Introducing DL-GLOBWB

a deep-learning surrogate of a process-based global hydrological model

Bram Droppers, Myrthe Leijnse,
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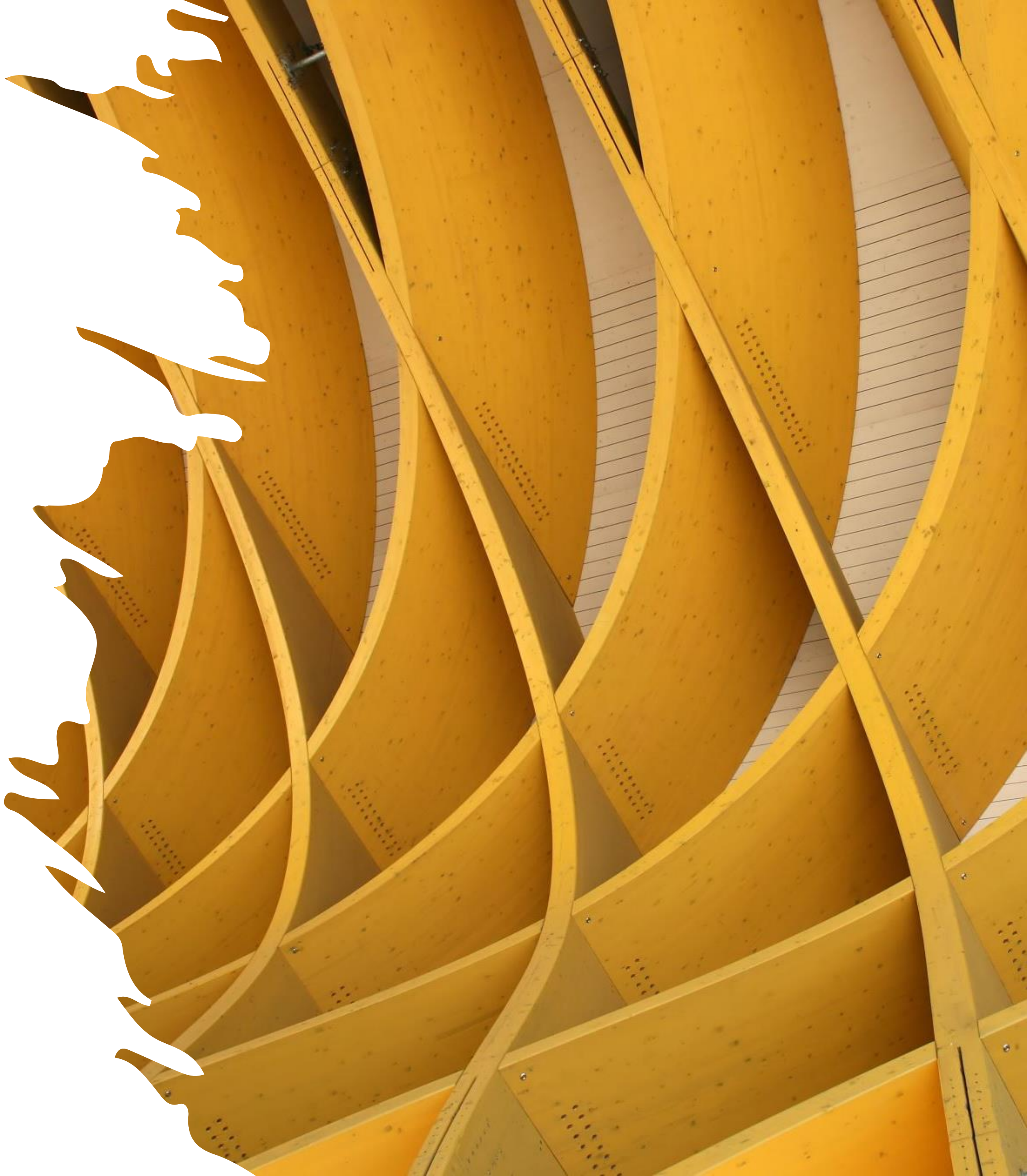
Sharing is encouraged

Why a deep-learning model surrogate?



Why a deep-learning model surrogate?

“Global hydrological models have become essential tools (…) in support of global change research and environmental assessments”

Satanudjaja et al. (2018) PCR-GLOBWB 2: a 5 arcmin global hydrological and water resources model. Geoscientific Model Development.

Why a deep-learning model surrogate?

30 arc-minute resolution

05 arc-minute resolution

30 arc-second resolution

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PCR-GLOBWB

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PCR-GLOBWB

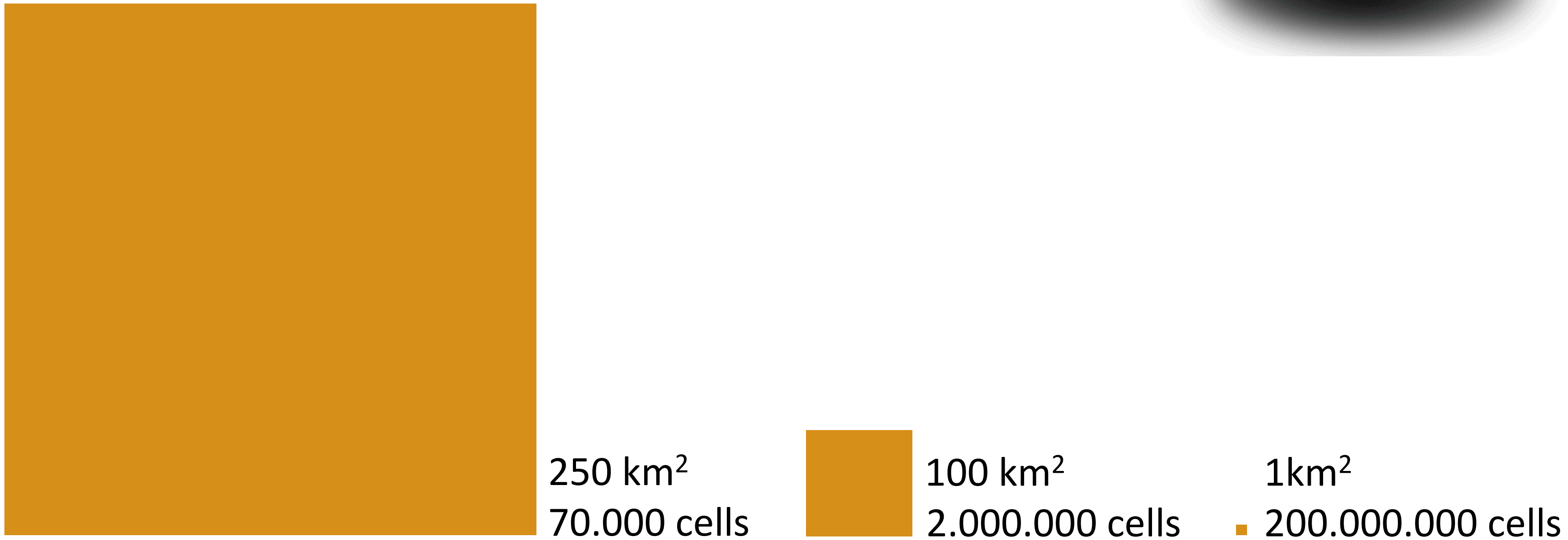
30 arc-minute resolution

↓

05 arc-minute resolution

↓

30 arc-second resolution



Why a deep-learning model surrogate?

Classical process-based approach

Scenario analysis

Sub-process states and fluxes

Computational limitations

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Classical deep-learning approach

Limited extrapolation

No intermediate processes

Very fast

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Train surrogate outside historical context and for all water-balance components

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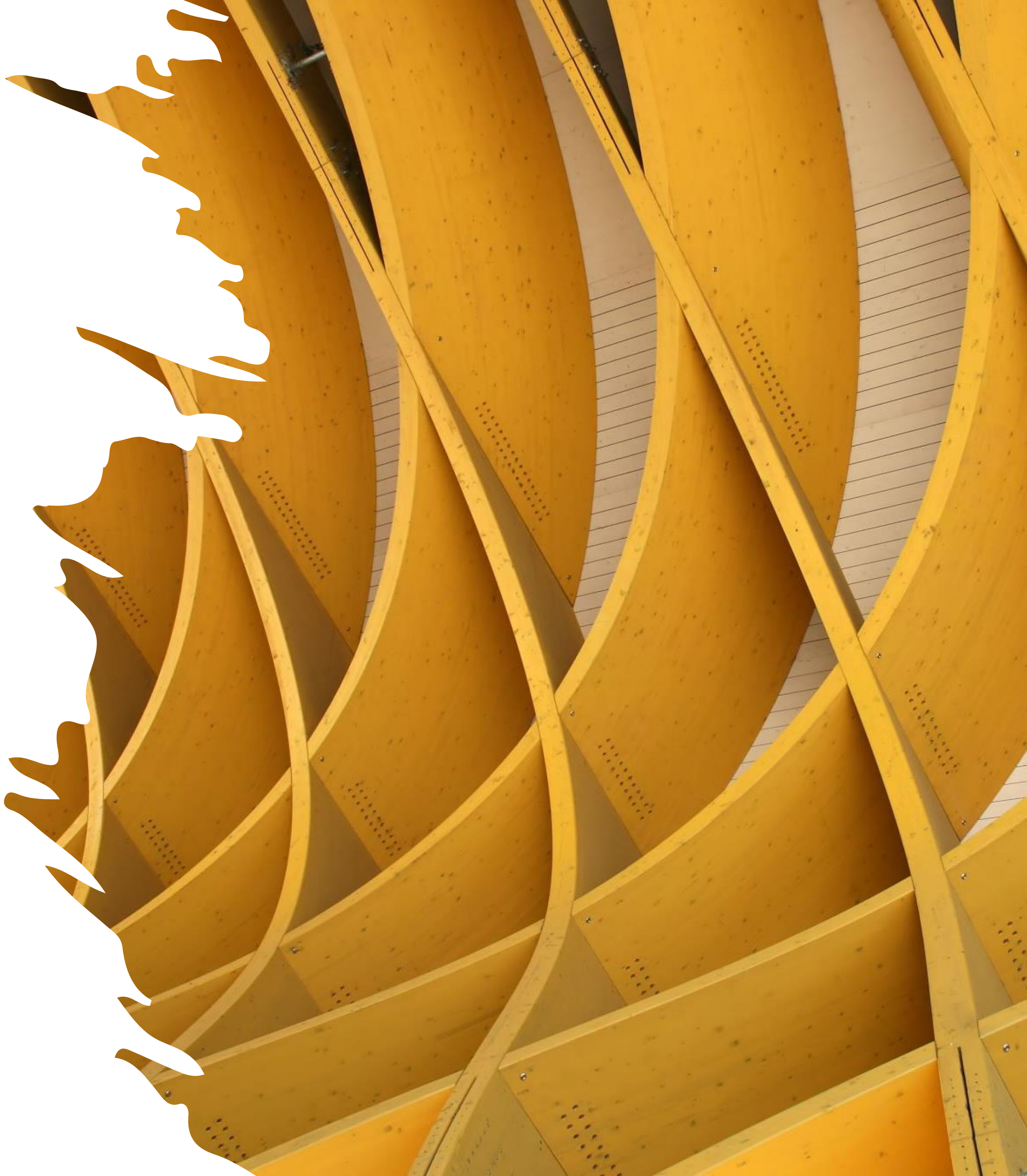
GPU computation

Deep-learning surrogate design



Deep-learning surrogate design

Network

- Primarily a LSTM neural network

Deep-learning surrogate design

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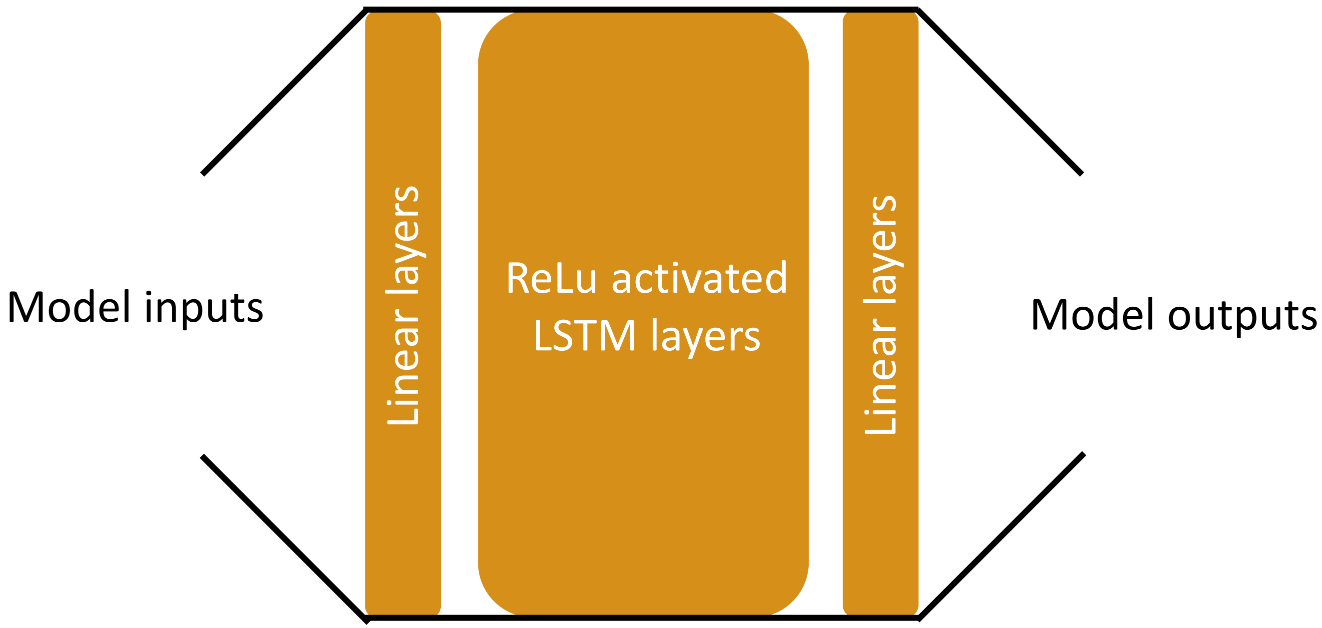
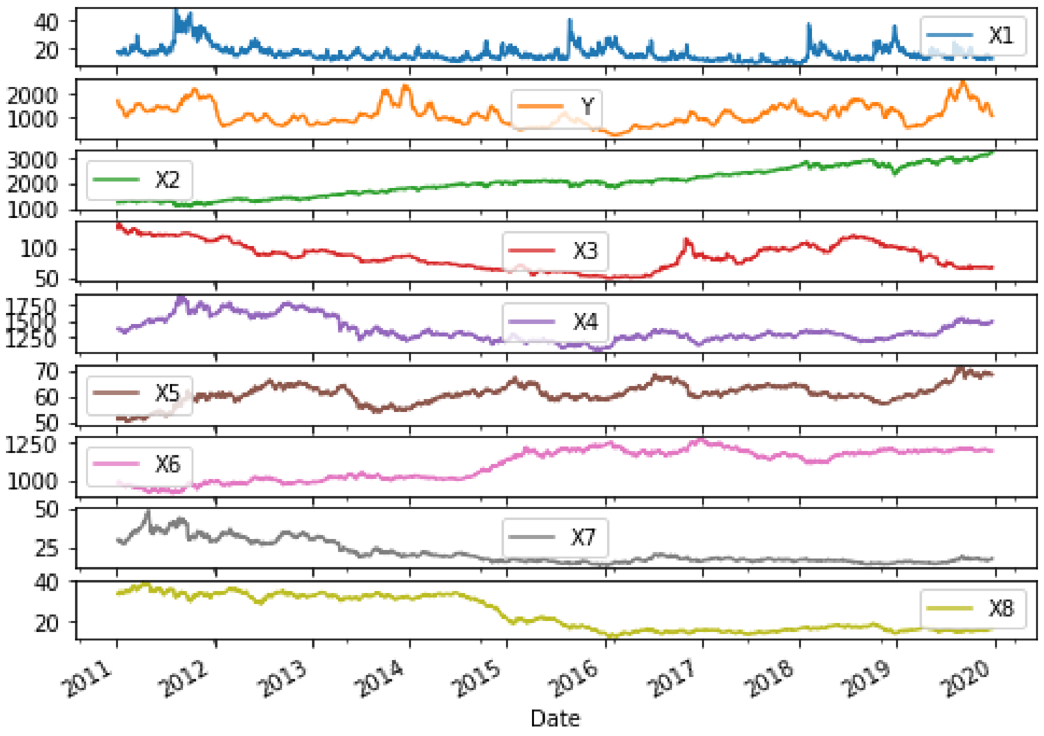
- Primarily a LSTM neural network



Deep-learning surrogate design

Training and testing

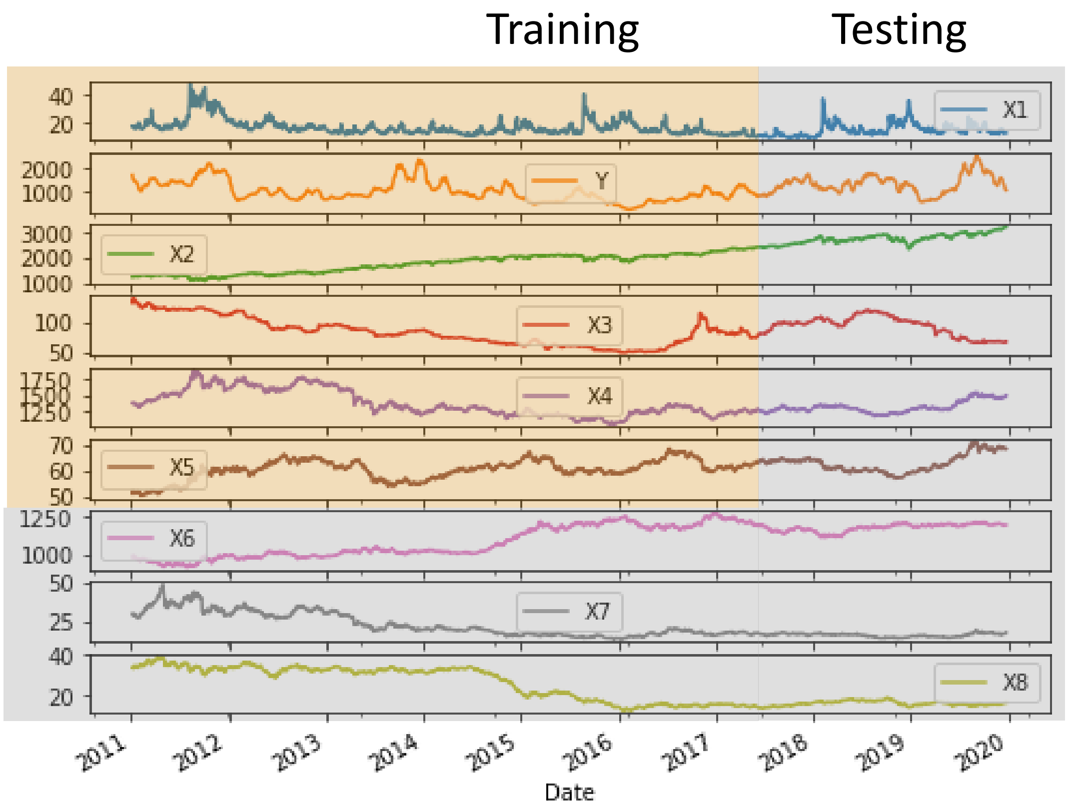
- Subsample of all global cells for training and testing



Deep-learning surrogate design

Training and testing

- Subsample of all global cells for training and testing
- Two thirds of both samples and dates for training, rest for testing



Deep-learning surrogate design

Multiple resolutions

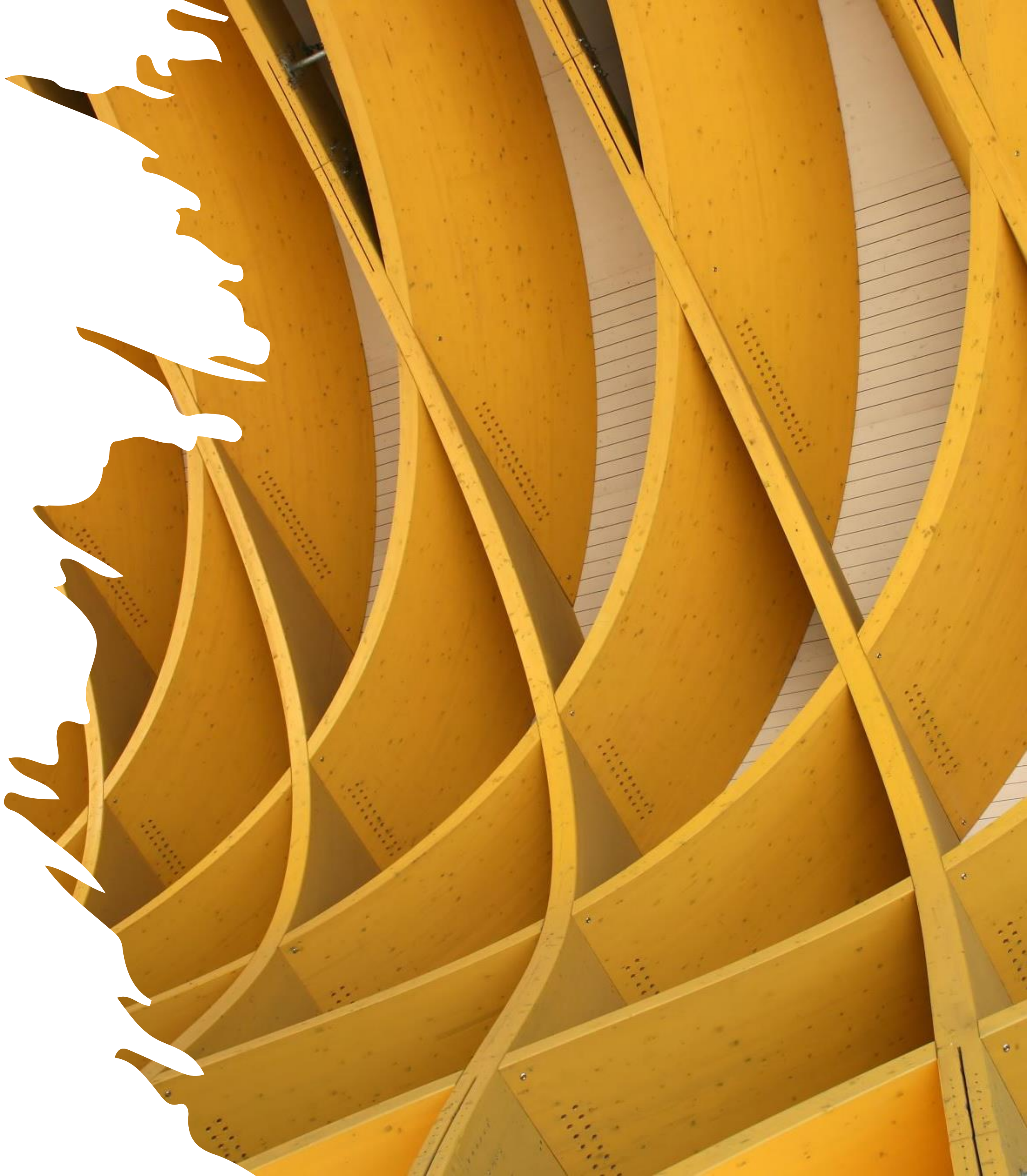
- Requirement for resolution scalability

Deep-learning surrogate design

Multiple resolutions

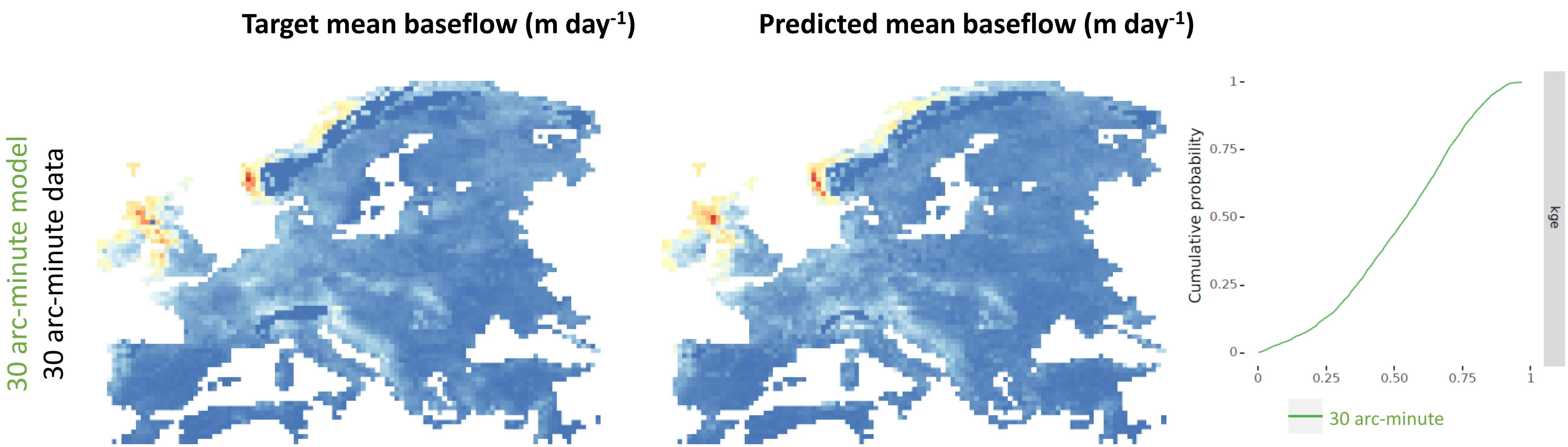
- Requirement for resolution scalability
- Train models at three different spatial resolutions
  - 30 arc-minute resolution
  - 05 arc-minute resolution
  - Multi-resolution (half of 30 arc-minute and half of 05 arc-minute)

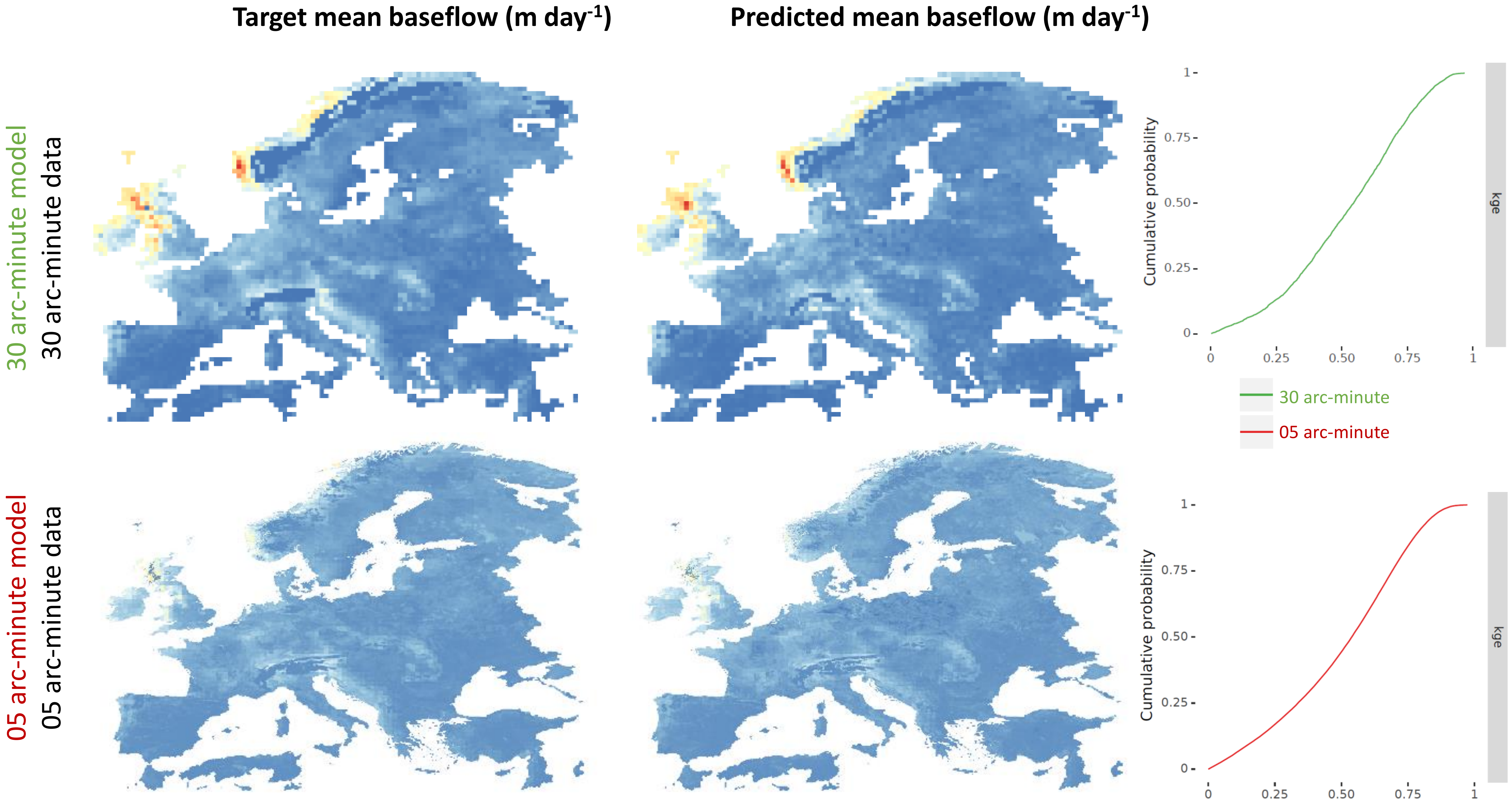
Performance



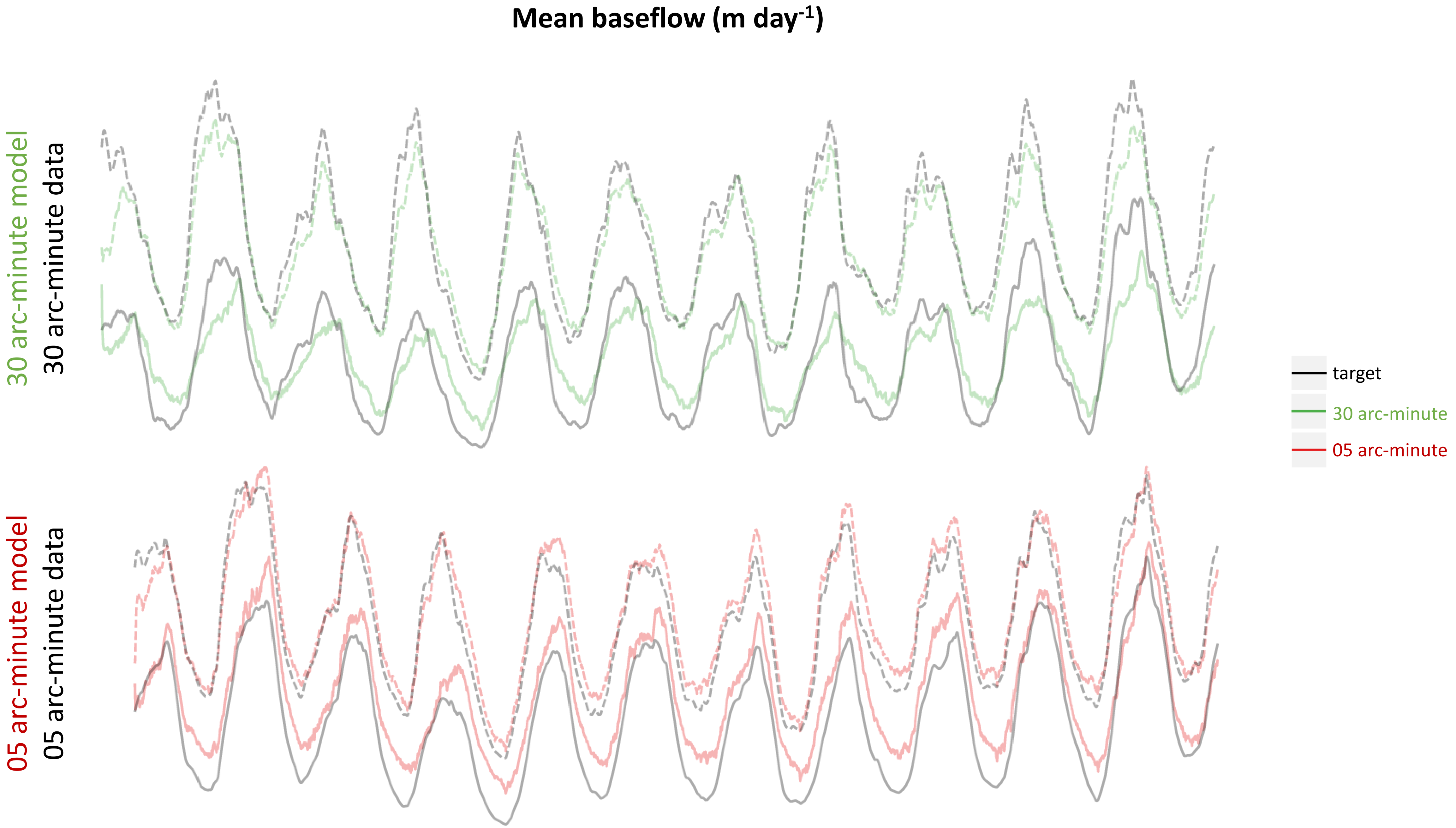
Performance

- Generally good spatiotemporal performance over all output variables


Target mean baseflow (m day-1)
Predicted mean baseflow (m day-1)
30 arc-minute model
30 arc-minute data
Cumulative probability
1
0.75
0.50
0.25
0
0
0.25
0.50
0.75
1
kge
30 arc-minute



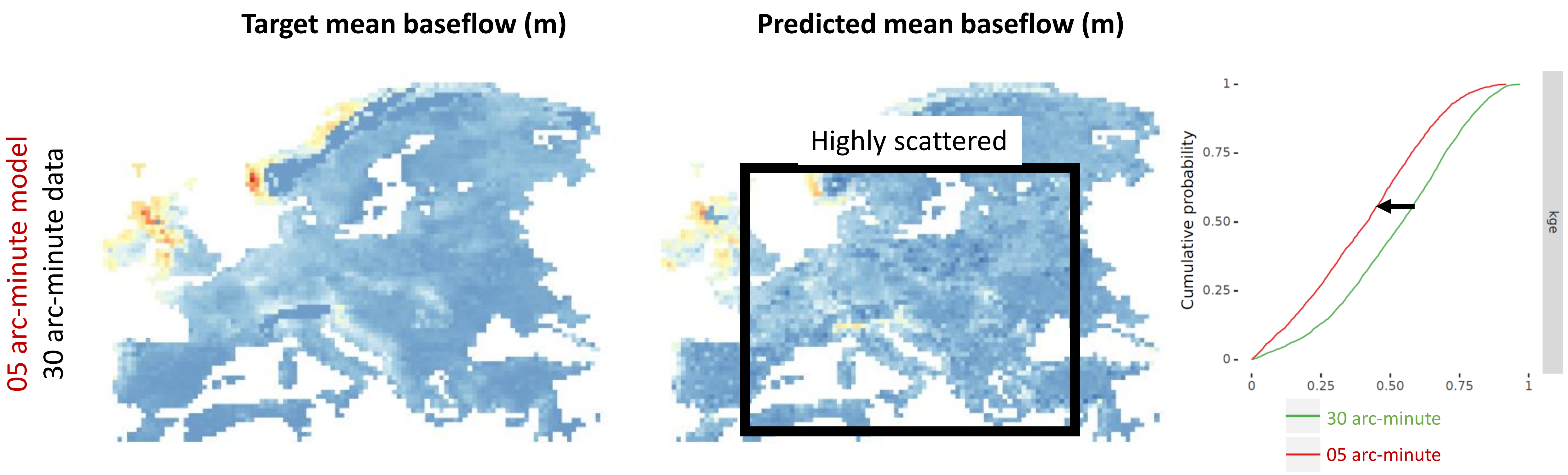
Target mean baseflow (m day-1)
Predicted mean baseflow (m day-1)
30 arc-minute model
30 arc-minute data
05 arc-minute model
05 arc-minute data
Cumulative probability
kge
30 arc-minute
05 arc-minute
0
0.25
0.50
0.75
1



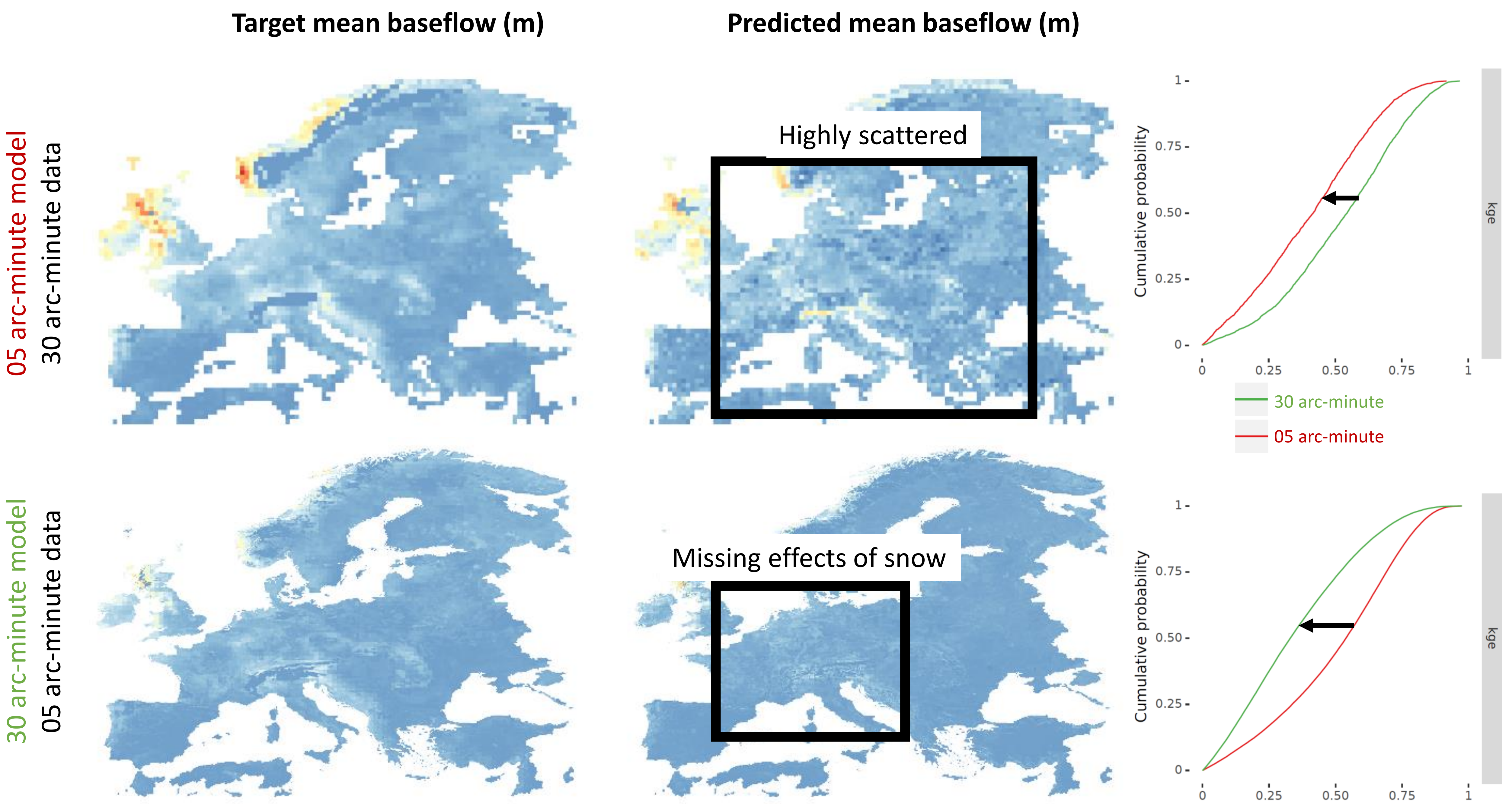
Mean baseflow (m day^{-1})
30 arc-minute model
30 arc-minute data
05 arc-minute model
05 arc-minute data
target
30 arc-minute
05 arc-minute

Performance

- Generally good spatiotemporal performance over all output variables
- Single-resolution models scale poorly to other resolutions



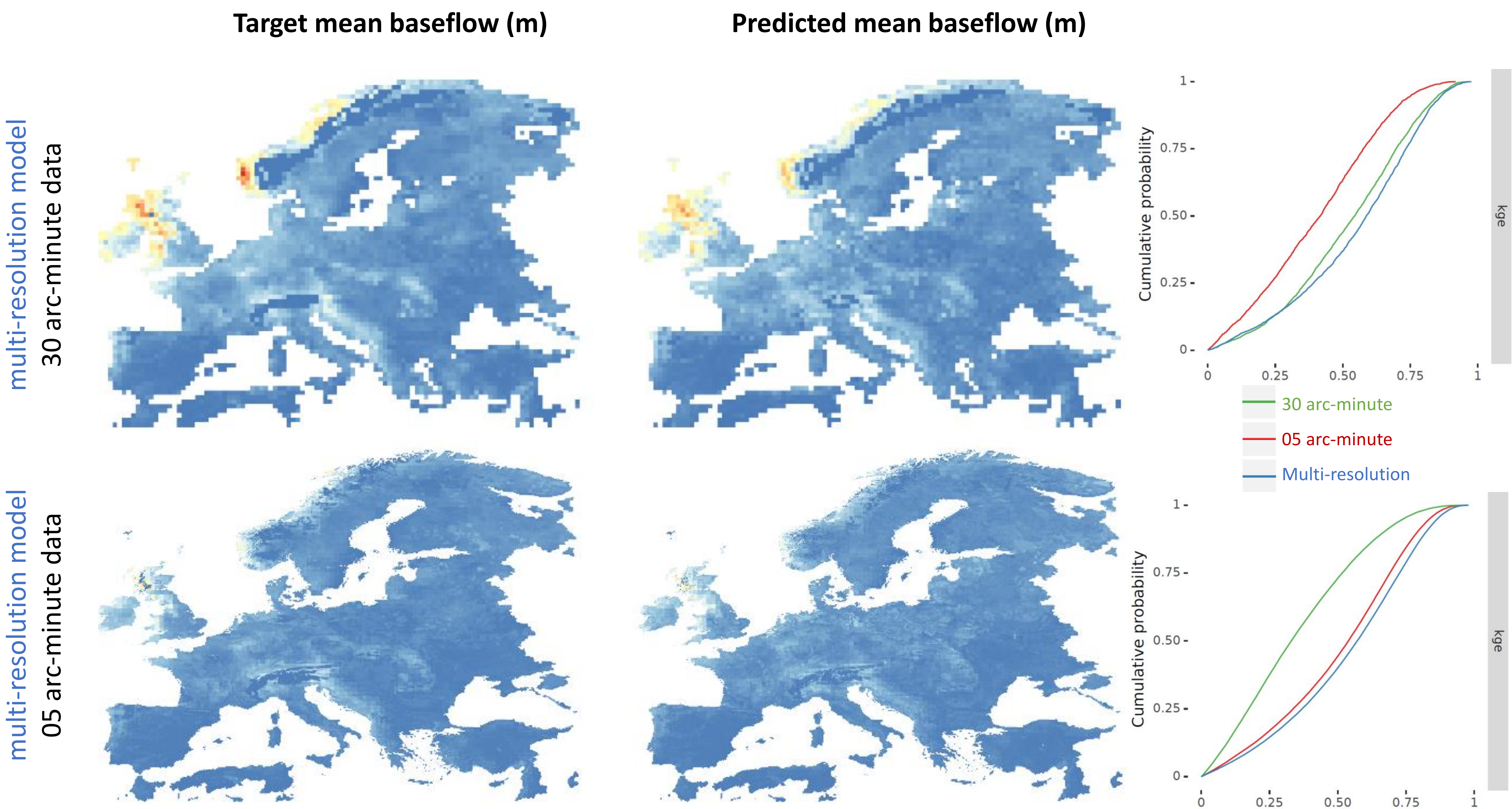
Target mean baseflow (m)
Predicted mean baseflow (m)
05 arc-minute model
30 arc-minute data
Highly scattered
Cumulative probability
1
0.75
0.50
0.25
0
0
0.25
0.50
0.75
1
kge
30 arc-minute
05 arc-minute



Target mean baseflow (m)
Predicted mean baseflow (m)
05 arc-minute model
30 arc-minute data
Highly scattered
30 arc-minute model
05 arc-minute data
Missing effects of snow
Cumulative probability
kge
30 arc-minute
05 arc-minute
0
0.25
0.50
0.75
1

Performance

- Generally good spatiotemporal performance over all output variables
- Single-resolution models scale poorly to other resolutions
- Multi-resolution models scale well to other resolutions
  - Multi-resolution models often even outperform single-resolution models on their target resolutions



Target mean baseflow (m)
Predicted mean baseflow (m)
multi-resolution model
30 arc-minute data
multi-resolution model
05 arc-minute data
Cumulative probability
kge
0
0.25
0.50
0.75
1
30 arc-minute
05 arc-minute
Multi-resolution

Conclusion

We successfully developed a deep-learning surrogate of a global process-based hydrological model

- Includes all water-balance components
- Scalable over different resolutions

This process-based model surrogate helps us to support global assessments

- Makes high-resolution modeling more accessible
- Allows for climate-change and adaptation scenario analysis

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From calibration to parameter learning: Harnessing the scaling effects of big data in geoscientific modeling

Wen-Ping Tsai, Dapeng Feng, Ming Pan, Hylke Beck, Kathryn Lawson, Yuan Yang, Jiangtao Liu & Chaopeng Shen

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