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Quantification of the effects of measurement precision on scaling estimators

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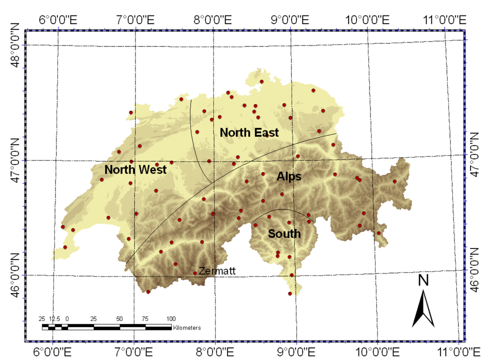
Abstract

In this study we explore the effects of quantization in temporal precipitation measurements on the most widely used scaling estimators. Specifically we investigate those effects by comparing two of the most common precipitation gauges and we generalize our finding by numerical (Monte Carlo) quantification of the bias introduced by the instrumental depth precision.

Data

The data used in this study are records from the automatic weather stations network (SwissMetNet) operated by MeteoSwiss. Those stations are equipped with rain gauges with a heated tipping bucket mechanism. The depth precision is 0.1mm and time resolution 10min. Also precipitation data from a weighing gauge (MPS) placed in the same location (Zermatt) as one of the tipping-bucket gauges will be used for the comparison.



The weighing gauge has a depth precision of 0.001mm and a time resolution of 1min. Also it does not suffer from snow melting water losses that affect the tipping bucket rain gauges, especially in low intensity winter events.

The collected data were examined on a seasonal basis. The weighing gauge records were not continuous so we examine them for five different time periods

a) Spring 09 ~ 22 January-02 April
b) Summer 09 ~ August
c) Autumn 09 ~ September – October - November
d) Winter 10 ~ December (09) – January – February
e) Spring 10 ~ March – April - May

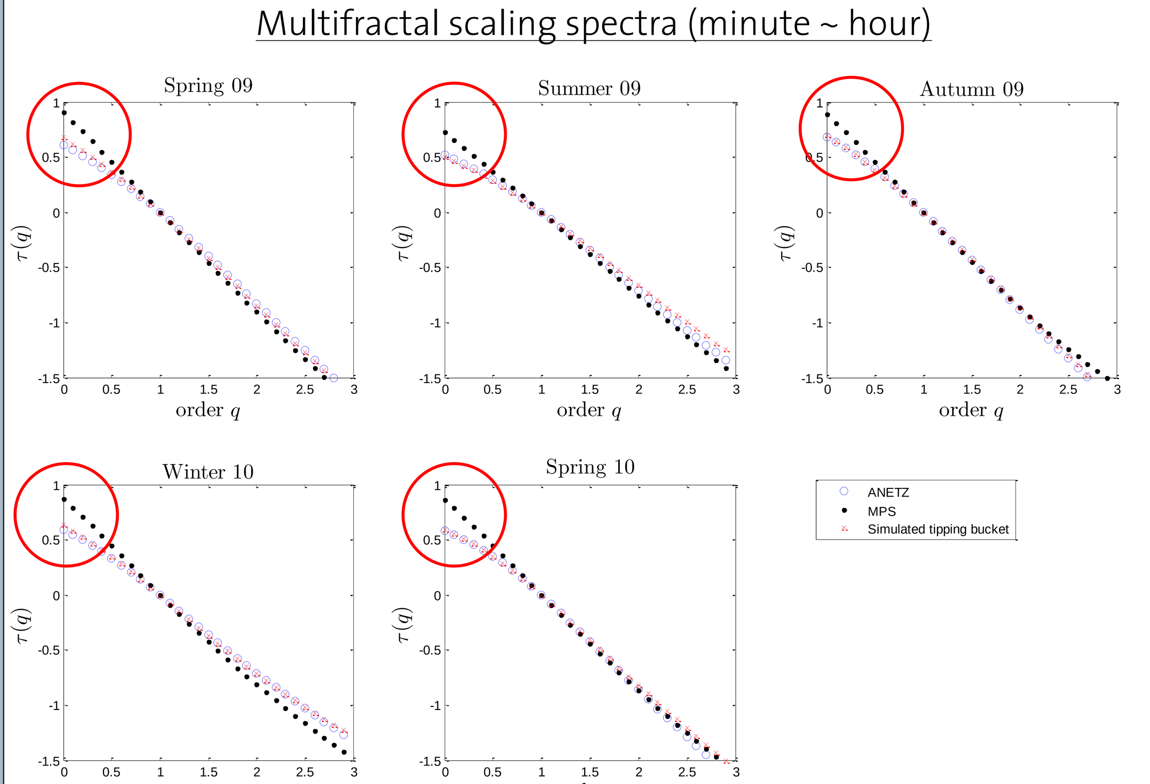
Data Analysis

The data analysis consists of the evaluation of the performance of the most widely used scaling estimators in hydrology. Since the last decades the concept of simple and multi scaling processes has attracted a lot of attention in hydrological research, we will focus on estimators that describe these processes. The estimators are:

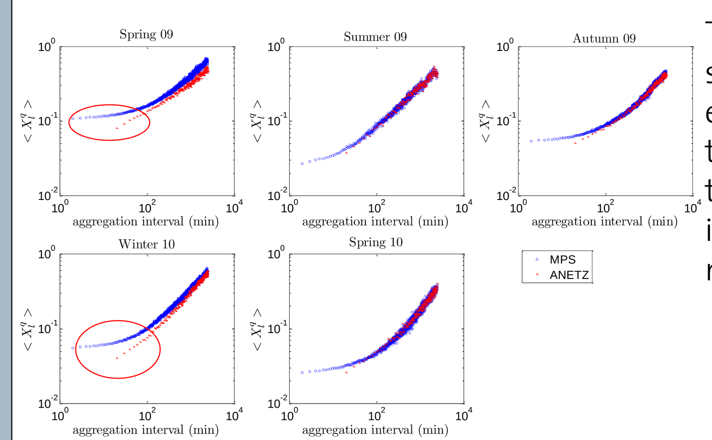
- Multifractal process descriptors. We adopt the notation of Over and Gupta (1994) and especially the intermittent beta lognormal model
- Hurst exponent (Koutsoyiannis, 2003)
- Power Spectrum analysis using periodogram and wavelet decomposition of the precipitation time series (Molini et al., 2009)

Our analysis is divided into two different time regimes. First the time scales from minute to hour will be explored. At this scale we see the effect of the low precision of the tipping bucket gauge. Then the scales from hour to day are explored where the effect of heating evaporation losses becomes dominant especially during winter.

Multifractal scaling spectra (minute ~ hour)

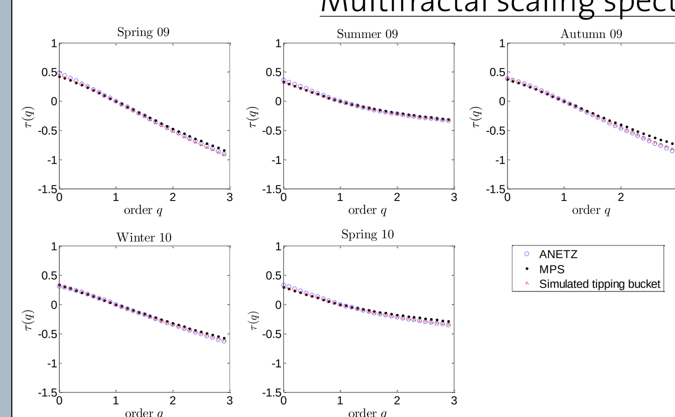


In this scaling regime, the effect of low depth precision becomes apparent on the moment scaling for orders of moments less than 1 (i.e. sensitive to low values) and can lead to an underestimation of the dimension of the support of about 50% for low intensity winter events



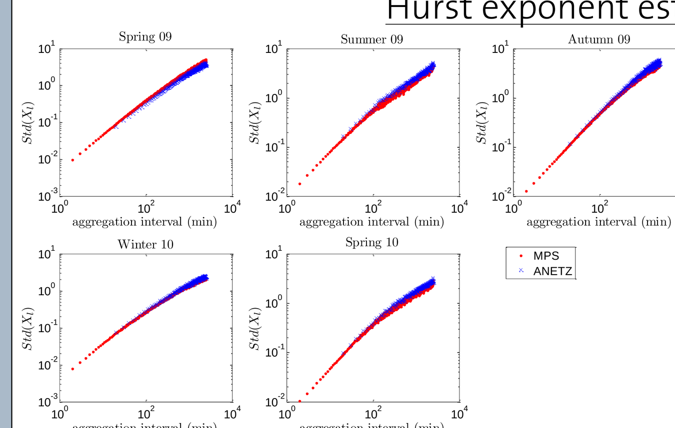
The quantization effects become strong in the moment scaling especially for $q \to 0$ (dimension of the support). Also a scaling transition regime cannot be identified by the tipping bucket measurements.

Multifractal scaling spectra (hour ~ day)



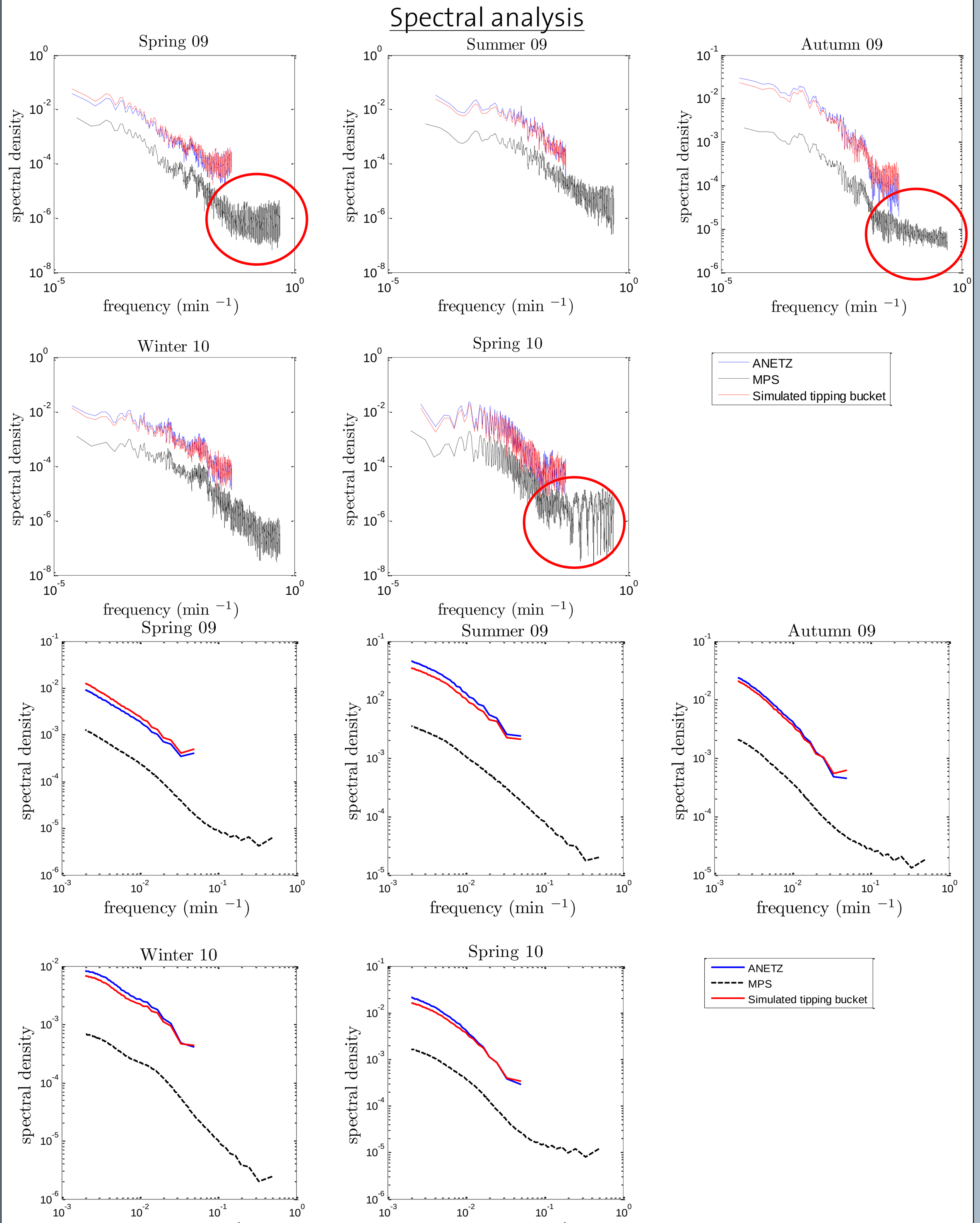
In the scaling regime of one hour to one day, the effect of quantization tend to disappear and the total water amount loses does not seem to have any strong effect on the estimation procedure

Hurst exponent estimation



The Hurst exponent calculation through the scaling of the unbiased estimation of the standard deviation seems to be robust at any scale of hydrological interest

Spectral analysis



From the calculation of the power spectra using classic periodogram analysis (upper) and wavelet analysis (lower) it appears that no significant bias is introduced due to low depth precision but coarse resolution data sets are not able to identify strong scaling breaks (~10 min). This fact can strongly affect disaggregating techniques especially in urban hydrology that deals with time scales of that magnitude.

A summary of the statistics

(minute - 1 hour)	Spring 2009			Summer 2009			Autumn 2009			Winter 2010			Spring 2010		
	ANETZ	MPS	Simulated tipping bucket	ANETZ	MPS	Simulated tipping bucket	ANETZ	MPS	Simulated tipping bucket	ANETZ	MPS	Simulated tipping bucket	ANETZ	MPS	Simulated tipping bucket
β	0.388	0.093	0.322	0.482	0.276	0.500	0.319	0.109	0.298	0.405	0.127	0.368	0.422	0.135	0.405
σ^2	0.000	0.024	0.000	0.000	0.000	0.000	0.000	0.075	0.000	0.000	0.111	0.000	0.000	0.036	0.000
Hurst exponent	0.909	0.950	0.918	0.854	0.879	0.828	0.942	0.933	0.929	0.853	0.906	0.853	0.930	0.932	0.907
Hurst exponent unbiased	0.944	0.979	0.958	0.897	0.941	0.858	0.948	0.917	0.973	0.883	0.984	0.902	0.985	0.928	0.972
wavelet spectral slope	-1.405	-1.673	-1.514	-1.387	-1.123	-1.296	-1.803	-1.305	-1.564	-1.623	-1.551	-1.489	-2.067	-1.789	-1.922

(1hour - 1 day)	Spring 2009			Summer 2009			Autumn 2009			Winter 2010			Spring 2010		
	ANETZ	MPS	Simulated tipping bucket	ANETZ	MPS	Simulated tipping bucket	ANETZ	MPS	Simulated tipping bucket	ANETZ	MPS	Simulated tipping bucket	ANETZ	MPS	Simulated tipping bucket
β	0.518	0.574	0.560	0.640	0.664	0.677	0.613	0.626	0.605	0.691	0.664	0.675	0.672	0.706	0.704
σ^2	0.000	0.000	0.000	0.193	0.180	0.157	0.000	0.000	0.000	0.000	0.029	0.000	0.149	0.149	0.121
Hurst exponent	0.793	0.797	0.800	0.606	0.607	0.600	0.777	0.760	0.768	0.697	0.692	0.687	0.618	0.602	0.613
Hurst exponent unbiased	0.867	0.877	0.879	0.682	0.664	0.689	0.853	0.838	0.842	0.751	0.757	0.745	0.710	0.694	0.701
wavelet spectral slope	-0.960	-0.991	-0.987	-0.488	-0.468	-0.463	-0.940	-0.905	-0.901	-0.666	-0.676	-0.673	-0.642	-0.616	-0.610

*Note that unbounded least square fit on the estimated scaling spectrum can lead to non feasible estimates of $\sigma^2<0$
** Periodogram log-slope estimation is not shown due to large uncertainty on the log-log power spectrum plot

Numerical quantification of the bias

In order to quantify the effects of the quantization due to low measurement precision and also due to the errors introduced by the tipping bucket mechanism we set up a numerical Monte Carlo simulation procedure.

1. Sampling realizations of "precipitation" series using a stochastic model
2. Quantizing the results by reproducing the tipping bucket procedure
3. Calculating among a large set of realization (1000 in our case) the mean value of the relative bias (simulated – estimated on the quantized series)

The stochastic model we use belongs to the class of the intermittent random multiplicative cascades. We use the intermittent beta lognormal version of the model (Over and Gupta., 1994) since it is the one that can reproduce efficiently the observed precipitation series structure with the most parsimonious parameterization that lead to few free parameters on the Monte Carlo procedure. The beta lognormal model simulates multifractal random measures with a specific moment scaling spectrum and an atom at zero. The simulation scheme is constructed as follows. The mass at each level of the cascade development n is

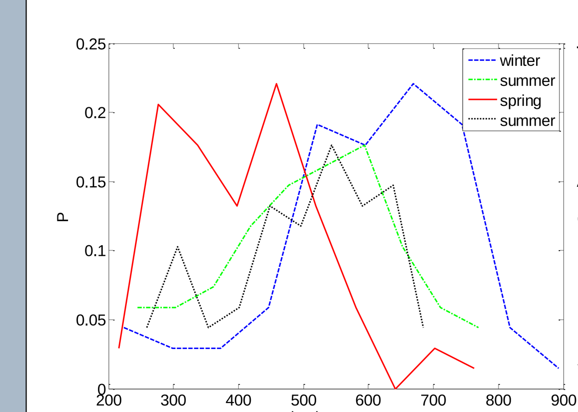
$$\mu_n(\Delta_n^i) = \mu_0(J) b^{-n} \left(\prod_{k=1}^{n} W_k^i \right)$$

where W is the cascade generator that consists of two parts, the intermittency part and the log-normally distributed part. The distribution of the generator is given by the following equations

$$P(W=0) = 1 - b^{-\beta},\ P(W = b^{\beta} Y) = b^{-\beta},\ Y = b^{\gamma + \sigma X}$$

where

$$X \sim N(0,1)$$



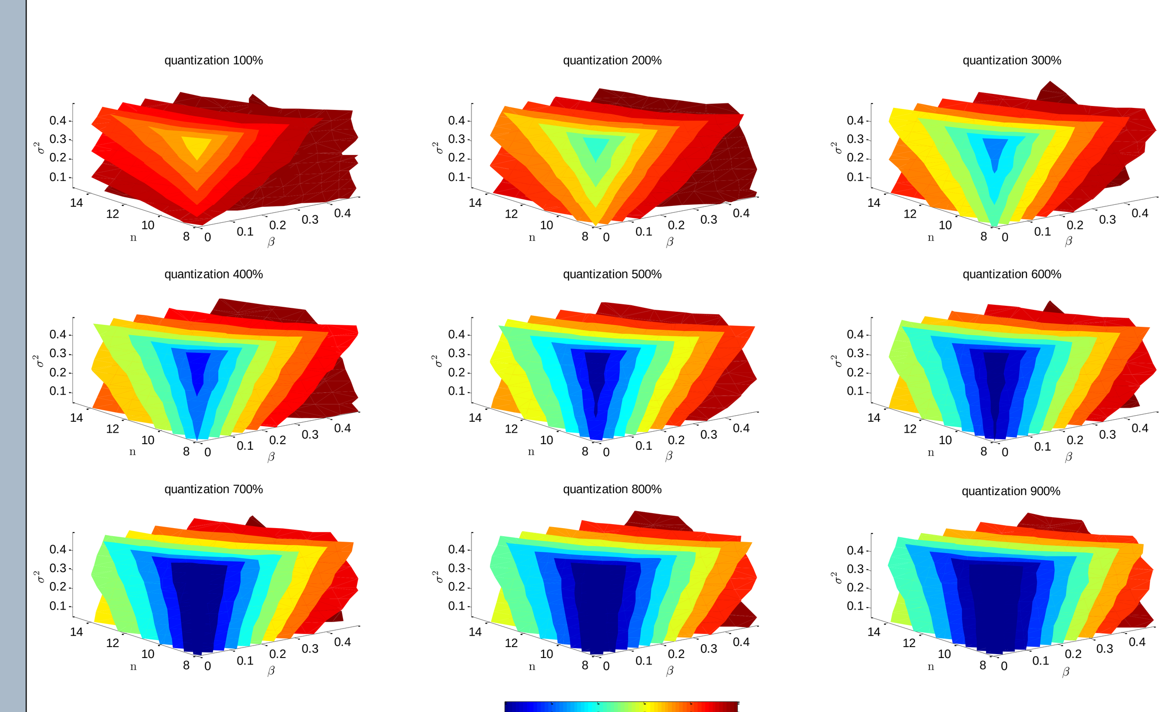
The Monte Carlo simulation procedure was performed for quantization levels indicated by the data analysis performed on the ANETZ precipitation records. As quantization level we define the quantity:

$$quantization\ level = \frac{depth\ precision}{mean\ depth} (\%)$$

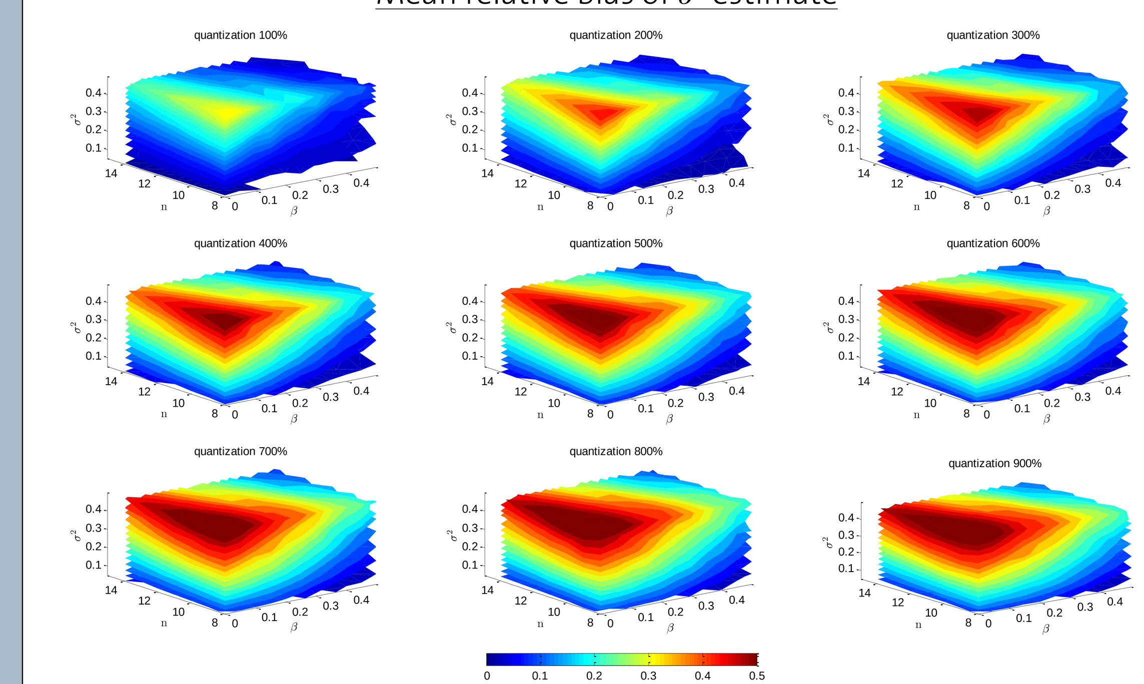
Where mean depth is the average seasonally recorded depth per 10 minutes

Also the parameter space that the model simulation took place was indicated by the values estimated from the data analysis of the record ANETZ network and also the rain gauge network of daily observations in Switzerland.

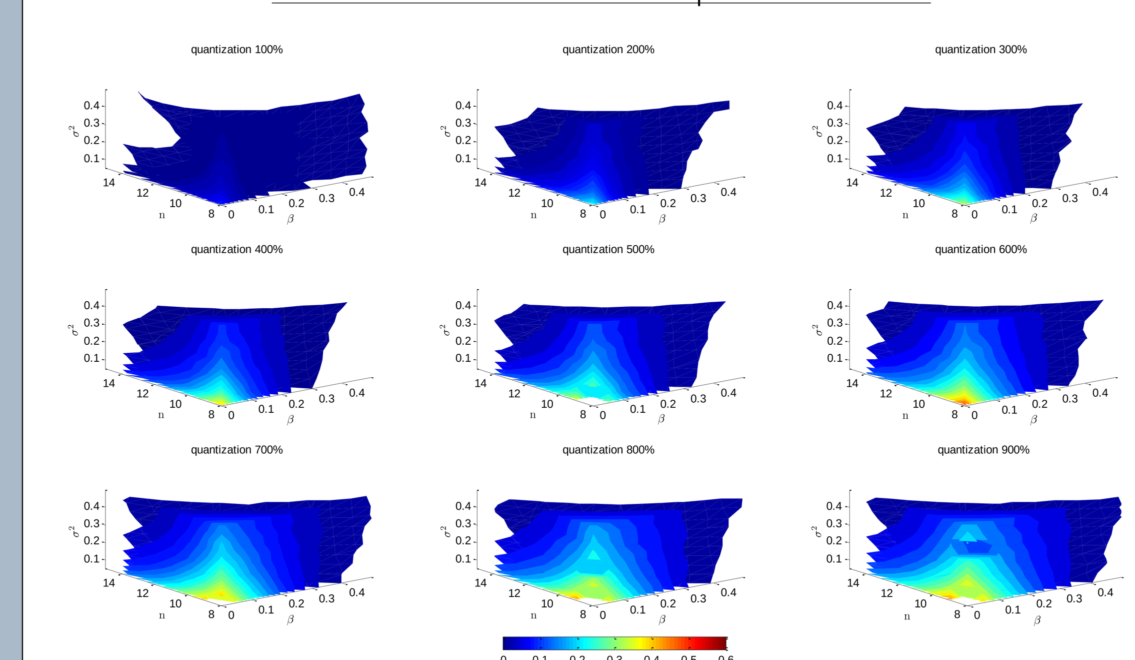
Mean relative bias of β estimate



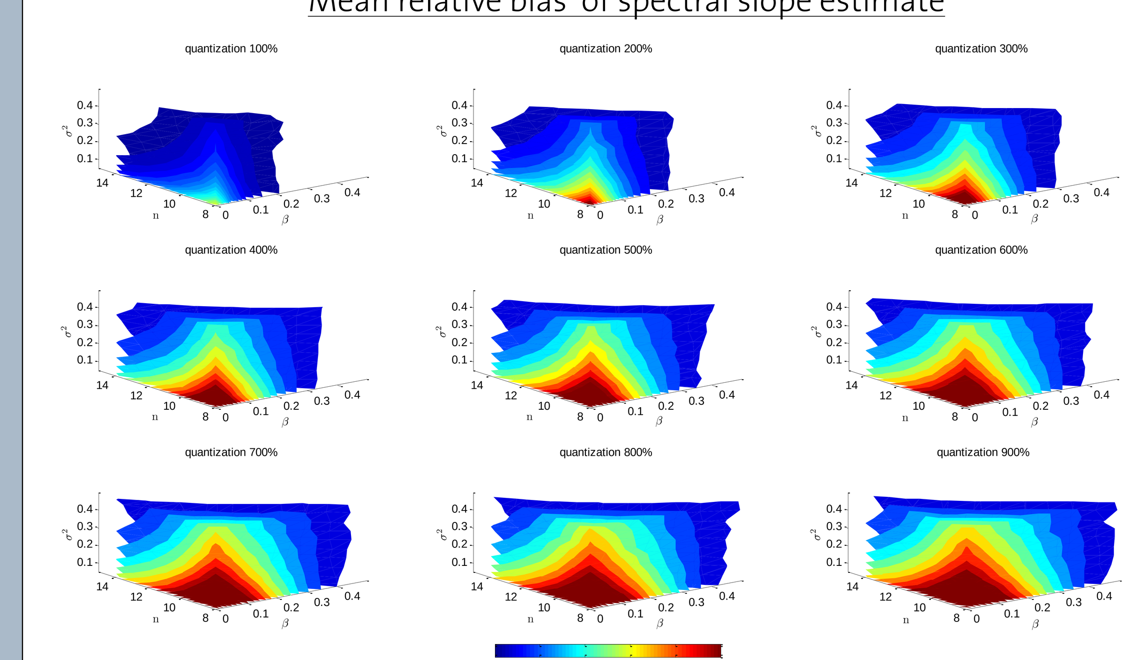
Mean relative bias of σ^2 estimate



Mean relative bias of Hurst exponent estimate



Mean relative bias of spectral slope estimate



Conclusions

- Measurement precision can have a strong effect on the scaling estimators
- The lag of the tip and the low depth precision effects appear to have the most dominant influence
- The total losses due to evaporation does not have significant influence on the scaling estimators
- Multifractal estimates that depend on a wide range of moments across scales suffer the most from measurement precision problems
- Scaling characteristics such as scaling transition regimes can remain unidentified by low precision measurements
- Special care should be taken when different scaling stochastic models are calibrated against data in order to take into account probable biases and large uncertainties due to the measurement.

References

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