Statistics of extremes for natural hazards: landslides and earthquakes^{\dagger}

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In this chapter, we illustrate the use of split bulk–tail models and subasymptotic models motivated by extreme-value theory in the context of hazard assessment for earthquake-induced landslides. A spatial joint areal model is presented for modeling both landslides counts and landslide sizes, paying particular attention to extreme landslides, which are the most devastating ones.

1 Introduction

Statistics of extremes has been used extensively in climate science for the modeling of lowprobability high-impact events, including natural hazards such as heavy precipitation (Katz et al., 2002; Cooley et al., 2007; Huser and Davison, 2014; de Fondeville and Davison, 2018), extreme heatwaves (Davison and Gholamrezaee, 2012; Winter and Tawn, 2016; Zhong et al., 2022; Vikki et al., 2023; Zhang et al., 2023), and strong windstorms or hurricanes (Opitz, 2016; Risser and Wehner, 2017; Dawkins and Stephenson, 2018; Huser et al., 2021), among others; such extreme-value models are often developed with the ultimate ambition to improve the state-of-the-art in performing hazard and/or risk assessment and mitigation, and in attributing specific catastrophic extreme events to human influence under climate change. By contrast, the application of extreme-value theory (EVT) and statistics to the modeling and prediction of geophysical processes, such as devastating landslides or earthquakes, is sparser in the literature, perhaps due to the different type of data involved and the added modeling difficulties that come with it. Unlike climate data that are often measured at fixed locations (e.g., monitoring stations, or on a spatial grid with climate model outputs) and regular intervals (e.g., hourly or daily) over a period of time, the exact location and timing of landslides and earthquakes are typically unknown before they occur—they are thus often treated as random; moreover, the exact conditions and triggering mechanisms often differ for each event, which implies that the data are rarely replicated (unless some kind of spatio-temporal aggregation is used), making any extreme-value analysis more challenging, and that they typically require other kinds of specialized statistical models such as point processes (Møller et al., 1998; Illian et al., 2008). Nevertheless, statistical methods based on EVT have still been used in data-driven geophysical sciences, e.g., for estimating the maximum earthquake magnitude (Beirlant et al., 2019; Darzi et al., 2023), for probabilistic seismic hazard analysis (Dutfoy and Senfaute, 2022), as well as for landslide hazard

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mapping over space (Yadav <u>et al.</u>, 2023; Dahal <u>et al.</u>, 2024); see also Kiriliouk <u>et al.</u> (2019) who fit a multivariate extreme-value model to extreme rainfall data, in order to (indirectly) understand the probability of rainfall-induced landslides through the rainfall intensity–duration thresholds for landslide initiation established by Guzzetti et al. (2007).

In this chapter, we focus on the spatial modeling of earthquake-induced landslides (Lombardo et al., 2019), and present a general Bayesian hierarchical modeling framework that has been used in the literature (in various forms and contexts, and with some variations) for jointly modeling multiple occurrences and sizes of various natural phenomena over space (Pimont et al., 2021; Koh et al., 2023; Yadav et al., 2023). While all (big or small) future landslides matter for appropriate hazard assessment, extreme landslides are particularly devastating and should therefore be given strong attention in modeling. In the model construction pipeline, we thus advocate using probability distributions motivated by EVT that can adequately capture the upper tail behavior, while simultaneously providing a good fit in the bulk. Specifically, we here review and compare two distinct approaches for modeling the full range of landslide sizes: (i) split (also called 'mixture', 'spliced', 'piecewise', or 'hybrid') bulk-tail models (Behrens et al., 2004; Carreau and Bengio, 2009; Scarrott and MacDonald, 2012; Opitz et al., 2018; Castro-Camilo et al., 2019; Pimont et al., 2021; Koh et al., 2023), wherein the upper tail is modeled with the asymptotically-justified generalized Pareto (GP) distribution (see Davison and Smith (1990); Davison and Huser (2015) and Chapter 2 for more details) and the bulk is modeled using another, essentially arbitrary distribution; and (ii) 'subasymptotic' distributions (see, e.g., Naveau et al. (2016); Yadav et al. (2021, 2022); Stein (2021a,b), and Chapter 5) capturing the lower tail and the upper tail flexibly in compliance with EVT with a smooth transition in between. While there are several possible subasymptotic distributions, we focus in this chapter on the extended generalized Pareto (eGP) distribution (Papastathopoulos and Tawn, 2013), which is a parsimonious parametric model that has found various applications in the study of natural hazards including extreme precipitation (Naveau et al., 2016), wildfires (Cisneros et al., 2024), and landslides themselves (Yadav et al., 2023). To streamline the analysis and the discussion, we here consider only one of the simplest eGP distributions, but see Chapter 5 for more details on other possible options and extensions. From a hazard assessment perspective, both landslide sizes and landslide counts (modeled using the Poisson distribution) are important (see Section 2 for details), and they are here modeled jointly using a latent Gaussian model, in which fixed effects and shared spatially-structured effects can be easily incorporated at the latent level to capture complex spatial trends, spatial and cross-dependencies, as well as covariate effects. Joint modeling of occurrences and sizes is especially key for properly assessing the uncertainty of hazard estimates, which are obtained as a function of both elements.

In this chapter, we showcase the versatility of the proposed general modeling framework using an inventory comprising thousands of landslides simultaneously initiated by the devastating 2008 Wenchuan earthquake in China, going beyond Lombardo et al. (2019) who studied the spatial distribution of landslides triggered by the same earthquake but did not consider the modeling of landslide sizes. Incorporating physical knowledge into probability models is important to improve both model fit and interpretability, and is one of the recommendations listed in the opinion piece by Huser et al. (2024); using informative geophysical and geomorphological covariates, and defining the model at the 'slope unit' resolution (more details in Section 3), are two possible ways to achieve this goal. Therefore, in our case study, both landslides and covariates are observed at the slope unit level, thus requiring a joint areal model for occurrences and sizes, instead of a continuous-space marked point process model. This chapter aims at illustrating this extreme-value-based modeling framework for the study of landslide data, and to compare the pros and cons of split bulk-tail models with subasymptotic models in practice. While we find no uniformly-better approach in this case, we argue that the eGP distribution has an overall better performance and is a more natural modeling solution in general. We also discuss how to perform scalable Bayesian inference in this framework based on a customized efficient Markov chain Monte Carlo (MCMC) algorithm, coupled with latent random effects with a sparse precision matrix (here, chosen with an intrinsic conditional autoregressive (iCAR) probabilistic structure; see Besag (1974)). The selection of highly informative covariates (e.g., peak ground acceleration) that can potentially replace the use of latent spatial effects is also discussed, and various latent model structures are compared.

The rest of this chapter is structured as follows: Section 2 gives a more precise definition of the 'hazard' according to the geoscience literature. Section 3 provides details on the Wenchuan landslide data inventory used in our case study. Section 4 presents the modeling framework and MCMC-based Bayesian inference. Section 5 discusses results for the Wenchuan data application. Finally, Section 6 concludes with a summary of some key points.

2 Hazard definition

Although processes such as floods, earthquakes, or landslides largely differ in their physical manifestation, geophysical and statistical properties, and their impacts, international guidelines on natural hazard prediction share some core requirements (Mitchell, 1993). Broadly speaking, hazard prediction should reflect where and when (or how frequently) a future natural hazard might occur, and if it does, <u>how big</u> (or how destructive) it might be. We also stress that in the geoscience literature, 'risk assessment' has a specific meaning that goes beyond 'hazard assessment' by additionally encapsulating the <u>exposure</u> and <u>vulnerability</u> of infrastructure and/or people at risk, and estimating the associated economic, societal and/or environmental costs. In this chapter, we thus distinguish these different notions and adopt the terminology commonly used in geoscience.

The first requirement ('where') involves the notion of <u>susceptibility</u>, which indicates how likely a given portion of the landscape is to undergo a given hazard (Karlsson <u>et al.</u>, 2017; Nicu <u>et al.</u>, 2022). Statistical models used to address this question in the literature include logistic regression models for presence-absence data, Poisson regression models for count data, or more advanced point process models such as log-Gaussian Cox processes (see, e.g., Lombardo et al. (2018, 2020)).

The second requirement ('when' or 'how frequently') relates to the <u>return period</u> of a given hazard and reflects its recurrence over time. The frequency of such devastating phenomena is often difficult to model because temporal replicates are rarely available and rich spatio-temporal inventories are scarce. Moreover, landslides often occur as part of a sequential compound extreme event (e.g., after a major earthquake or heavy rain), which also complicates the estimation of their return period as this requires an understanding of the frequency of the main triggering factor(s). This aspect of hazard assessment is, therefore, often the most neglected one (but see Dahal <u>et al.</u> (2024) for a recent attempt to take it into account in a study of rainfall-induced landslides).

The third requirement ('how big' or 'how destructive') involves the notion of <u>intensity</u> of an event, which indicates the energy and level of threat associated with a given hazard when it occurs (Peng <u>et al.</u>, 2005; Hungr, 2018). Note this notion of intensity differs from that classically used in statistics with point process models.

In the context of landslides, David J. Varnes and the International Association of Engineering Geology, Commission on Landslides and Other Mass Movements on Slopes defined the landslide hazard more specifically through statistical terms as "the probability of occurrence within a specified period and a given area of a potentially damaging phenomenon" (Varnes, 1984). This definition was

later updated by Guzzetti <u>et al.</u> (1999) to explicitly include the intensity of the event. While this general definition was proposed in the context of landslides, the same formulation can be interpreted more broadly and applied similarly in other contexts with various types of natural hazards.

In Section 4, we present an extreme-value-based latent Gaussian modeling pipeline that complies with the first and third requirements of the hazard definition. That is, the proposed model can be used to jointly estimate both the susceptibility and the intensity of a natural phenomenon—here, in the context of earthquake-induced landslides. As there are different ways to characterize the intensity of a natural phenomenon, there is no clear consensus in the literature on how to represent and model it. For instance, flood intensity (Vojtek and Vojteková, 2016) is usually expressed as a function of the water height (e.g., Van den Bout et al. (2023)) or peak flow (the maximum rate of discharge; Formetta et al. (2021)). Earthquake intensity (Hough, 2014) is commonly expressed as the peak of either the displacement (Trugman et al., 2019), velocity (Dahal et al., 2023), or acceleration (Murphy and O'brien, 1977) experienced at a given location. Similarly, landslide intensity (Lari et al., 2014) can also be expressed in multiple ways: for instance, the velocity (He et al., 2023) or kinetic energy (Pudasaini and Krautblatter, 2021) associated with a failing mass, the force that the landslide body may exert onto an object (Tang et al., 2014), its volume (Jaboyedoff et al., 2020), planimetric area (Di Napoli et al., 2023) or other shape indices (Rana et al., 2023), are all accepted as valid ways to describe the landslide intensity. However, most of these elements cannot be measured in the context of large landslide populations. Velocities over large landscapes are measurable through Interferometric Synthetic Aperture Radar (InSAR) but only for slow movements (Ahmad et al., 2024). Kinetic energy and force can only be estimated through demanding numerical simulations (Pudasaini and Krautblatter, 2022), and their real measurement is conditional on the availability of very expensive instruments installed on a slope for monitoring purposes (Mazzanti et al., 2015). Similarly, landslide volumes cannot be measured unless topographic data are available before and after the failure (Tseng et al., 2013). Among these landslide intensity parameters, the landslide area (or derivatives thereof) is the easiest one to collect because it is a byproduct of any rigorous landslide mapping procedure (Lombardo et al., 2021). Hence, out of all the metrics listed above, the landslide area is the most relevant one to support statistical analyses. In the case study presented in this chapter, we model the square root of the landslide area (easily measurable through remote sensing), which roughly describes the 'diameter' of the affected area and can be understood as a proxy for the landslide size and its destructiveness.

References

- Ahmad, S. M., Sadhasivam, N., Lisa, M., Lombardo, L., Emil, M. K., Zaki, A., Van Westen, C. J., Fadel, I. and Tanyas, H. (2024) Standing on the shoulder of a giant landslide: A six-year long InSAR look at a slow-moving hillslope in the western Karakoram. Geomorphology 444, 108959.
- Behrens, C., Lopes, H. and Gamerman, D. (2004) Bayesian analysis of extreme events with threshold estimation. Statistical Modelling 4, 227–244.
- Beirlant, J., Kijko, A., Reynkens, T. and Einmahl, J. H. J. (2019) Estimating the maximum possible earthquake magnitude using extreme value methodology: the groningen case. <u>Natural Hazards</u> 98, 1091–1113.
- Besag, J. (1974) Spatial interaction and the statistical analysis of lattice systems. <u>Journal of the</u> Royal Statistical Society: Series B (Methodological) **36**, 192–225.
- Van den Bout, B., Jetten, V., van Westen, C. J. and Lombardo, L. (2023) A breakthrough in fast flood simulation. Environmental Modelling & Software 168, 105787.

- Carreau, J. and Bengio, Y. (2009) A hybrid Pareto model for asymmetric fat-tailed data: the univariate case. <u>Extremes</u> **12**, 53–76.
- Castro-Camilo, D., Huser, R. and Rue, H. (2019) A spliced Gamma-generalized Pareto model for short-term extreme wind speed probabilistic forecasting. <u>Journal of Agricultural, Biological and</u> Environmental Statistics 24, 517–534.
- Cisneros, D., Richards, J., Dahal, A., Lombardo, L., and Huser, R. (2024) Deep graphical regression models for jointly moderate and extreme australian wildfires. Spatial Statistics **59**, 100811.
- Cooley, D., Nychka, D. and Naveau, P. (2007) Bayesian spatial modeling of extreme precipitation return levels. Journal of the American Statistical Association **102**, 824–840.
- Dahal, A., Castro-Cruz, D. A., Tanyaş, H., Fadel, I., Mai, P. M., van der Meijde, M., van Westen, C., Huser, R. and Lombardo, L. (2023) From ground motion simulations to landslide occurrence prediction. Geomorphology 441, 108898.
- Dahal, A., Huser, R. and Lombardo, L. (2024) At the junction between deep learning and statistics of extremes: formalizing the landslide hazard definition. arXiv preprint 2401.14210.
- Darzi, Hrafnkelsson, В. Halldorsson, В. (2023)mod-Α., and Bayesian elling in engineering seismology: spatial earthquake magnitude model. In Bayesian Modelling in Engineering Seismology: Spatial Earthquake Magnitude Model, ed. B. Hrafnkelsson, pp. 171–192. Springer.
- Davison, A. C. and Gholamrezaee, M. M. (2012) Geostatistics of extremes. <u>Proceedings of the Royal Society A: Mathematical, Physical & Engineering Sciences</u> 468, 581–608.
- Davison, A. C. and Huser, R. (2015) Statistics of extremes. <u>Annual Review of Statistics and its</u> Application **2**, 203–235.
- Davison, A. C. and Smith, R. L. (1990) Models for exceedances over high thresholds (with discussion). Journal of the Royal Statistical Society: Series B (Statistical Methodology) 52, 393–442.
- Dawkins, L. C. and Stephenson, D. B. (2018) Quantification of extremal dependence in spatial natural hazard footprints: independence of windstorm gust speeds and its impact on aggregate losses. Natural Hazards and Earth System Sciences 18, 2933–2949.
- Di Napoli, M., Tanyas, H., Castro-Camilo, D., Calcaterra, D., Cevasco, A., Di Martire, D., Pepe, G., Brandolini, P. and Lombardo, L. (2023) On the estimation of landslide intensity, hazard and density via data-driven models. Natural Hazards.
- Dutfoy, A. and Senfaute, G. (2022) The randomized gutenberg-richter model: a recurrence model based on extreme value theory—impacts on probabilistic seismic hazard analyses and comparison with the standard approach. Bulletin of Earthquake Engineering **20**, 6349–6376.
- de Fondeville, R. and Davison, A. C. (2018) High-dimensional peaks-over-threshold inference. Biometrika **105**, 575–592.
- Formetta, G., Over, T. and Stewart, E. (2021) Assessment of peak flow scaling and its effect on flood quantile estimation in the United Kingdom. Water Resources Research 57, e2020WR028076.
- Guzzetti, F., Carrara, A., Cardinali, M. and Reichenbach, P. (1999) Landslide hazard evaluation: A review of current techniques and their application in a multi-scale study, central Italy. Geomorphology **31**, 181–216.
- Guzzetti, F., Peruccacci, S., M., R. and Stark, C. P. (2007) Rainfall thresholds for the initiation of landslides in central and southern europe. Meteorology and Atmospheric Physics 98, 239–267.

- He, K., Tanyas, H., Chang, L., Hu, X., Luo, G. and Lombardo, L. (2023) Modelling InSARderived hillslope velocities with multivariate statistics: A first attempt to generate interpretable predictions. Remote Sensing of Environment 289, 113518.
- Hough, S. E. (2014) Earthquake intensity distributions: A new view. <u>Bulletin of earthquake</u> engineering **12**, 135–155.
- Hungr, O. (2018) Some methods of landslide hazard intensity mapping. In Landslide risk assessment, pp. 215–226. Routledge.
- Huser, R. and Davison, A. C. (2014) Space-time modelling of extreme events. Journal of the Royal Statistical Society: Series B **76**, 439–461.
- Huser, R., Opitz, T. and Thibaud, E. (2021) Max-infinitely divisible models and inference for spatial extremes. Scandinavian Journal of Statistics 48, 321–348.
- Huser, R., Opitz, T. and Wadsworth, J. (2024) Modeling of spatial extremes in environmental data science: Time to move away from max-stable processes. arXiv preprint 2401.17430.
- Illian, J., Penttinen, A., Helga, S. and Stoyan, D. (2008) <u>Statistical Analysis and Modelling of</u> Spatial Point Patterns. John Wiley & Sons, Ltd.
- Jaboyedoff, M., Carrea, D., Derron, M.-H., Oppikofer, T., Penna, I. M. and Rudaz, B. (2020) A review of methods used to estimate initial landslide failure surface depths and volumes. <u>Engineering</u> Geology 267, 105478.
- Karlsson, C. S., Kalantari, Z., Mörtberg, U., Olofsson, B. and Lyon, S. W. (2017) Natural hazard susceptibility assessment for road planning using spatial multi-criteria analysis. <u>Environmental</u> management **60**, 823–851.
- Katz, R. W., Parlange, M. B. and Naveau, P. (2002) Statistics of extremes in hydrology. <u>Advances</u> in Water Resources 25, 1287–1304.
- Kiriliouk, A., Rootzén, H., Segers, J. and Wadsworth, J. L. (2019) Peaks over thresholds modeling with multivariate generalized Pareto distributions. Technometrics 61, 123–135.
- Koh, J., Pimont, F., Dupuy, J.-L. and Opitz, T. (2023) Spatiotemporal wildfire modeling through point processes with moderate and extreme marks. Annals of Applied Statistics, **17**, 560–582.
- Lari, S., Frattini, P. and Crosta, G. (2014) A probabilistic approach for landslide hazard analysis. Engineering geology 182, 3–14.
- Lombardo, L., Bakka, H., Tanyas, H., van Westen, C., Mai, P. M. and Huser, R. (2019) Geostatistical modeling to capture seismic-shaking patterns from earthquake-induced landslides. <u>Journal</u> of Geophysical Research: Earth Surface **124**, 1958–1980.
- Lombardo, L., Opitz, T., Ardizzone, F., Guzzetti, F. and Huser, R. (2020) Space-time landslide predictive modelling. Earth-Science Reviews 209, 103318.
- Lombardo, L., Opitz, T. and Huser, R. (2018) Point process-based modeling of multiple debris flow landslides using INLA: an application to the 2009 Messina disaster. Stochastic Environmental Research and Risk Assessment **32**, 2179–2198.
- Lombardo, L., Tanyas, H., Huser, R., Guzzetti, F. and Castro-Camilo, D. (2021) Landslide size matters: A new data-driven, spatial prototype. <u>Engineering Geology</u> 293, 106288.
- Mazzanti, P., Bozzano, F., Cipriani, I. and Prestininzi, A. (2015) New insights into the temporal prediction of landslides by a terrestrial SAR interferometry monitoring case study. <u>Landslides</u> 12, 55–68.

- Mitchell, J. K. (1993) Natural hazard predictions and responses in very large cities. <u>Prediction and</u> <u>Perception of Natural Hazards. Dordrecht, The Netherlands: Kluwer Academic Publishers pp.</u> 29–37.
- Møller, J., Syversveen, A. R. and Waagepetersen, R. P. (1998) Log Gaussian Cox processes. Scandinavian Journal of Statistics 25, 451–482.
- Murphy, J. u. and O'brien, L. (1977) The correlation of peak ground acceleration amplitude with seismic intensity and other physical parameters. <u>Bulletin of the Seismological Society of America</u> 67, 877–915.
- Naveau, P., Huser, R., Ribereau, P. and Hannart, A. (2016) Modeling jointly low, moderate, and heavy rainfall intensities without a threshold selection. Water Resources Research 52, 2753–2769.
- Nicu, I. C., Elia, L., Rubensdotter, L., Tanyas, H. and Lombardo, L. (2022) Multi-hazard susceptibility mapping of cryospheric hazards in a high-Arctic environment: Svalbard Archipelago. Earth System Science Data Discussions 2022, 1–26.
- Opitz, T. (2016) Modeling asymptotically independent spatial extremes based on Laplace random fields. Spatial Statistics 16, 1–18.
- Opitz, T., Huser, R., Bakka, H. and Rue, H. (2018) INLA goes extreme: Bayesian tail regression for the estimation of high spatio-temporal quantiles. Extremes **21**, 441–462.
- Papastathopoulos, I. and Tawn, J. A. (2013) Extended generalised Pareto models for tail estimation. Journal of Statistical Planning and Inference 143, 131–143.
- Peng, R. D., Schoenberg, F. P. and Woods, J. A. (2005) A space-time conditional intensity model for evaluating a wildfire hazard index. <u>Journal of the American Statistical Association</u> 100, 26-35.
- Pimont, F., Fargeon, H., Opitz, T., Ruffault, J., Barbero, R., Martin-StPaul, N., Rigolot, E., Rivière, M. and Dupuy, J.-L. (2021) Prediction of regional wildfire activity in the probabilistic Bayesian framework of firelihood. Ecological Applications **31**, e02316.
- Pudasaini, S. P. and Krautblatter, M. (2021) The mechanics of landslide mobility with erosion. Nature communications 12, 6793.
- Pudasaini, S. P. and Krautblatter, M. (2022) The landslide velocity. <u>Earth Surface Dynamics</u> 10, 165–189.
- Rana, K., Bhuyan, K., Ferrer, J. V., Cotton, F., Ozturk, U., Catani, F. and Malik, N. (2023) Landslide Topology Uncovers Failure Movements. <u>arXiv preprint arXiv:2310.09631</u>.
- Risser, M. D. and Wehner, M. F. (2017) Attributable human-induced changes in the likelihood and magnitude of the observed extreme precipitation during Hurricane Harvey. <u>Geophysical Research</u> Letters 28, 12457–12464.
- Scarrott, C. and MacDonald, A. (2012) A Review of Extreme Value Threshold Estimation And Uncertainty Quantification. REVSTAT 10, 33–60.
- Stein, M. L. (2021a) A parametric model for distributions with flexible behavior in both tails. Environmetrics **32**, e2658.
- Stein, M. L. (2021b) Parametric models for distributions when interest is in extremes with an application to daily temperature. Extremes 24, 293—323.
- Tang, H., Hu, X., Xu, C., Li, C., Yong, R. and Wang, L. (2014) A novel approach for determining landslide pushing force based on landslide-pile interactions. Engineering Geology 182, 15–24.

- Trugman, D. T., Page, M. T., Minson, S. E. and Cochran, E. S. (2019) Peak ground displacement saturates exactly when expected: Implications for earthquake early warning. <u>Journal of</u> Geophysical Research: Solid Earth 124, 4642–4653.
- Tseng, C.-M., Lin, C.-W., Stark, C. P., Liu, J.-K., Fei, L.-Y. and Hsieh, Y.-C. (2013) Application of a multi-temporal, LiDAR-derived, digital terrain model in a landslide-volume estimation. <u>Earth</u> Surface Processes and Landforms **38**, 1587–1601.
- Varnes, D. J. (1984) Landslide Hazard Zonation: A Review of Principles and Practice. Natural Hazards. UNESCO, Paris.
- Vikki, T., Mitchell, D., Hegerl, G. C., Collins, M., Leach, N. J. and Slingo, J. M. (2023) The most at-risk regions in the world for high-impact heatwaves. Nature Communications 14, 2152.
- Vojtek, M. and Vojteková, J. (2016) Flood hazard and flood risk assessment at the local spatial scale: a case study. Geomatics, Natural Hazards and Risk 7, 1973–1992.
- Winter, H. C. and Tawn, J. A. (2016) Modelling heatwaves in central france: a case-study in extremal dependence. Journal of the Royal Statistical Society: Series C 65, 345–365.
- Yadav, R., Huser, R. and Opitz, T. (2021) Spatial hierarchical modeling of threshold exceedances using rate mixtures. Environmetrics **32**, e2662.
- Yadav, R., Huser, R. and Opitz, T. (2022) A flexible Bayesian hierarchical modeling framework for spatially dependent peaks-over-threshold data. Spatial Statistics, 51, 100672.
- Yadav, R., Huser, R., Opitz, T. and Lombardo, L. (2023) Joint modeling of landslide counts and sizes using spatial marked point processes with sub-asymptotic mark distributions. <u>Journal of the Royal Statistical Society Series C: Applied Statistics</u>, 10.1093/jrsssc/qlad077.
- Zhang, L., Risser, M. D., Wehner, M. F. and O'Brien, T. A. (2023) Explaining the unexplainable: leveraging extremal dependence to characterize the 2021 Pacific Northwest heatwave. arXiv preprint 2307.03688.
- Zhong, P., Huser, R. and Opitz, T. (2022) Modeling non-stationary temperature maxima based on extremal dependence changing with event magnitude. Annals of Applied Statistics 16, 272–299.