Responses on the Referees 1 comments on the submitted manuscript "Geostatistical interpolation by Quantile Kriging" hess-2018-276

We are very thankful to the anonymous referees for their remarks on our submitted manuscript. We believe that they will significantly improve the quality of the manuscript.
We use the nomination e.g. A1.13 (i.e. A(nswer)1 (no. of reviewer).13 (no. of comment)) and numbers (page, line, figures, tables) of the original manuscript submitted in order to address all queries raised:

RC 1:
The proposed manuscript presents a new geo-statistical interpolation method (Quantile Kriging – QK) that is able to relax three of the main assumption/limitations of the most used Ordinary Kriging: 1) spatial stationarity of the process mean, 2) Gaussianity of the interpolated variable and 3) independence of the uncertainty on the estimation value. The work extends the formulations of other well-known kriging methods with logic and statistical rigour. Although the presented technique still has a major limitation in the ability to handle the presence of many zero values (as often happens when dealing with rainfall, especially at finer scales than the presented one), it can be considered an improvement on the state of the art and a contribution to the advancement of the field. Additionally, although the authors do not mention it in the manuscript (and should) there are many applications to a variety of environmental variables where the presence of zeros is not a problem and the presented technique could be better applied. The manuscript is very well written and easy to follow. I suggest the following improvements:

1. The introduction explains a lot about the evolution of kriging techniques. However a little bit more discussion about applications (especially to rainfall) their limitations in hydrology, the main challenges, etc… could help defining the framework.

   A1.1: see A1.3

2. P.4 l. 18, many of the presented geostatistical techniques were developed in geological sciences, where the temporal evolution of the studied variables is often irrelevant. I would mention this to explain why the temporal variability is often ignored in kriging.

   A1.2: see A1.3

3. I would mention spatio-temporal kriging and other similar techniques as attempts to incorporate the temporal variability. How is this method better/different (e.g. Gaussianity)? Examples:

   - Snepvangers, J. J. J. C., Heuvelink, G. B. M., & Huisman, J. A. (2003). Soil water content interpolation using spatio-temporal kriging with external drift. Geoderma, 112, 253–271. https://doi.org/10.1016/S0016-7061(02)00310-5
   - Sideris, I. V., Gabella, M., Erdin, R., & Germann, U. (2014). Real-time radar-rain-gauge merging using spatio-temporal co-kriging with external drift in the alpine terrain of Switzerland. Quarterly Journal of the Royal Meteorological Society, 140(April), 1097–1111. https://doi.org/10.1002/qj.2188

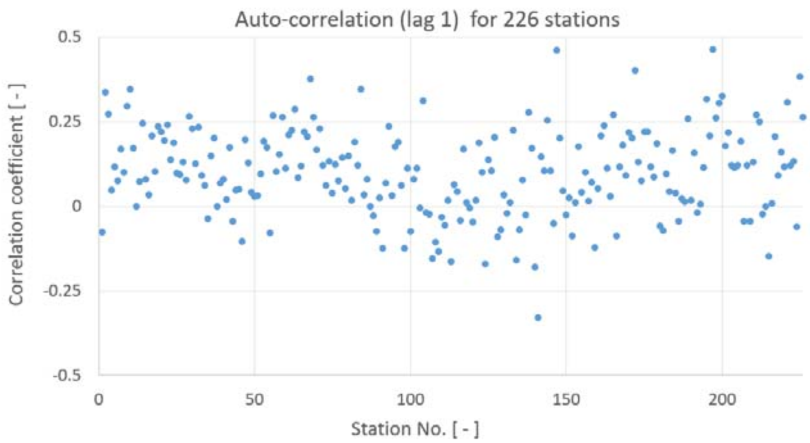
   A1.3: We try to address all three comments (i.e. A1.1, A1.2 and A1.3) by rephrasing and extending the existing paragraph by the following, starting at p.4, l.18:

   […]. The inclusion of a temporal behavior into the geostatistic models is mostly irrelevant for the original geological variables. However, the temporal variability of a variable becomes more prominent for other sciences, e.g. hydrology, where observations from raingauges over several time steps are implemented into the geostatistical models in order to generate spatial precipitation estimates. These estimates subsequently serve as input to the hydrological modelling (e.g. Syed et al. 2003; Basistha et al. 2008; Cole et al. 2008) over multiple time steps. Associated errors in the precipitation estimates may ultimately lead to greater errors in the subsequent discharge modelling (Kobold et al. 2005). These errors

strongly depend on the spatial and temporal distribution of the input precipitation (Gabellani et al. 2007, Moulin et al. 2009) and may limit the accuracy of rainfall-runoff simulations.

There are geostatistical space-time models in order to incorporate the temporal variability of the variable, but they are primarily aiming on the extrapolation of the variable in time (Snepvangers et al. 2003). Therefore, they require a strong dependence of the variable over time, suited e.g. for groundwater modeling where temporal changes occur relative slowly. This temporal dependence might be absent for other variables, e.g. monthly precipitation. […]

For demonstration purposes, we remove the seasonality from our observations by subtracting the mean precipitation of the specific calendar month from the observed precipitation. The graph below shows the autocorrelation (with lag 1) for all 226 raingauges (see graph below). There is hardly any (linear) dependence between the monthly precipitation of two successive months, i.e. if a specific month becomes "wet" or "dry" does hardly depend on if the preceding month was relative "wet" or "dry".



References:

- Syed, K.H., Goodrich, D.C.. & Myers, D. E. (2003). Spatial characteristics of thunderstorm rainfall fields and their relation to runoff. Journal of Hydrology, 271, 1–21. https://doi.org/10.1016/S0022-1694(02)00311-6
- Basistha, A., Arya, D.S.. & Goel, N. K. (2008). Spatial Distribution of Rainfall in Indian Himalayas -- A Case Study of Uttarakhand Region. Water resources Management, 22, 1325–1346. http://dx.doi.org/10.1007/s11269-007-9228-2
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- Kobold, M., Suselj, K. (2005). Precipitation forecasts and their uncertainty as input into hydrological models. Hydrology and Earth System Sciences, 9, 322-332. https://www.hydrol-earth-syst-sci.net/9/322/2005/
- Gabellani, S., Boni, G. Ferraris, L., von Hardenberg J., & Provenzale A. (2007). Propagation of uncertainty from rainfall to runoff: A case study with a stochastic rainfall generator. Advances in Water Resources, 30, 2061 - 2071. https://doi.org/10.1016/j.advwatres.2006.11.015
- Moulin, L., Gaume, E. & Obled C. (2009). Uncertainties on mean areal precipitation: assessment and impact on streamflow simulations. Hydrology and Earth System Sciences, 13, 99-114. https://www.hydrol-earth-syst-sci.net/13/99/2009/
- Snepvangers, J. J. J. C., Heuvelink, G. B. M., & Huisman, J. A. (2003). Soil water content interpolation using spatio-temporal kriging with external drift. Geoderma, 112, 253–271. https://doi.org/10.1016/S0016-7061(02)00310-5

4. Eq. 5: I am not sure why you fit a Beta distribution to the quantiles: isn't the Normal Score Transformation (NST) designed to work with empirical distributions?

   A1.4: We used the Beta-distribution due to its definition on the interval [0,1], thus avoiding conditioning of the resulting distribution (from interpolation) at the extremes.

5. Eq.6 and Eq.7: You applied the NST, so isn't this E[F(U)] = m and same for Variance? Maybe I'm missing something

   A1.5: Yes, you could rewrite Eq.6 and Eq.7 by using $E[U(F_x(Z(\mathbf{x},t))]$ instead. However, to our opinion, it does not make a difference.

6. Nowhere is explained how you calculate the variograms for all the interpolations you do. Maybe worth mentioning it somewhere.

   A1.6: We add the following sentence at the end of the paragraph (p.8, l.4):

   […]. The corresponding variograms are calculated using Kendall's tau for a robust interpolation (Lebrenz et al. 2017). […]

   Reference:

   - Lebrenz, H. & Bárdossy, A. (2017). Estimation of the variogram using Kendall's tau for a robust geostatistical interpolation. Journal of Hydrological Engineering, 22(9), 04017038. 10.1061/(ASCE)HE.1943-5584.0001568

7. Pg 7 top: you introduce the elevation dataset, but you don't explain why. Mention you use it for both EDK of the parameters and for the reference EDK of the rainfall process.

   A1.7: We extend the adding the additional sentence at p.7, l.2:

   […] The upscaled elevation ultimately serves as external drift for EDK of the parameters within QK and for the reference EDK with the original variable. […]

8. is the dry ratio the number of stations that recorded zero rainfall over the whole month over the total number of stations? Can you state this a bit more explicitly?

   A1.8: We rephrase the sentence at p.7,l.9 in order to clarify the definition of the "dry ratio":

   […] The observed average monthly precipitation over the twelve calendar months c is illustrated in Fig.3 along with the percentage of zero-value observations over all observations of the specific calendar month c (hereafter referred to as dry ratio), revealing a seasonal variation. […]

9. P.7, l. 18: if you fit a PDF for each month for each station, you have only 22 points to do it, it seems a very little number to be statistically robust. maybe one of the reasons why you need to fit mean and variance rather than the parameters?

   A1.9: The 22 points might be a contributing factor but we rather believe that the resulting (very small) parameters $\vartheta_{2,c}$ are an outcome from the extrapolation.

10. Eq. 8 and eq. 9: you here present both the distributions but don't explain why. Do you want to compare their performance? How did you select Gamma and Weibull distributions? Nowhere in the paper you comment on which one performs best overall.

    A1.10: We used Gamma & Weibull – distributions as exemplary distribution, because:

    1. they are both defined on the interval [0, ∞];
    2. they are frequently used for the variable of monthly distribution;

3. they have only 2 parameters to be interpolated.

The intention of this paper is not to evaluate the distributions but rather to implement the general idea of Quantile Kriging. However, we agree on the inclusion of a statement on which one preforms best (see A1.16)

11. P.8, l.27: You need to state that you do EDK with elevation as the drift. One of the problems I have in this comparison is that often EDK is performed with radar data, which probably would do better than elevation in defining the spatial pattern of rainfall. Can you comment on this?

A1.11: We didn't use radar data for two reasons: First, the availability of radar data is limited in South Africa: they are only available for a relatively short time, limited to urban centers and are not preprocessed/converted into rainfall sums. Secondly, radar images might be useful for real-time predictions but not for long-time (i.e. monthly or yearly) sums, where they show strong systematical errors (Pfaff, 2013).

Reference:

- Pfaff, T. (2013). Processing and analysis of weather radar data for use in hydrology. Ph.D. Thesis, Institute for Modelling Water and Environmental Systems, University of Stuttgart, http://dx.doi.org/10.18419/opus-487

12. P.9, l. 19: One of the drawbacks I observe is that QK does not estimate a higher uncertainty where there are less rain gauges, eg. top left corner of Figure 5f.

A1.12: Since the entire area (e.g. top left corner, Fig. 5f) shows the same standard deviation σ_K, the estimation uncertainty appears to be less dependent from the position of the raingauges.

13. Explain what rho (eq. 12) represent, why you use it, what is its range, and what the optimal value)

A1.13: We use the Spearman rank correlation ρ_S as a non-parametric measure to describe the monotonic relation between estimator Z* and estimation standard deviation σ_K, instead of the standard Pearson correlation coefficient, describing only the linear relation. We add the following explanation at p.9, l.26:

[…]. The non-parametric Spearman rank correlation ρ_S describes the monotonic relation between the estimator Z and estimation standard deviation σ_K, ranging from -1 (negative) to + 1 (positive) with 0 indicating its absence. […].*

14. P 13: I find the explanation about chi squared a bit confusing. I could not understand what had to be uniform and why, until later on you introduce the histogram. Maybe worth introducing the histograms first? or at least explain more in details.

A1.14: Yes, we agree: the explanation could be more precise. We will explain in more detail by rewording the existing explanation on p.13, l.14 by:

[…]. The test on uniformity verifies the estimated, conditional distribution F_{Z^*} by calculating its value $F_{Z^*}(z(\mathbf{x}_i, t))$ for every original observation $z(\mathbf{x}_i,t)$. The resulting values (or quantiles) should be uniformly distributed on the interval [0,1] (Bárdossy and Li,2008). […].

15. Conclusions: You need to write more here, and remove one of the two paragraphs that are repeated (l. 20-26 or 27-3).

A1.15: Yes, they are actually repeating and we remove the first paragraph (p.14,ll.20-26) and write more in an additional, subsequent paragraph (see A1.16)

16. I feel in general a little bit more discussion of the overall results could be introduced either in the Results and Discussion or the Conclusion section, including many of the comments I mentioned before.

A1.16: We include an additional paragraph at p.15,l.4, including comments from above:

[…]. The variable of monthly precipitation, observed at 226 raingauges over 264 consecutive time steps, serves as input data. We selected the two parametric Γ-distribution and Weibull distribution, because they are defined on the interval [0, ∞] and are suitable to describe the variable of monthly precipitation. The selected distributions are fitted to the observations of a specific calendar month, implying an absence of temporal dependence between two sample members (e.g. between the monthly precipitation of December 2002 and December 2003). However, QK does accommodate temporal independence between consecutive observations, unlike existing spatio-temporal Kriging methods. In general, other types of distributions, with a higher number of parameters could be selected, especially in case of other variables of interest. Finally, we used elevation as external drift, both for the interpolation of the parameters within QK as well as for the reference EDK. […].

And add the following sentences into the last paragraph:

at p.15,l.6: […] In case of the estimator, QK-Γ performs slightly better than QK-Wei for most of the selected objective functions. […].

at p.15,l.8: […] In general, QK-Wei shows a superior estimation of the associated uncertainty than QK-Γ. […].