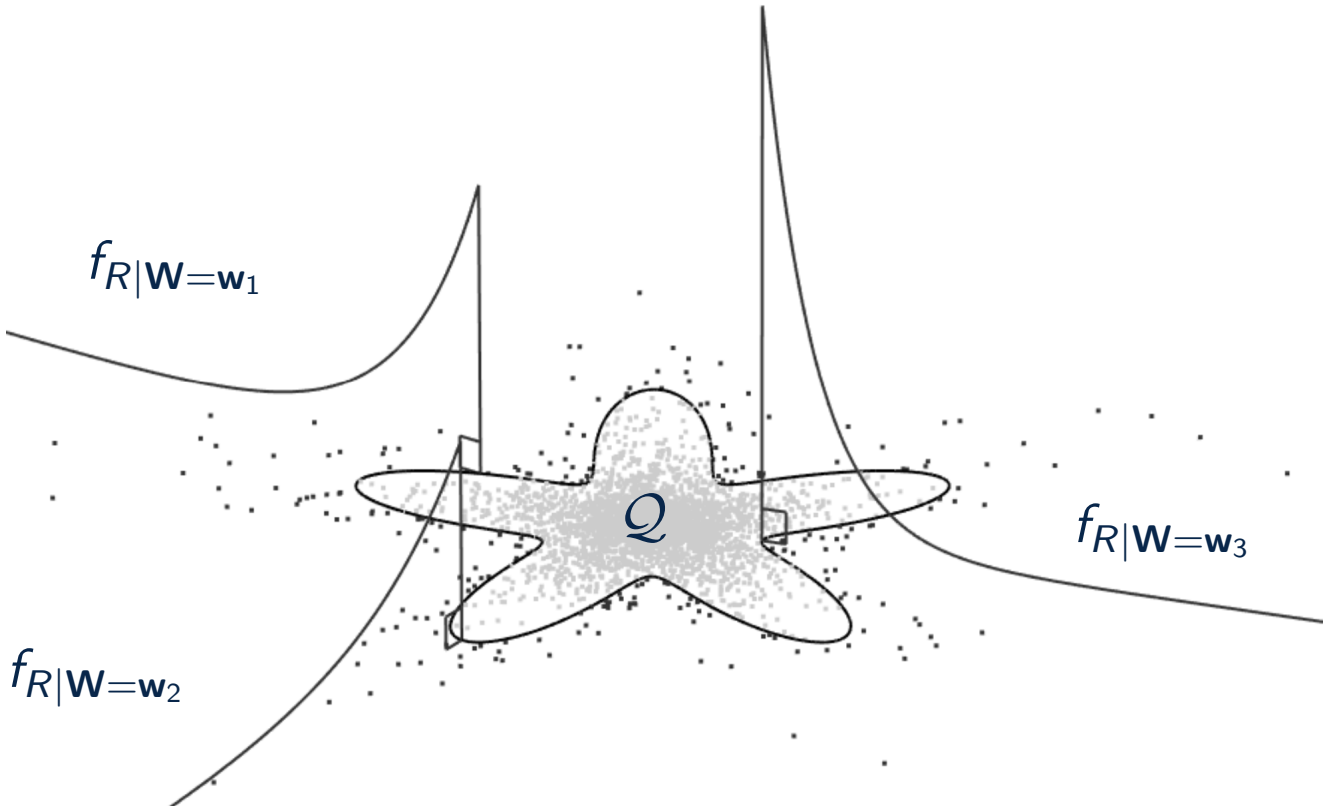






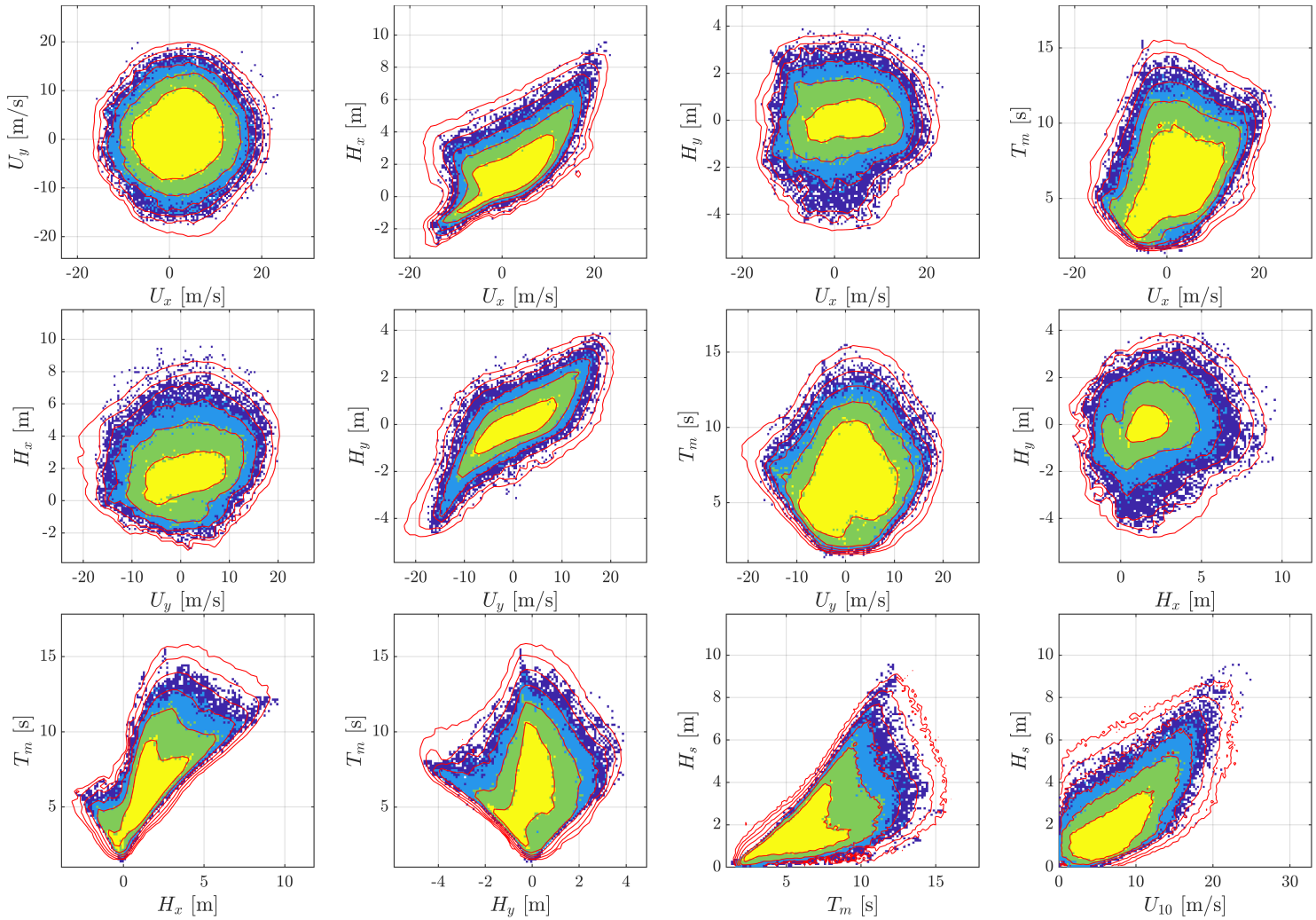
Murphy-Barltrop, Richards, Zscheischler (2026+). Exploring temporal changes in concurrent Alpine runoff extremes via statistical deep learning.

Compound and multivariate extremes



De Monte, Huser, Papastathopoulos, & Richards. (2025+). Generative modelling of multivariate geometric extremes using normalising flows. arXiv:2505.02957.

Metocean Extremes - Celtic Sea (Mackay et al., 2025)



Mackay, Murphy-Barltrop, Richards, Jonathan (2025). Deep Learning Joint Extremes of Metocean Variables Using the SPAR Model. JOMAE.

US Wind Extremes (De Monte et al., 2025)

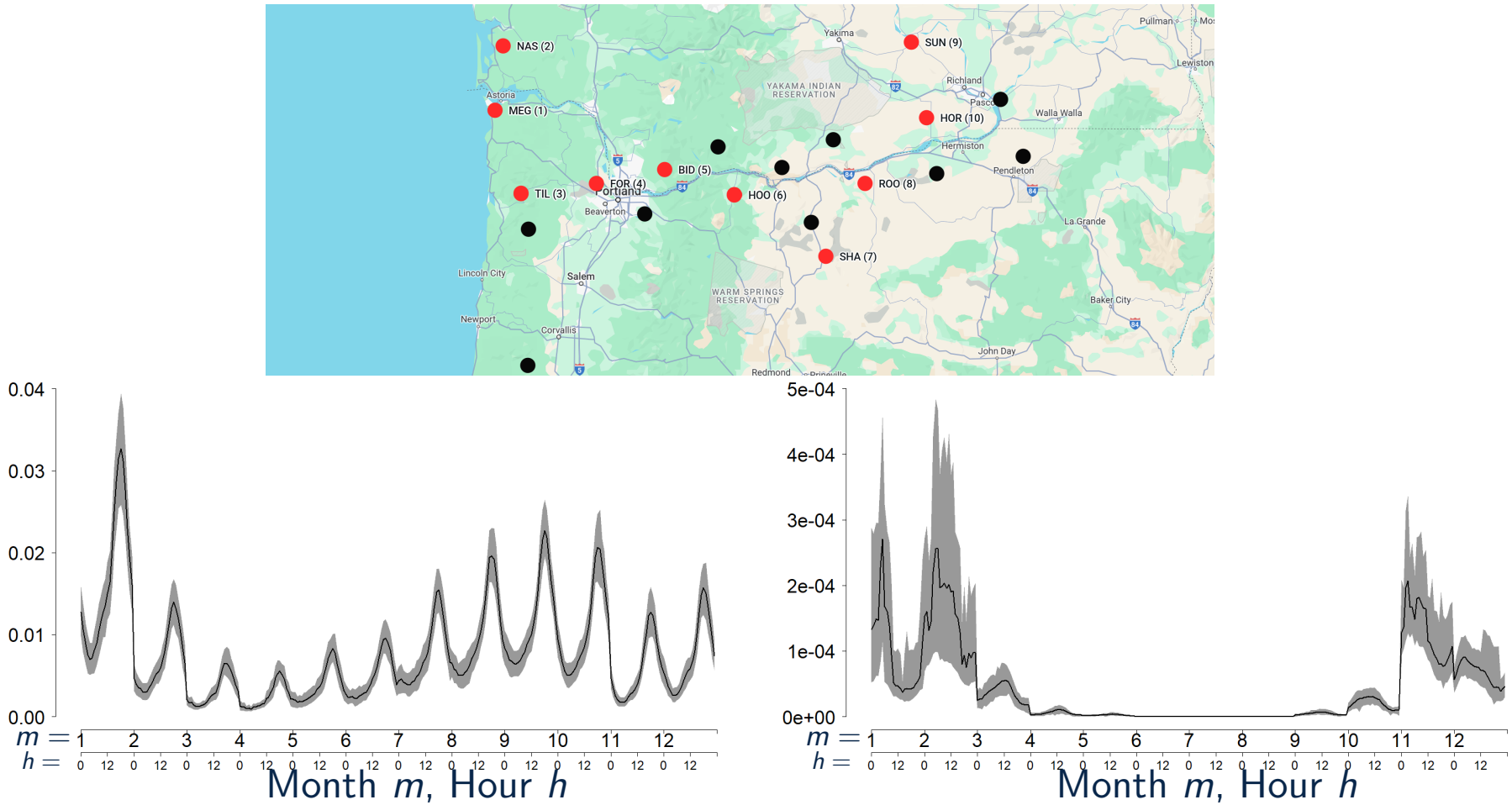
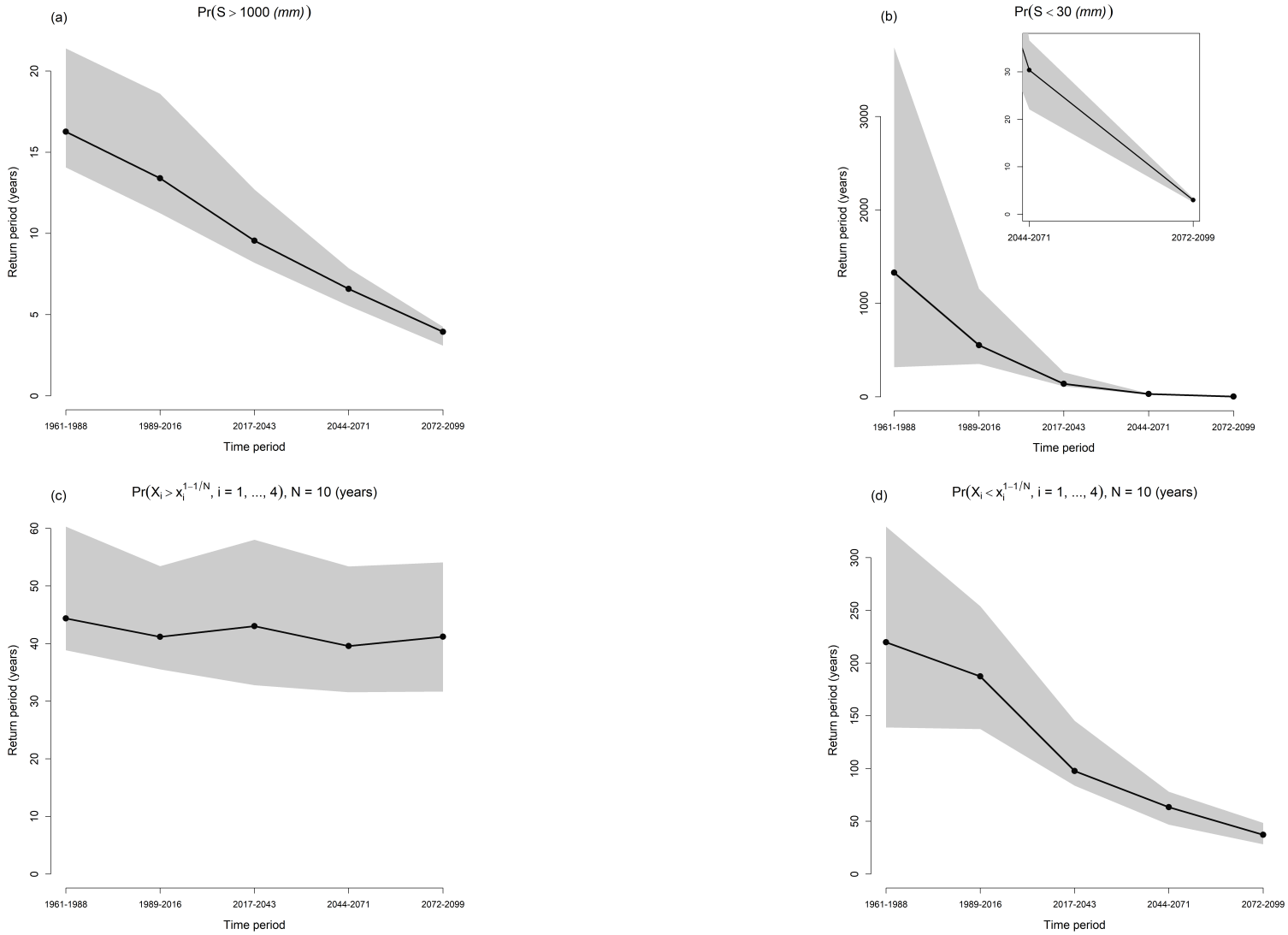


Figure: Estimated probability of no power (left) and maximum power (right).

De Monte, Huser, Papastathopoulos, & Richards. (2025+). Generative modelling of multivariate geometric extremes using normalising flows. arXiv:2505.02957.

Joint Alpine runoff extremes



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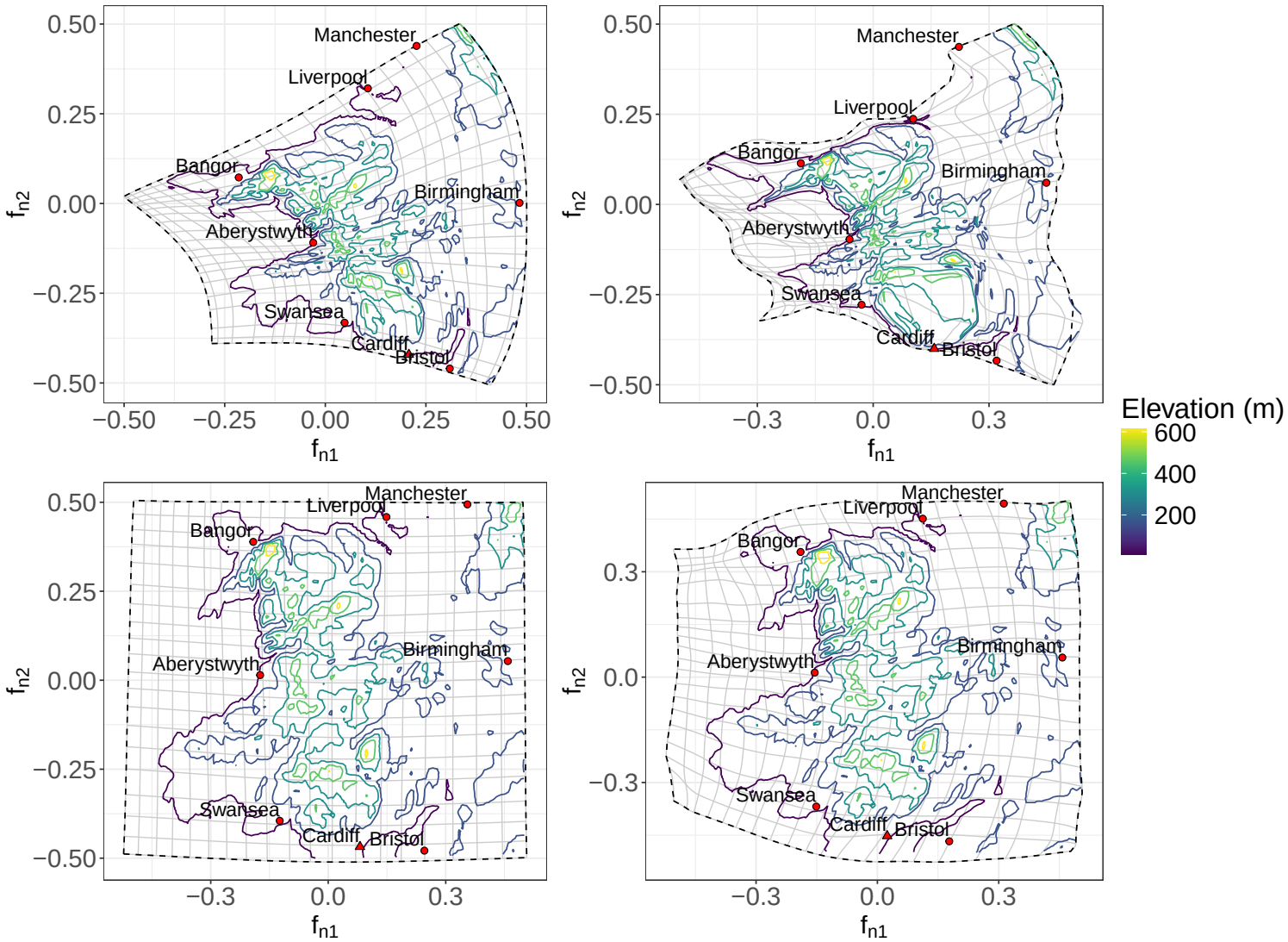
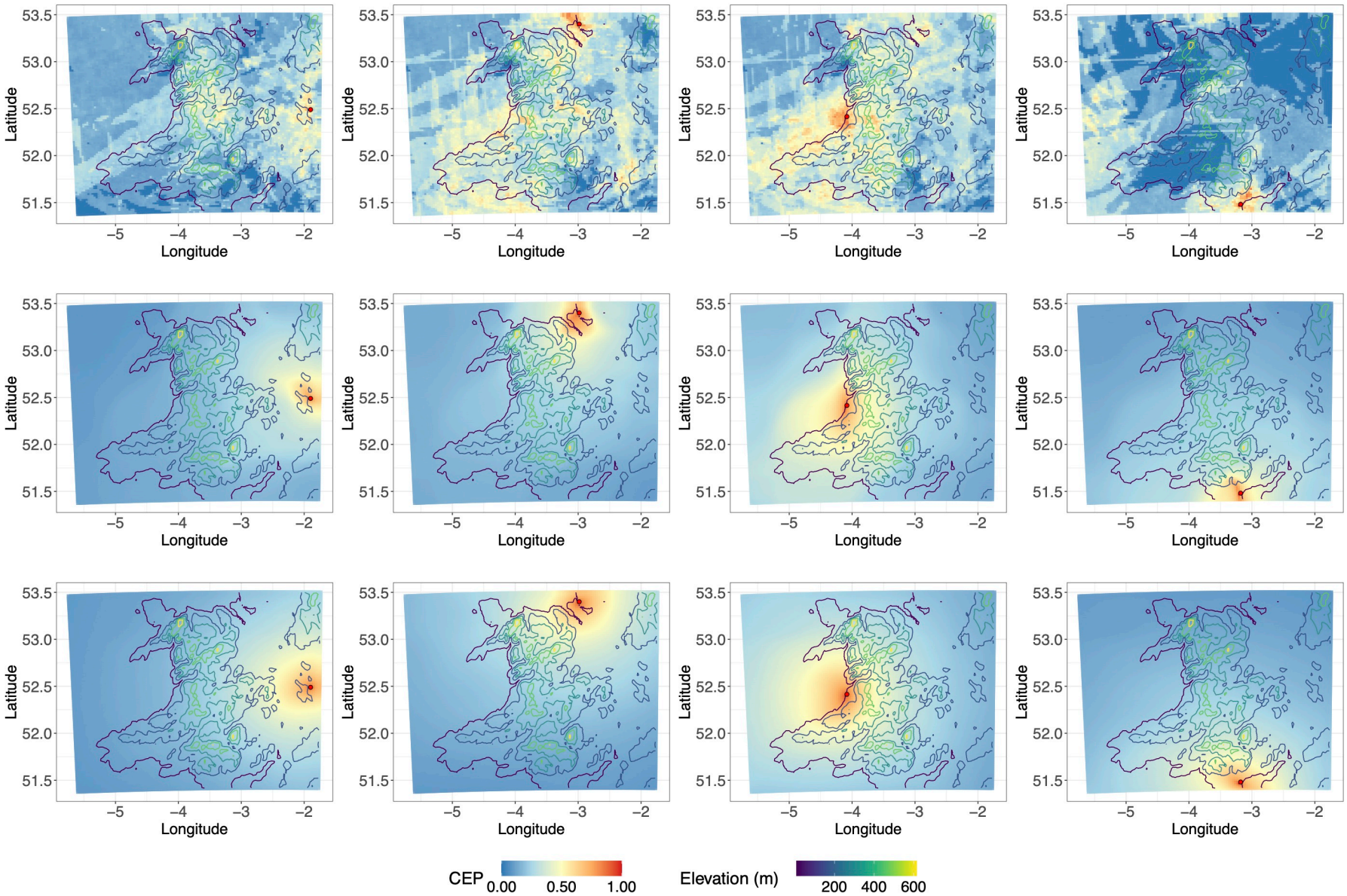
UK rainfall spatial extremal extent (Shao et al., 2025)



Shao, Richards, and Huser. (2025+). Modeling nonstationary extremal dependence via deep spatial deformations.

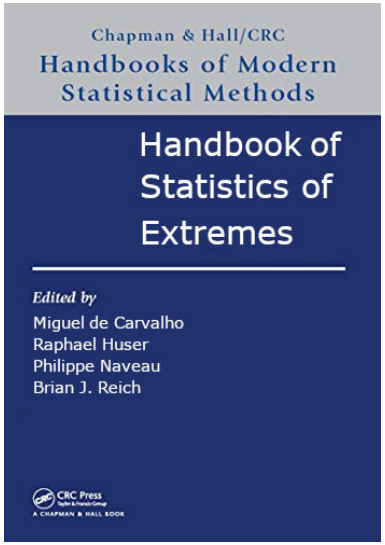
UK rainfall spatial extremal extent (Shao et al., 2025)



Conclusion

- Deep extremal regression models are conceptually simple yet powerful tools for modelling extremes - both **univariate** and **multivariate**.
- Despite their black box nature, neural networks can be used alongside statistical models to create something (atleast partially-)interpretable.
- Very useful in many environmental applications.

- Easy to implement - lots of code available on GitHub:
  - Jbrich95/pinnEV/USWildfireExtremes;
  - CASE2025_shortcourse/extQuantRegressDL/cde-RKeras-intro;
  - callumbarltrop/DeepSPAR/DeepGauge;
  - reetamm/SPQRx



Richards and Huser (2026a).
Extreme Quantile Regression with Deep Learning.
Code and short courses on GitHub - `https://github.com/Jbrich95/`

Gimeno-Sotelo, Richards, Hazra, Mhalla, and de Zea Bermudez. (2026).
A Review of Applications of Extreme Value Theory to Environmental Risk Assessment. Environmental Statistics: Innovative Methods and Applications. Taylor & Francis. To appear.

References I

Carreau, J. and Bengio, Y. (2007). A hybrid Pareto model for conditional density estimation of asymmetric fat-tail data. In *Artificial Intelligence and Statistics*, pages 51–58. PMLR.

Cisneros, D., Richards, J., Dahal, A., Lombardo, L., and Huser, R. (2024). Deep graphical regression for jointly moderate and extreme Australian wildfires. *Spatial Statistics*, 59:100811.

De Monte, L., Huser, R., Papastathopoulos, I., and Richards, J. (2025). Generative modelling of multivariate geometric extremes using normalising flows. *arXiv preprint arXiv:2505.02957*.

Mackay, E., Murphy-Barltrop, C. J. R., Richards, J., and Jonathan, P. (2025). Deep Learning Joint Extremes of Metocean Variables Using the SPAR Model. *Journal of Offshore Mechanics and Arctic Engineering*, 148(021201).

Richards, J. and Huser, R. (2026a). Extreme Quantile Regression with Deep Learning. In de Carvalho, M., Huser, R., Naveau, P., and Reich, B. J., editors, *Handbook on Statistics of Extremes*. Chapman & Hall/CRC, Boca Raton, FL.

Richards, J. and Huser, R. (2026b). Regression modelling of spatiotemporal extreme US wildfires via partially-interpretable neural networks. *JCGS, to appear*.

Richards, J., Huser, R., Bevacqua, E., and Zscheischler, J. (2023). Insights into the drivers and spatiotemporal trends of extreme mediterranean wildfires with statistical deep learning. *Artificial Intelligence for the Earth Systems*, 2(4):e220095.

Shao, X., Richards, J., and Huser, R. (2025). Modeling nonstationary extremal dependence via deep spatial deformations. *arXiv preprint arXiv:2505.12548*.

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