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COASTAL COMPOUND FLOODING AND THE ROLE OF INTERNAL CLIMATE VARIABILITY

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Western University · Canada

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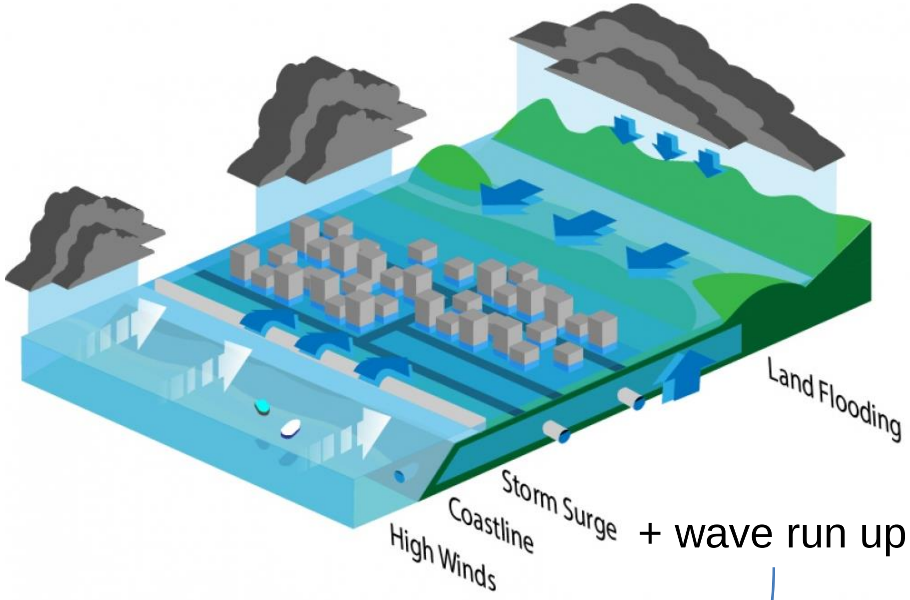
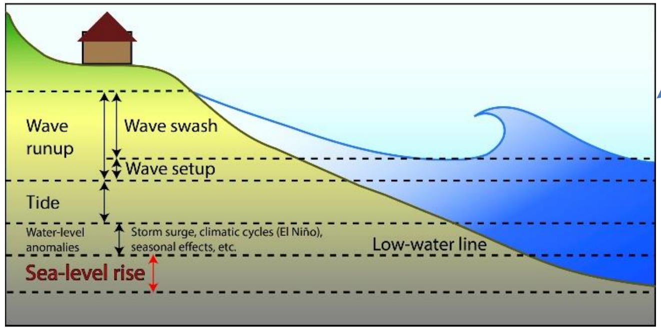
Canada

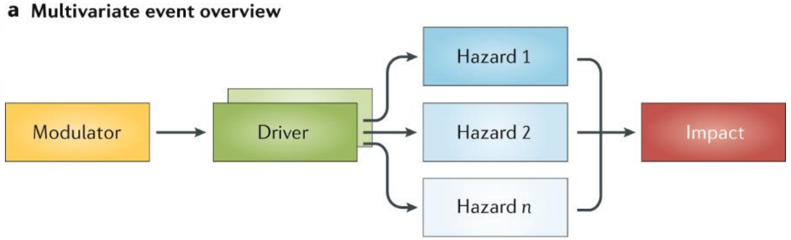
CONTENTS

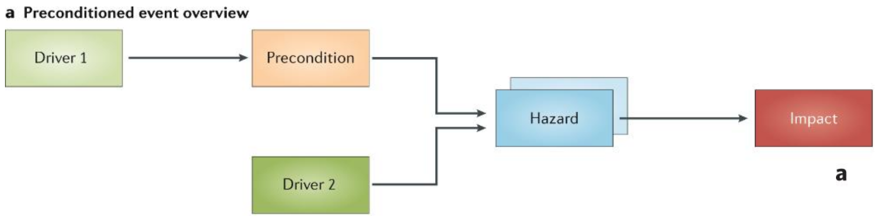
COASTAL COMPOUND FLOODING



+ wave run up



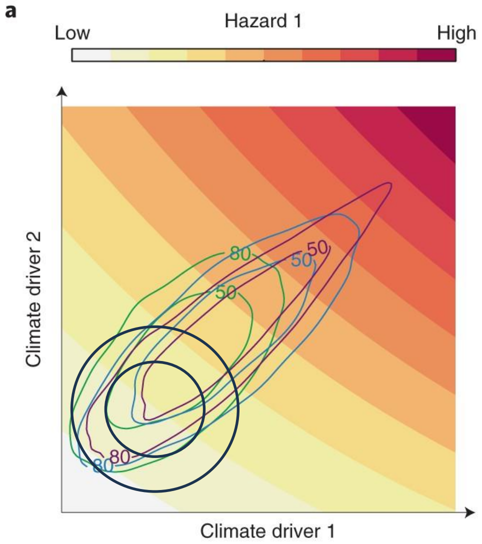




(Zscheischler et al, 2020)

Other types: temporally & spatially compounding events

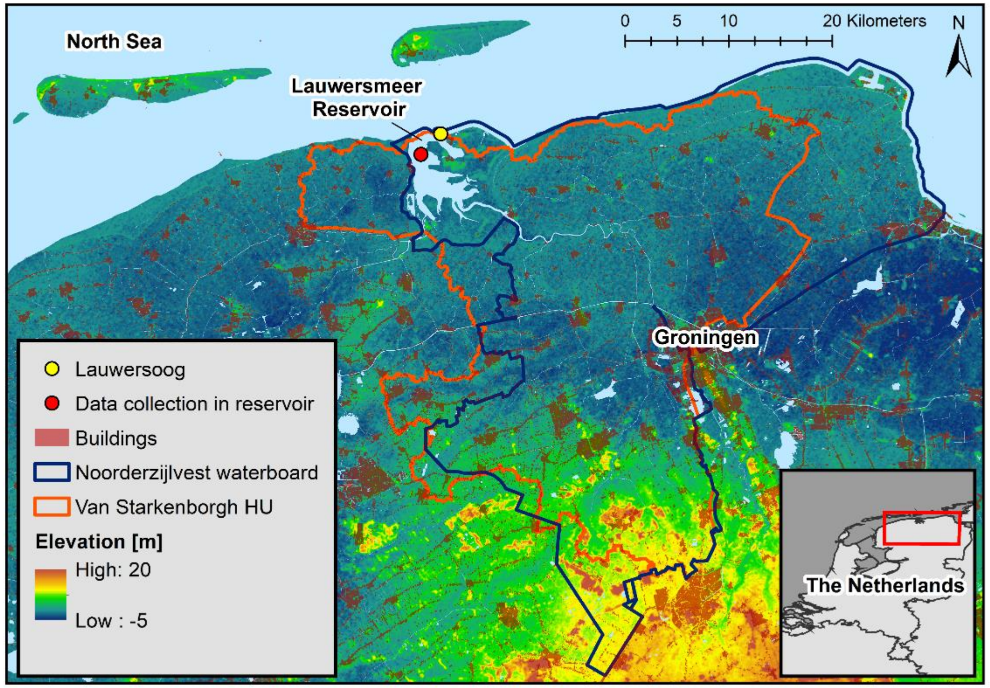
Drivers usually exhibit dependences



(Adapted from Zscheischler et al, 2018)

COASTAL MANAGED RESERVOIR STUDY

MOTIVATION



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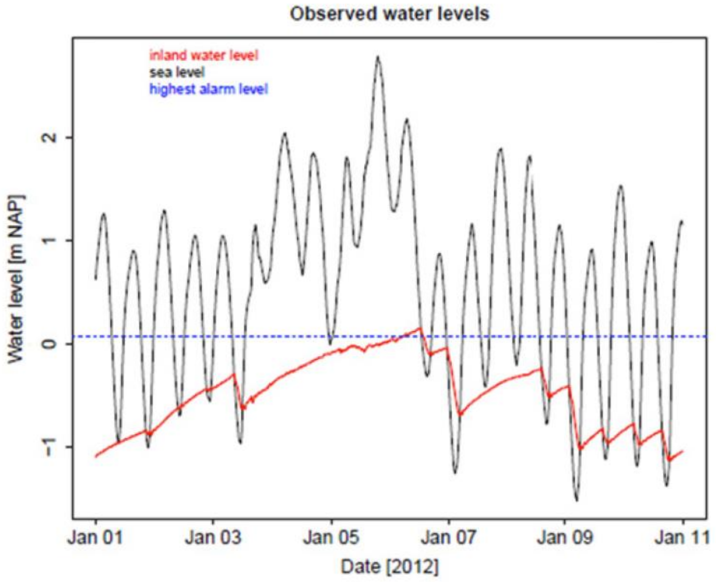
Hydrology and Earth System Sciences

Statistical modelling and climate variability of compound surge and precipitation events in a managed water system: a case study in the Netherlands

Víctor M. Santos[1,2,★], Mercè Casas-Prat[3,★], Benjamin Poschlod[4,★], Elisa Ragno[5], Bart van den Hurk[6], Zengchao Hao[7], Tímea Kalmár[8], Lianhua Zhu[9], and Husain Najafi[10]

Near-flooding event in 2012



(van den Hurk et al., 2015)

Resulted from combination of mild/extreme weather conditions.
A series of low-pressure systems caused:

- >60 mm rain accumulated (5 days).
- Soil was already saturated.
- Storm surge impeding drainage over 5 tidal periods.

COASTAL MANAGED RESERVOIR STUDY

DATASETS

Environmental Research Letters

LETTER (van den Hurk et al., 2015)

Analysis of a compounding surge and precipitation event in the Netherlands

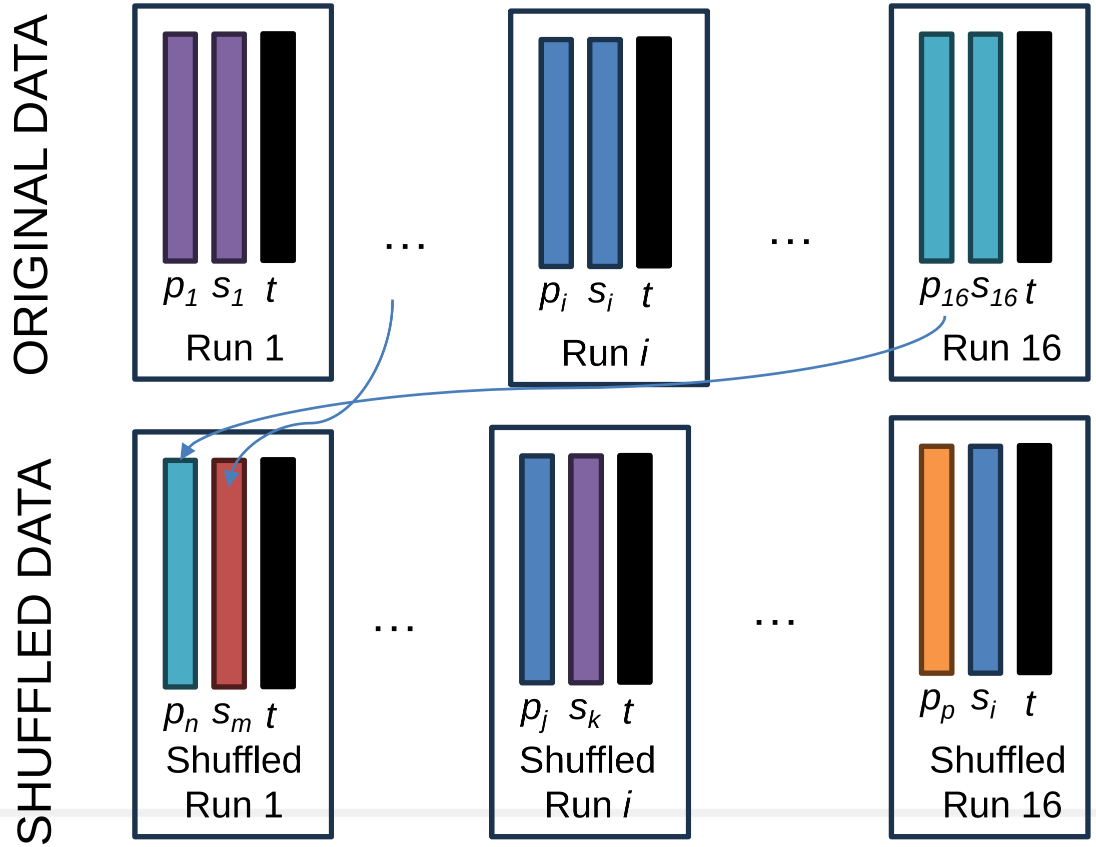
<u>Regional climate model (RACMO – EC-EARTH) SMILE</u>
(Single Model Initial Condition Large Ensemble)

16 realizations 1950-2000 (50 years each)
= **800 years**

Precipitation, surge, tides
(surge was obtained empirically from wind)

<u>Hydrological model (RTC-Tools)</u>

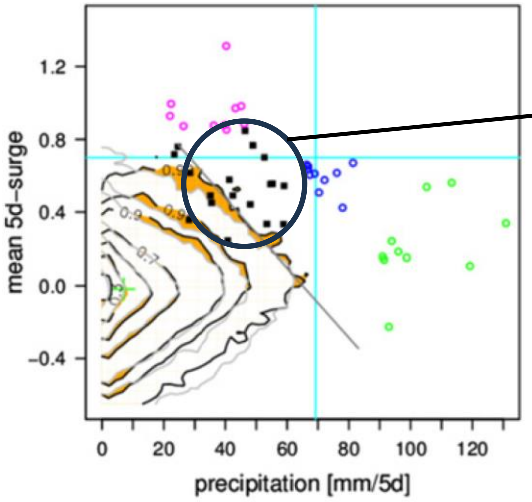
Inland water level



X 10 times

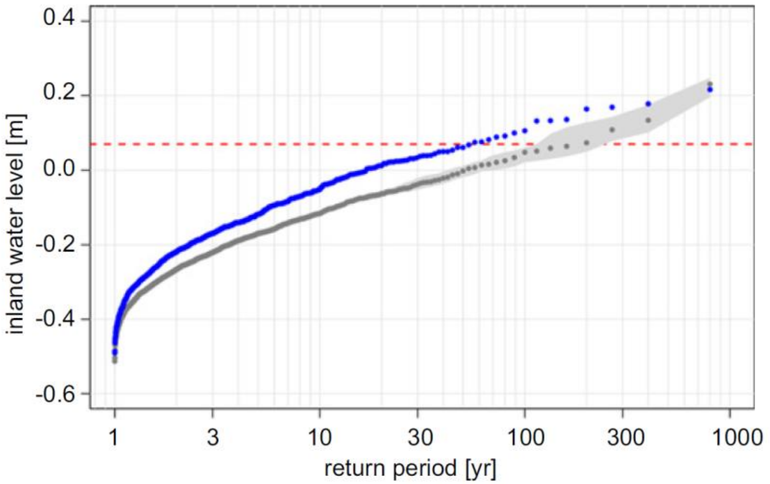
Any dependence is eliminated in the Shuffled data

COASTAL MANAGED RESERVOIR STUDY



Associated to largest WL

Increased probability due to positive dependence



Original data

Shuffled

Extreme water level are not associated with most extreme surge/precipitation events

Empirical analysis shows positive dependence between surge & precipitation leading to large water levels

This positive dependence leads to lower return periods for a given WL

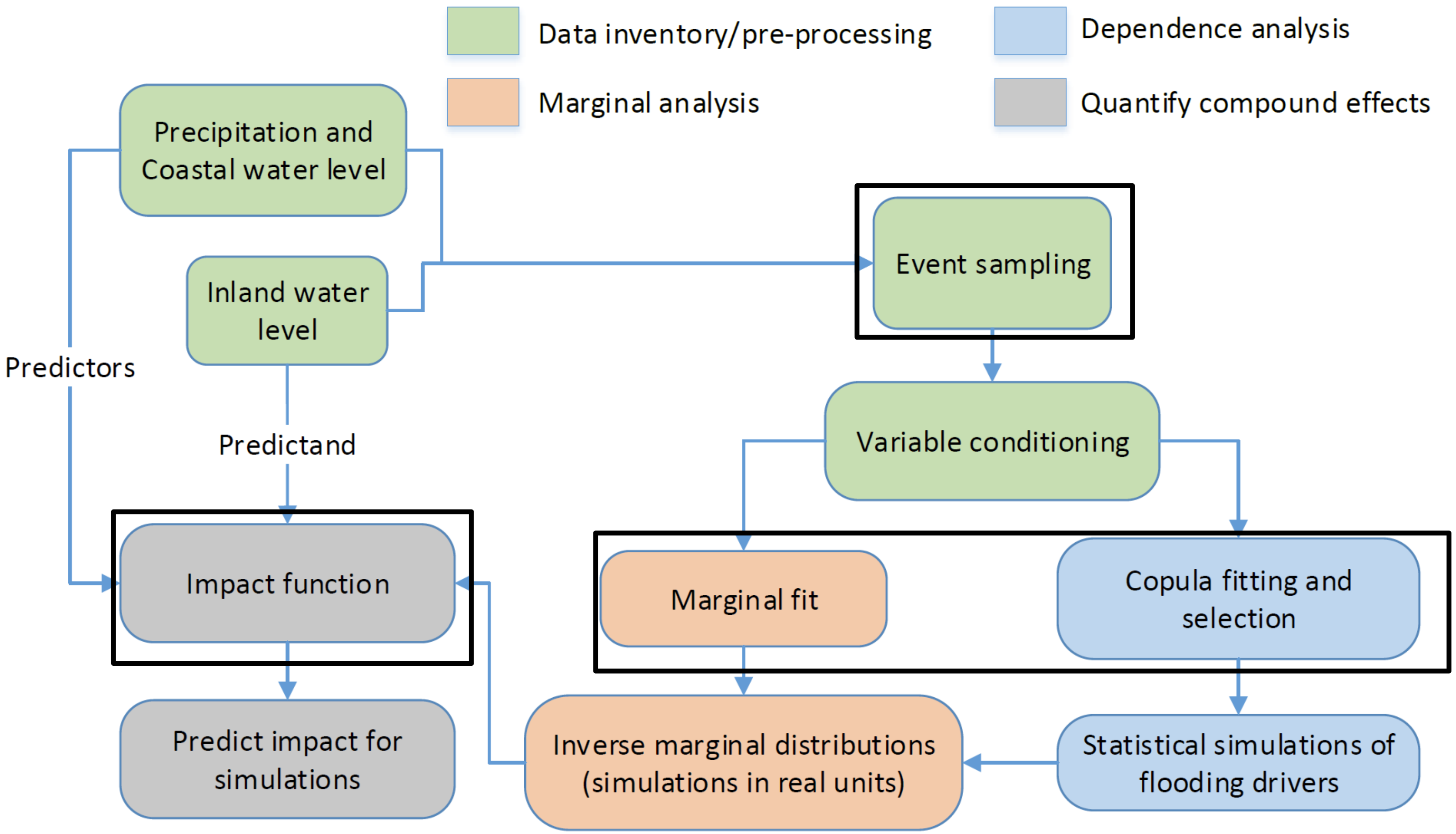
<u>Question:</u>

?

How do these dependencies & return level extend beyond 800 years?

Statistical modelling framework

STATISTICAL MODELLING FRAMEWORK



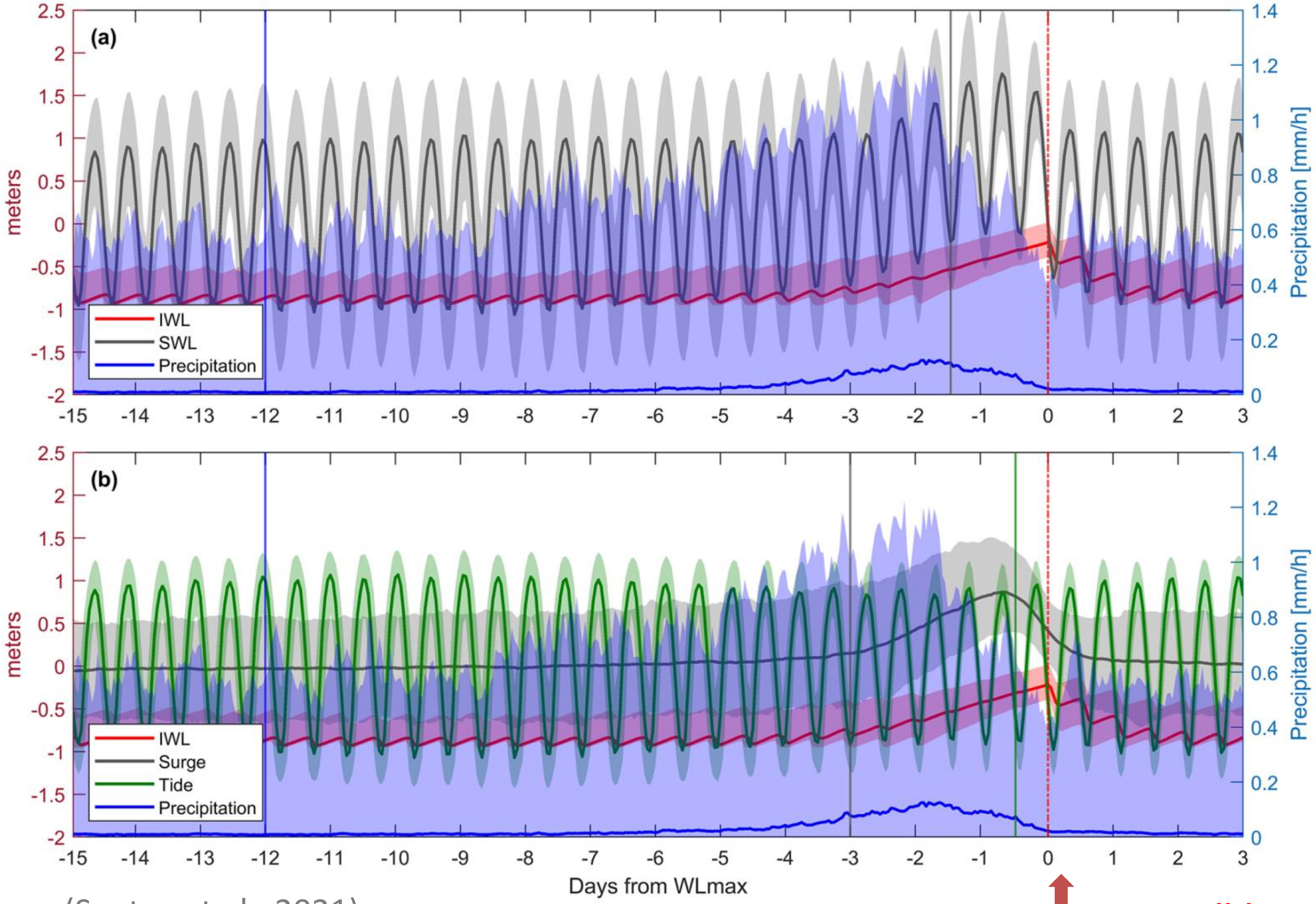
<u>Event sampling</u>

It is non-trivial to decide what combination of surge and precipitation leads to high water levels. The objective of this step is to identify precipitation, surge and tide predictors that explain most of the dependence structure and can be used to explain large water levels. Event sampling affects impact function and marginal/copula

Iterative process

EVENT SAMPLING

We used compositional analysis as a tool to identify potential candidates of predictors



(Santos et al., 2021)

2D

Water levels optimally explained by:

- Precip. (12 days);
- Min. coastal (still) WL (36 hours)

3D

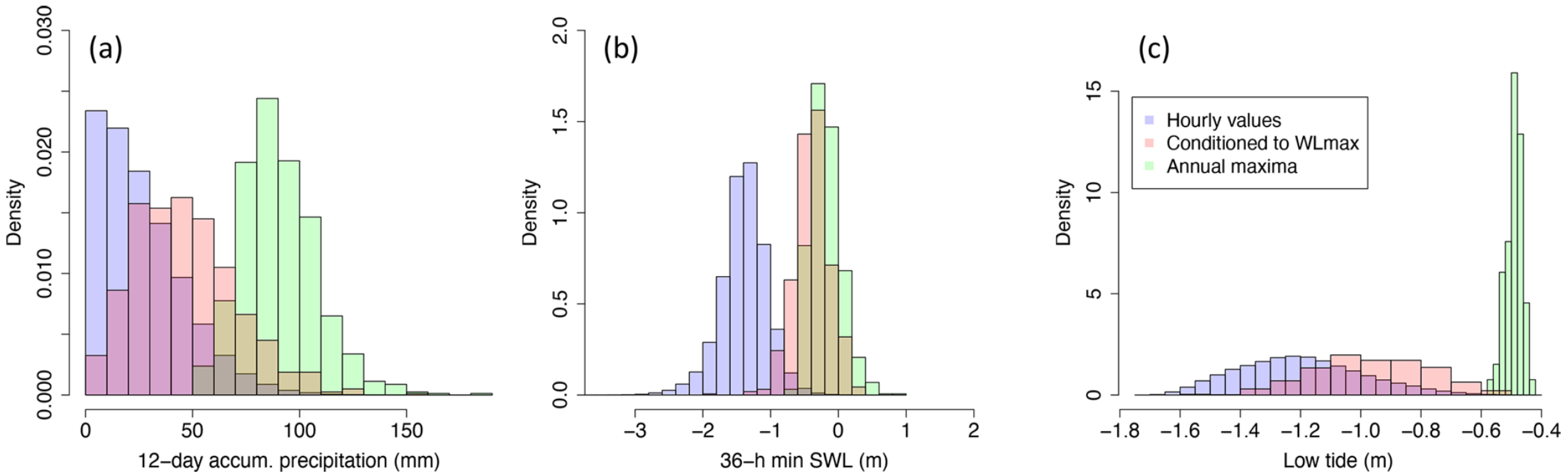
Water levels optimally explained by:

- Precip. (12 days);
- Mean Surge (36 hours)
- Min. tide (12 hours)

Conditioned to Annual max WL

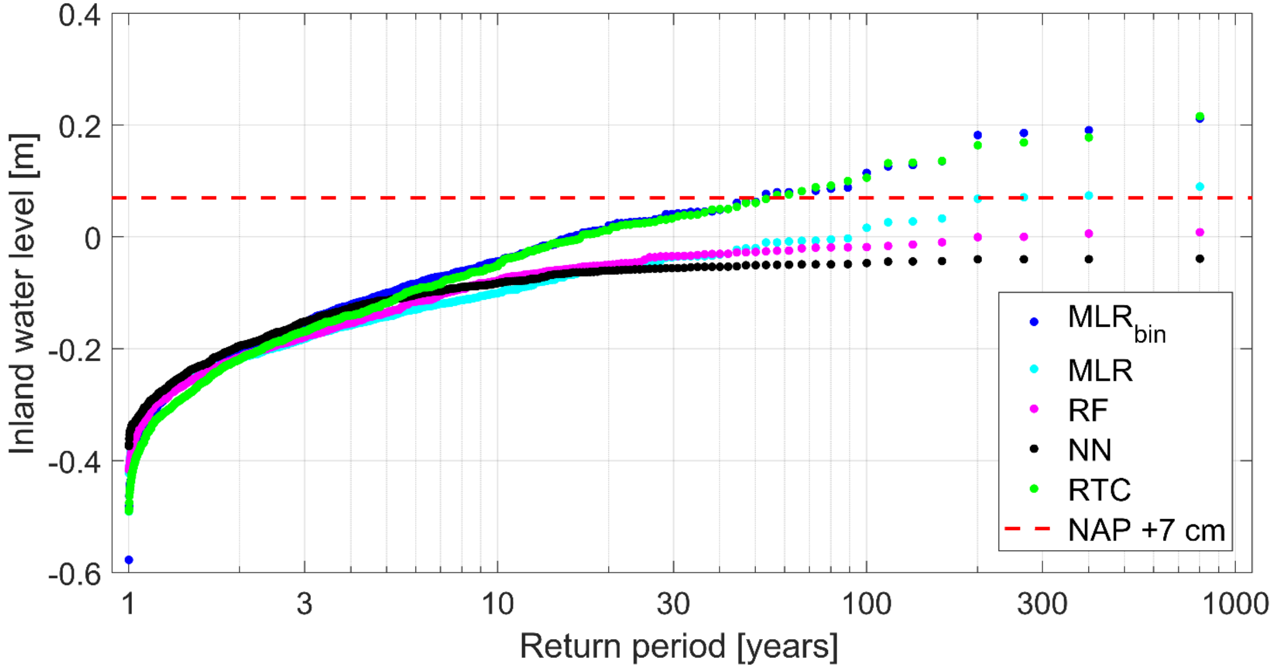
MARGINAL DISTRIBUTIONS

PRECIPITATION SURGE TIDES



This confirms that extreme water levels are not associated with the largest surge/precipitation. Extreme surges (which impede drainage) seem to be more relevant.

IMPACT FUNCTION

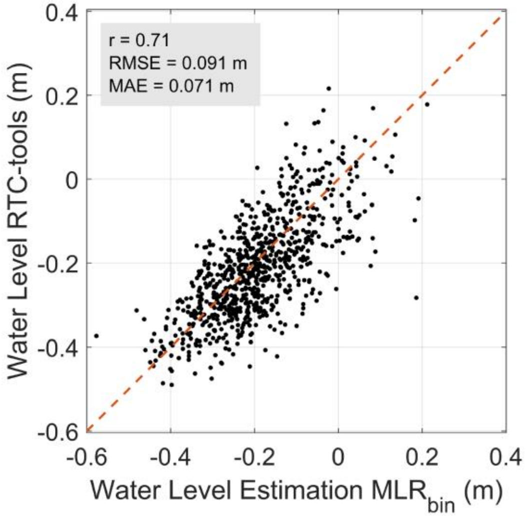


We tested different approaches, from multilinear regression (MLR) to machine learning approaches such as random forest. They all failed to capture largest water levels.

Problem: most data includes low to mild events, which explains the underestimation of extremes.

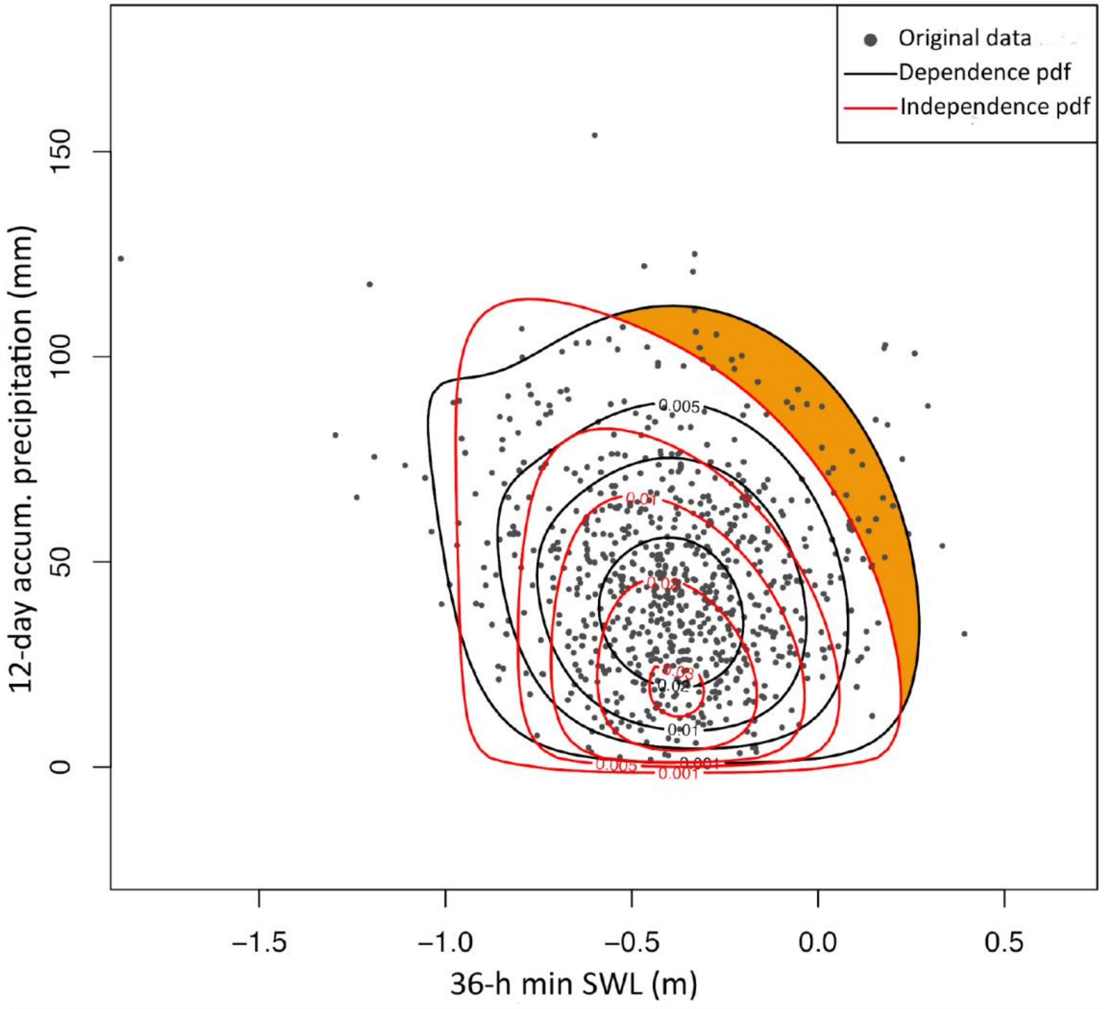
Table 2. Distribution of the bin-sampling classes.

bin	WL1	WL2	WL3	WL4	WL5	WL6	WL7	WL8	WL9	WL10	WL11	WL12
WL (m)	<-0.4	(-0.4,-0.35)	(-0.35,-0.3)	(-0.3,-0.25)	(-0.25,-0.2)	(-0.2,-0.15)	(-0.15,-0.1)	-(0.1,-0.05)	(-0.05,0)	(0 0.05)	(0.05,0.1)	>0.1
# samples	31	55	109	122	136	123	82	63	32	27	11	9



Solution: Implement a **<u>bin-sampling approach</u>** to calibrate MLR with samples with equal distribution across bins (10 data points per bin). This is repeated 1000 times via boostrapping and the final coefficients are averaged from these 1000 fits.

JOINT PROBABILITY DISTRIBUTION



$$f_{XY}(x,y) = C[F_X(x), F_Y(Y)]f_X(x)f_Y(y)$$

Copula fitting: 40 possible Vine copulas. Select one with lowest Akaike information criterion AIC). Result: Rotated Tawn type-I copula with tau=-0.05

Comparison with shuffled (uncorrelated) data shows that the joint probability distribution has larger co-occurrence probability for original data.

Surprisingly, correlation for shuffled data is not zero, and it is negative for the original data.

Are the drivers (surge, precipitation) negatively correlated?

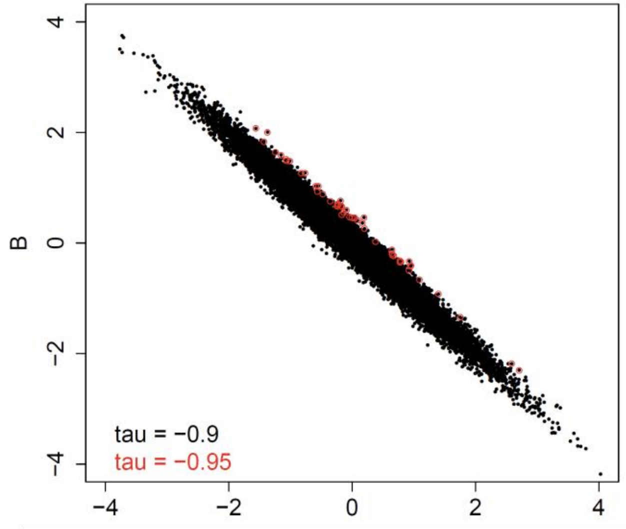
DEPENDENCE FOR IMPACT-CONDITIONED DRIVERS

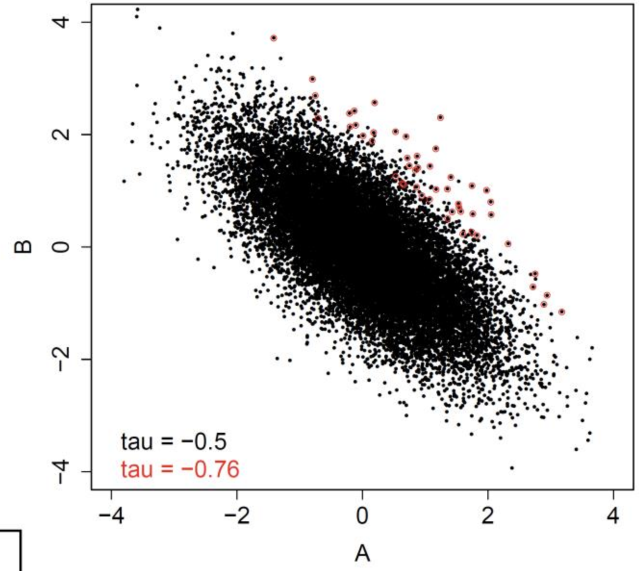
Drivers A & B, leading to impact I (I = A + B)

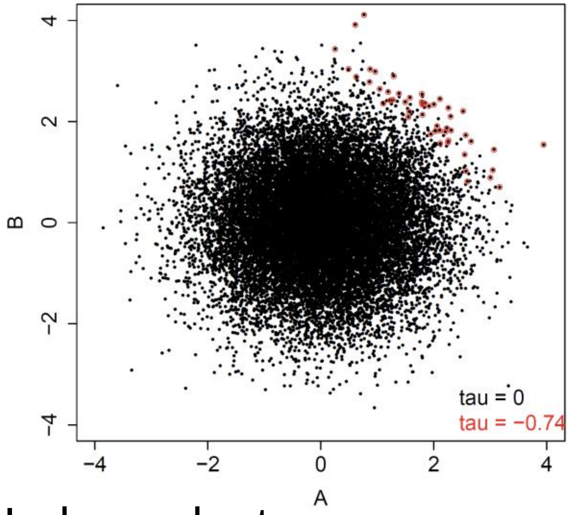
Predictors: A & B conditioned to annual maximum I

If drivers have positive contribution to impact, positive dependence between drivers is not necessarily reflected in positive dependence between impact-conditioned predictors. Dependence ≠ correlation

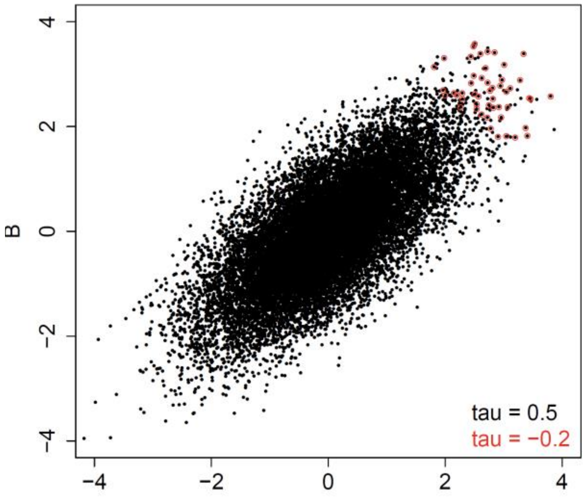
Comparison against case of zero dependence can help determine whether dependence between drivers is positive or negative.

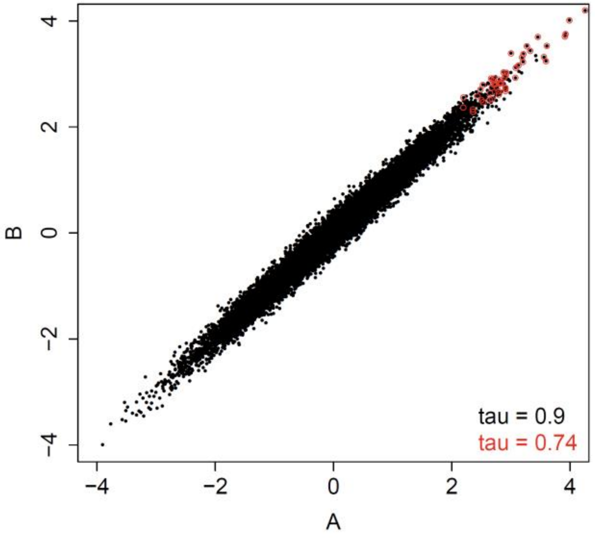




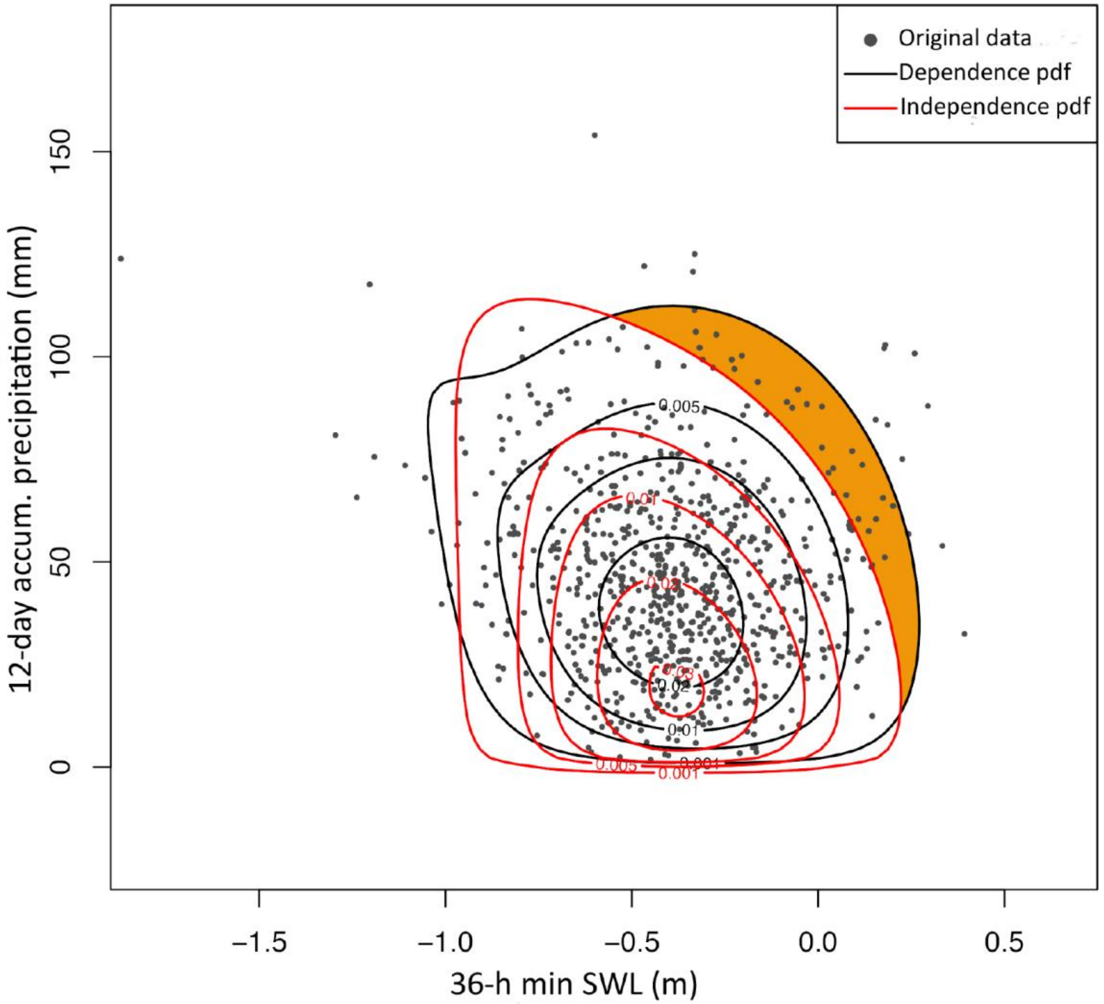


Independent case





JOINT PROBABILITY DISTRIBUTION



$$f_{XY}(x,y) = C[F_X(x), F_Y(Y)]f_X(x)f_Y(y)$$

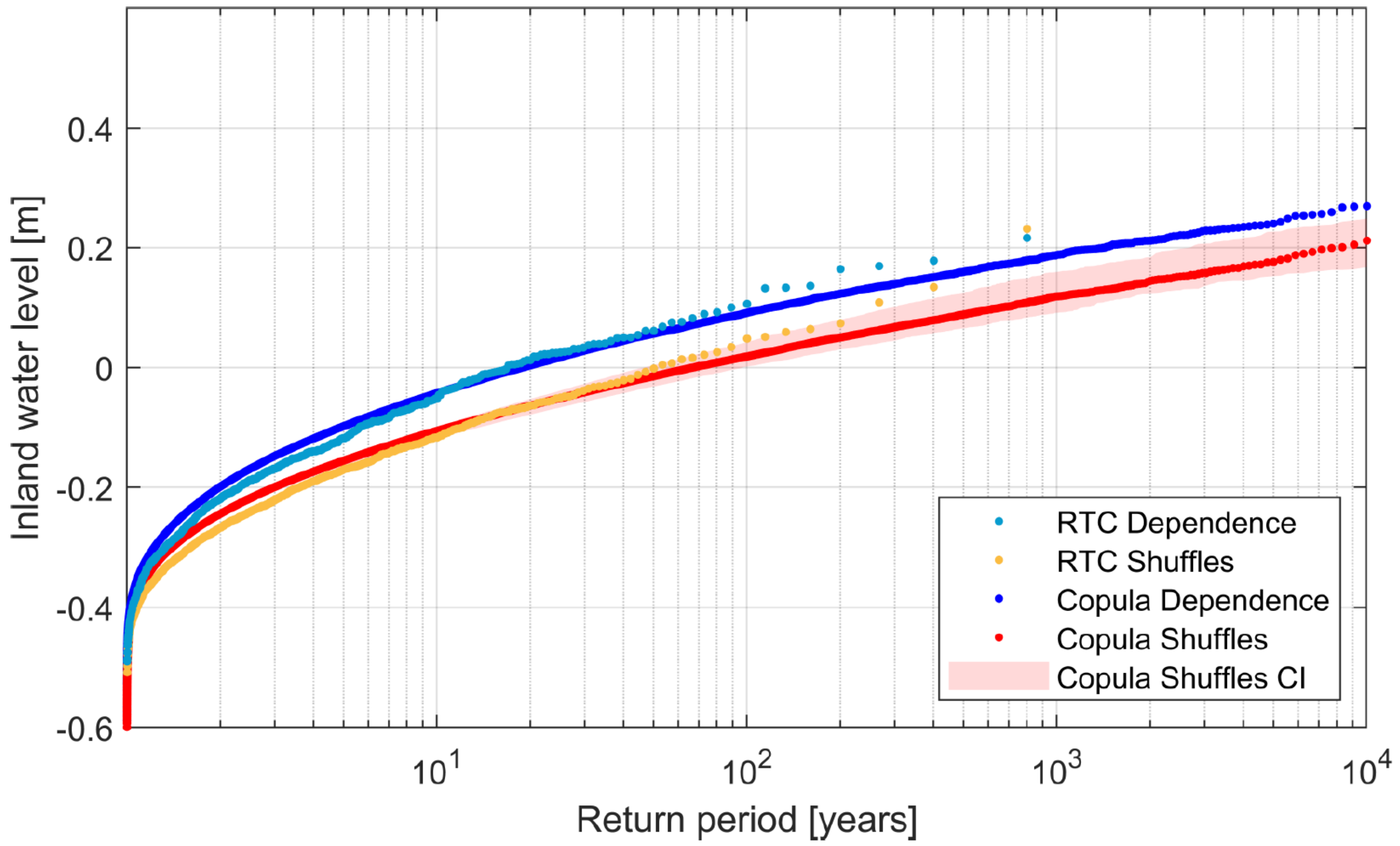
Copula fitting: 40 possible Vine copulas. Select one with lowest Akaike information criterion AIC). Result: Rotated Tawn type-I copula with tau=-0.05

Comparison with shuffled (uncorrelated) data shows that the joint probability distribution has larger co-occurrence probability for original data.

Surprisingly, correlation for shuffled data is not zero, and it is negative for the original data.

Are the drivers (surge, precipitation) negatively correlated? **No!**
Shuffled predictors have a correlation of -0.15, which is even more negative than -0.05, meaning drivers in original data have positive dependence.

RETURN LEVELS



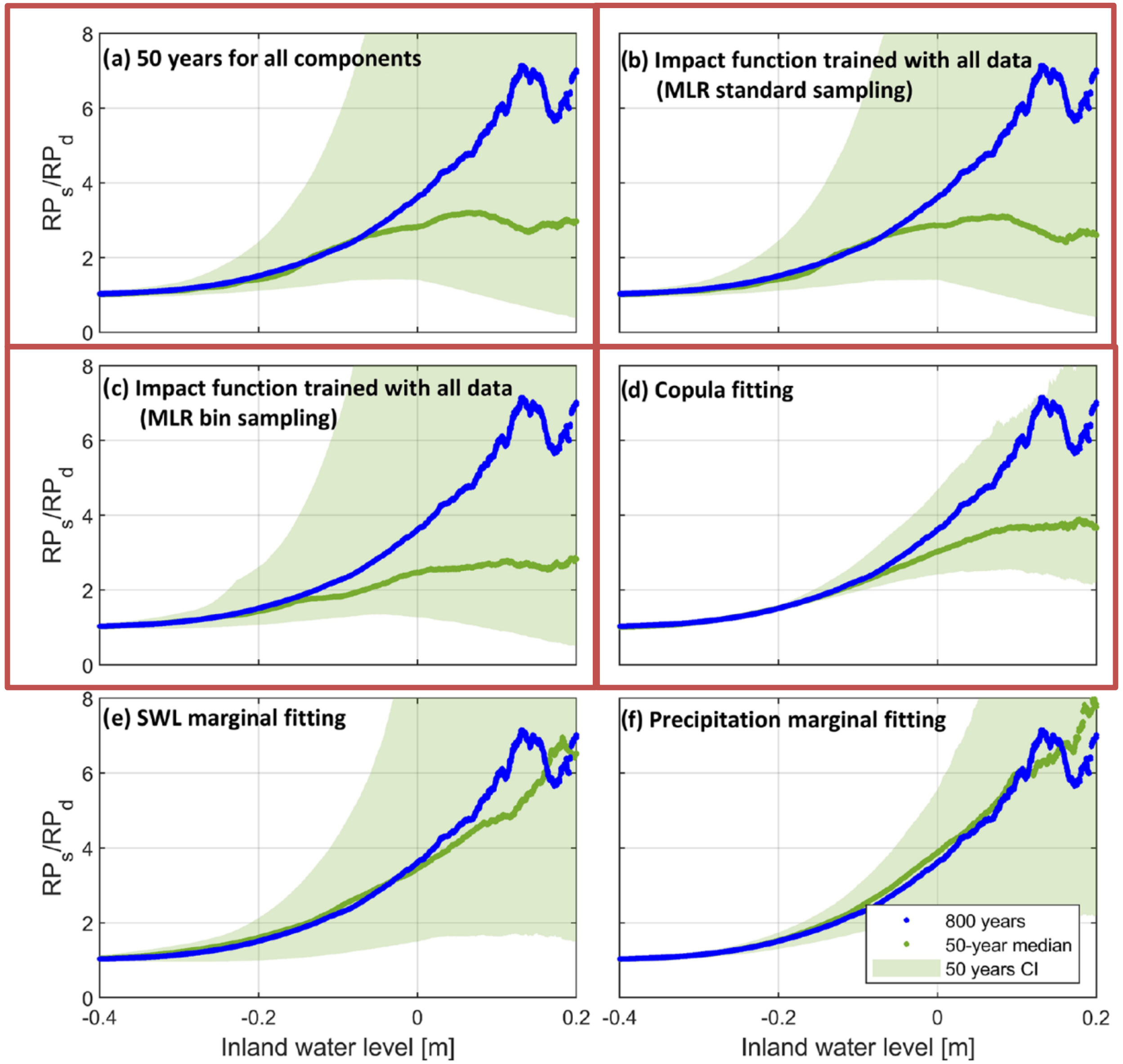
THE ROLE OF INTERNAL CLIMATE VARIABILITY

We use **50 years of data** (instead of **800 years**) for different parts of the statistical framework, and assess the impact on **Return Period Ratio** (= Increased probability due to compound effect)

	50-year runs			
Subpanels	Impact function	Copula	SWL PDF	Precipitation PDF
a	x	x	x	x
b		x	x	x
c		x	x	x
d		x		
e			x	
f				x

* Impact function based on MLR with standard sampling; i.e. the bin-sampling approach is not implemented.

	800-year ensemble			
Subpanels	Impact function	Copula	SWL PDF	Precipitation PDF
a				
b	x*			
c	x			
d	x		x	x
e	x	x		x
f	x	x	x	



(Santos et al., 2021)

CONCLUSIONS

- We studied a multivariate compound event with preconditioning.
- The proposed statistical framework captures compound flooding processes robustly for the study area. This framework can be applied to other areas, but simulations of drivers and impact are needed to fit the marginals/copula and calibrate the impact function.
- Compositional analysis is a useful tool to define/identify compound events.
- For the study area, we obtain that the dependence structure between surge and precipitation that led to the near flooding event in 2012 event occurs >4 times more frequent in average due to dependence between precipitation and surge. Therefore, these cannot be considered independent.
- The interpretation of dependence measures for impact-conditioned predictors is counterintuitive. Zero correlation does not necessarily mean independence (or negative correlation does not necessarily mean negative dependence). One possible way to interpret this is to stablish a reference independent case.
- It is important to calibrate the impact function with a focus on extremes.
- Internal climate variability can be a significant source of uncertainty. Using 50-year time series might not be enough to capture relationship between drivers and impact, and the compound effects, as shown for the study area.

Thanks! Questions?