Lecture 2a
Compound weather and climate events:

Impacts

Bart van den Hurk (Deltares)
What causes extreme impacts?

› Generally very difficult to determine
What causes extreme impacts?

› Generally very difficult to determine
› Typically multiple causes – what are the most important ones?
› Requires “backward assessment” / “bottom-up assessment”
› Very common in vulnerability assessment, e.g. when analyzing causes of individual disasters (“poor man’s analysis”)
› But: difficult to generalize from individual events
› how to derive general relationships?
Forward and backward assessment

Drivers
- Detect extremes

Forward assessment

Responses
- Analyze impacts
Applicable methods

› Variable selection
› Compositing/Superposed Epoch Analysis (SEA)
› Classification
› Factorial model simulations
› ...

Diagram: Analyze causes → Backward assessment → Detect extremes
Impact varies with combination of drivers
e.g. human heat stress
Extreme drivers vs. extreme impacts

Van der Wiel et al. (subm.)
Examples

› Climate drivers of the 2016 yield failure in France
Yield anomalies in France

Ben-Ari et al. (2018) Nature Communications
Climate conditions in 2016

Ben-Ari et al. (2018) Nature Communications
Logistic regression

\[
\text{logit}(p_i) = \beta_0 + \beta_1 x_i + \beta_2 x_i + \ldots
\]

Selected best predictor variables:

1) #days with Tmax between 0 and 10°C in December
2) November precipitation
3) Minimum June temperature
4) AMJJ precipitation
5) Interaction between 1) and 3)
6) Interaction between 3) and 4)
Examples

› Climate drivers of the 2016 yield failure in France
› Drivers behind disasters
Bottom-up assessment of disasters

Averaged over entire years and countries.

Tschumi & Zscheischler (in press) Climatic Change

Disaster data: EM-DAT
Climate data: CRU
Time period: 1950-2015
Relevance of vulnerability

- Climate anomalies during disaster years are larger in developed countries

- Climate anomalies in rich countries need to be very large to cause a disaster

Examples

› Climate drivers of the 2016 yield failure in France
› Drivers behind disasters
› Drivers of the 2010 Russian heatwave
Factorial model simulations

Hauser et al. (2016) Earth’s Future
Examples

- Climate drivers of the 2016 yield failure in France
- Drivers behind disasters
- Drivers of the 2010 Russian heatwave
- Coastal flood impacts (see next lecture)
Thank you
Lecture 2b
Compound weather and climate events: Coastal areas

Bart van den Hurk (Deltares)
The scientific attention on CF has increased recently...
Hydrological mechanisms causing CF

River confluences

- Germany, 2013. In Passau, from high discharges into the confluence of the rivers Danube, Inn and Ilz. [Wahl, 2018; Blschl, 2013]
- Italy, 2014. Between the river Parma and the Po: "the rain over the Parma basin was only justifying a moderate river level but..."
Hydrological mechanisms causing CF

**Coastal Compound Flooding:** Different weather/climate and topography can lead to different flooding mechanisms: [Wahl et al., 2015; Bevacqua et al., 2019]:

- In estuaries where river runoff and sea level may combine initiating or exacerbating flooding (e.g., due to a moderate storm surge)
Hydrological mechanisms causing CF

River confluences near to the coast

Combination of the previous two main mechanisms [Bevacqua et al., 2017].

Hydrologically non-interacting concurring extremes (Spatially compounding events)
The impacts resulting from concurrent flooding may combine non-linearly (e.g., if rescue teams are overloaded [Barton et al., 2016] [Martius et al., 2016]).
Data of the *contributing variables* to the CF

- Observations, often limited.

[CF in river estuaries: Ward et al., 2018]
How to quantify the actual CF water level?

(Sea level, Pluvial/fluvial flooding) → CF water level

- Explicit modelling of the CF water level: Combining sea and pluvial/fluvial levels via: hydrodynamical or statistical models.

- Considering the probability of potential CF.
Statistical modelling of the CF - Ravenna (Italy)

Multivariate stat. downscaling via \( f_{Y|X} \) (PCCs):

\[
(X_{23}, X_1)^{ERA} \rightarrow (Y_1, Y_2, Y_3)^{sim}
\]

\[
\rightarrow h^{sim} = h(Y_1, Y_2, Y_3)^{sim}
\]

Bevacqua et al. (2017), HESS
How to quantify the actual CF water level?

**Potential compound flooding**: if data from models or observations are not available, bivariate return periods:

- **OR** considers both CF and univariate flooding.
- **AND** allows for disentangling better CF.

Serinaldi, 2015
Analysing compound return periods

Example for Venice

$D_{FIT}$

$S_{95}$

$S_{99.7}$

$p_{95}$

$p_{99.7}$

1/yr level

5% highest values used for copula definition

Intermezzo: some info on copulas

Copula

A copula is the joint distribution of random variables, \( U_1, U_2, \ldots, U_p \), each of which is marginally uniformly distributed as \( U(0,1) \)

\[
C(u_1, u_2, \ldots, u_p) = P(U_1 \leq u_1, U_2 \leq u_2, \ldots, U_p \leq u_p)
\]

If the variables are independent

\[
C(u_1, u_2, \ldots, u_p) = u_1 \times u_2 \times \ldots \times u_p
\]
Intermezzo: some info on copulas

Joint cumulative density function

Copulas are useful because of Sklar’s Theorem:

For any $p$ random variables with joint cumulative density function (c.d.f.)

$$ F(x_1, x_2, \ldots x_p) = P(X_1 \leq x_1, X_2 \leq x_2, \ldots X_p \leq x_p) $$

and marginal c.d.f.s

$$ F_j(x) = P(X_j \leq x) j = 1,2,\ldots,p $$

there exists a copula such that

$$ F(x_1, x_2, \ldots, x_p) = C\{F_1(x_1), F_2(x_2),\ldots, F_p(x_p)\} $$

This allows us to separate the modeling of the **marginal distributions** from the **dependence structure**, which is expressed by the **copula**.
Intermezzo: some info on copulas

Joint probability density function

For any \( p \) random variables with joint cumulative density function (c.d.f.)

\[
    f(x_1, x_2, \ldots, x_p) = f_1(x_1)f_2(x_2) \cdots f_p(x_p) \cdot c\{F_1(x_1), F_2(x_2), \ldots, F_p(x_p)\}
\]

The pdf of the copula distribution can be seen as the adjustment needed to convert the independence pdf into the joint pdf
Intermezzo: some info on copulas

Classes of copulas

- Elliptical
  - Gaussian
  - Student-t
- Archimedian
  - Gumbel
  - Clayton
  - Frank
- Others

(J. Li, 2015)
Intermezzo: some info on copulas

Elliptical copulas

Gaussian copula
If the joint c.d.f. is a multivariate normal distribution, then the copula is Gaussian.

Student-t copula
If the joint c.d.f. is a multivariate t-distribution, then the copula is Student-t.

Archimedean copula

Gumbel
\[ C(u_1, u_2) = \exp\left(-[-\ln u_1]^{\theta} + [-\ln u_2]^{\theta}/\theta\right) \quad \theta \geq 1 \]

\[ \tau = \frac{\theta - 1}{\theta} \]

Clayton
\[ C(u_1, u_2) = \left((u_1)^{\theta} + (u_2)^{\theta} - 1\right)^{-1/\theta} \quad \theta > 1 \]

\[ \tau = \frac{\theta}{\theta + 2} \]

Classes of copulas

Frank
\[ -\infty < \theta < \infty \]

Joe
\[ \theta \geq 1 \]

Symmetric copula with a wide range of dependence parameter, can include negative correlation

Stronger right tail dependence
Configuration of compound coastal flood events

1/yr 1d precipitation and storm surge (ERA-int)

(A) 1-year return level of precipitation

(B) 1-year return level of sea level

Return time of 1/yr combined precipitation and storm surge

Return time of 1/yr combined precipitation and storm surge – climate change

Effect of change in compound structure

A Dependence-driven CF probability change
B Sea-driven CF probability change
C Precipitation-driven CF probability change

Present-day CF and storm tracks

- No CF around the equator

- Track density of extratropical cyclones

- Track density of tropical cyclones
Summary of the processes causing concurring $P_{ext}$ and $S_{ext}$

- Are there cyclones? Yes/No
- Do cyclones drive $P_{ext}$? Yes/No
- Does the same cyclone type drive $P_{ext}$ and $S_{ext}$? Yes/No

CF (co-occurring $P_{ext}$ and $S_{ext}$)  No CF (No co-occurring $P_{ext}$ and $S_{ext}$)

(In addition, astronomical tides.)
The compound nature of an hazard might "emerge" in the future due to climate change, which can modify the multivariate distribution of the actual drivers of an hazard (Bevacqua, 2018).
Extreme sea level rise

- Sea level rise may reduce return time of extremes considerably

SROCC (Fig 4.12)
Memory effects for combined river/surge
Memory effects for combined river/surge

Khanal et al. (2019) *Atmosphere*
Memory effects for combined river/surge

Khanal et al. (2019) *Atmosphere*
Memory effects for combined river/surge

Khanal et al. (2019) *Atmosphere*
Thank you