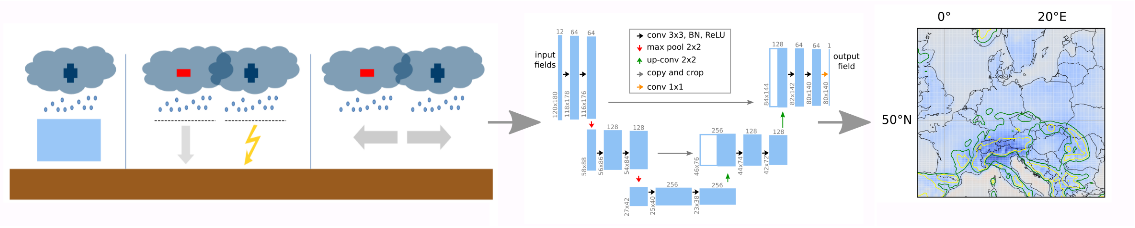

Causal DL models for studying relations in the Earth system

Impact of soil moisture changes on precipitation

ECMWF ML Workshop 2022 | Tobias Tesch, Stefan Kollet, Jochen Garcke | IBG-3, Forschungszentrum Jülich

JÜLICH Forschungszentrum

Motivation

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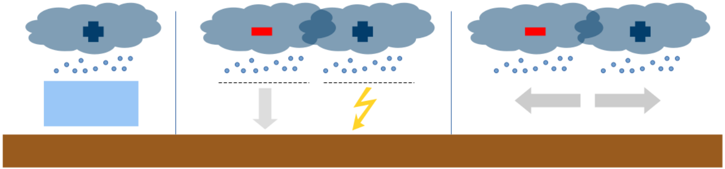
Different effects of soil moisture increases and their impact on precipitation (+/-).



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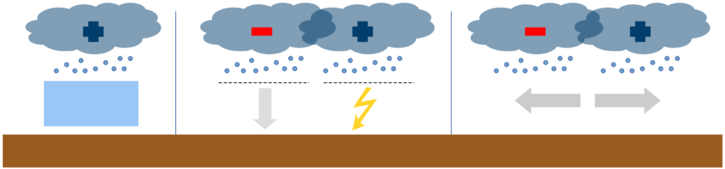

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⇒ Better understanding might improve precipitation prediction with numerical models.

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Combining DL and causality research, we can overcome these limitations!

Method

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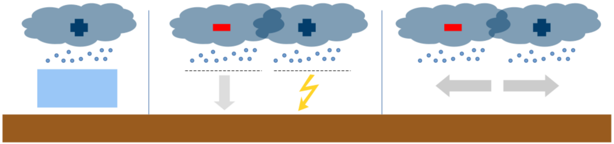

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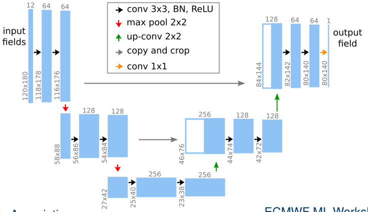

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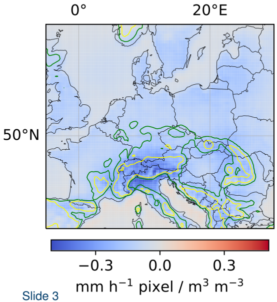

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Forschungszentrum

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- The right expectation contains this confounding effect.
- The left expectation does not, because the do-operator represents an intervention into the system that breaks the link between soil moisture and recent precipitation.

Causal deep learning model

Given a target variable $Y \in \mathbb{R}^n$, input variables $X \in \mathbb{R}^d$ and $\{C_i\}_{i=1}^k \in \mathbb{R}^{d_i}$, and a suitable loss function, a DL model approximates the map

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We can obtain a causal DL model by choosing suitable additional input variables C_i, because then it holds

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Causal deep learning model

Theorem

Pearl[1]: "For multivalued variables X and Y, finding a sufficient set S of multivalued variables $C_i \in \mathbb{R}^{d_i}, i = 1, \ldots, k$, permits us to write

$$\mathbb{E}[Y|do(X = x), \{C_i = c_i\}_{i=1}^{k}] = \mathbb{E}[Y|X = x, \{C_i = c_i\}_{i=1}^{k}]. \text{"} \tag{1}$$

Sufficient set:

- "no element of S is a descendant of X",
- "the elements of S block all back-door paths from X to Y, namely all paths that end with an arrow pointing to X".

[1] Pearl, J. "Causal inference in statistics: An overview." Statist. Surv. 3, 96, 2009.

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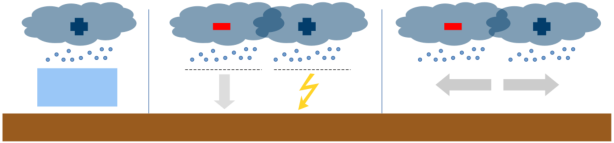

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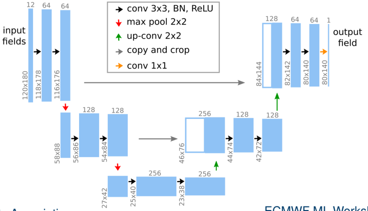

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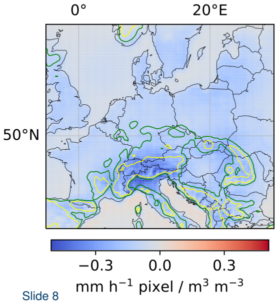

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- From step 2, we have a causal DL model, i.e. a DL model that approximates the map
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- To answer how Y_{i_1} changes on average if we intervened into the system and changed X_{i_2}, we consider the expected value of $s_{i_1 i_2}$ w.r.t. the joint distribution of X and $\{C_i\}_{i=1}^k$

$$\overline{s_{i_1 i_2}} = \mathbb{E}_{x, \{c_i\}_{i=1}^k}[s_{i_1 i_2}] = \mathbb{E}_{x, \{c_i\}_{i=1}^k}\left[\frac{\partial \mathbb{E}[Y_{i_1}|do(X = x), \{C_i = c_i\}_{i=1}^k]}{\partial X_{i_2}}\right].$$

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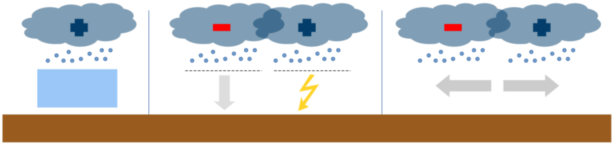

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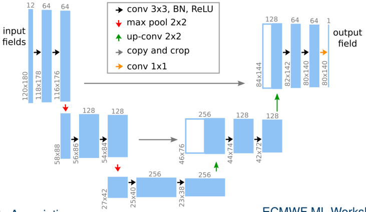

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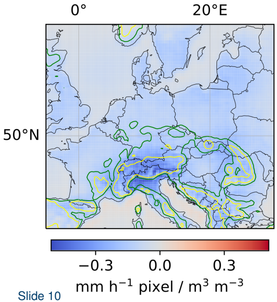

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Train a causal DL model to predict one variable given the other

Given soil moisture[t] and further variables[t] , which approximate a sufficient set, at the 120x180 pixels in the input region,

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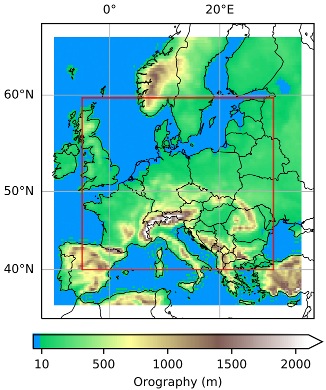

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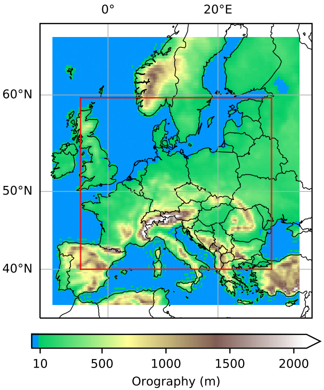

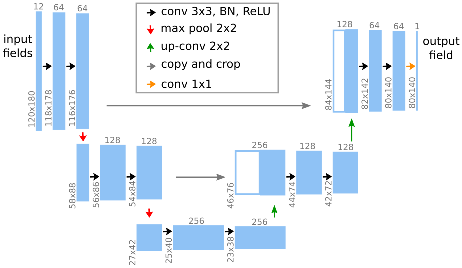

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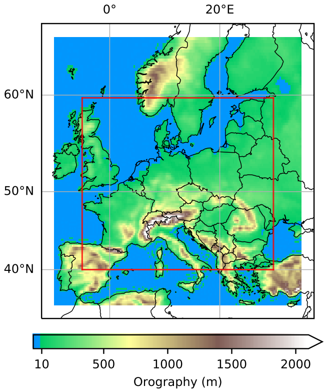

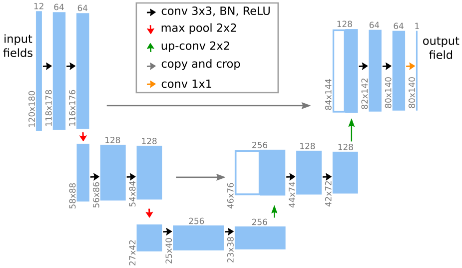

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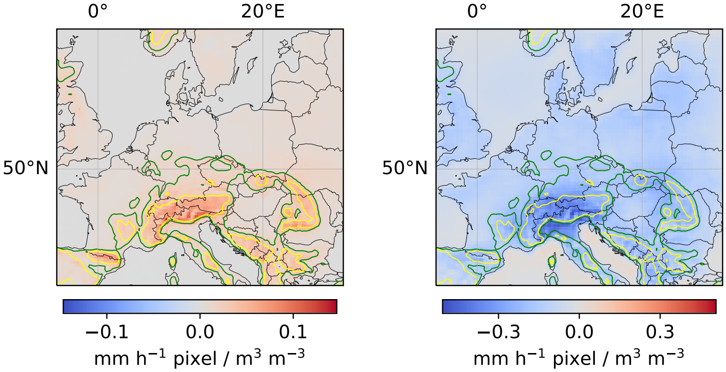
Impact of an increase in local soil moisture on local (left) and regional (right) precipitation.



For each pixel ij: $\overline{\frac{\partial P_{ij}}{\partial x_{SM,ij}}(x)}$

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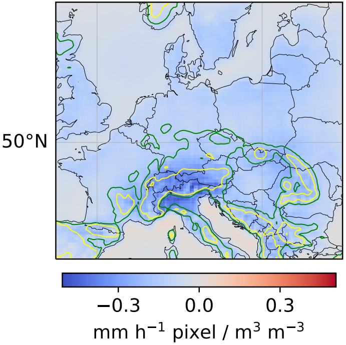
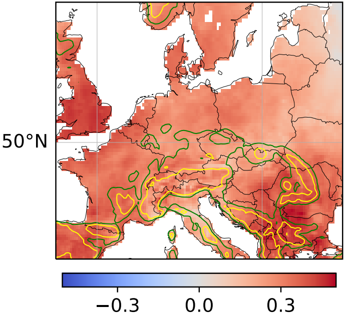
Comparison to linear correlation

Left: impact of an increase in local soil moisture on regional precipitation (our method).
Right: linear correlation between local soil moisture and regional precipitation.





For each pixel *ij*: $\overline{\frac{\partial \sum_{nk} P_{nk}}{\partial x_{SM,ij}}(x)}$ For each pixel *ij*: $corr_t(SM_{ij}, \sum_{nk} P_{nk})$

Data from convection-permitting simulations

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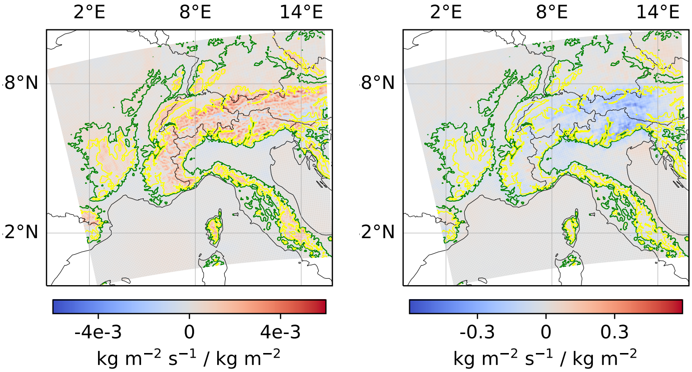

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Data courtesy: CORDEX Flagship Pilot Study on convection-permitting regional climate modelling, WRF simulation results from Aristotle University of Thessaloniki-Dept Meteorology & Climatology, see also Ban, N. *et al.* The first multi-model ensemble of regional climate simulations at kilometer-scale resolution, part I: evaluation of precipitation. *Clim Dyn* **57**, 275–302 (2021).

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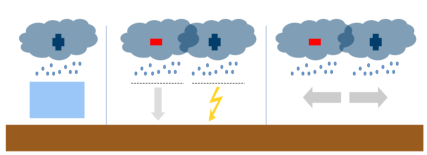

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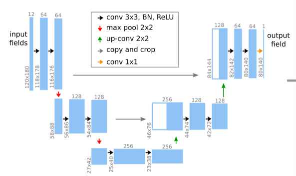

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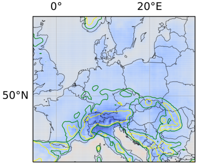

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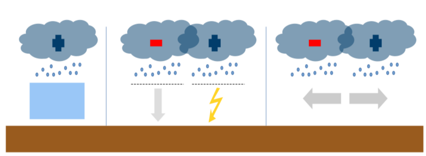

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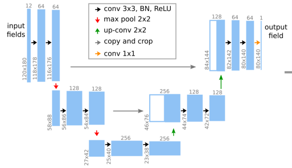

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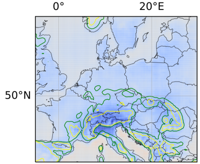

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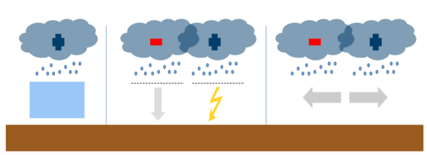

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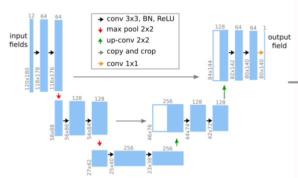

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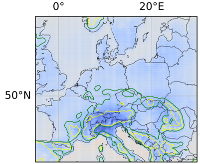

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Get in touch: t.tesch@fz-juelich.de