

Interactive comment on “Brief Communication: Statistical detection and modeling of the over-dispersion of winter storm occurrence” by M. Raschke

M. Raschke

mathiasraschke@t-online.de

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Author's Response to the Referee's Comments

to General comments:

Dear Francesco Serinaldi,

Thank you very much for your comments and opinions. I will eliminate your concerns (including the statement of overlooked concepts) by arguments and references. Some of your opinions are not in line with the state-of-the-art of the mathematical statistics. Beside this, I draw attention that my contribution is not only the introduction of the GPD.

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According to my opinion the data are explained well enough, so that further details which can be found in Karremann et al. (2014) are not necessary for the analysis.

After studying all of your comments, I change the phrase in the abstract “Moreover, I derive the relation between expectation and variance of a thinned inhomogeneous Poisson process.” to “I derive the relation between expectation and variance of the number of events per season derived from a thinned inhomogeneous Poisson process.”. The 100-word-limit is still fulfilled by this modification.

to Specific comments:

Section 2: I do not follow your suggestions because a mixed Poisson process is an inhomogeneous Poisson processes with special characteristics, according to Daley and Vere-Jones (2003, chapter 2). Inhomogeneous means only that the intensity is not constant over time. Furthermore, the details of the point process at the time scale which generates the over-dispersion of the number of storm are not subject to my brief communication. I just detect and model the over-dispersion of the number of storms.

P1777L22: I follow your suggestion and will change this formulation in the final version.

P1778L5-6: Some estimation methods, which are applied in different scientific communities, are not in line with the state-of-the-art of mathematical statistics. An example: Karremann et al. (2014) apply the least square estimator for the parameter estimation of a discrete distribution. But this estimation method is not intended for a discrete distribution according to Johnson et al. (2005). I could replace the phrase by “and should follow further rules of the mathematical statistics.”

Section 3: It was suggested by a professional editor. An alternative: “A cluster in an auto-correlated time series consists of a number of observations that are a partial series of exceedances of a threshold (Coles, 2001, Fig.5.4), e.g. of the time series of river discharge.”

P1778L19: I change the term “return level $RL_{>=1}$ ” to “return level $RL_{>=1a}$ ” in the final

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version of the paper. However, return period and return level do mean the same both in my communication. The return level (period) and the corresponding storm intensities are a bijective function.

P1778L22-25: see my response for section 2.

Section 4: I strongly disagree with you. Your opinion is in contrast to the state-of-the-art of statistics and stochastics. At first, there is a link between the likelihood ratio test and the AIC and BIC: The difference of the log-likelihoods is applied in all three concepts. This means for the storm samples: If Model A has one additional parameter and a lower BIC than model B, then this is equivalent to acceptance of model A by a likelihood ratio test with significance level $\alpha < 6.5\%$ and sample size $n=30$ (historic storms). The significance level is $\alpha < 0.4\%$ for the equivalent likelihood ratio test in case of the storms of the climate simulation with sample size $n=4092$. The smaller alpha is, the stronger the likelihood ratio test is. Statistical criteria for model selection provide implicitly statistical significance by avoiding over-fitting. They even work if classical significance tests do not, e.g. the t-test in regression analysis with dummy variables (Fahrmeir et al. 2013).

Furthermore, the information criteria AIC and BIC and their application are explained and applied in many statistical publications (e.g. Lindsey, 1996; Zucchini, 2000; Burnham and Anderson, 2002; Upton and Cook, 2006; Fahrmeir et al., 2013). The practice of different scientific communities is in contrast to the state-of-the-art of mathematical statistics: model selection/performance criteria are simply formulated without a mathematical derivation; the number of estimated model parameters is not considered therein and an over-fit of the selected model is likely. An example is your list of performance criteria (Serinaldi et al., 2012, Tab.2). No one of these criteria for regression models is mentioned by Fahrmeier et al. (2013, section 2.4) although they mention different criteria beside AIC and BIC.

P1782L3-14: I guess that it is acceptable for a brief communication if the entire idea is

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understood after reading a share of the brief communication and all elements of the approach are bonded. However, my approach, which is based on different elements such as the AIC and BIC, can only be understood in detail if these elements are understood. If the reader is not familiar with these, he/she has to use the references.

Of course, the acronyms are modified for a final version. But a larger explanation of data is not necessary because I use these only to demonstrate the modelling and detection of over-dispersion.

Section 5: I have not claimed that the GPD would be the only possibility and you do not mention a concrete alternative. But the replacement of the NBD by the GPD is obviously an improvement because the GPD considers the Poisson distribution explicitly and can also model under-dispersion. However, I only state that the combination of the modelling elements is necessary for the detection and modelling of over-dispersion of storms. That over-dispersion decreases with increasing return level is caused by the thinning and is explained in the communication (Fig.1). This implies that the difference between GPD and PD gets small. As aforementioned, the AIC and BIC and corresponding model selection has to be understood for understanding the entire approach.

Uncertainty does not need to be presented in Fig.1 of section 3 because it is just an example with equal parameters as estimated in section 4. Additionally, the confidence intervals or estimation error are not needed for the used approach for detecting the over-dispersion. As aforementioned, the statistical significance is ensured by the AIC and BIC.

to Editing notes: Spellings will be corrected and acronyms will be modified in the final version.

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