Statistical downscaling with deep learning: A contribution to CORDEX-CORE

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Statistical Downscaling

Dynamical Downscaling

Statistical Downscaling

Approaches:
- Model Output Statistics (MOS)
  Pred => OBS
- Perfect Prog
  OBS (Rean.) => OBS

Local data (points)  Gridded data (~10 km)

- Hydrology  - Energy
- Agriculture - Health

\[ \frac{dv}{dt} = -\alpha \nabla p - \nabla \phi + F - 2\Omega \times v \]
\[ \frac{\partial \rho}{\partial t} = -\nabla \cdot (\rho \mathbf{v}) \]
\[ p\alpha = RT \]
\[ Q = \frac{C_p}{\nu \frac{dT}{dt}} - \alpha \frac{dp}{dt} \]
\[ \frac{\partial \rho q}{\partial t} = -\nabla \cdot (\rho \mathbf{v} q) + \rho (E - C) \]
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Statistical Downscaling

MODEL SPACE

\[
\begin{align*}
\frac{dv}{dt} &= -\alpha \nabla p - \nabla \phi + F - 2\Omega \times v \\
\frac{\partial \rho}{\partial t} &= -\nabla \cdot (\rho \mathbf{v}) \\
p \alpha &= RT \\
Q &= C_p \frac{dT}{dt} - \alpha \frac{dp}{dt} \\
\frac{\partial \rho q}{\partial t} &= -\nabla \cdot (\rho \mathbf{v} q) + \rho (E - C)
\end{align*}
\]

GCM outputs (~200 km)

Predictors (from a renalysis, ERA-Interim):
- Large-scale variables well reproduced by GCMs.

REAL WORLD

Local data (points)
Precip

\[ \hat{Y}_n = a \, X_n + b \]

Gridded data
E-OBS (0.5° ~50km)

Linear regression
K-NN (analog) SVMs, NNs, RFs

\( X_n \)

\( Y_n \)
Common Methods:
- Linear regression
- K-NN (analogs)
- SVMs,
- NNs,
- RFs

Limitations:
- High-Dimensionality
- Feature Selection (e.g., selection of gridboxes)
- Feature Reduction (e.g., PCs)
- No method clearly outstands against the other

Traditional approaches **can not treat** continental-sized domains

Therefore, the **spatial information** is very **limited**

¿**How** can we **statistically downscale** continental-sized domains?
**Common Methods:**

- Linear regression
- K-NN (analogs)
- SVMs
- NNs
- RFs

**Limitations:**

- High-Dimensionality
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- No method clearly outstands against the other

---

Can deep learning treat continental-sized domains?

Therefore, **contribute** to **CORDEX-CORE**
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Common Methods:
- Linear regression
- K-NN (analogs)
- SVMs, NNs, RFs

Limitations:
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  (e.g., selection of gridboxes)
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  (e.g., PCs)
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Deep Learning?

Pros:
Outline the possible benefits of using deep learning in statistical downscaling under big domains

Cons:
Not applicable in more realistic applications

A recent Nature publication outlined future research towards the applicability of deep learning in the climate science

Reichstein et al., 2019

Simple illustrative examples of applications of deep learning in statistical downscaling have been developed in the last years

Vandal et al., 2017
Rodrigues et al., 2019

Downscale GCMs future climate projections
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Deep Learning
Statistical Downscaling

More realistic applications under the perfect-prognosis approach

Article

Improving Monsoon Precipitation Prediction Using Combined Convolutional and Long Short Term Memory Neural Network

Qinghua Miao¹, Baoxiang Pan², Hao Wang¹,³, Kuolin Hsu² and Soroosh Sorooshian²

Statistical downscaling of precipitation using long short-term memory recurrent neural networks

Saptarshi Misra¹ · Sudeshna Sarkar¹ · Pabitra Mitra¹

Improving Precipitation Estimation Using Convolutional Neural Network

Baoxiang Pan¹, Kuolin Hsu¹, Amir AghaKouchak¹,², Soroosh Sorooshian¹,²

Downscaling rainfall using deep learning long short-term memory and feedforward neural network

Duong Tran Anh¹,² ³ | Song P. Van² | Thanh D. Dang³ ³ | Long P. Hoang⁴

Intercomparison of Machine Learning Methods for Statistical Downscaling: The Case of Daily and Extreme Precipitation

Thomas Vandal¹, Evan Kodra¹, and Auroop R Ganguly¹

¹Sustainability and Data Science Lab, Civil Engineering Dept Northeastern University
²risQ Inc.
Deep Learning
Statistical Downscaling

More realistic applications under the perfect-prognosis approach

Different conclusions about their performance

Lack of a common validation framework and small case studies

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Complex off-the-shelf deep learning topologies

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Complex off-the-shelf deep learning topologies

Lack of a common validation framework and small case studies

Different conclusions about their performance

Not clear the role of every element in the net

Do not test the extrapolation capability

Crucial in climate change
More realistic applications under the perfect-prognosis approach

Different conclusions about their performance

- Lack of a common validation framework and small case studies
- Complex off-the-shelf deep learning topologies
- Not clear the role of every element in the net
- Do not test the extrapolation capability
- Crucial in climate change

Configuration and Intercomparison of Deep Learning Neural Models for Statistical Downscaling

Jorge Baño-Medina 1, Rodrigo Manzanares 2, and José Manuel Gutiérrez 3
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2 Santander Meteorology Group, Dept. of Applied Mathematics and Computer Science, University of Cantabria, Santander (Spain)

The largest-to-date downscaling intercomparison project: VALUE

Develop and intercompare deep learning topologies of increasing level of complexity

Evaluate a simple test to evaluate the extrapolation capability of classical and deep learning models
Deep Learning as a statistical downscaling model

1) Can Deep Learning explain the local variability with NO PREDICTOR SELECTION?
   State-of-the-art methods overfit with no predictor selection

2) Can Deep Learning show a stable behaviour when projecting to future climate with NO PREDICTOR SELECTION?
   State-of-the-art methods show unstable behaviour with no predictor selection when extrapolating
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Validation framework
- VALUE
- Deep Learning
  - Continental-sized domains
  - Different DL topologies
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RESEARCH ARTICLE

VALUE: A framework to validate downscaling approaches for climate change studies

Douglas Maraun, Martin Widmann, José M. Gutiérrez, Sven Kotlarski, Richard E. Chandler, Elke Hertig, Joanna Wibig, Radan Huth and Renate A. Wilcke

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- VALUE

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- ERA-Interim
  (2° resolution)
- U 500
- Z 1000
- T 1000
- Q 1000
- 19x22 (20 vars: Q, T, Z, U, V at 1000, 850, 700 and 500 mb)
- 50 kernels (3x3x20)

- Convolutions

- Dense
  - 25 kernels (3x3x50)
  - 10 kernels (3x3x25)
  - (50x50)

- Outputs:
  - E-OBS precip.
    (0.5° resolution)
  - 76x88 (3 vars)
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Classical ....

- **GLM1**: generalized linear model using as predictor the closest gridpoint.

- **GLM4**: generalized linear model using as predictor 4 closest gridpoints.

... and **deep learning methods** are intercompared

- **CNN-LM, CNN1, CNN10, CNN-PR, CNNdense**

According to these metrics...

Deep Learning outperform classical methods

The model **CNN1** achieves the best validation scores

We chose this one (CNN1) for downscaling climate change scenarios
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GLM1: generalized linear model using as predictor the closest gridpoint.

GLM4: generalized linear model using as predictor 4 closest gridpoints.

... and deep learning methods are intercompared

- CNN-LM, CNN1, CNN10, CNN-PR, CNNdense

CNN1 achieves ROCSS and spearman correlation over the whole domain than classical approaches

CNN1 is.... able to treat the whole domain simultaneously

Why?

Baño-Medina et al., 2019

Convolutions

Baño-Medina and Gutiérrez, 2019

Convolutions + Multi-task
Deep Learning as a statistical downscaling model

2) Can Deep Learning show a stable behaviour when projecting to future climate with NO PREDICTOR SELECTION?

State-of-the-art methods show unstable behaviour with no predictor selection when extrapolating.

Can the statistical models preserve the deltas (i.e., ratio between future and historical values)? INSTABILITY DETECTOR

We apply the function learned in perfect conditions to the GCM predictors → Downscaling GCM
Deep Net preserves the deltas and thus it does not show instabilities in future conditions!
Conclusions

- Deep Learning can handle continental-sized domains without leading to overfitting
- Deep learning explains better the local variability than classical approaches
- The extrapolation capability of deep learning seems plausible

Future Work

- Extend the study to other CORDEX domains