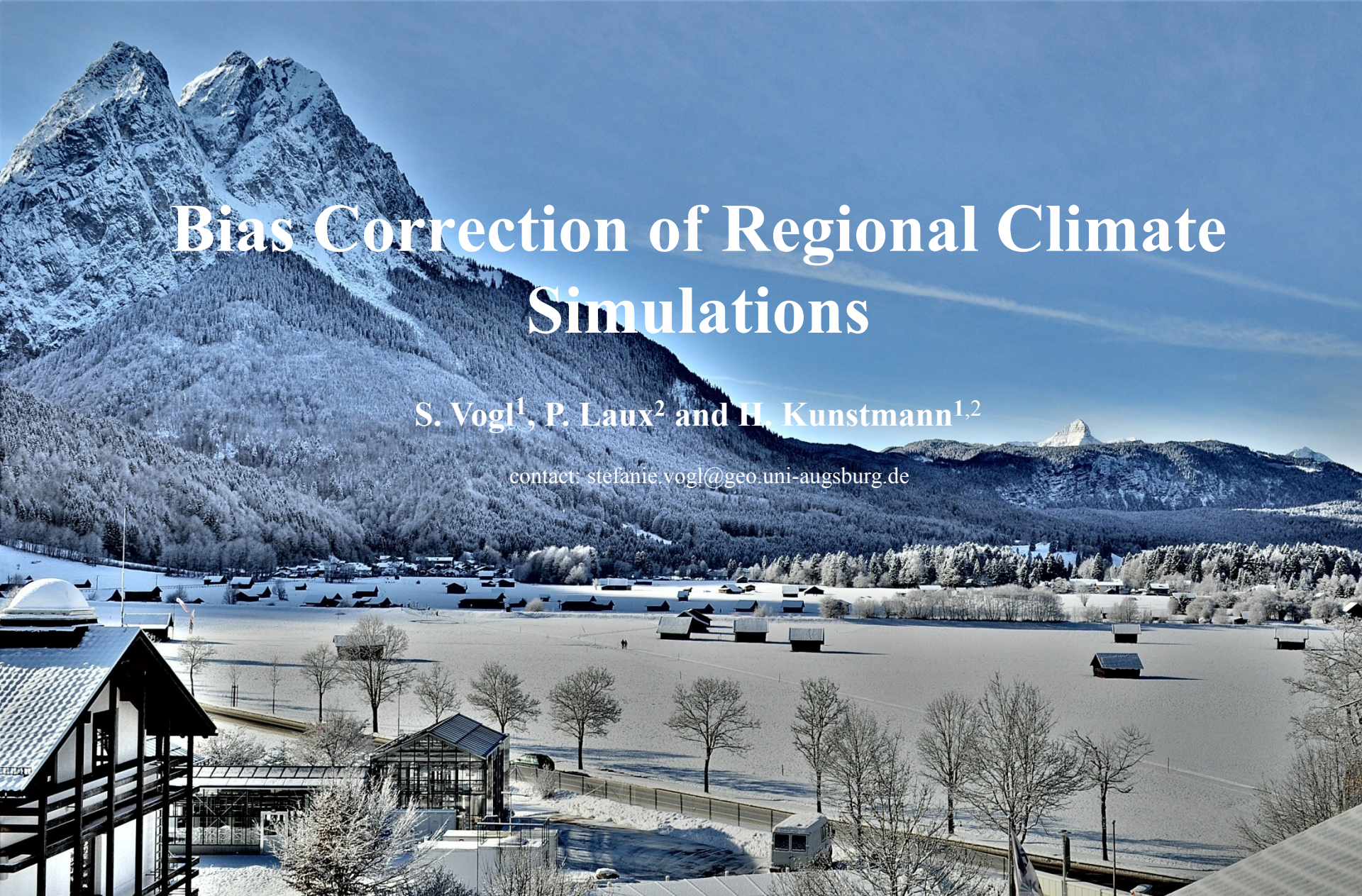


# Bias Correction of Regional Climate Simulations

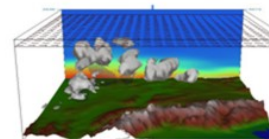
S. Vogl<sup>1</sup>, P. Laux<sup>2</sup> and H. Kunstmann<sup>1,2</sup>

contact: stefanie.vogl@geo.uni-augsburg.de



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<sup>2</sup> Karlsruhe Institute of Technology (KIT), Institute for Meteorology and Climate Research (IMK-IFU), Garmisch-Partenkirchen



**IGUA**  
Institut für Geographie

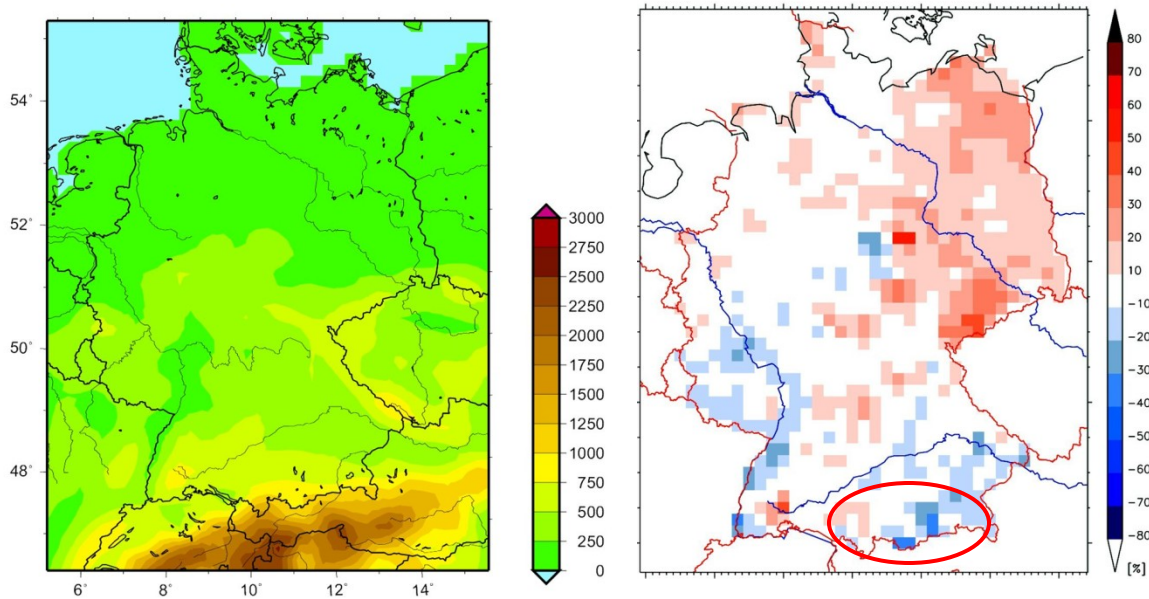
Lehrstuhl für  
Regionales Klima und Hydrologie  
Prof. Dr. Harald Kunstmann

**UNA**  
Universität  
Augsburg  
University



## Application:

# Bias-correction of regional climate modeling in the alpine space



Domain and topography of regional climate simulations with MM5, 19.2 km spatial resolution (left).

Bias of mean annual total precipitation for the MM5 with respect to the DWD reference data set [%] (right)

- Rainfall is overestimated by MM5 for the whole eastern part of Germany, and strongly underestimated for the Rhine valley and the Alpine region of Germany.
- The underestimation in the Alpine region is possibly due to the complex terrain with very steep gradients of altitude.

Theory:

random sample from  $(X, Y)$ :

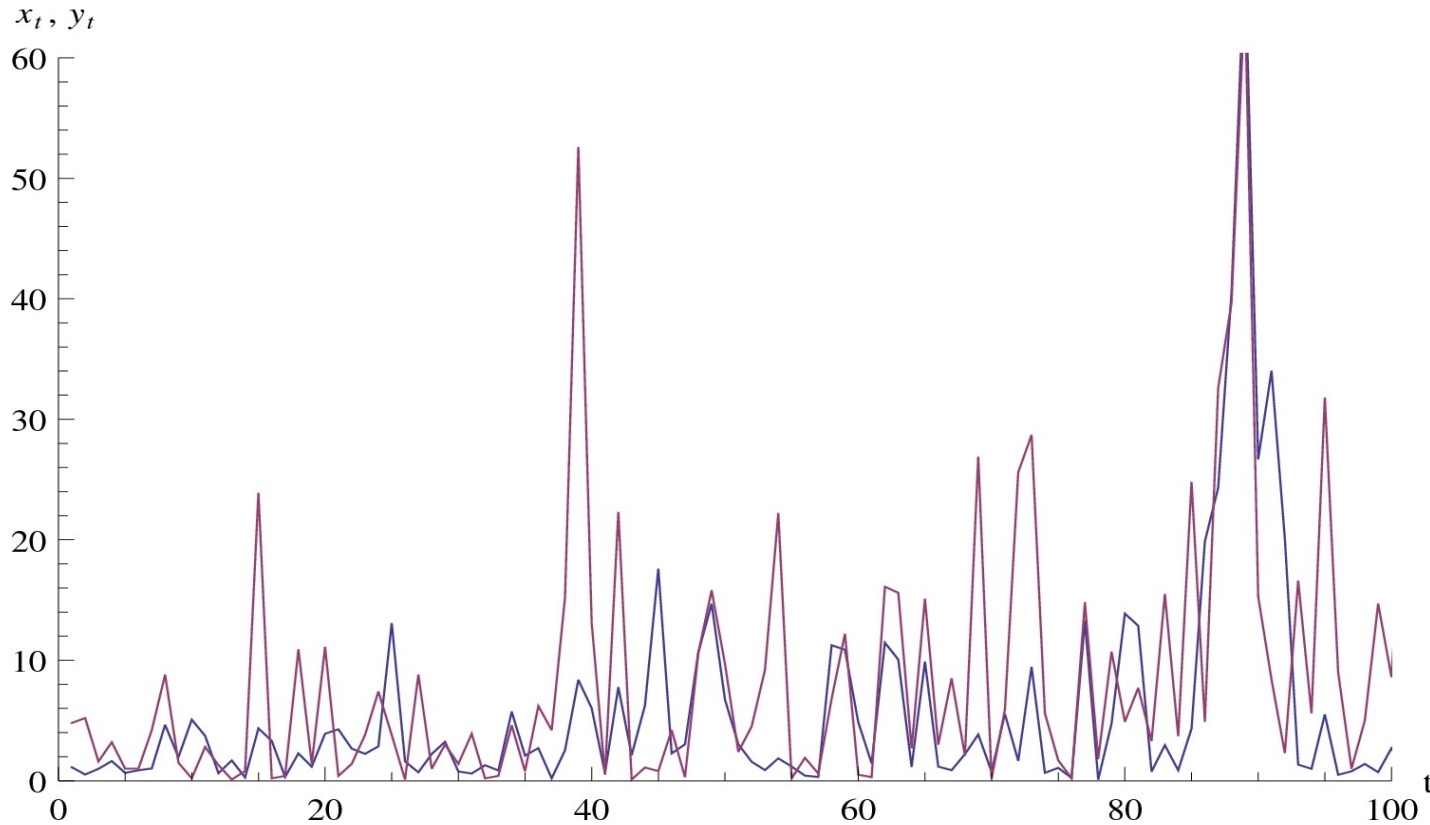
$$(X_1, Y_1), \dots, (X_n, Y_n)$$



In practice we have two time series: e.g.

- modeled temperature and measured temperature
- modeled precip. and measured precip.

$x_t$  model (blue),  $y_t$  measurement (red), station GAP



**The joint dependence between these variables is fully characterized by their Copula  $C(x, y)$ .**

- every Copula is the representation of the dependence structure of the two (or more) variables
- by using a Copula it is possible to derive a bi- or multivariate PDF  $f(x,y)$  just by knowing the single marginal distributions  $F_X(x)$  and  $F_Y(y)$

$$f(x, y) = c(F_X(x), F_Y(y)) \cdot f_X(x) \cdot f_Y(y)$$

joint density
pdf of Copula (copula density)
pdfs of the marginals

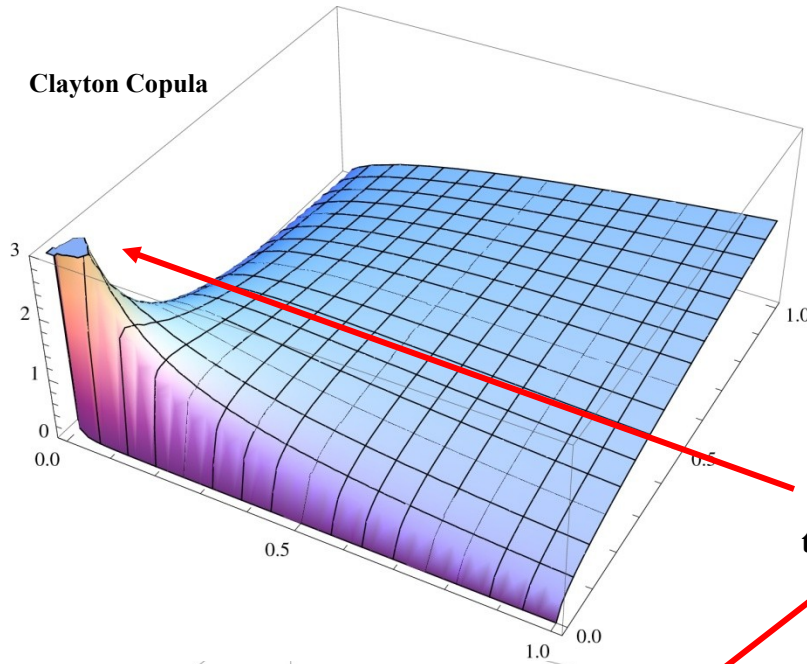


$$c(u, v) = \frac{\partial^2 C(u, v)}{\partial u \partial v}$$

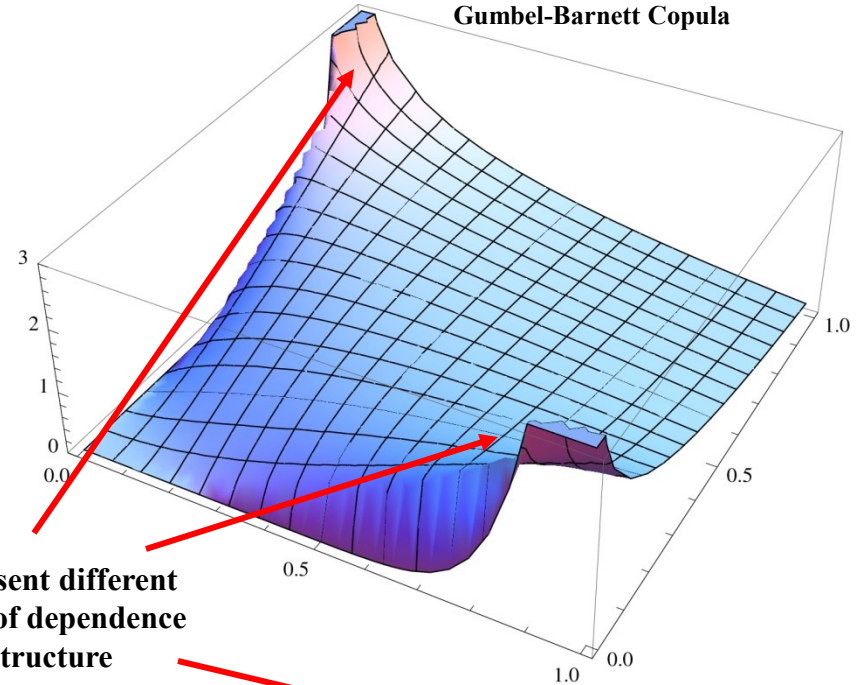
➔ **the copula density  $c(u,v)$  is often called “dependence function”**

# PDFs of different Copula families

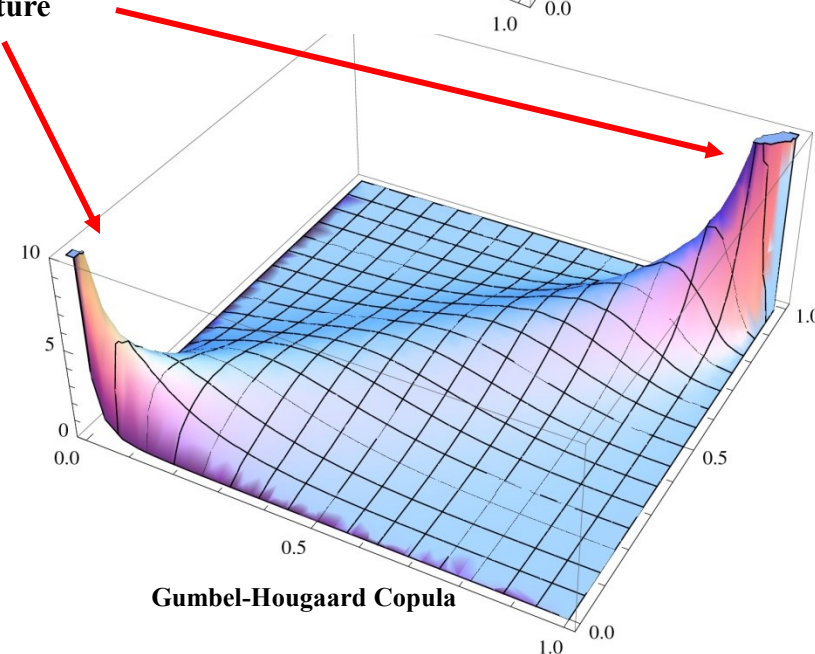
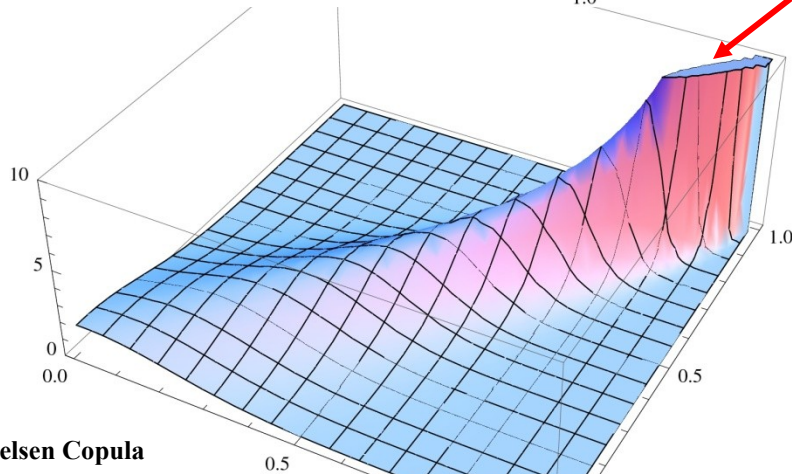
Clayton Copula



Gumbel-Barnett Copula



represent different  
types of dependence  
structure



Nelsen Copula

Gumbel-Hougaard Copula

# Connection of the Copula parameter to rank based dependence estimators - Kendalls tau

$$(+)$$

$$\tau = \frac{1}{n(n-1)} \iint_{\mathcal{I}^2} \dots$$

tau is a measure of dependence based on ranks

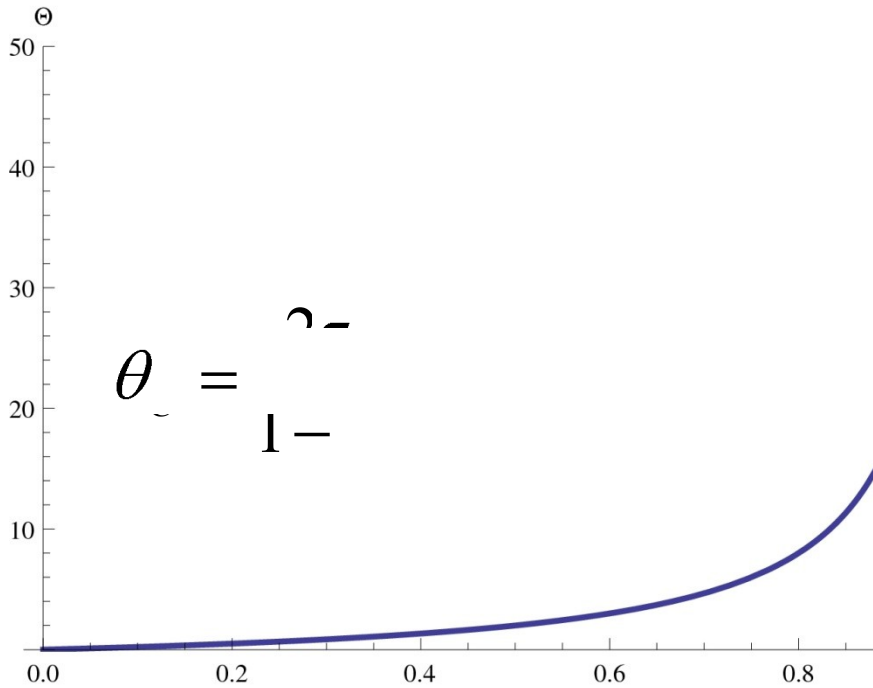
$$C_{\theta}(u, v) = \left( \begin{matrix} 1 \\ 1 \end{matrix} \right) \text{ Clayton Copula}$$

$$C_{\theta}(u, v) = \left( \begin{matrix} - \\ - \end{matrix} \right) \text{ Gumbel-Hougaard Copula}$$



There is a relationship between Kendalls tau and the Copula parameter theta via (+)

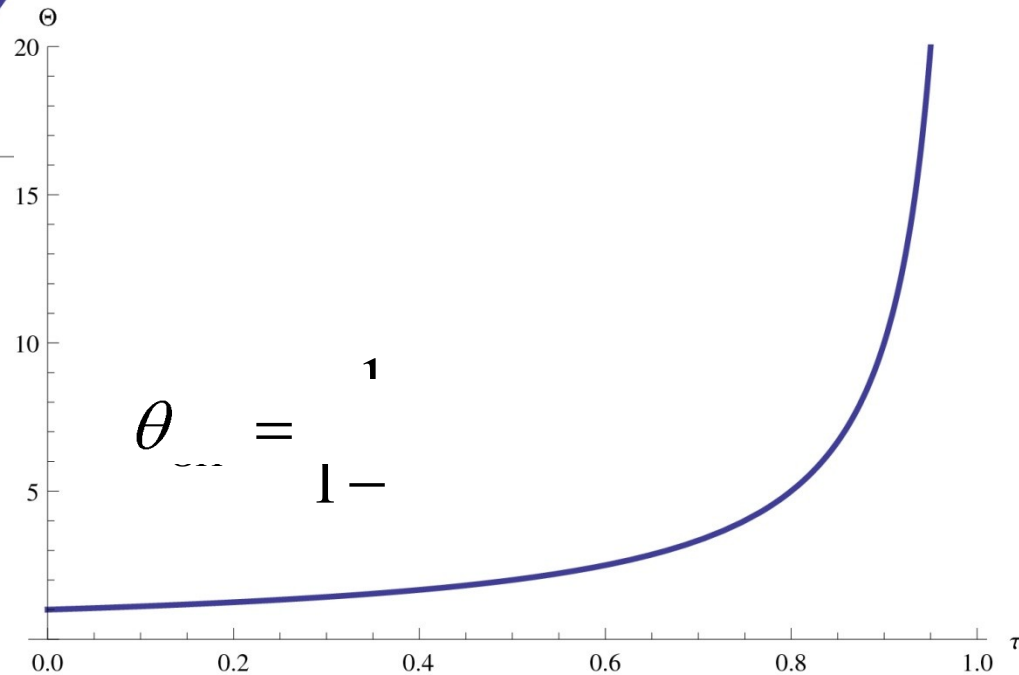




Clayton Copula

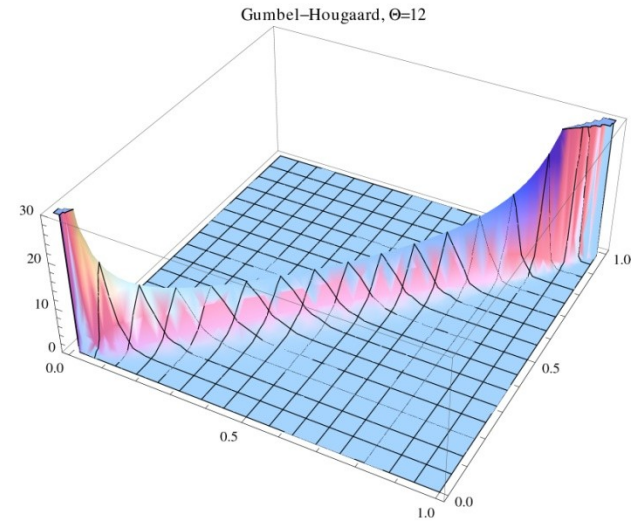
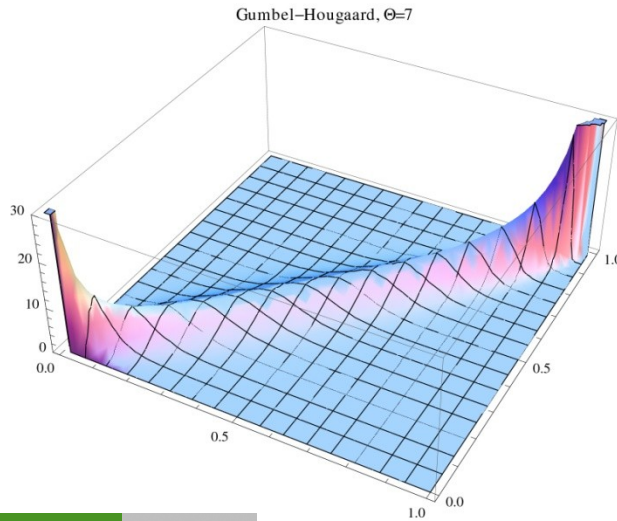
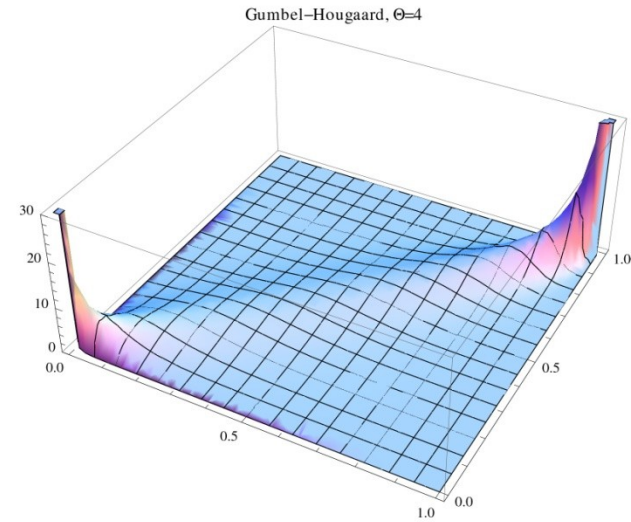
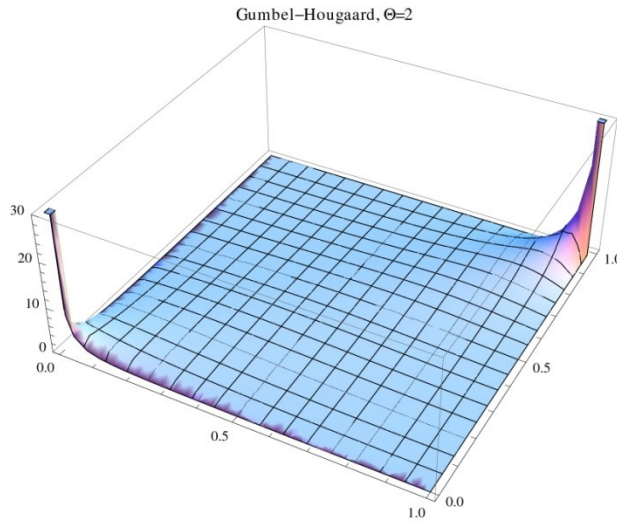
**theta is a monotonically increasing function of tau**

**high Copula parameters indicate strong correlation**



Gumbel-Hougaard Copula

# larger Copula parameter - higher dependence



PDF of GH Copula for 4 different values of theta

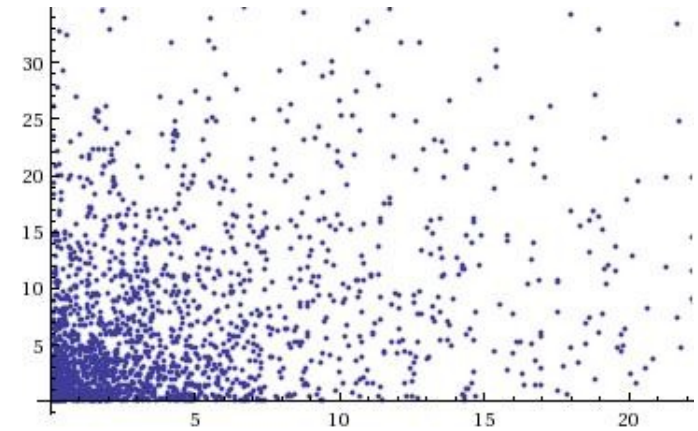


# Find a theoretical Copula to model the dependency between model output and measurement

data  $(X_i, Y_i)$



needs to be i.i.d. (independent and identically distributed)



scatter plot of the original data

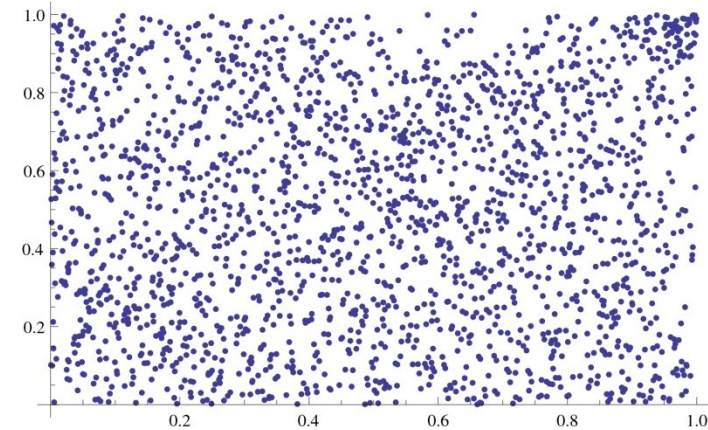
# Find a theoretical Copula to model the dependency between model output and measurement

data  $(X_i, Y_i)$

needs to be i.i.d. (independent and identically distributed)

transform data to  
an i.i.d. data set  
 $(X_i^*, Y_i^*)$

ARMA-GARCH  
transformation is applied to get  
i.i.d. data



scatter plot of the iid residuals

# Find a theoretical Copula to model the dependency between model output and measurement

data  $(X_i, Y_i)$

needs to be i.i.d. (independent and identically distributed)

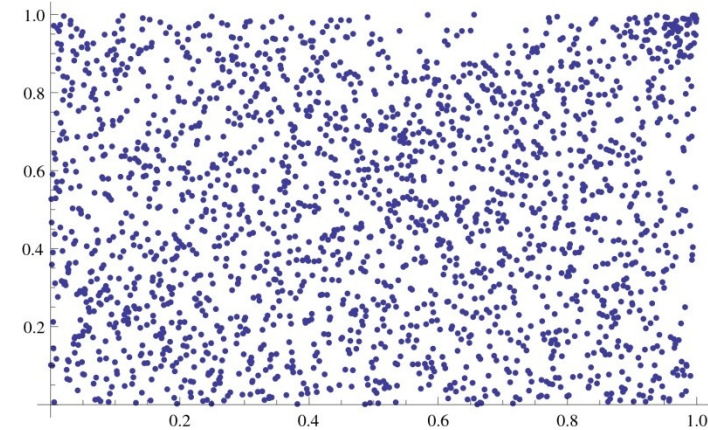
transform data to  
an i.i.d. data set  
 $(X_i^*, Y_i^*)$

ARMA-GARCH  
transformation is applied to get  
i.i.d. data

ranks  $(R_i, S_i)$  of  
the i.i.d. data

ranks have the same dependence  
structure as original data

➔ same Copula



scatter plot of the ranks of the iid  
residuals



# Find a theoretical Copula to model the dependency between model output and measurement

data  $(X_i, Y_i)$

needs to be i.i.d. (independent and identically distributed)

transform data to  
an i.i.d. data set  
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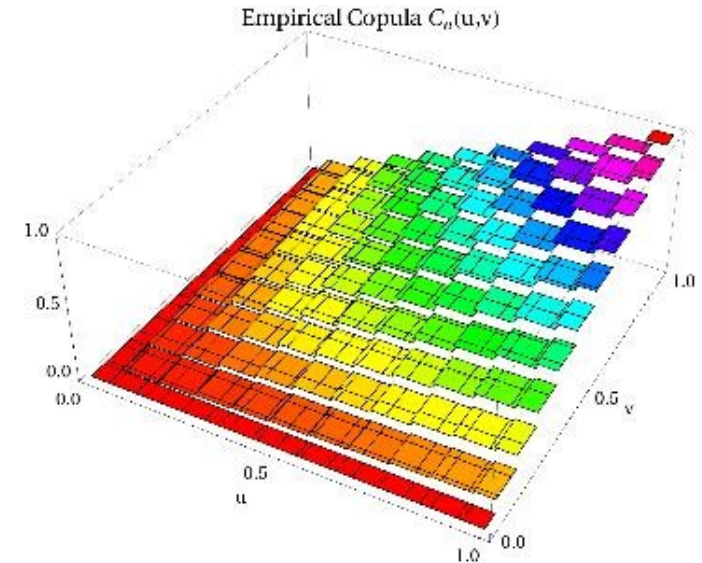
ARMA-GARCH  
transformation is applied to get  
i.i.d. data

ranks  $(R_i, S_i)$  of  
the i.i.d. data

ranks have the same dependence  
structure as original data

➔ same Copula

calculate the empirical  
copula  $C_n(u, v)$



CDF of the empirical Copula

# Find a theoretical Copula to model the dependency between model output and measurement

data  $(X_i, Y_i)$

needs to be i.i.d. (independent and identically distributed)

transform data to  
an i.i.d. data set  
 $(X_i^*, Y_i^*)$

ARMA-GARCH  
transformation is applied to get  
i.i.d. data

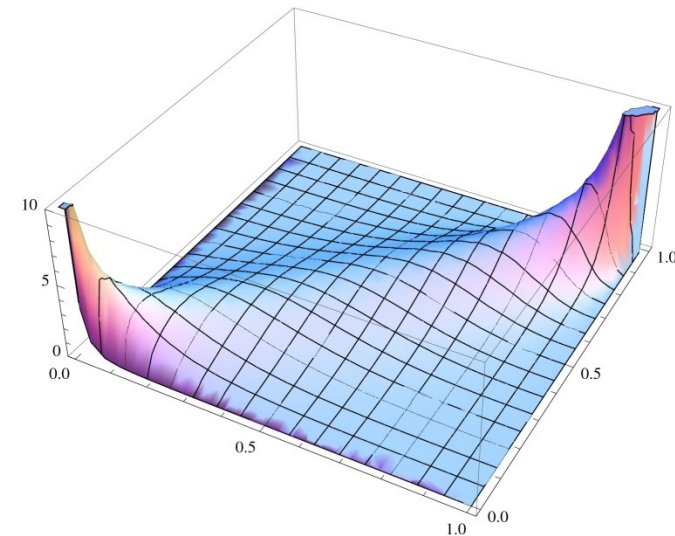
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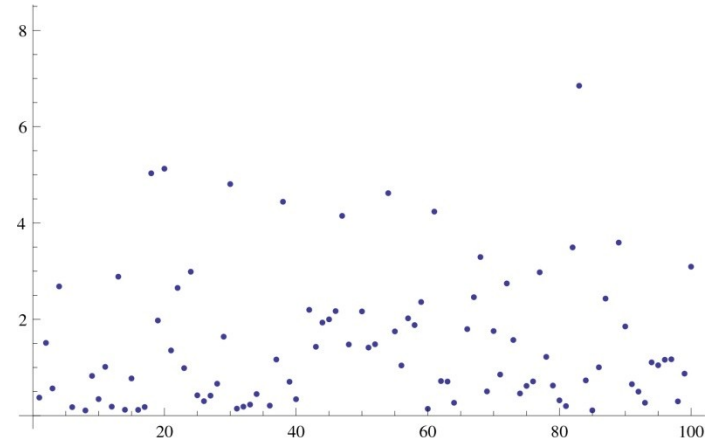
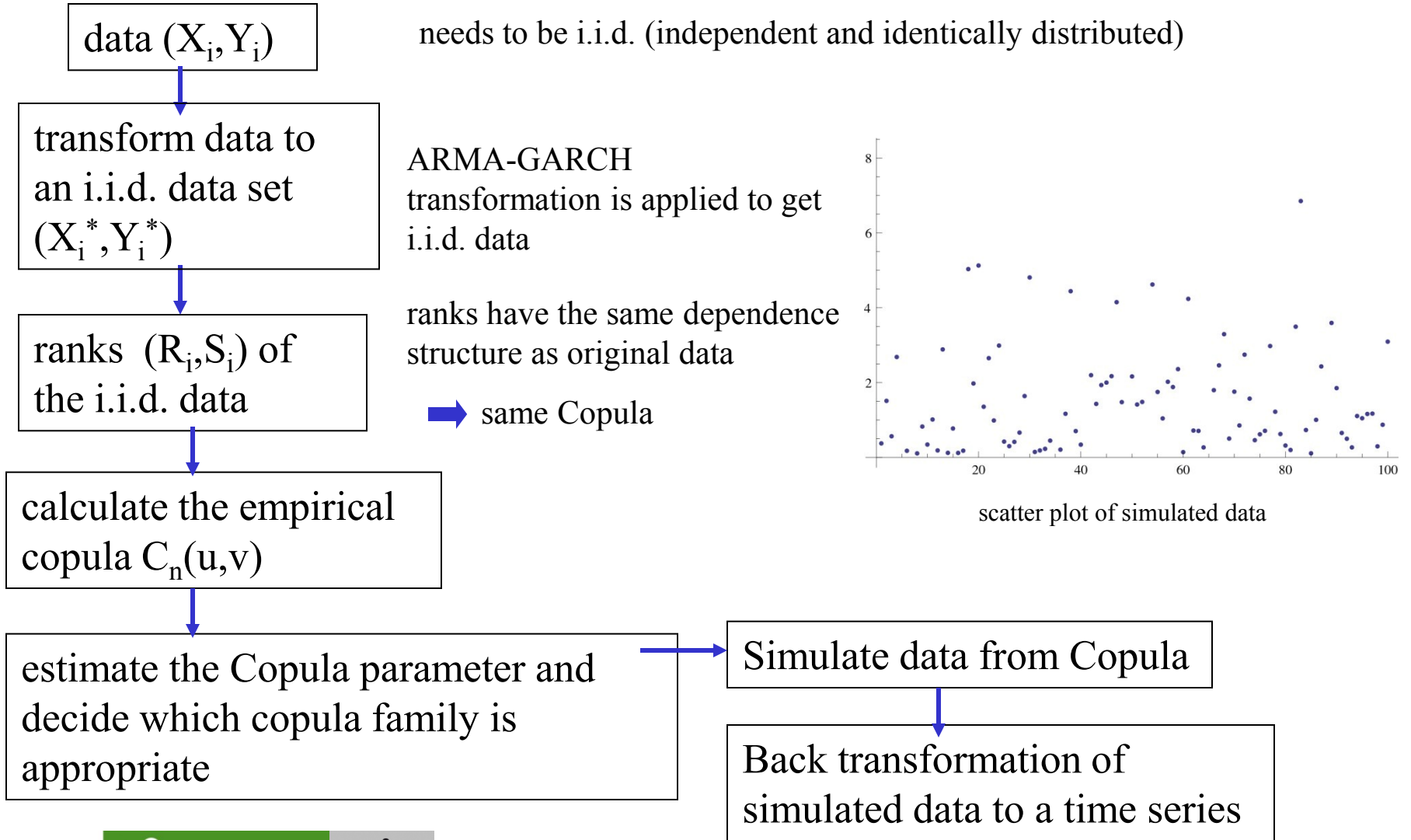
calculate the empirical  
copula  $C_n(u, v)$

decide which copula family is  
appropriate and estimate the copula  
parameter



PDF of the Gumbel-Hougaard Copula

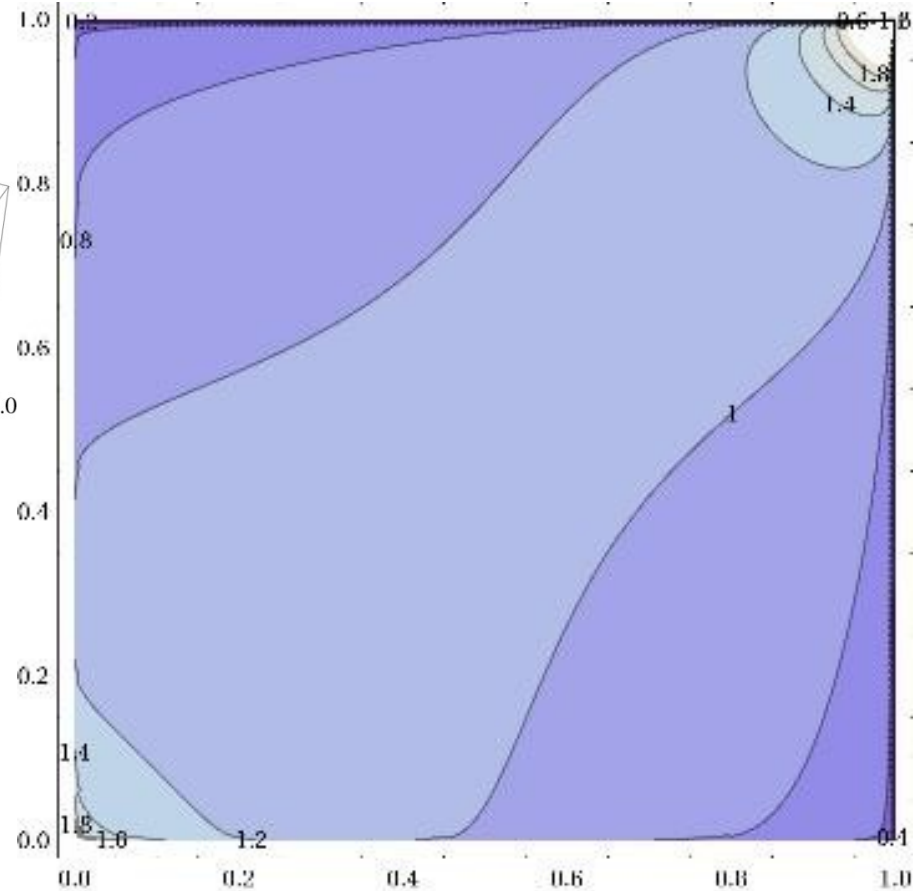
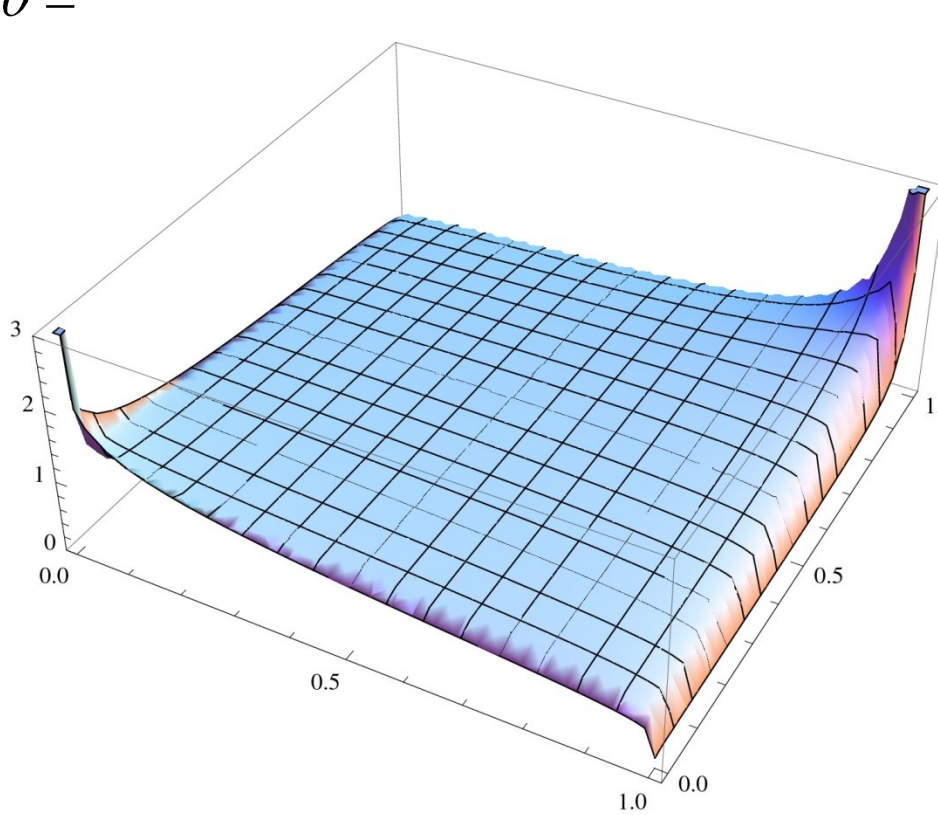
# Find a theoretical Copula to model the dependency between model output and measurement





After GOF-tests the Gumbel-Hougaard Copula was identified as appropriate

$\theta =$



PDF of the Gumbel-Hougaard Copula with  $\theta =$

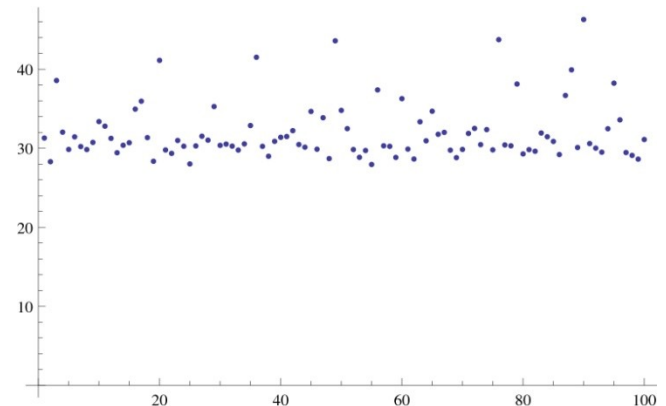
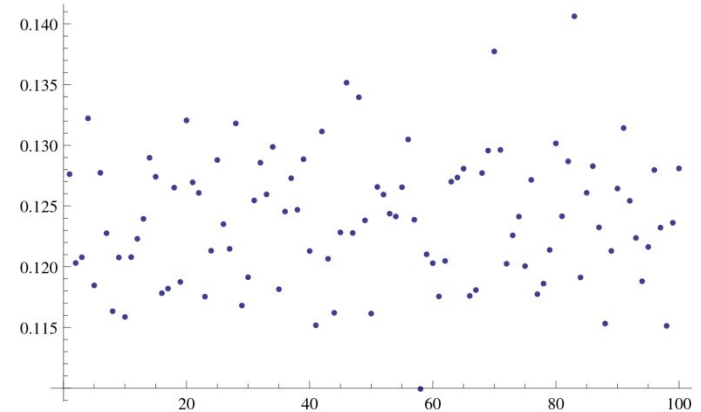
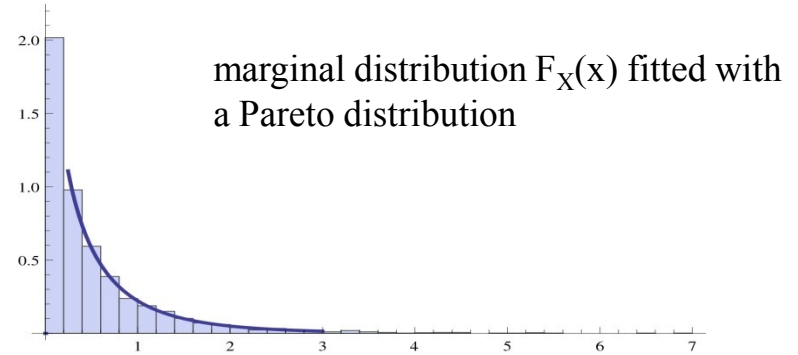
# Algorithm for a conditional simulation of (X, Y)

- calculate  $u = \dots$
- create random samples of  $v$  under the condition  $u$  using

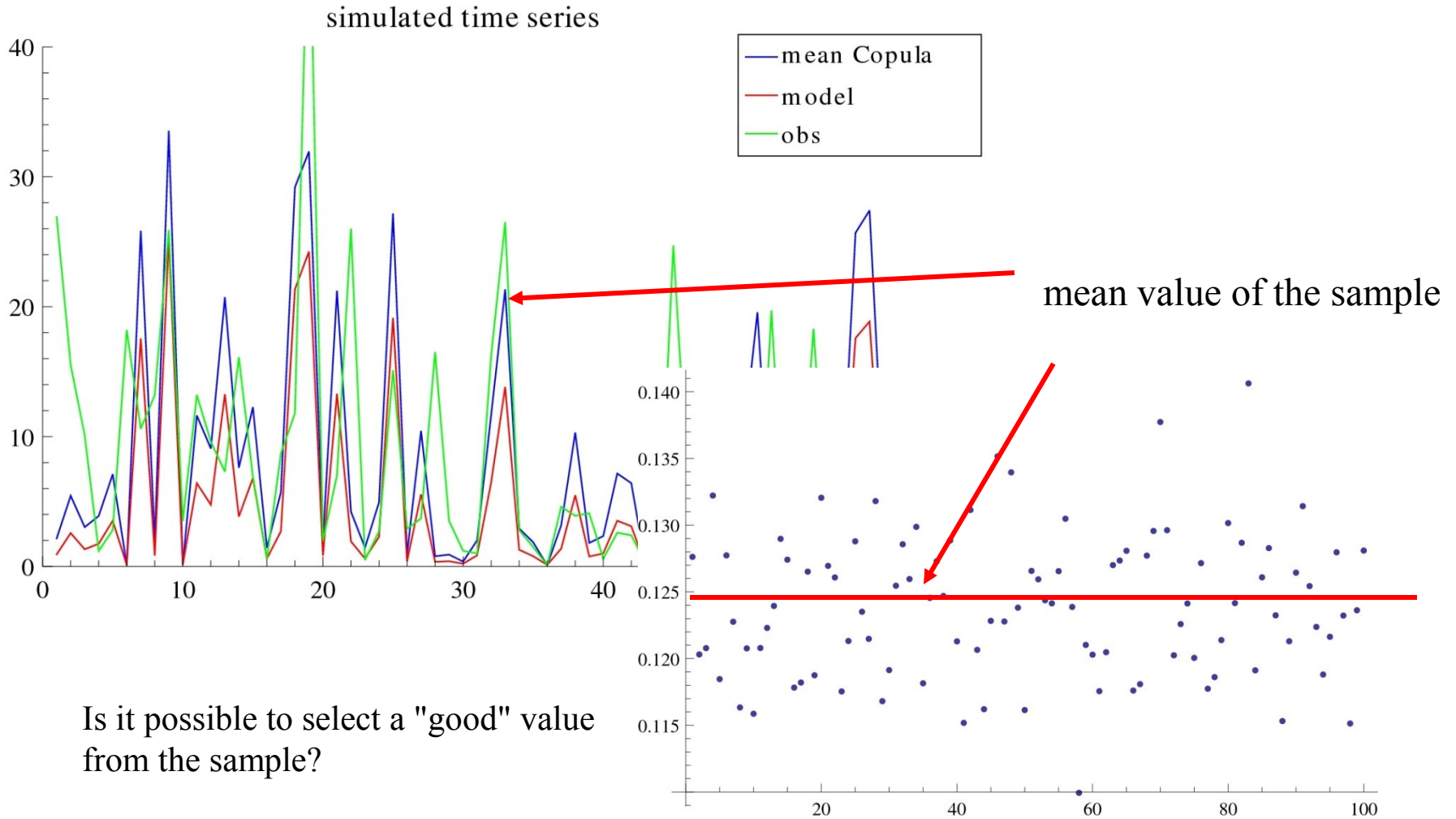
$$\frac{\partial}{\partial v} F_{Y|X}(v|u) = \dots \leq \dots = \dots$$

- use  $F_{Y|X}^{-1}(v|u) = \dots$  to calculate a sample of model values  $y$
- based on the conditional CDF there is a **range of possible values for the variable  $y$**

Samples of 100 pseudo-obs.  $y$  for two different values of  $u$



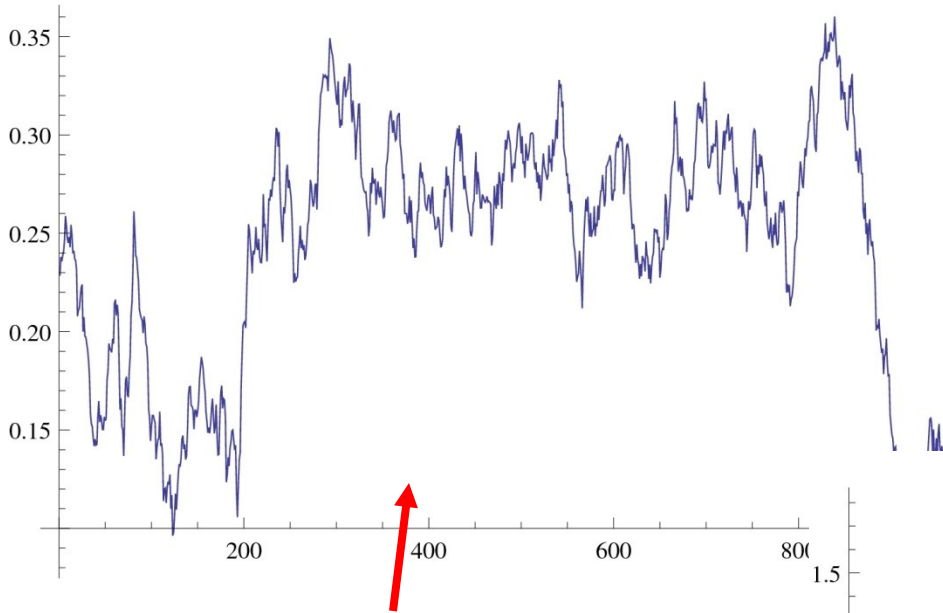
# First results





# Possible improvement

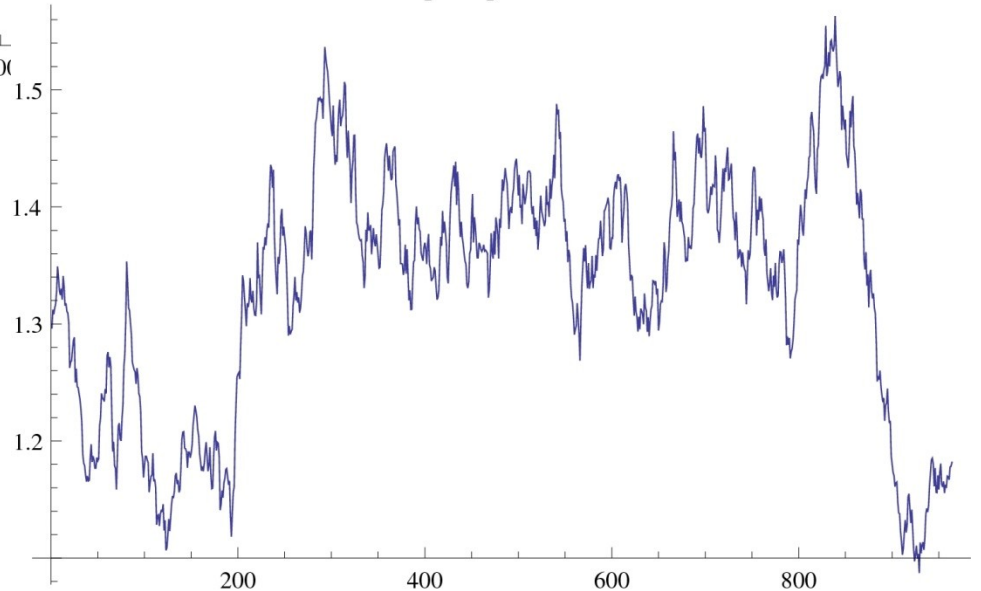
$$\theta = \frac{1}{1 - \tau}$$



theta is not constant over the range of data



Copula parameter



tau is not constant over the range of data