



# Bias correction with CDF-Transform

Komlan A. KPOGO-NUWOKLO, Henning W. RUST, Uwe ULBRICH, Christos VAGENAS and Edmund MEREDITH

Institut für Meteorologie, Freie Universität Berlin, Berlin, Germany

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- Systematic biases in the Regional Climate Models

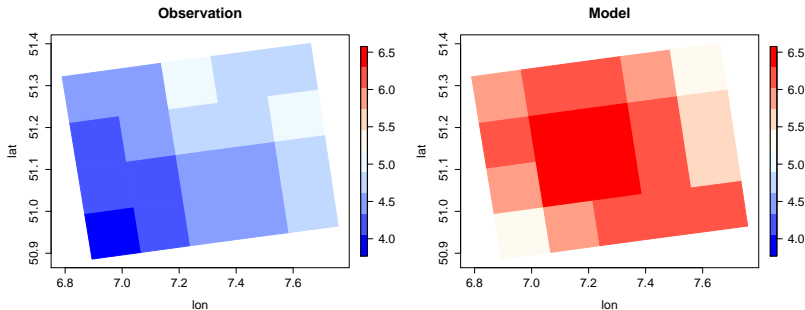
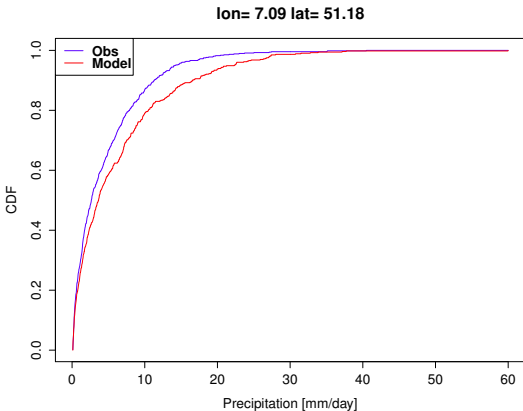


Figure: Mean of daily precipitation (mm/day) at Wupper catchment (case of July)

- Difference in the distribution



- Need to correct the whole distribution and not only the mean



## Existing bias correction methods



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### Mean-based approaches

- Linear scaling [*Lenderink et al., 2007*]
- Local intensity scaling [*Schmidli et al., 2006*]
- Variance scaling [*Leander and Buishand, 2007*]
- Power transformation (for precipitation) [*Chen et al., 2013*]



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- Power transformation (for precipitation) [*Chen et al., 2013*]

### Distribution-based approaches

- Quantile-mapping [*Panofsky and Brier, 1968*]
- CDF-Transform [*Michelangeli et al., 2009*]



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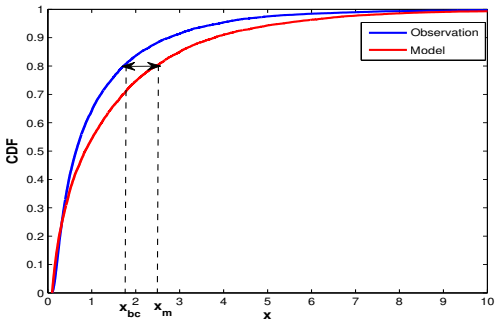
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## Quantile-mapping

- $F_o \rightarrow$  CDF of observations
- $F_m \rightarrow$  CDF of model output

$$F_o(x_o) = F_m(x_m) \implies x_{bc} = F_o^{-1}[F_m(x_m)]$$



- Quantile-mapping can be used with both empirical and parametric CDF





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Example:

- Model output → 1980 – 2026 (historical+future)
- Observations → 1980 – 2016 (historical)

QQ-mapping → CDF observations (1980 – 2016) = CDF observations (1980 – 2026)



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Example:

- Model output → 1980 – 2026 (historical+future)
- Observations → 1980 – 2016 (historical)

QQ-mapping → CDF observations (1980 – 2016) = CDF observations (1980 – 2026)

- Quantile mapping does not take into account any information on the distribution of the future modelled dataset

## CDF-Transform

	Historical period	Future period
Observation	$F_{o,h}(x)$	$F_{o,f}(x)$
Model	$F_{m,h}(x)$	$F_{m,f}(x)$



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- If it is possible to estimate  $F_{o,f}$ , then future model output can be corrected through quantile-mapping:

$$x_{bc} = F_{o,f}^{-1}[F_{m,f}(x)]$$



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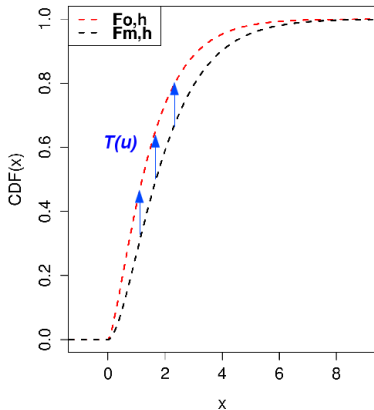
$$x_{bc} = F_{o,f}^{-1}[F_{m,f}(x)]$$

How can we approximate  $F_{o,f}$ ?



## A solution to approximate $F_{o,f}$

	Historical period	Future period
Observation	$F_{o,h}(x)$	$F_{o,f}(x)$
Model	$F_{m,h}(x)$	$F_{m,f}(x)$



- $T: [0, 1] \rightarrow [0, 1]$ ,

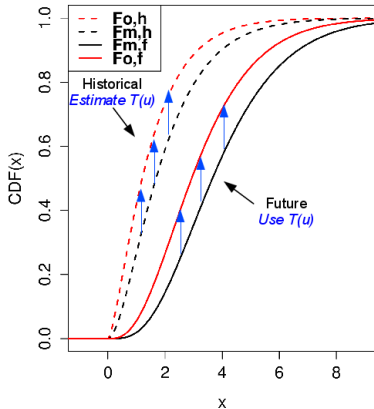
$$T(F_{m,h}(x)) = F_{o,h}(x) \quad (1)$$





## A solution to approximate $F_{o,f}$

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Observation	$F_{o,h}(x)$	$F_{o,f}(x)$
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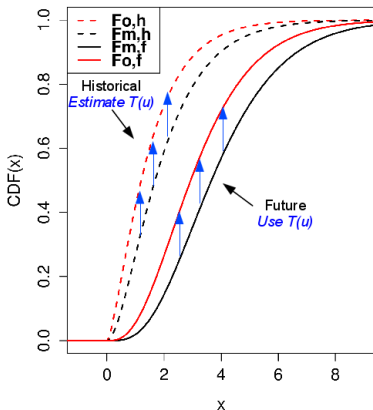
$$T(F_{m,h}(x)) = F_{o,h}(x) \quad (2)$$

$$T(F_{m,f}(x)) = F_{o,f}(x) \quad (3)$$



## A solution to approximate $F_{o,f}$

	Historical period	Future period
Observation	$F_{o,h}(x)$	$F_{o,f}(x)$
Model	$F_{m,h}(x)$	$F_{m,f}(x)$



- $T: [0, 1] \rightarrow [0, 1]$ ,

$$T(F_{m,h}(x)) = F_{o,h}(x) \quad (4)$$

$$T(F_{m,f}(x)) = F_{o,f}(x) \quad (5)$$

$T$  is modelled by replacing  $x$  by  $F_{m,h}^{-1}(u)$ ,

$$T(u) = F_{o,h}(F_{m,h}^{-1}(u)) \quad (6)$$

ans thus,

$$F_{o,f}(x) = F_{o,h}(F_{m,h}^{-1}(F_{m,f}(x))) \quad (7)$$

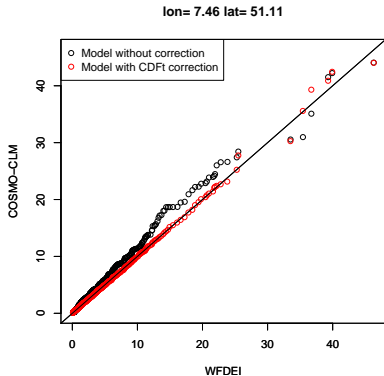
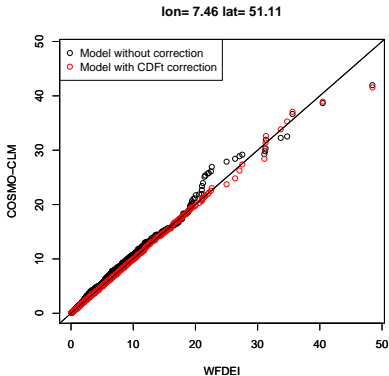


## Application

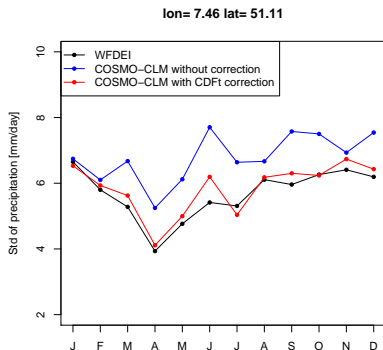
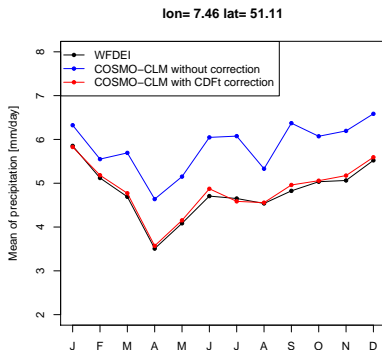
- Wupper catchment (Germany)
- Model output from COSMO-CLM (1979-2015)
- WFDEI used as reference data (1979-2013)

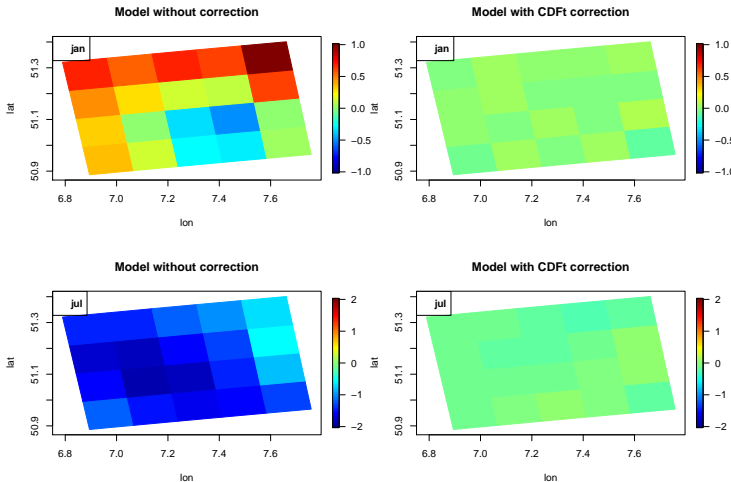


## QQplot of daily precipitation (mm/day): January (left) - July (right)



## Monthly mean (left) and standard deviation (right) of daily precipitation



Deviation in the mean [ $Mean(reference) - Mean(model)$ ] for January and July



## Bias correction for decadal climate predictions with CDF-t

- Goal:** Bias correction of daily MiKlip decadal predictions ( spatial resolution =  $0.11^\circ$  )

	Historical (1979-2014)	Future (2015-2004)
MiKlip	$F_h^{(M11)}$	$F_f^{(M11)}$
WATCH	$F_h^{(W11)}$	$F_f^{(W11)}$

$$\text{CDF-t} \implies F_f^{(W11)}(x) = F_h^{(W11)} \left\{ F_h^{(M11)-1} \left[ F_f^{(M11)}(x) \right] \right\}$$



## Bias correction for decadal climate predictions with CDF-t

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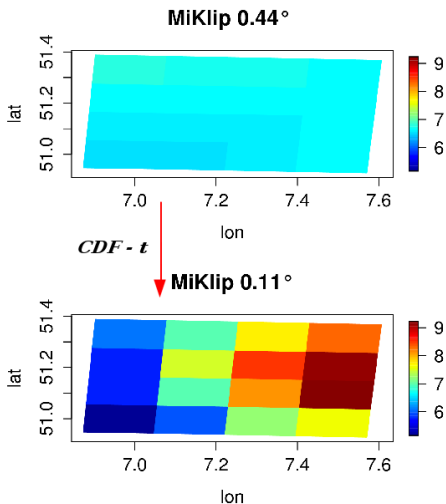
	Historical (1979-2014)	Future (2015-2004)
MiKlip	$F_h^{(M11)}$	$F_f^{(M11)}$
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$$\text{CDF-t} \implies F_f^{(W11)}(x) = F_h^{(W11)} \left\{ F_h^{(M11)-1} \left[ F_f^{(M11)}(x) \right] \right\}$$

- **Problem:** MiKlip historical simulations are only available for spatial resolution of  $0.44^\circ$



## Use CDF-t as statistical downscaling method





## Summary

- Compared to the quantile-mapping, CDF-t has advantage to take into account the change in the distribution for the future period
- Satisfactory results are obtained with CDF-t
- CDF-t can be used for statistical downscaling
- Need of reliable multivariate and spatial bias correction methods

# References I



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THANK YOU FOR YOUR ATTENTION

## Future simulation CDFs off the range of the historical ones

$$F_{o,f}(x) = F_{o,h}(F_{m,h}^{-1}(F_{m,f}(x)))$$

