



A (c)loud revolution in weather and climate research

Wilco Hazeleger

Reading, 27/09/2018

Acknowledgement: the team at the Netherlands eScience Center



100+ projects

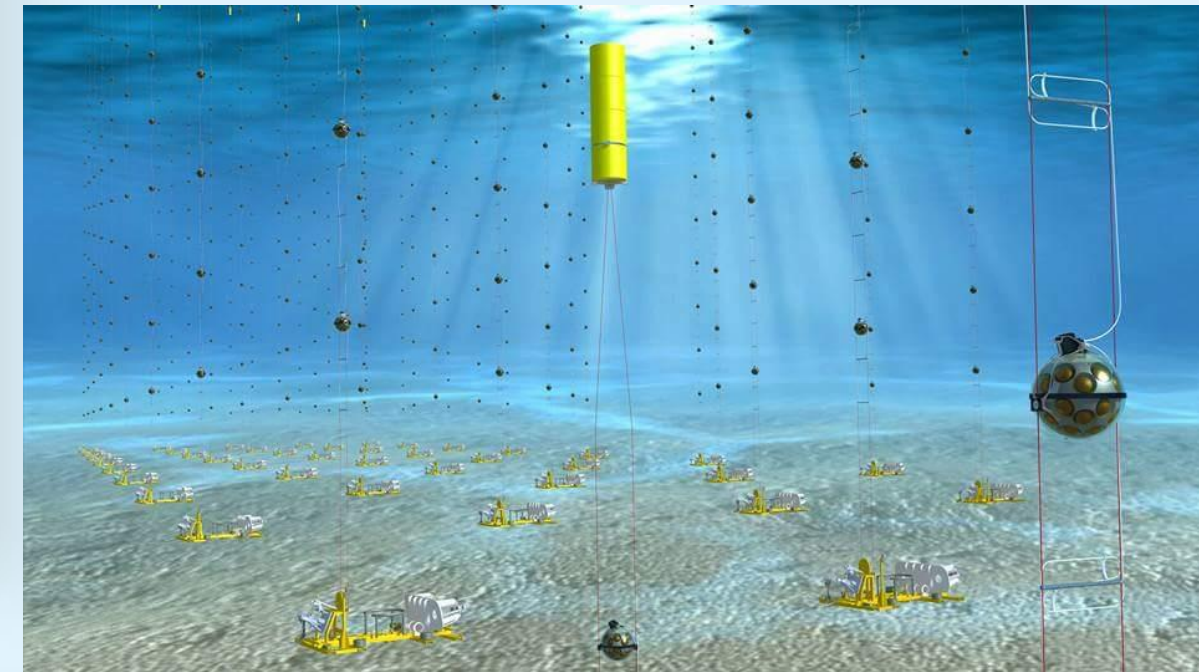


Humanities & Social Sciences

incl. SMART cities,
text analysis, crea-
tive technologies

Physics & Beyond

incl. astronomy,
high-energy physics,
advanced materials

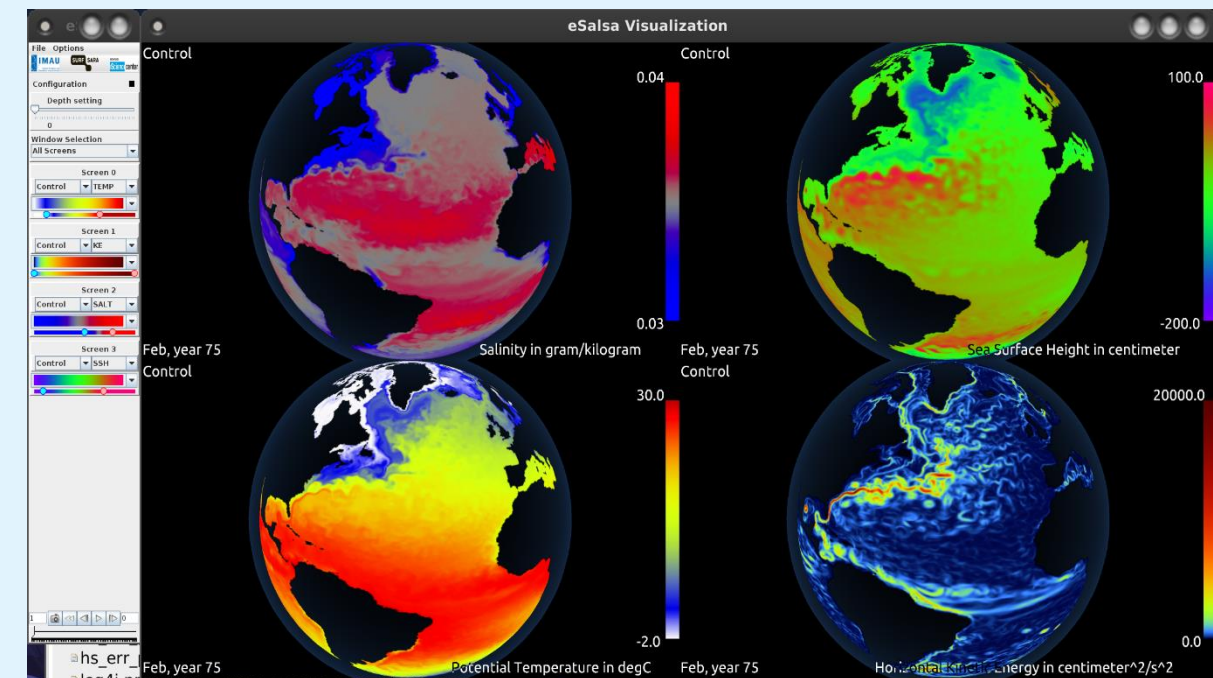
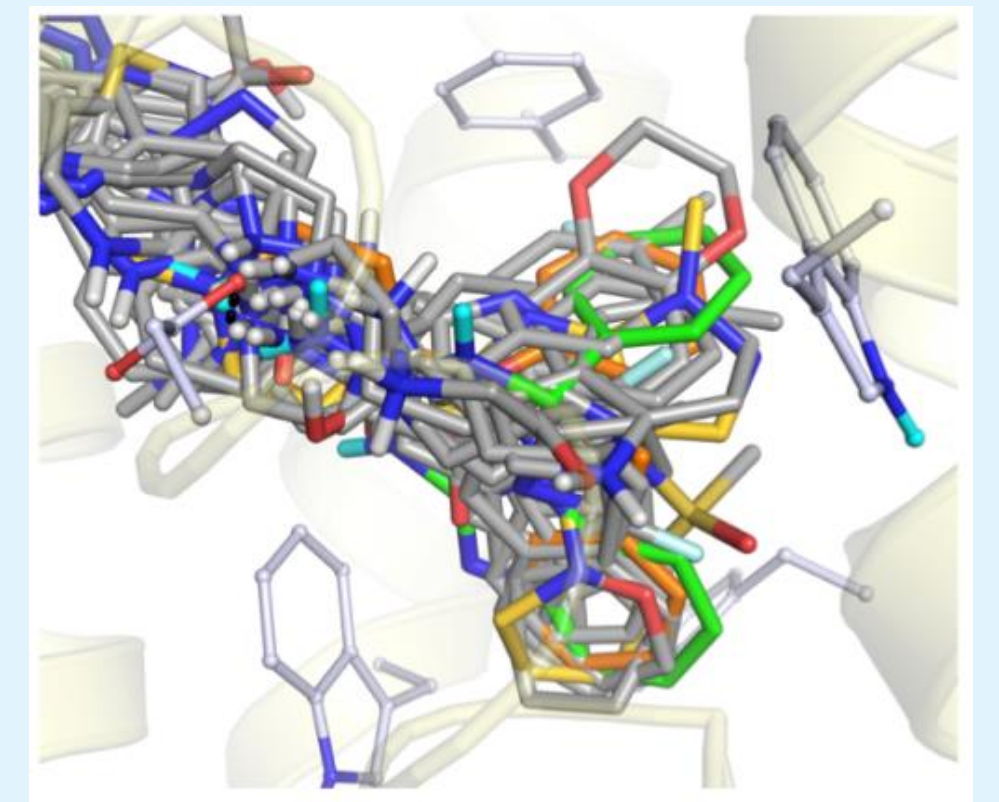


Sustainability & Environment

incl. climate, ecolo-
gy, energy, logistics,
water management

Life Sciences & eHealth

incl. bio-imaging,
next generation se-
quencing, molecules



Research Software Directory

FAIR software:

- Finding software
- Making software accessible
- Quickly judge relevance and quality
- Indicating return on investment

www.research-software.nl

mcfly

By Christiaan Meijer, Dafne van Kuppevelt, Vincent van Hees, Patrick Bos, Mateusz Kuzak, Atze van der Ploeg

5 mentions
6 contributors

Do you want to use deep learning on your time series data, but don't know where to start? mcfly helps you find a suitable model, building upon state-of-the-art deep learning research.

Get started



421 commits | Last update: March 14, 2018

Cite this software

DOI:

10.5281/zenodo.596127

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Choose a citation style:

BibTeX

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What mcfly can do for you

- Provides starting point for researchers to use deep learning
- Creates deep learning models to classify time series data
- Derives features automatically from raw data
- Helps with finding a suitable model architecture and hyperparameters
- Has a tutorial in Python to get you started!

+ Read more

Tags

Machine learning

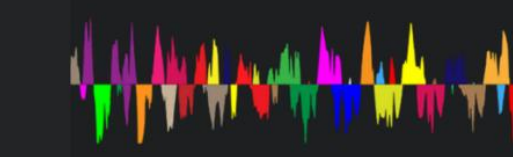
Programming Language

Python

License

Apache-2.0

Mentions



mcfly: time series classification made easy

By Dafne van Kuppevelt
March 20, 2017

Visit our blog

Presentations

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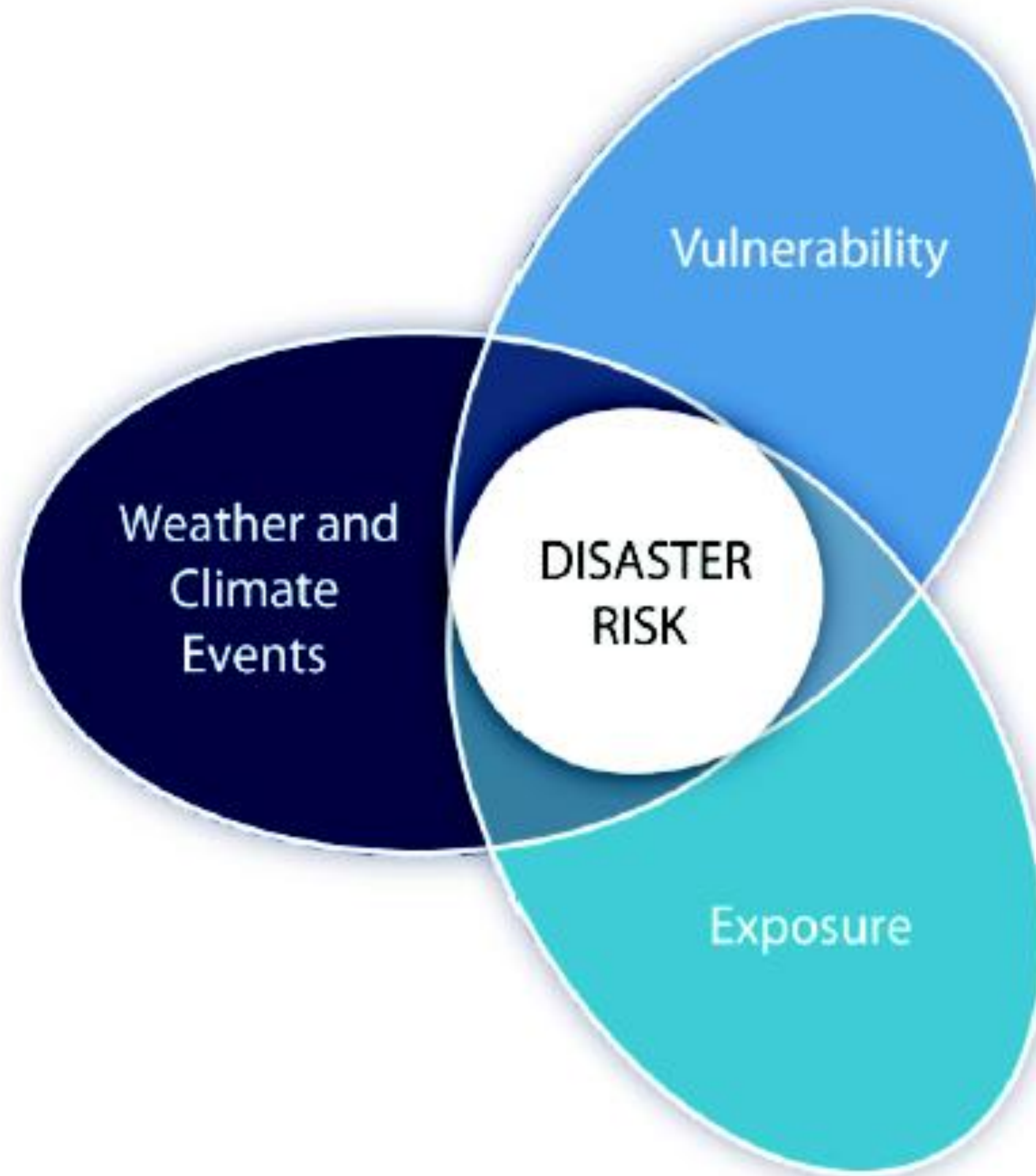
Mateusz Kuzak
Netherlands eScience Center

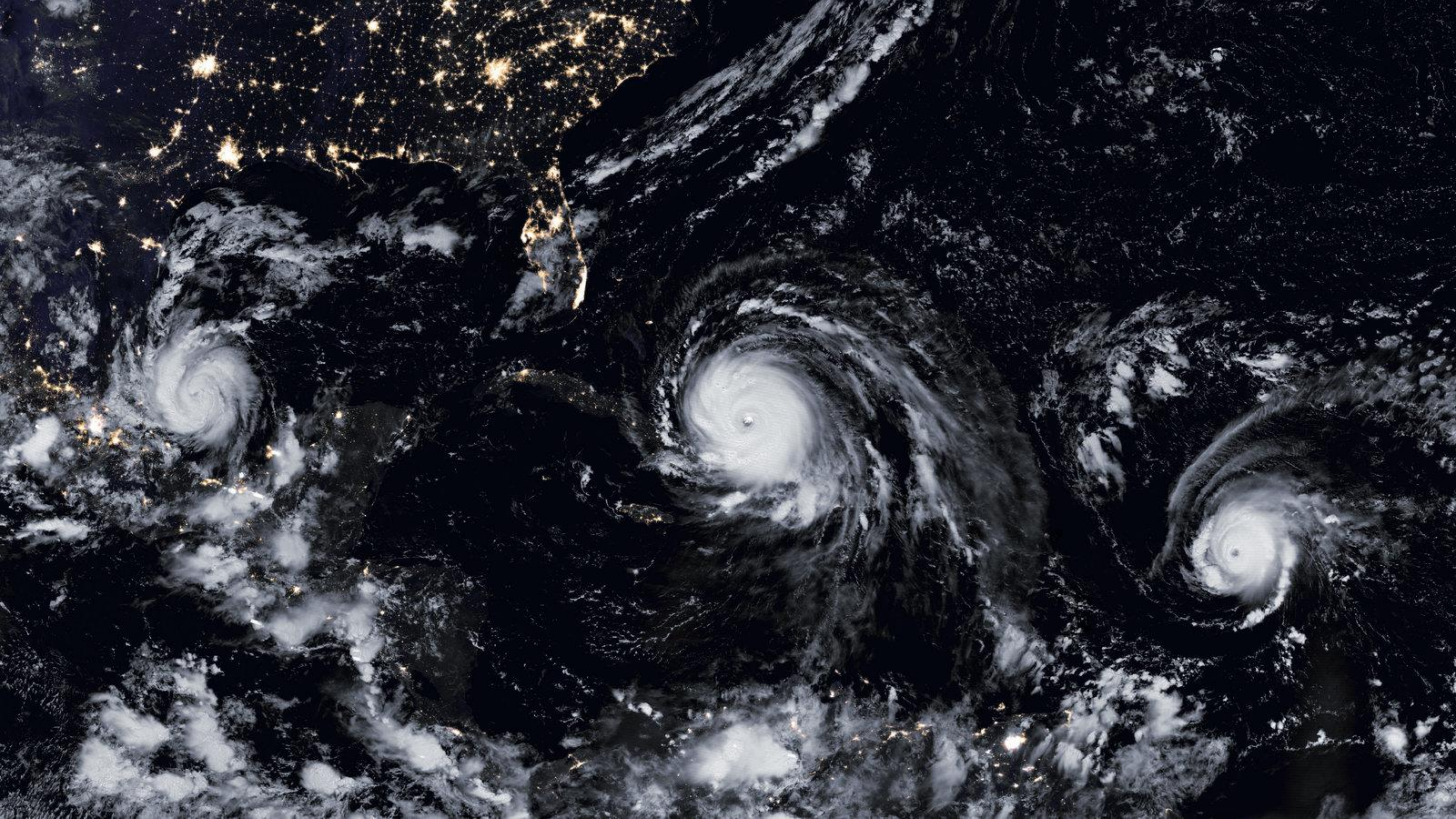
Atze van der Ploeg
Netherlands eScience Center

CONTACT PERSON



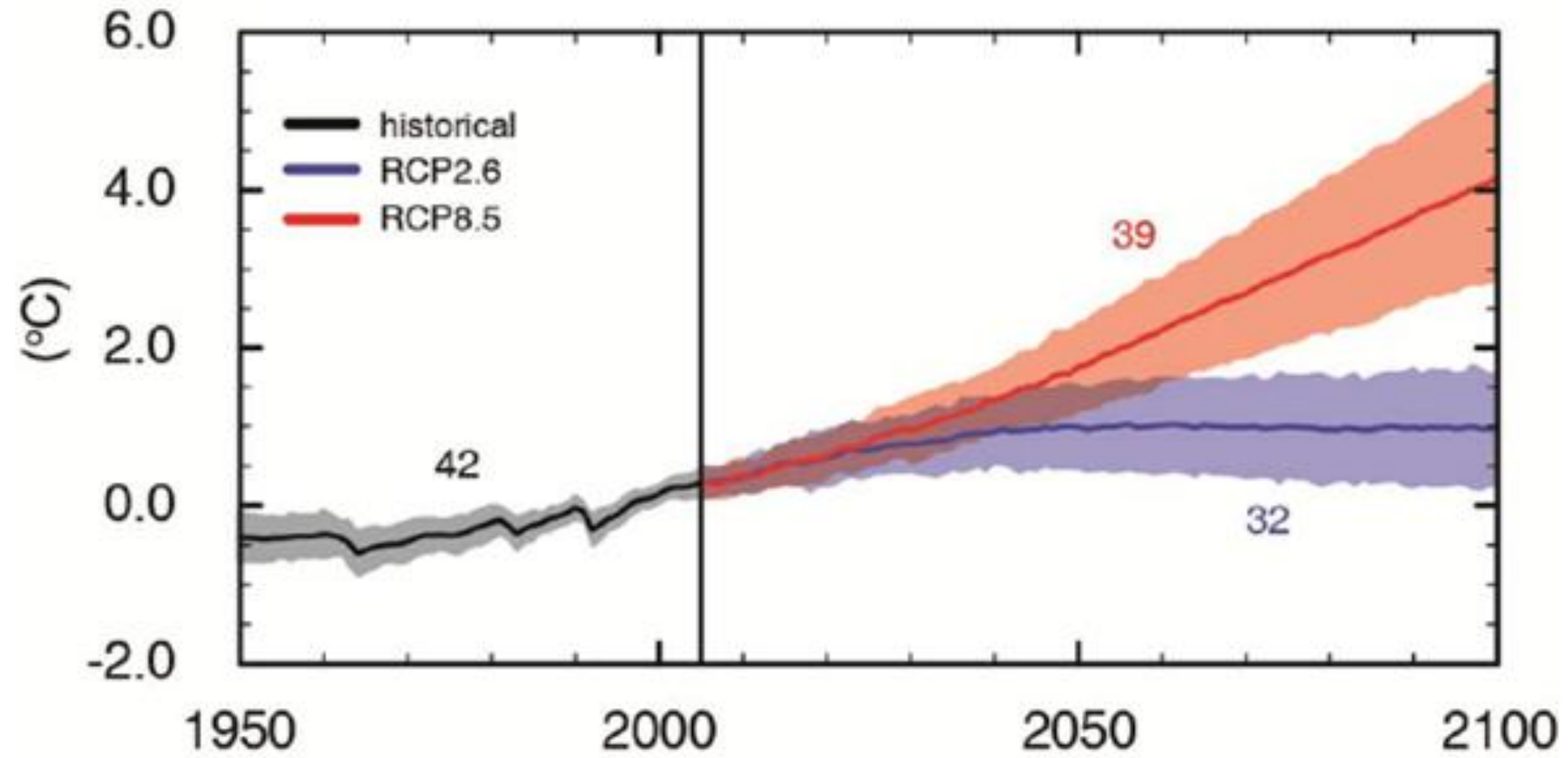
Christiaan Meijer
Netherlands eScience Center
Mail Christiaan Meijer

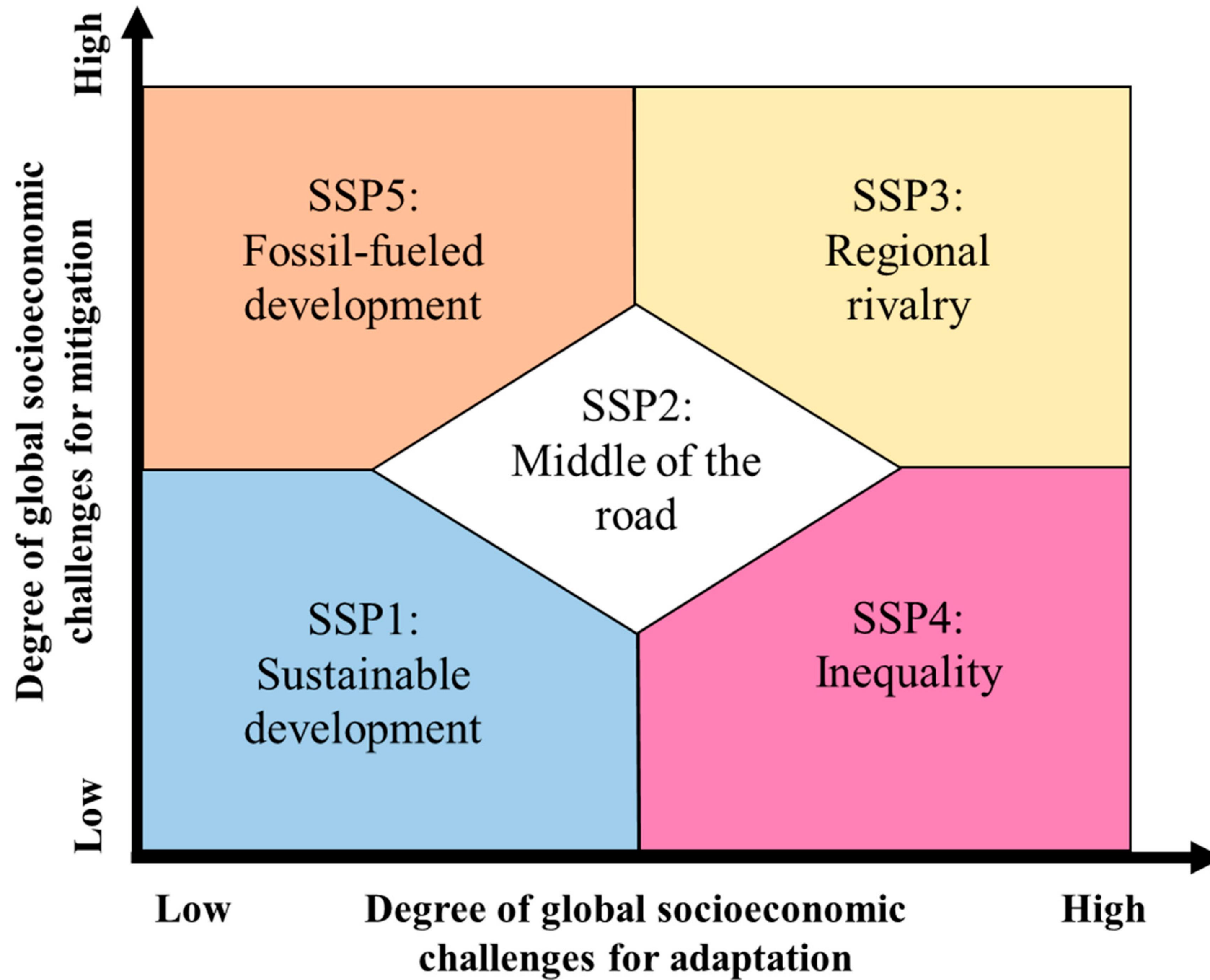


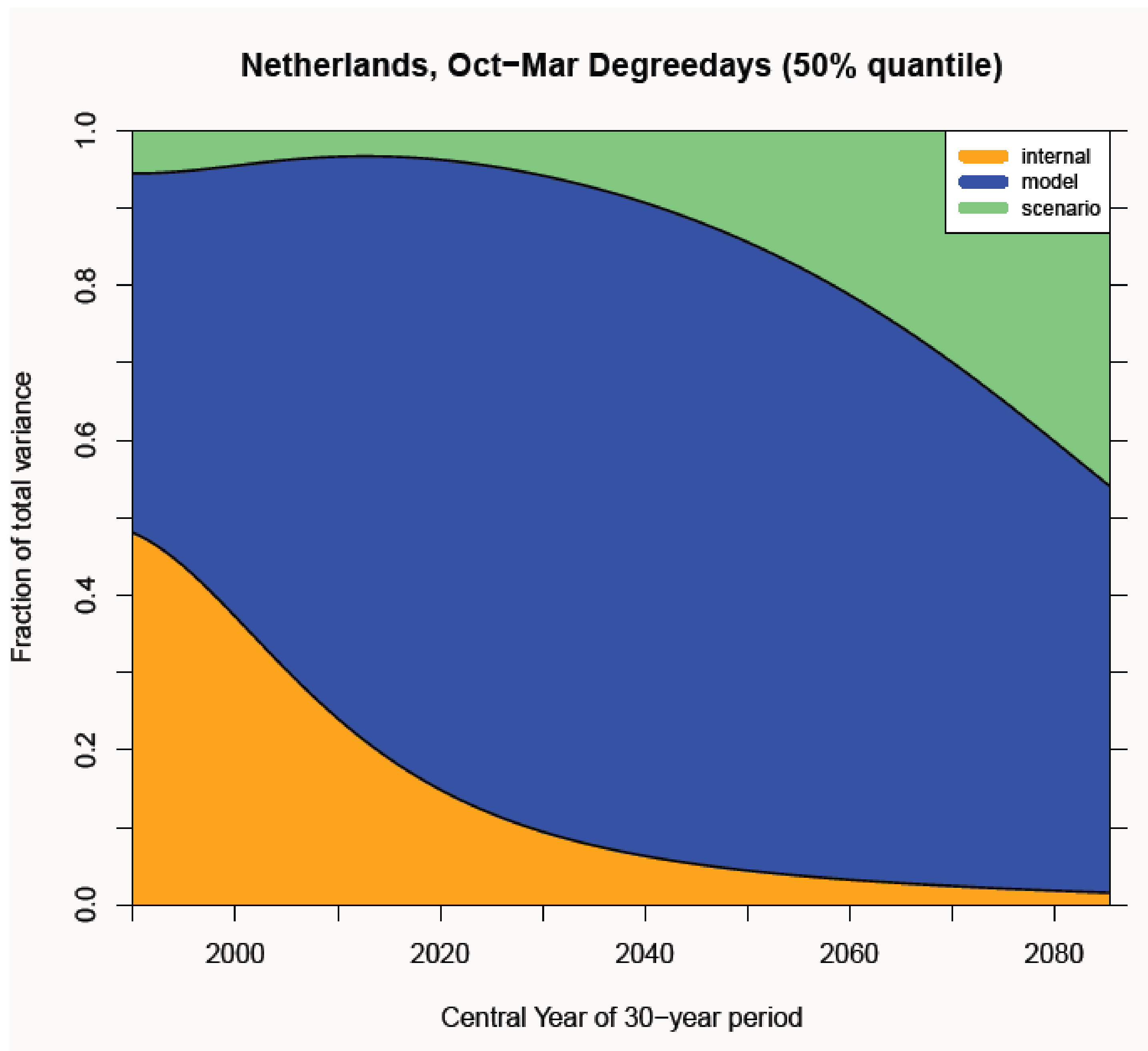




Global climate change (IPCC 5AR)

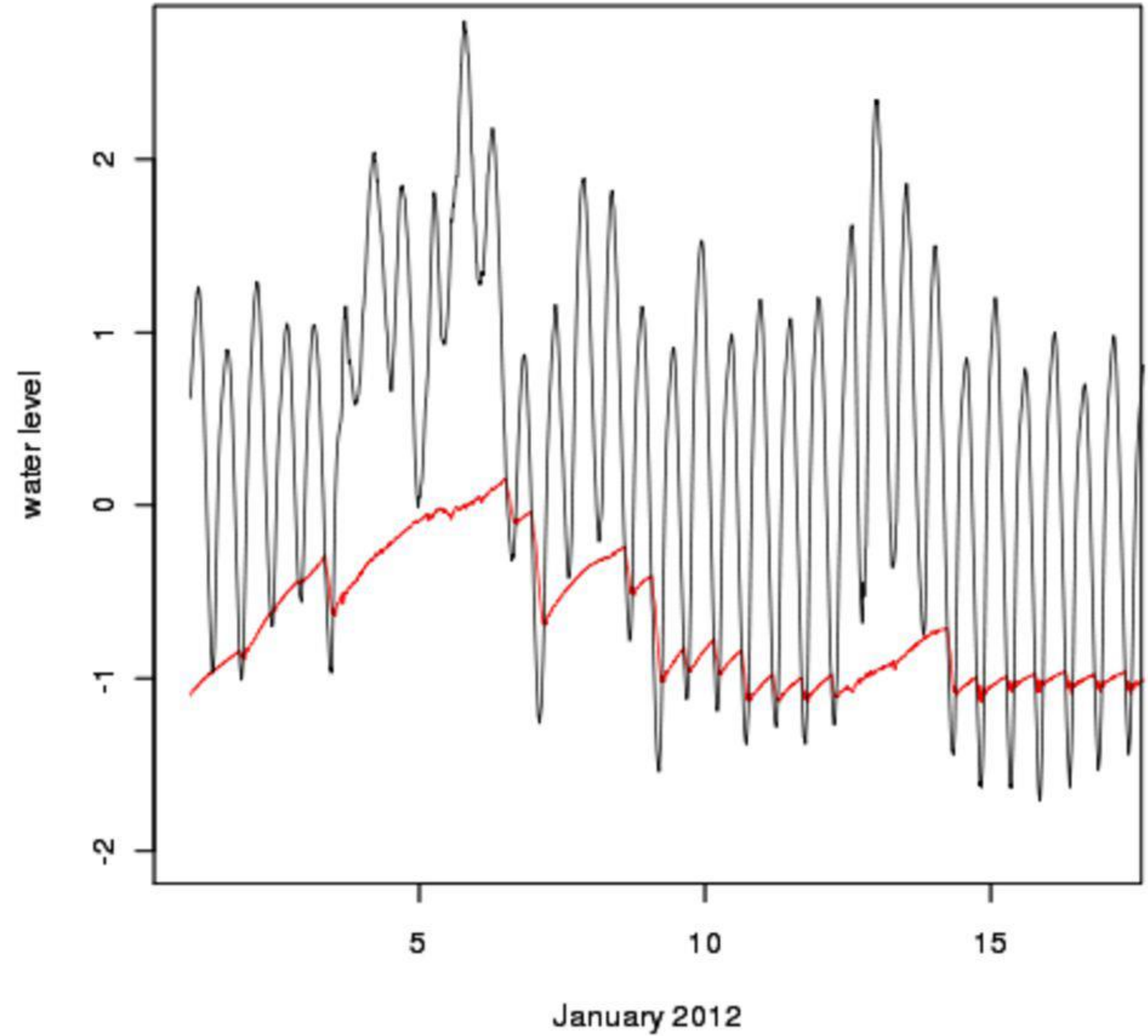


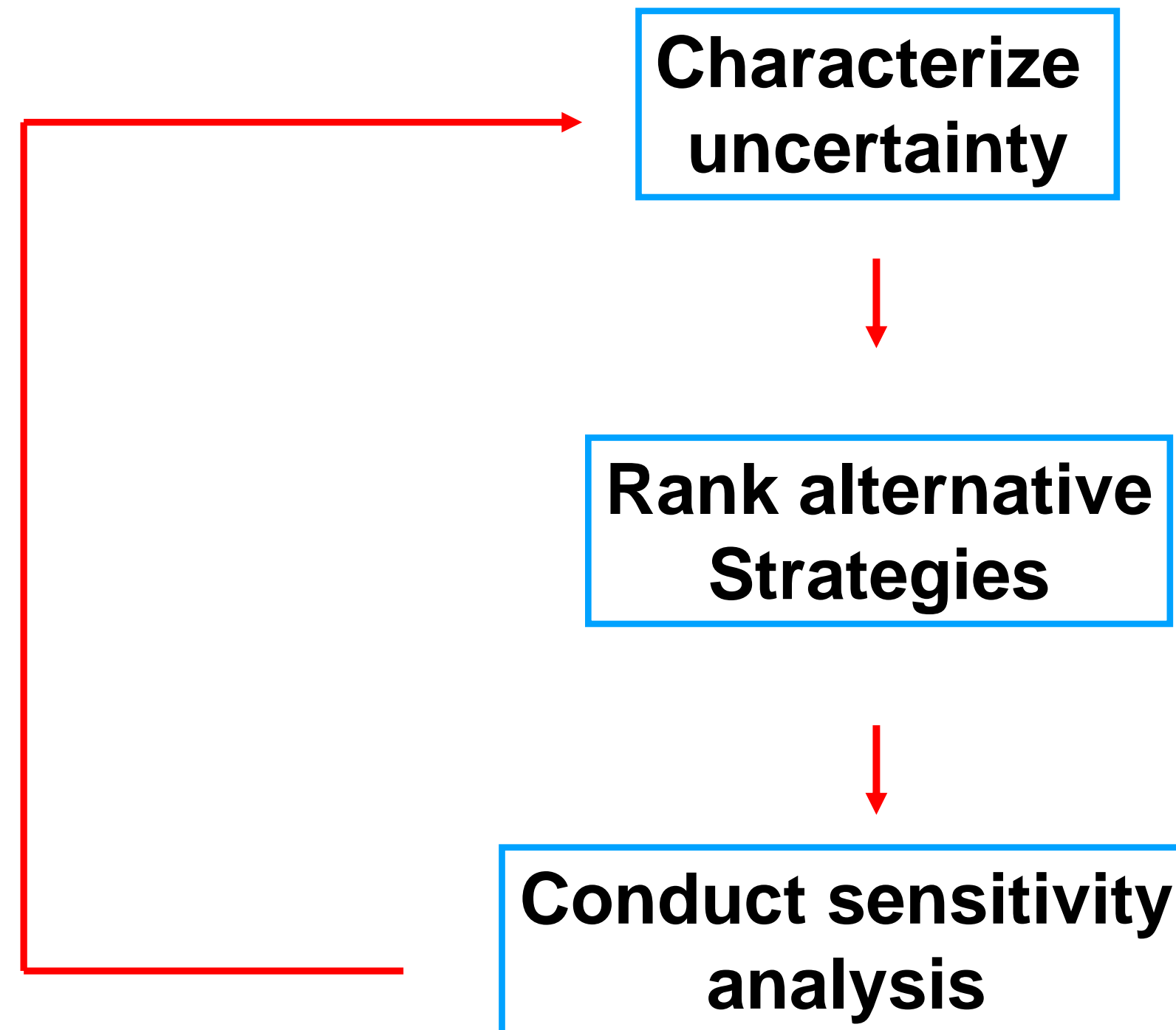




Incident January 2012: evacuation after rising inland water levels (Hazeleger et al 2015)

— inland water level
— sea level



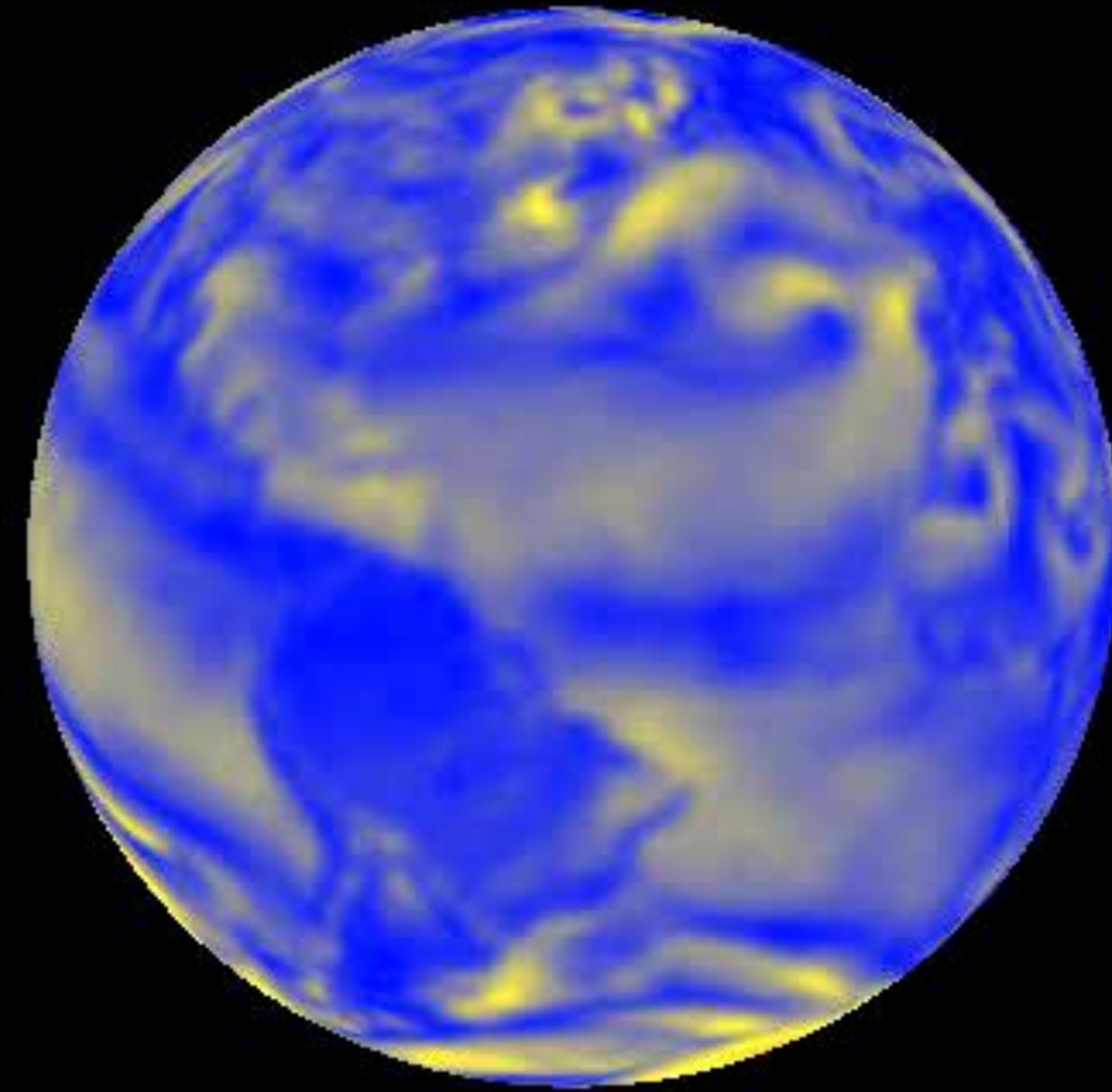
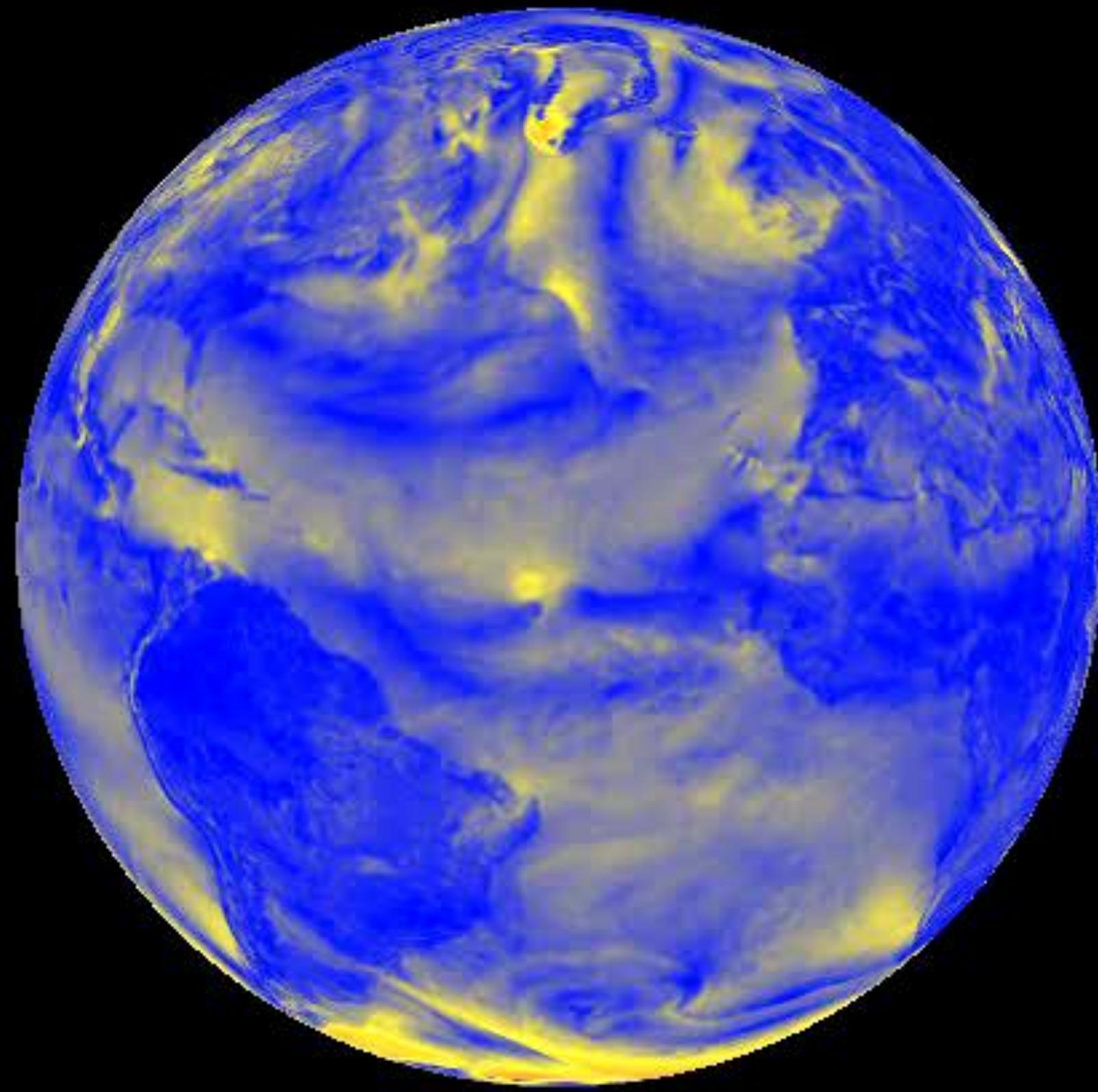


Tales of future weather

W. Hazeleger^{1,2,3*}, B.J.J.M. van den Hurk^{1,4}, E. Min¹, G.J. van Oldenborgh¹, A.C. Petersen^{4,5},
D.A. Stainforth^{6,9,10}, E. Vasileiadou^{4,8} and L.A. Smith^{6,7}

Society is vulnerable to extreme weather events and, by extension, to human impacts on future events. As climate changes weather patterns will change. The search is on for more effective methodologies to aid decision-makers both in mitigation to avoid climate change and in adaptation to changes. The traditional approach uses ensembles of climate model simulations, statistical bias correction, downscaling to the spatial and temporal scales relevant to decision-makers, and then translation into quantities of interest. The veracity of this approach cannot be tested, and it faces in-principle challenges. Alternatively, numerical weather prediction models in a hypothetical climate setting can provide tailored narratives of high-resolution simulations of high-impact weather in a future climate. This 'tales of future weather' approach will aid in the interpretation of lower-resolution simulations. Arguably, it potentially provides complementary, more realistic and more physically consistent pictures of what future weather might look like.

*We need an alternative framework to translate the scenarios to the daily lives of users
“Feeding the imagination” not for the sake of forecasting, but preparedness.*



WG10

20

40

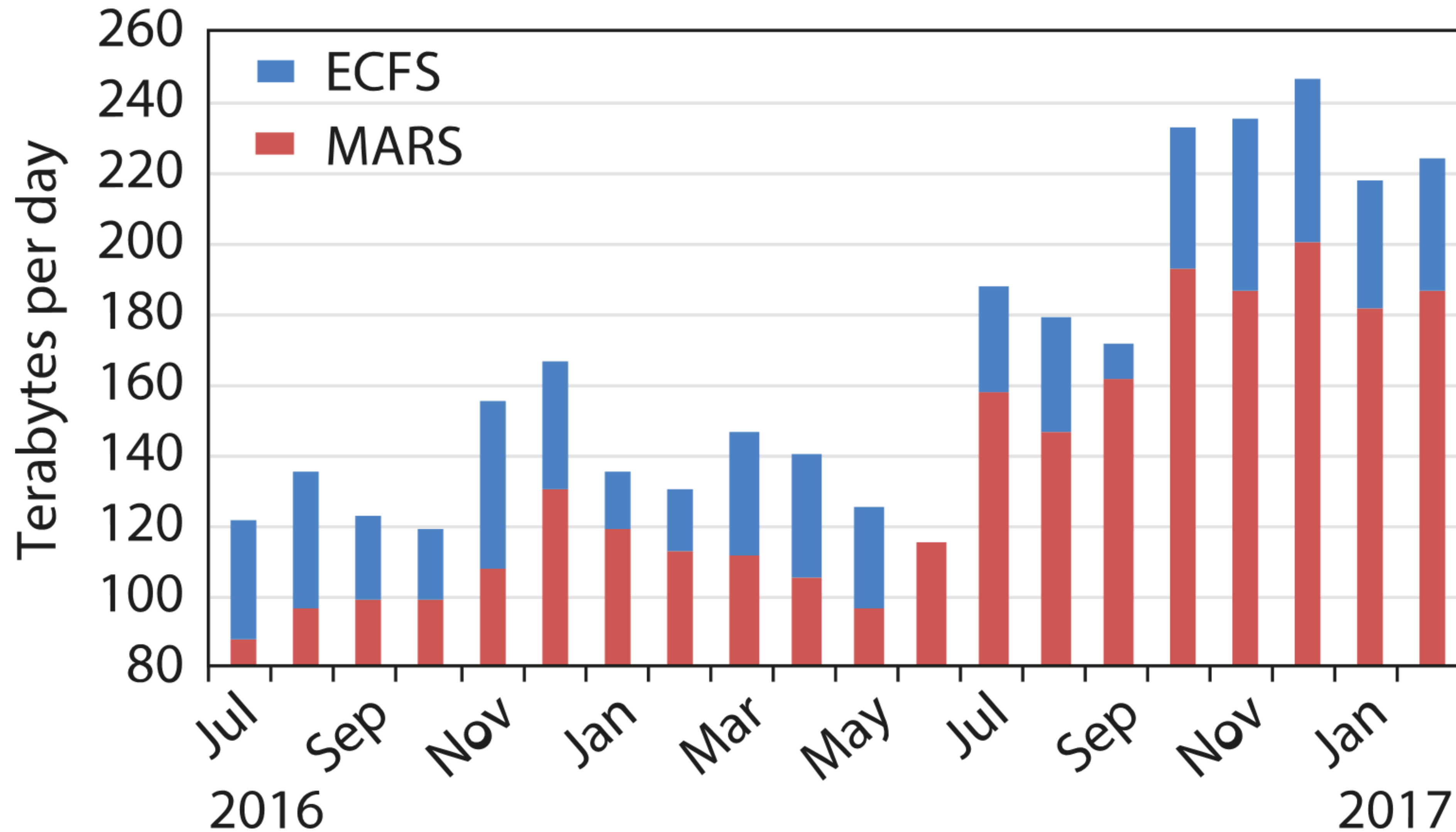
1

60

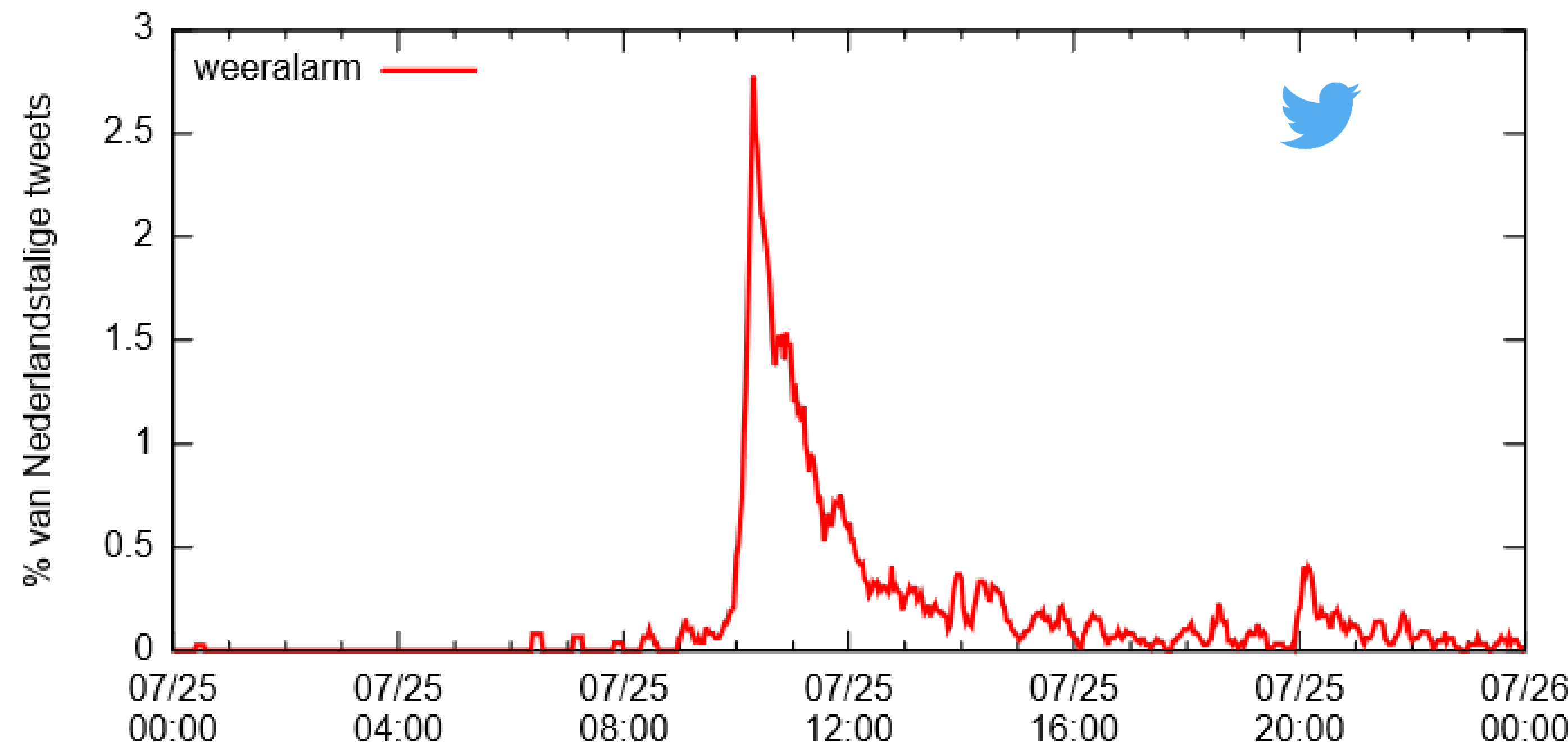
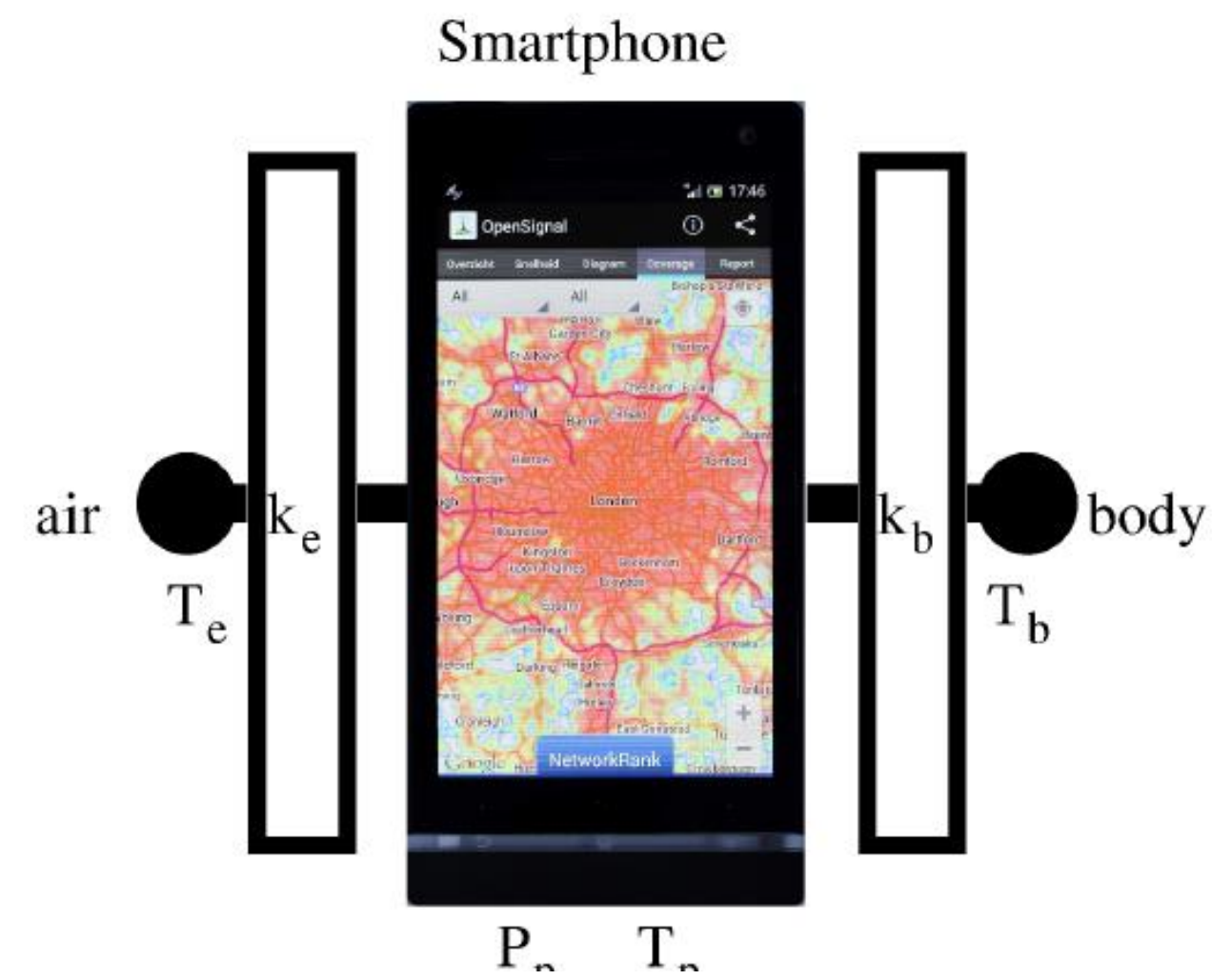
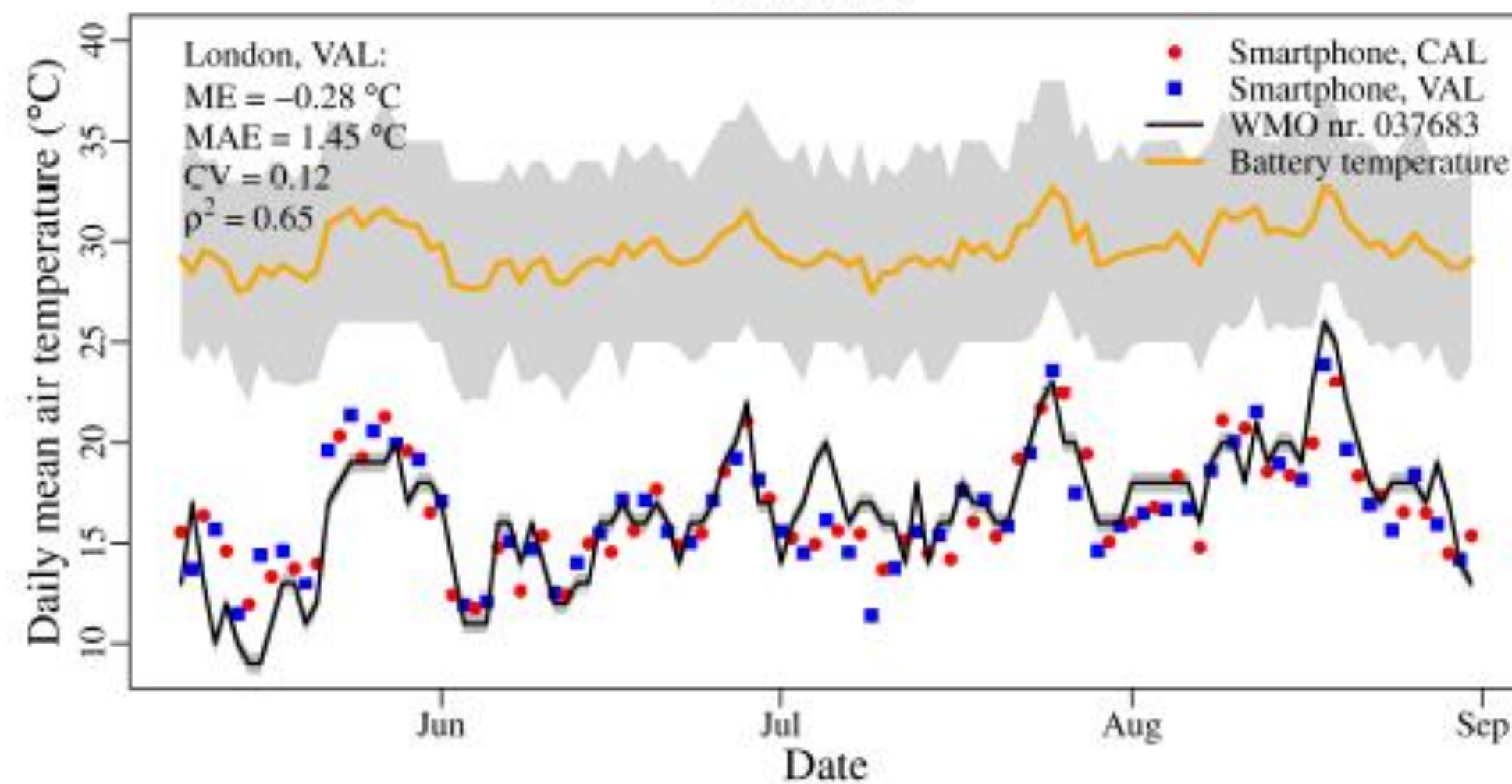
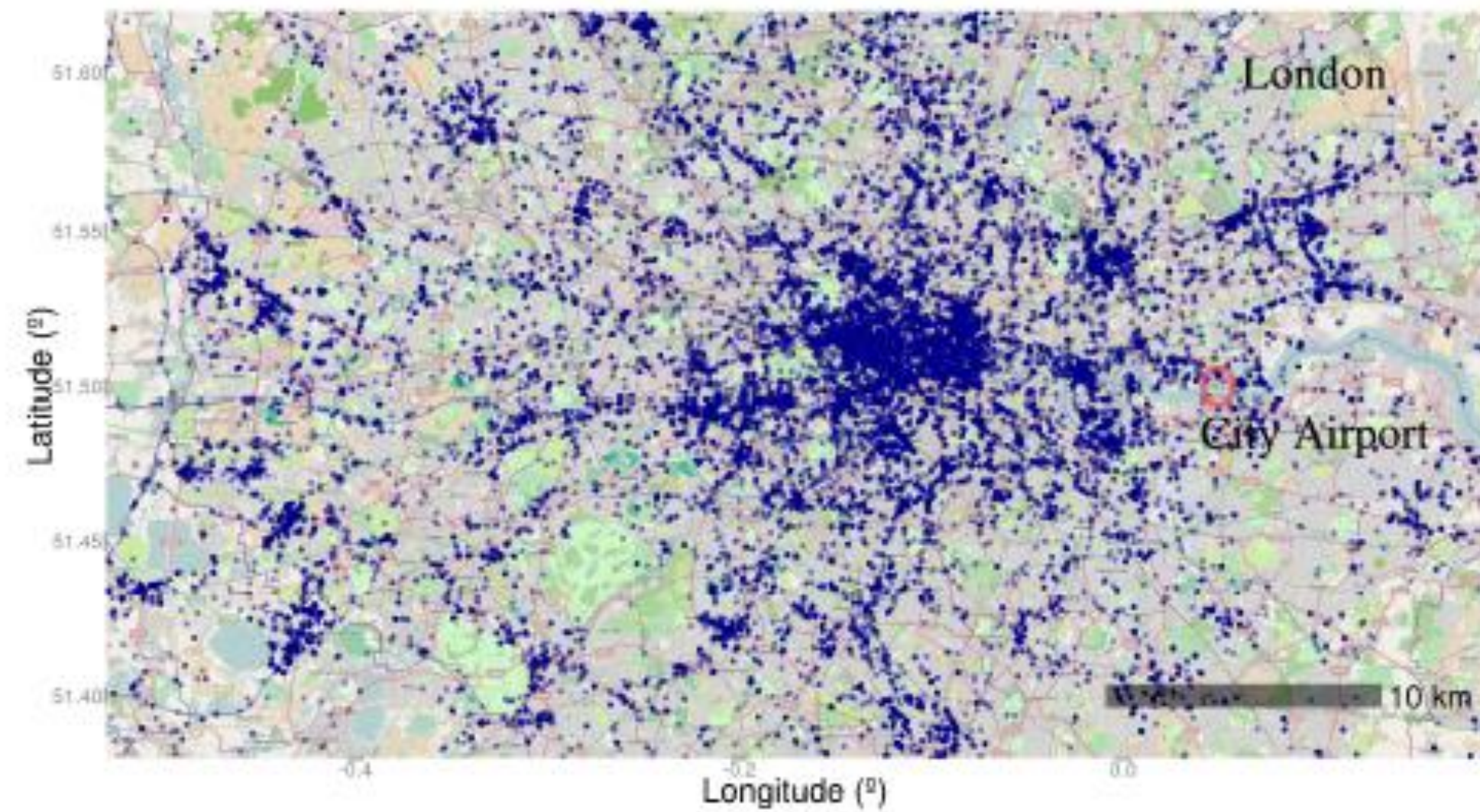


Big science, big data challenge

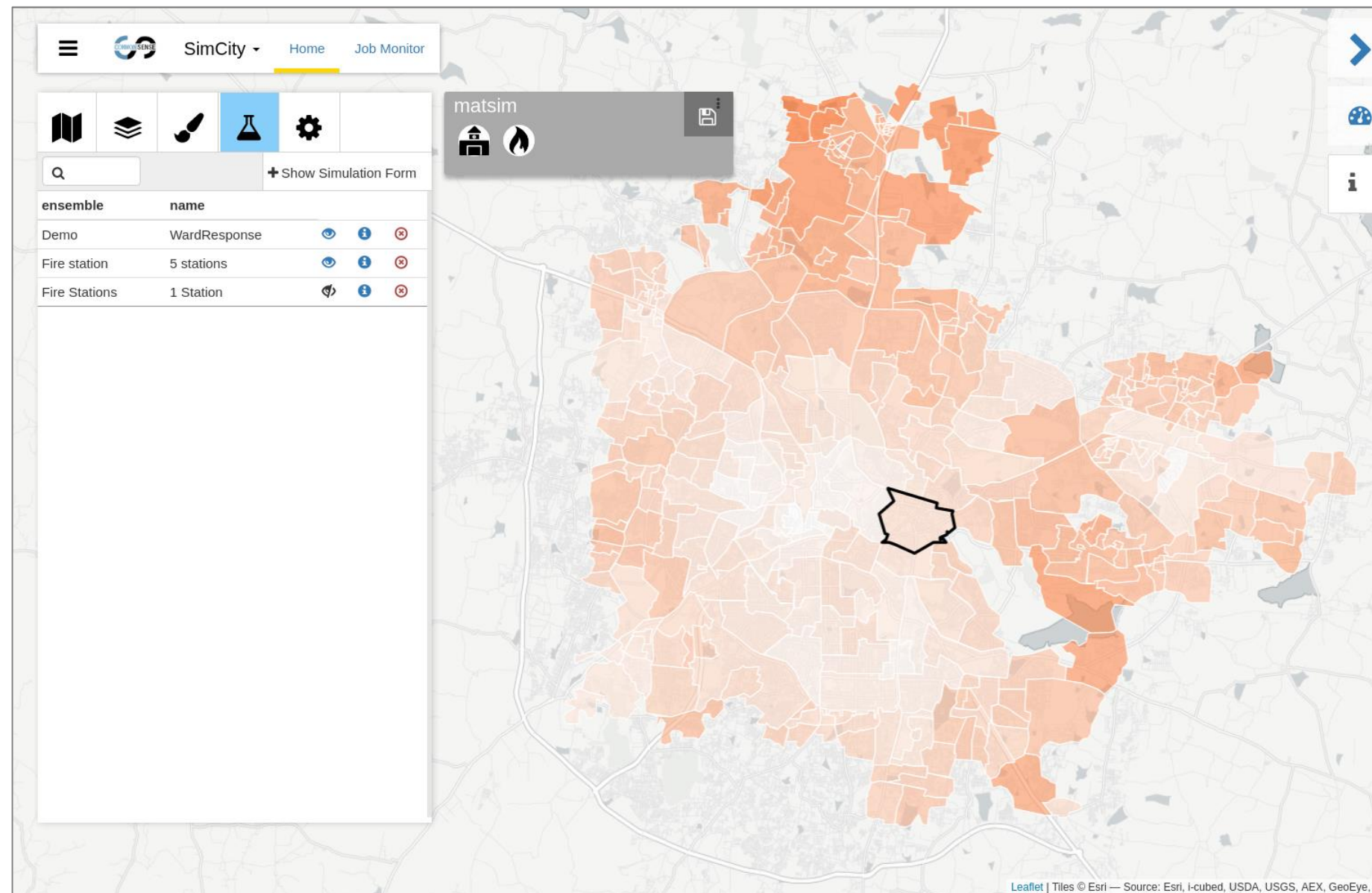




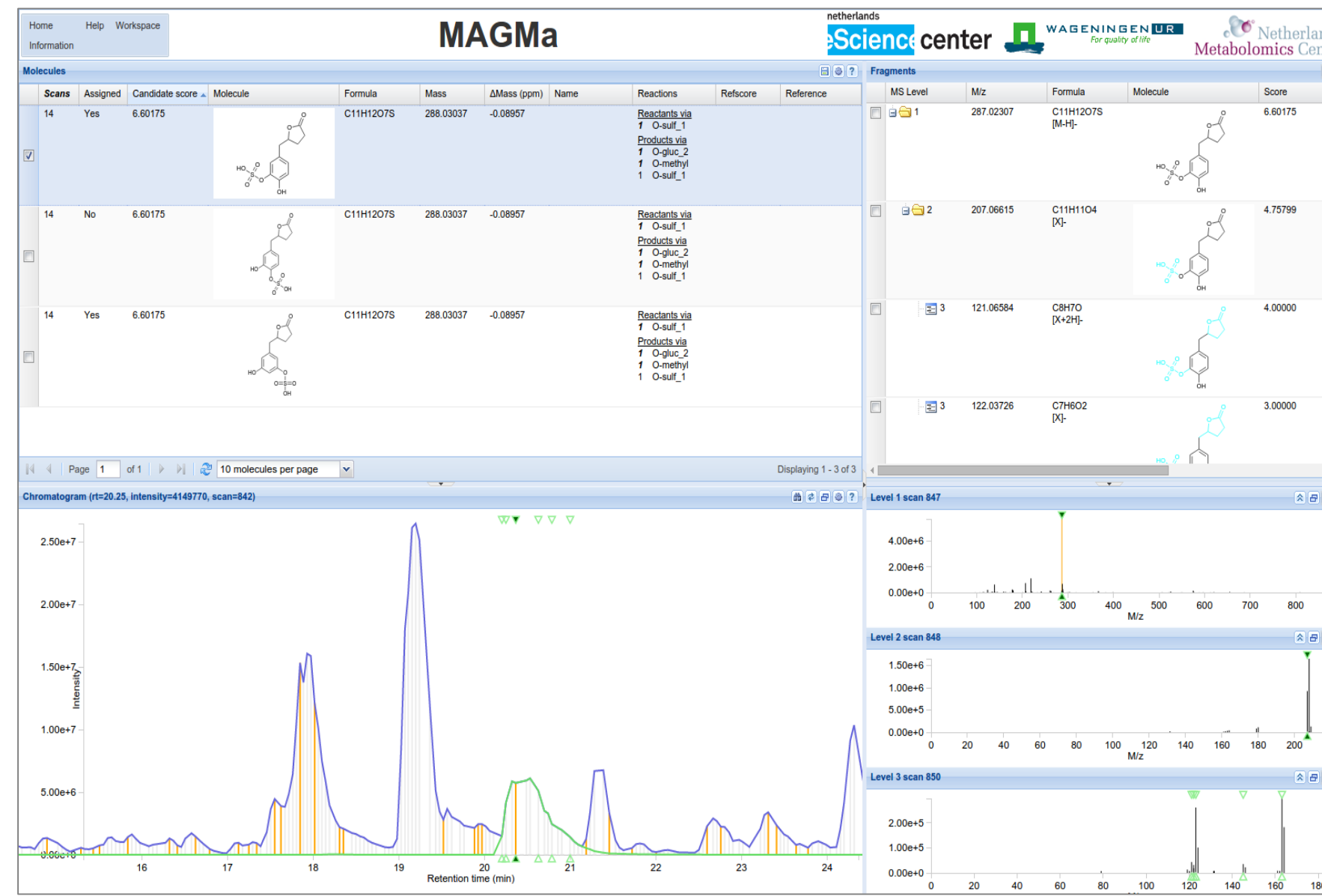
Other big data in meteorology



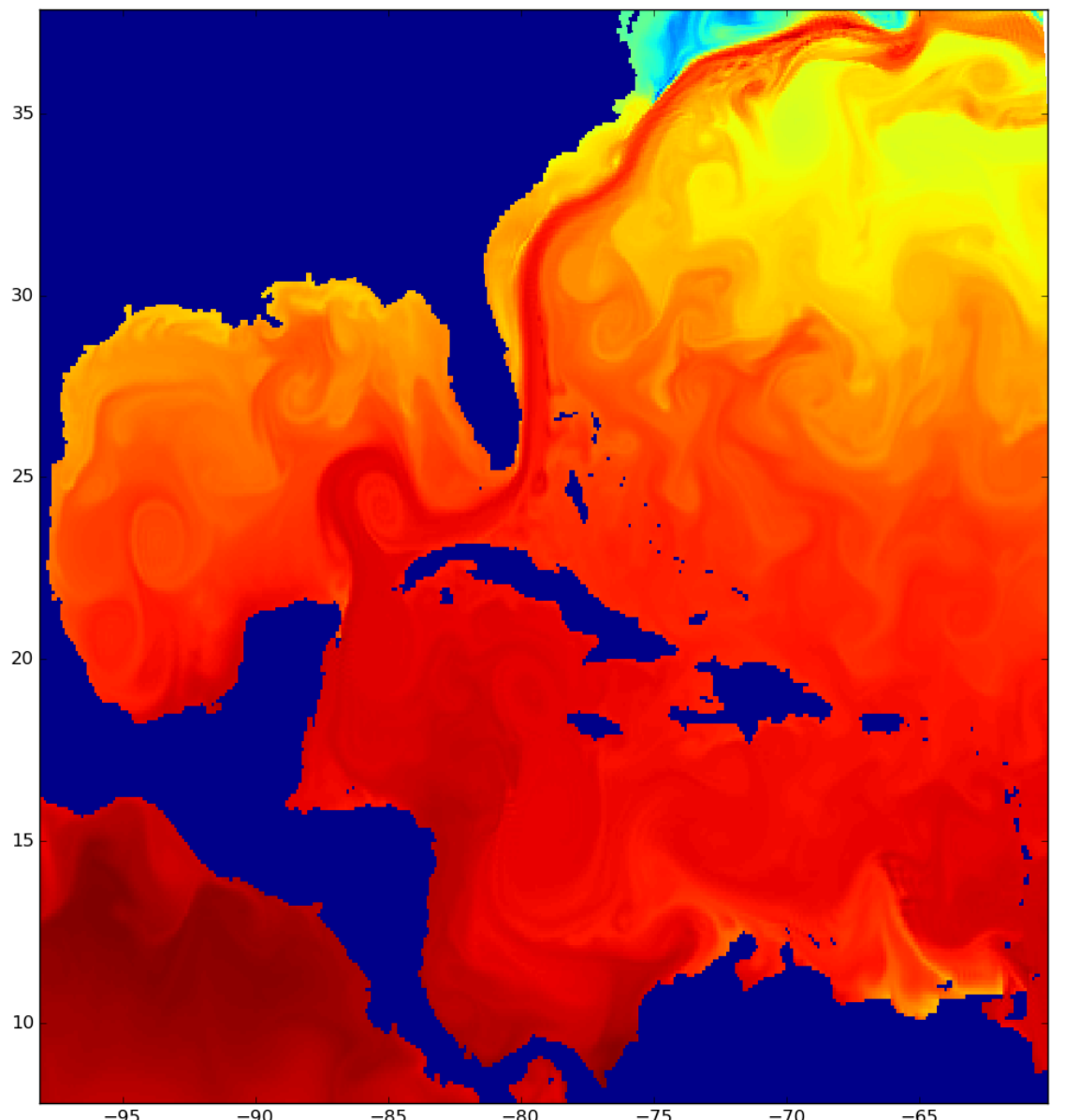
Compute at the touch of a button



SIMCITY



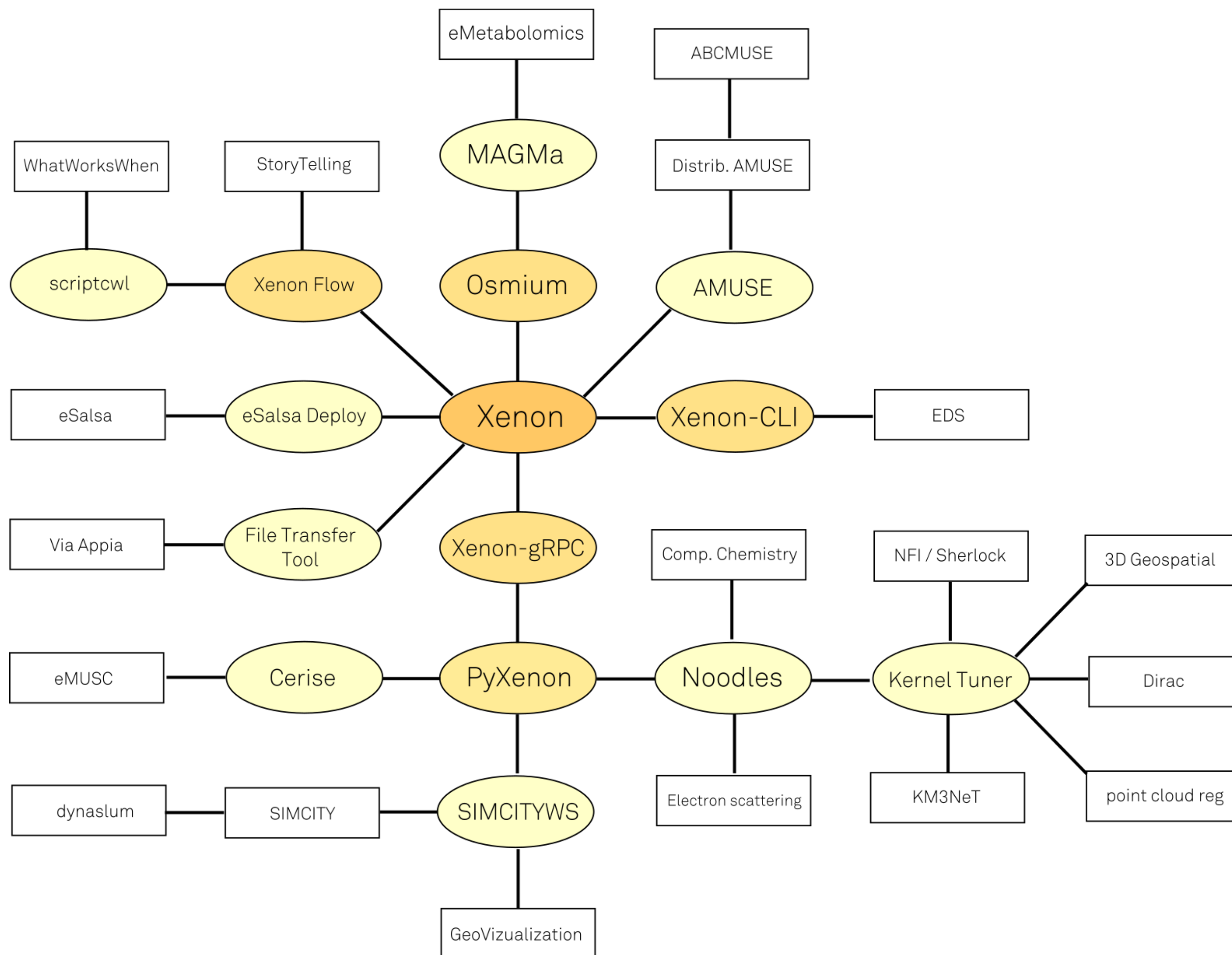
MAGMa



OMUSE

**This “deployment and coupling” is a recurring theme in many of our projects:
easy access to compute and storage and babysitting applications**

Xenon and friends



Xenon is a software library that provides easy access to compute and storage.

<https://github.com/NLeSC/Xenon>

Flexible software tools

The image displays a JupyterLab interface with a Python notebook on the left and a data catalogue and map on the right. The notebook contains the following code:

```
[ ]: from ewatercycle.models import PcrGlobWB
      from ewatercycle.forcings import Gfs
      from ewatercycle.plotting import geo_plot, timeseries_plot

[ ]: parameterset = PcrGlobWB.parametersets['RhineMeuse30min']
      # Or generate a parameterset for a region
      parameterset = PcrGlobWB.parameterset_from_region(latmin=4, latmax=10, lonmin=45, lonmax=55)

[ ]: forcing = Gfs()

[ ]: start = '1999-01-01T00:00:00Z'
      end = '2010-31-12T23:59:59Z'

[ ]: model = PcrGlobWB(parameterset=parameterset,
                      forcing=forcing,
                      start=start,
                      end=end,
                      )

[ ]: discharge_over_time = []
      while model.current_time < model.end_time:
          model.update()
          discharge_over_time.append(model.discharge)

[ ]: # Plot discharge of last time step
      geo_plot(model.discharge)

[ ]: # Plot discharge of all time steps, with time series
      geo_plot(discharge_over_time)

[ ]: # Plot discharge over time for that location
      timeseries_plot(discharge_over_time, location=(5.0, 51.5))

[ ]:
```

The data catalogue on the right shows the following structure:

- Data Catalogue | My Data
- Search the catalogue
- eWaterCycle Datasets
 - eWaterCycle Models
 - PCR-GLOBWB
 - Global 30 Min.
 - Rhine Meuse 30 Min.
 - WFLOW
 - Rhine 5Min.
 - WALRUS
 - Hupsel Brook

The map interface shows a map of Europe with a blue box highlighting the Rhine region. The map includes a search bar, a search button, and a "Remove from the map" button. The map also displays the following information:

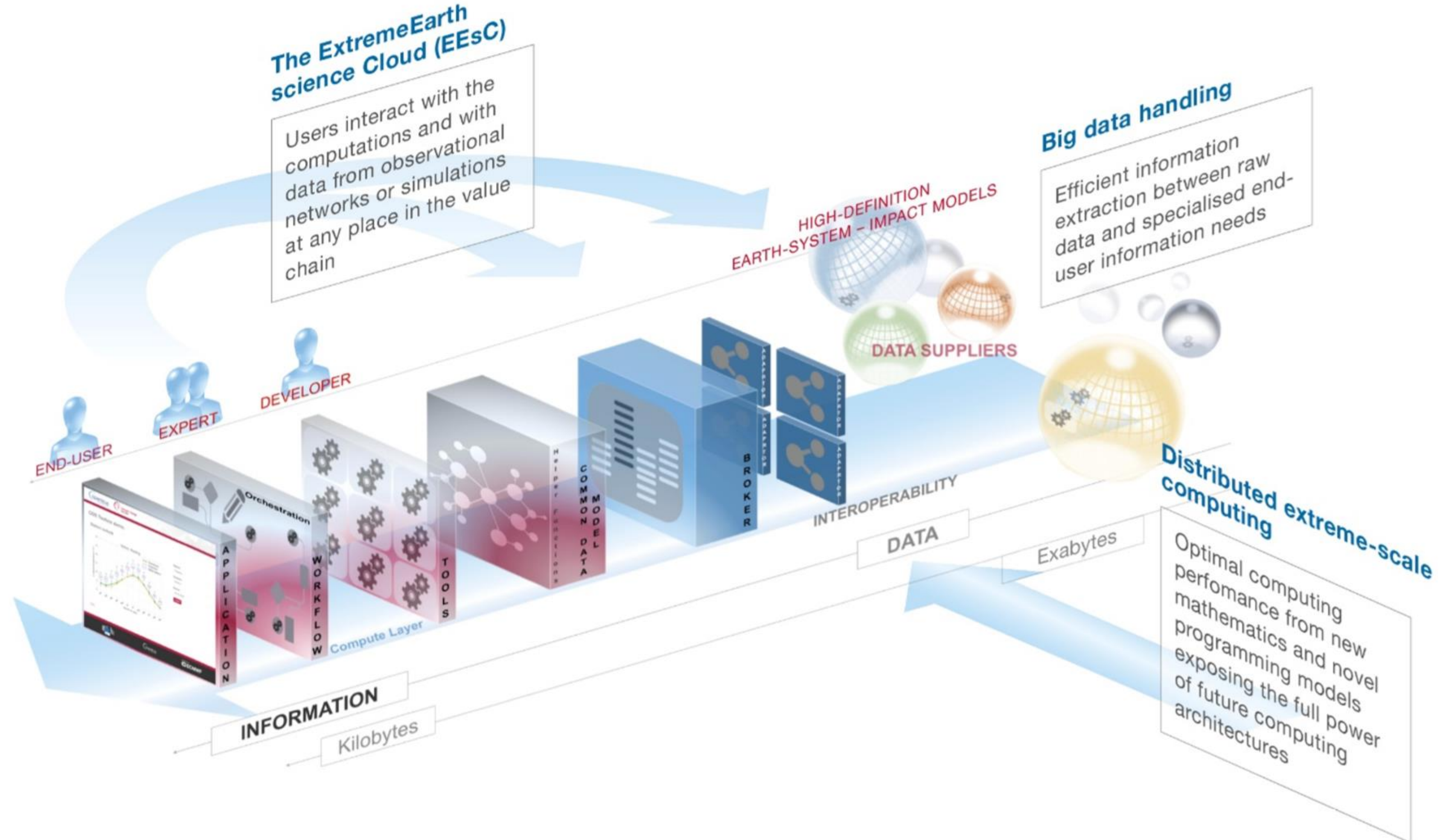
- Feature Information
- DATA PREVIEW
- Rhine 5Min. Please contact the provider of this data for more information, including information about usage rights and constraints.
- GeoJSON URL: `datasets/wflow-rhine.geojson`
- Data URL: Use the link below to download the data directly. datasets/wflow-rhine.geojson

The map also shows the following coordinates: Lat 52.07060°N Lon 6.59733°E Elev 1 km.

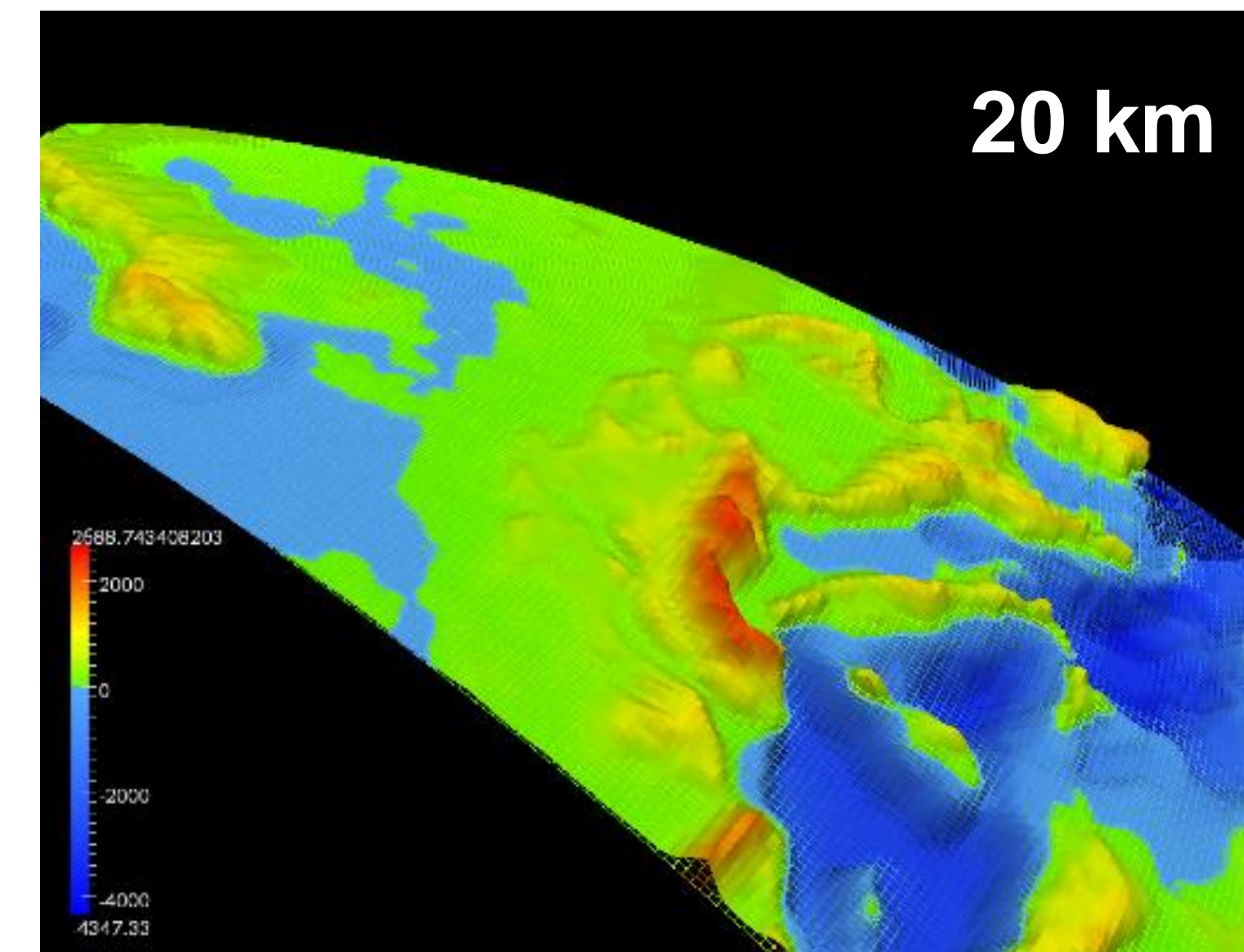
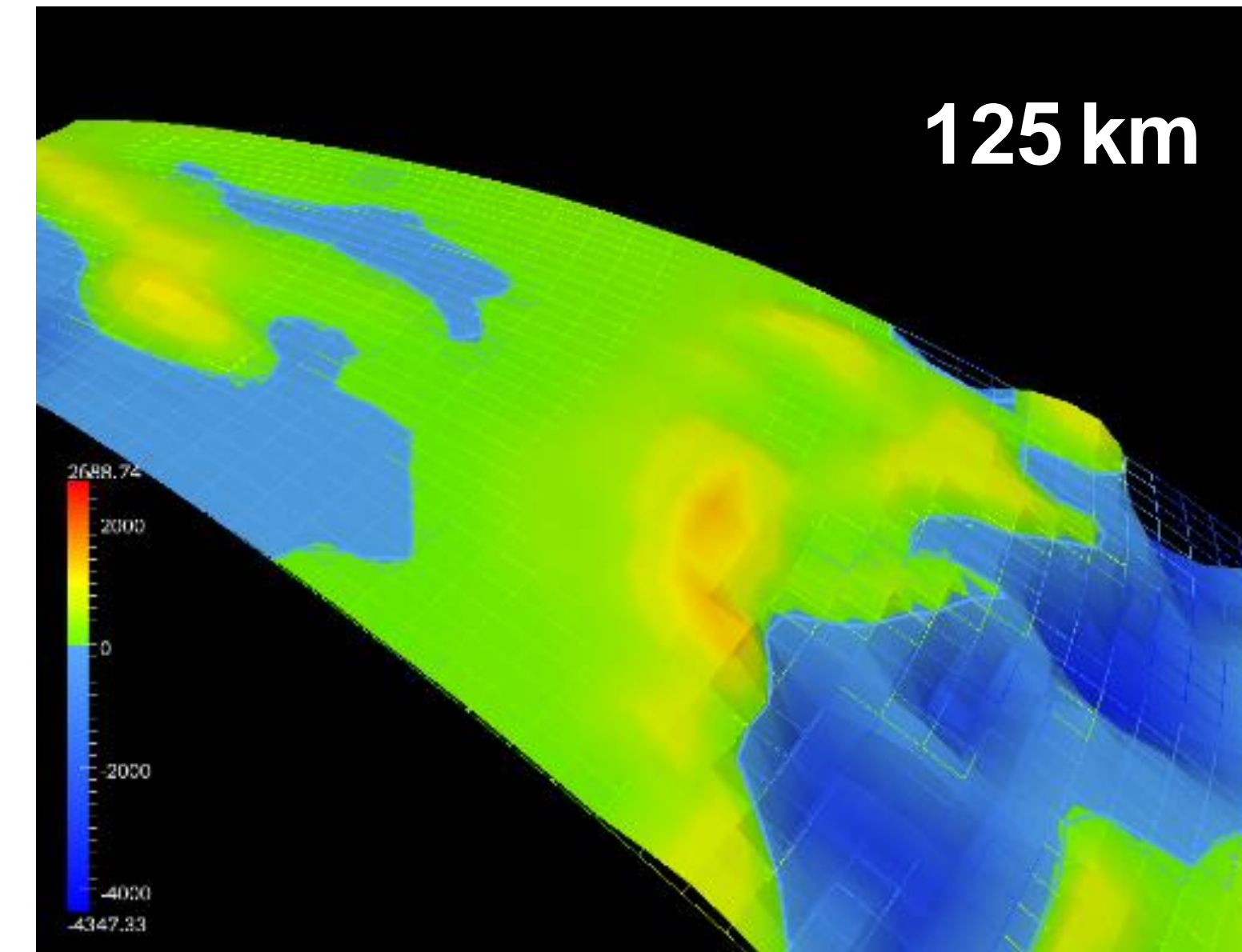
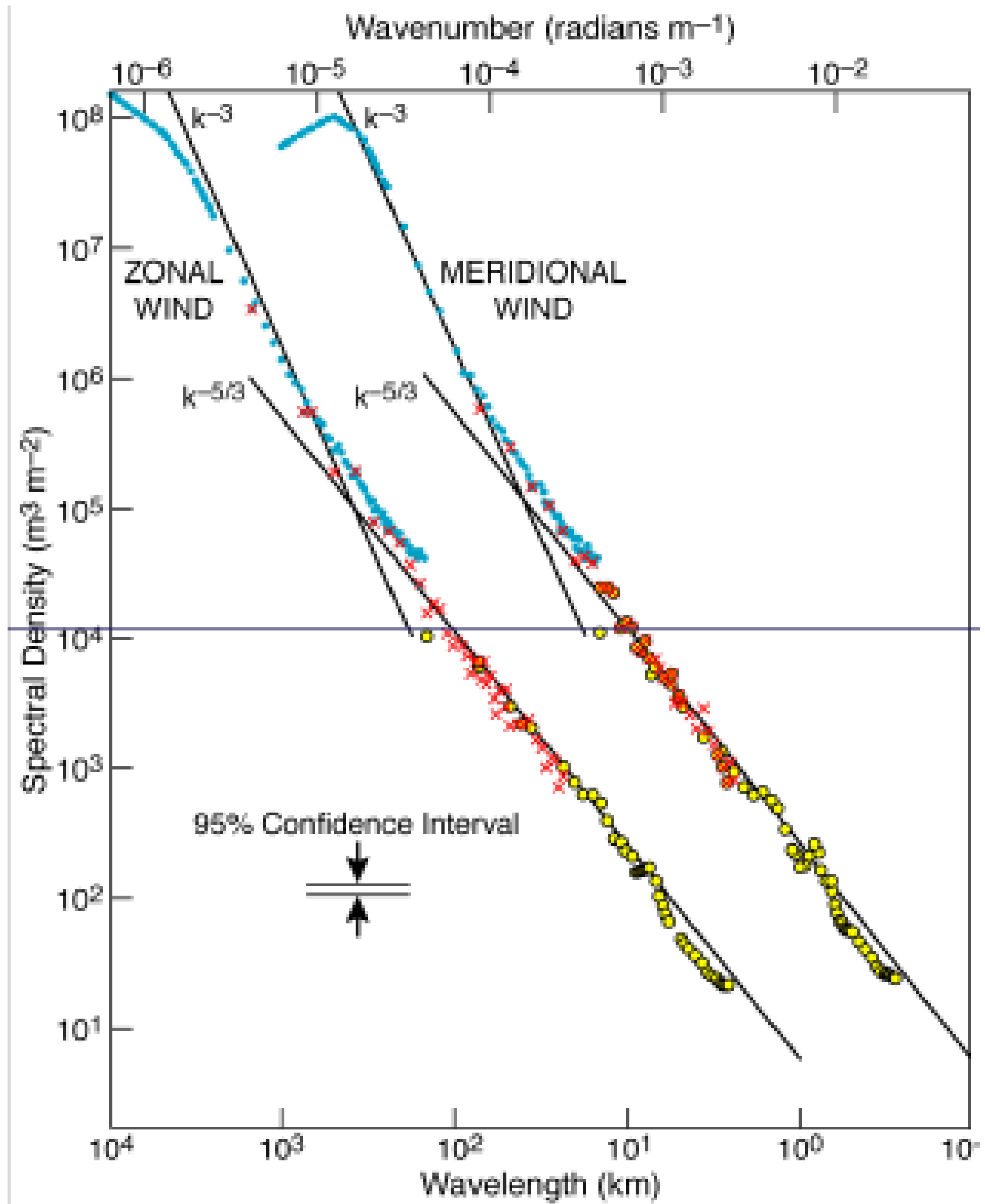
Flexible steering, execution of models and data handling

```
...  
[ ]: from ewatercycle.models import PcrGlobWB  
     from ewatercycle.forcings import Gfs  
     from ewatercycle.plotting import geo_plot, timeseries_plot  
  
[ ]: parameterset = PcrGlobWB.parametersets['RhineMeuse30min']  
     # Or generate a parameterset for a region  
     parameterset = PcrGlobWB.parameterset_from_region(latmin=4, latmax=10, lonmin=45, lonmax=55)  
  
[ ]: forcing = Gfs()  
  
[ ]: start = '1999-01-01T00:00:00Z'  
     end = '2010-31-12T23:59:59Z'  
  
[ ]: model = PcrGlobWB(parameterset=parameterset,  
                       forcing=forcing,  
                       start=start,  
                       end=end,  
                       )  
  
[ ]: discharge_over_time = []  
     while model.current_time < model.end_time:  
         model.update()  
         discharge_over_time.append(model.discharge)  
  
[ ]: # Plot discharge of last time step  
     geo_plot(model.discharge)
```

What e-infrastructure does it take?

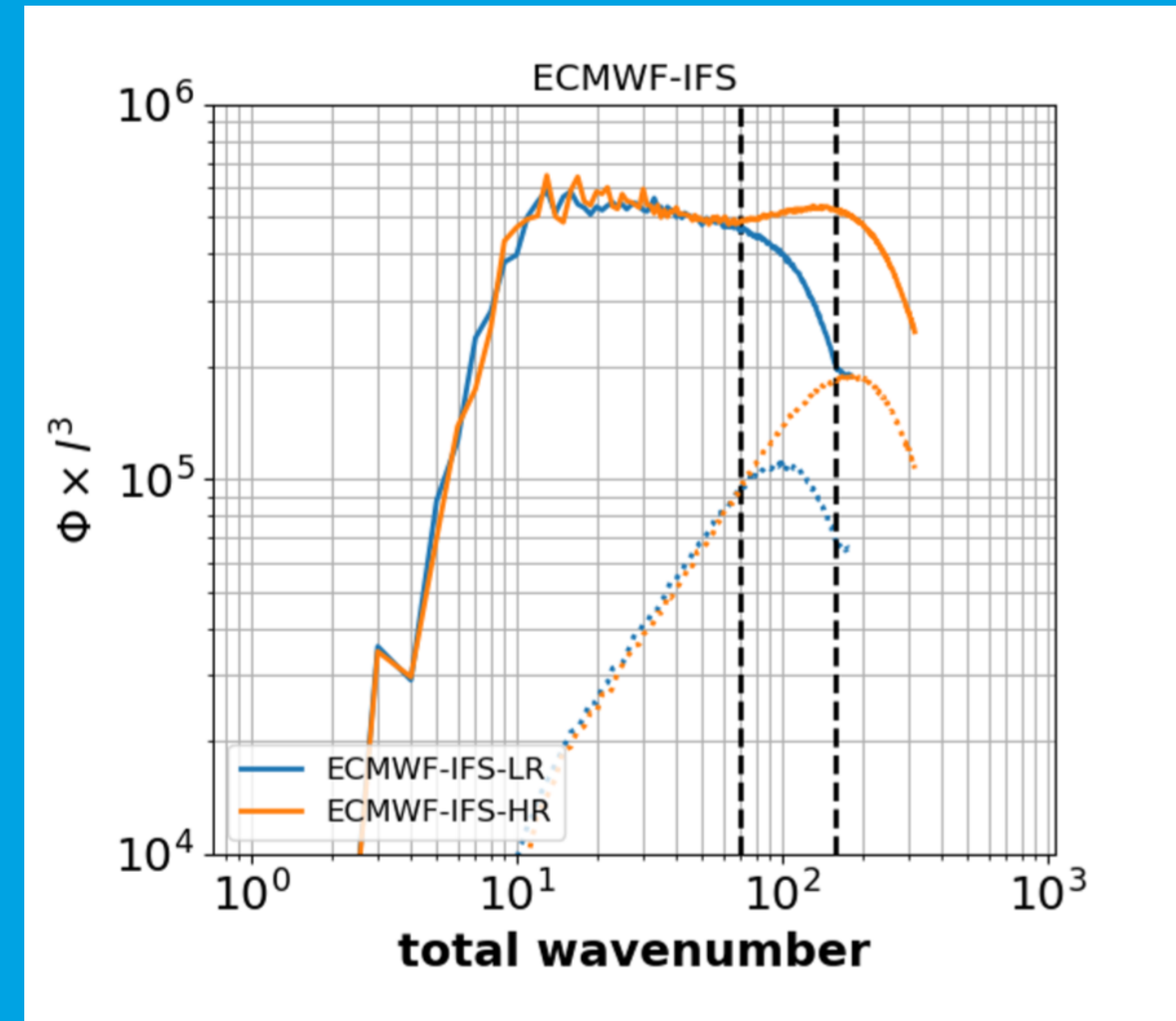


The need for resolution

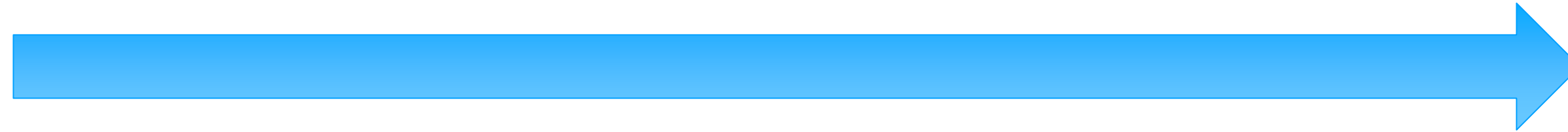


Kinetic energy spectrum at two grid resolutions

- ECMWF-IFS-LR spectral reduced TCO255
123 290 2.4 ECMWF-IFS-HR spectral
reduced TCO511 62.6 125 2.0
- To resolve deep convection, at least factor
10 horizontal resolution (factor 1000
computing) needed



More energy efficient



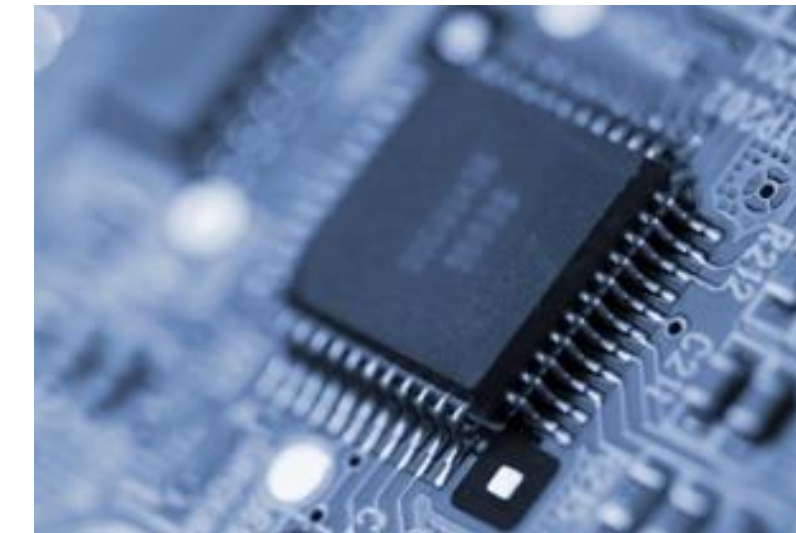
CPU



GPU



FPGA

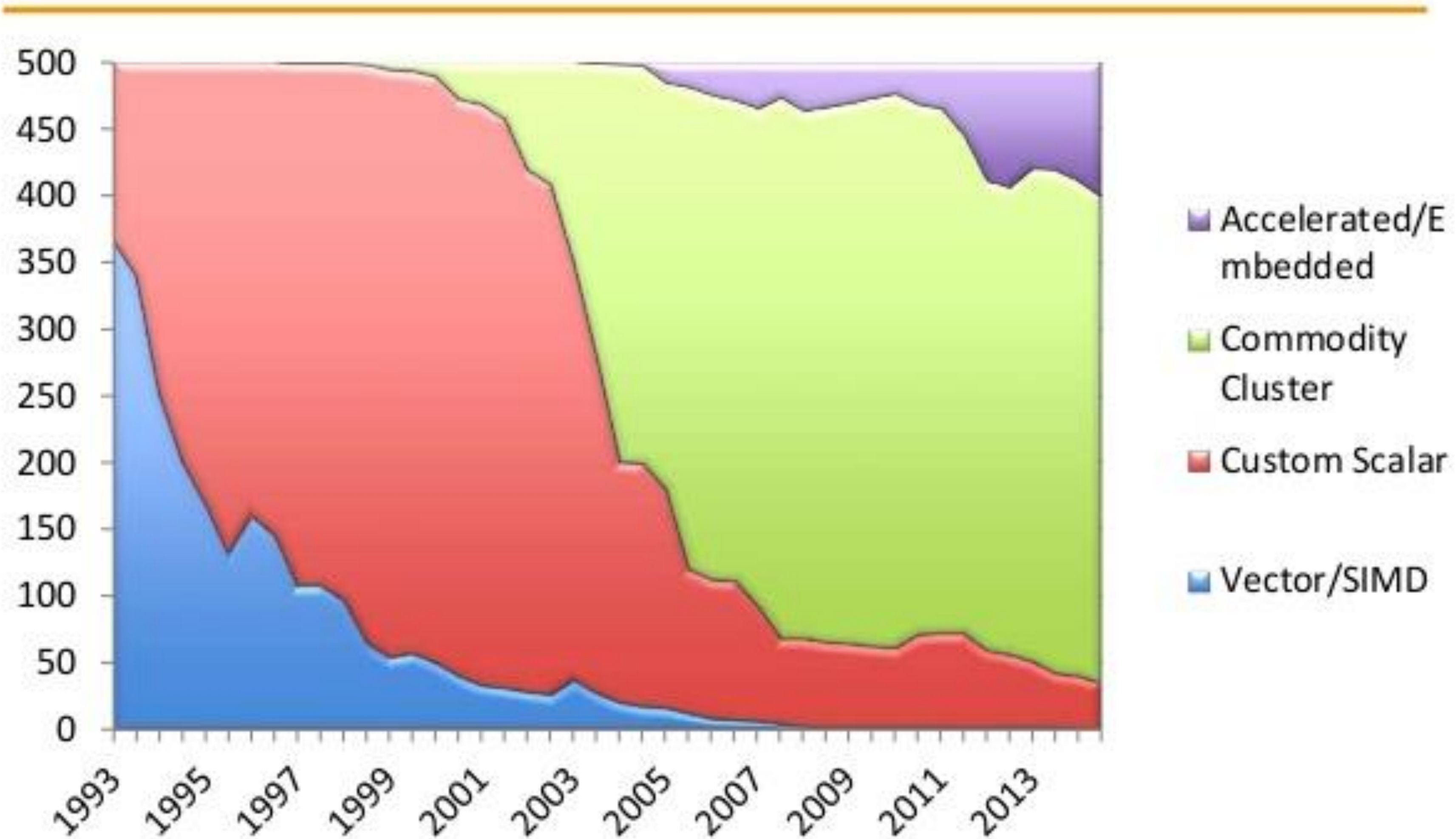


ASIC

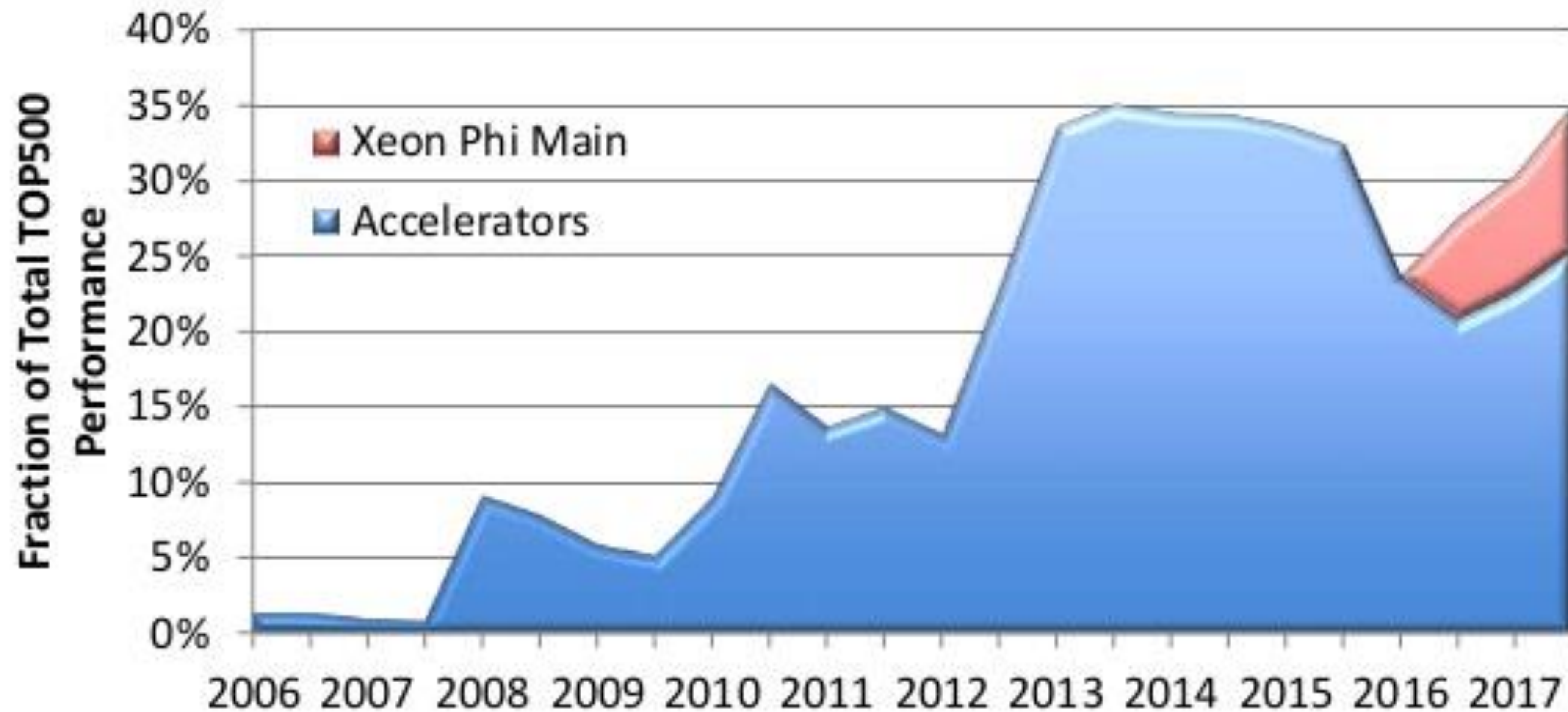


Easier to program

BELL'S LAW

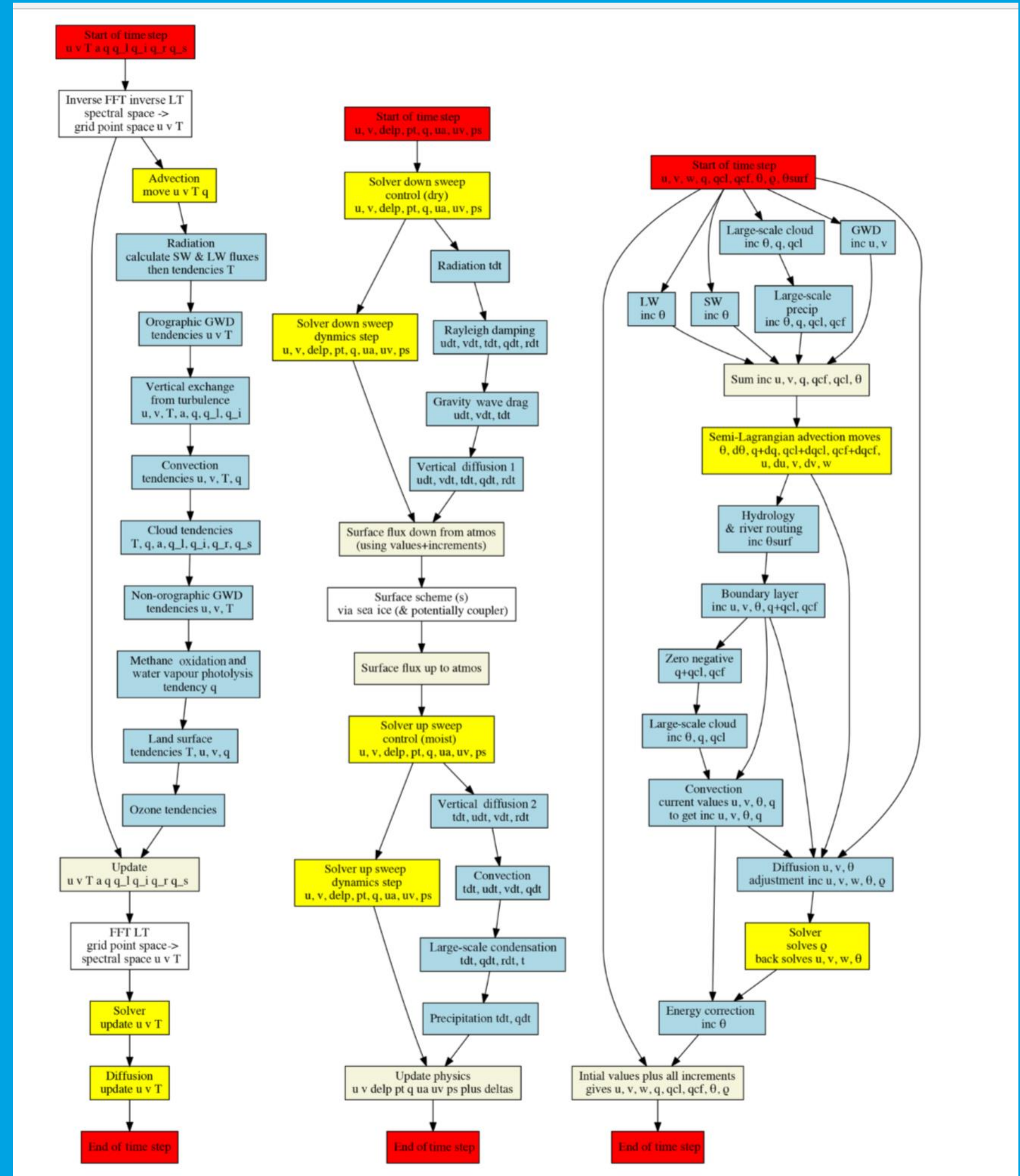


PERFORMANCE SHARE OF ACCELERATORS

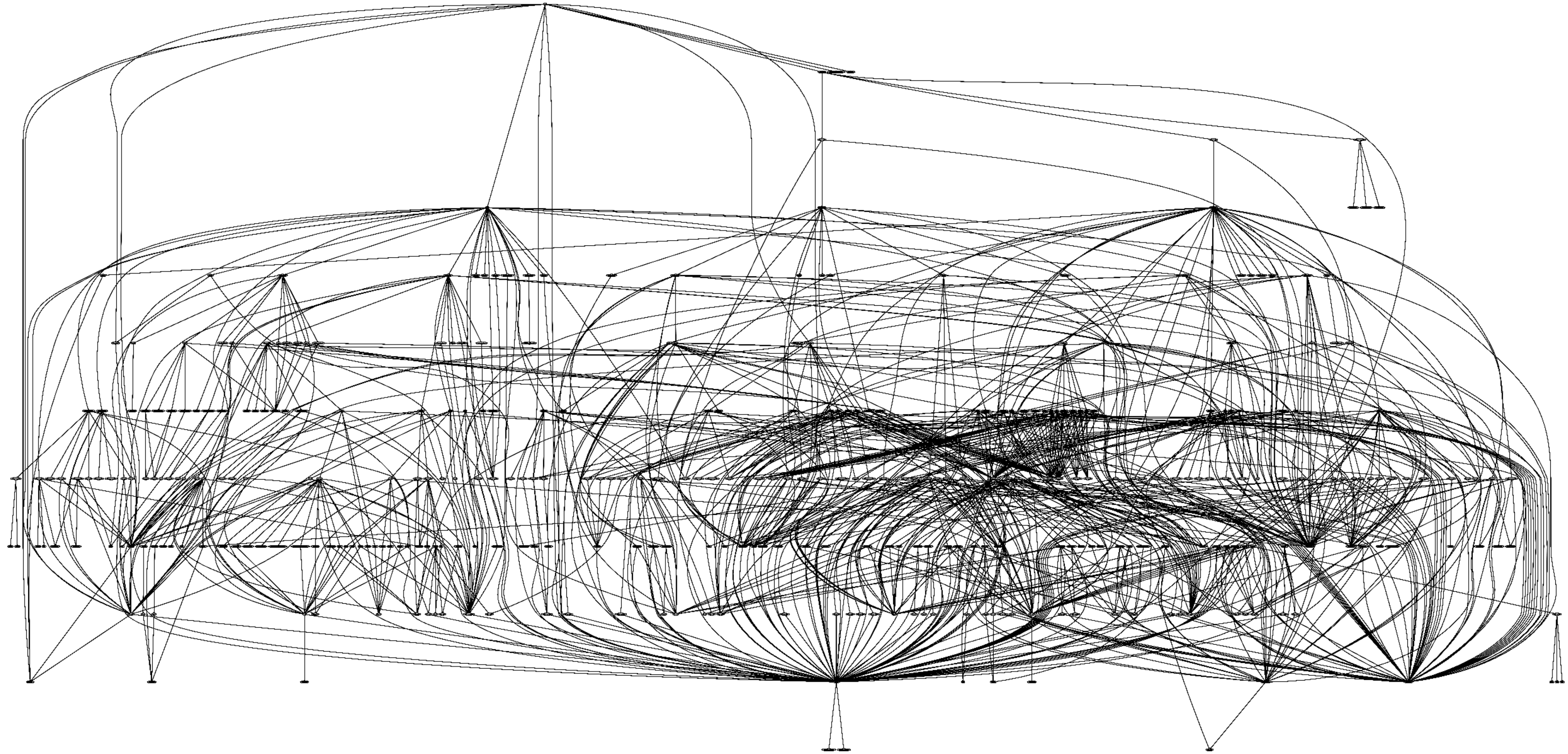


A climate model

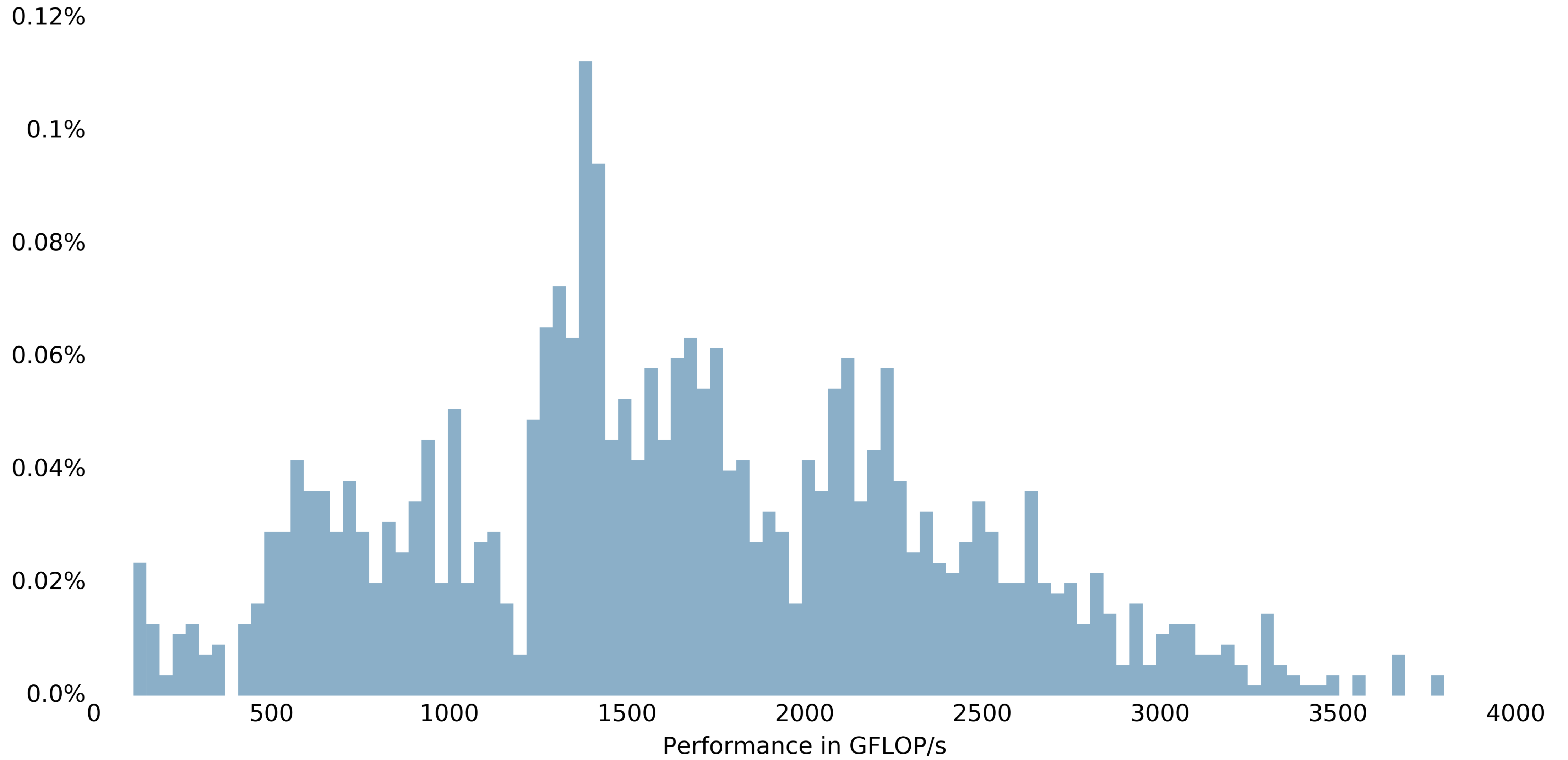
- Initialize
- Start loop
- Dynamics
- Physics
- Update
- End loop
- I/O



Reality check: call graph of ocean GCM POP (courtesy B van Werkhoven)



Tuning for performance: 2D Convolution on GTX Titan X (Maxwell; van Werkhoven, FCGS accepted)

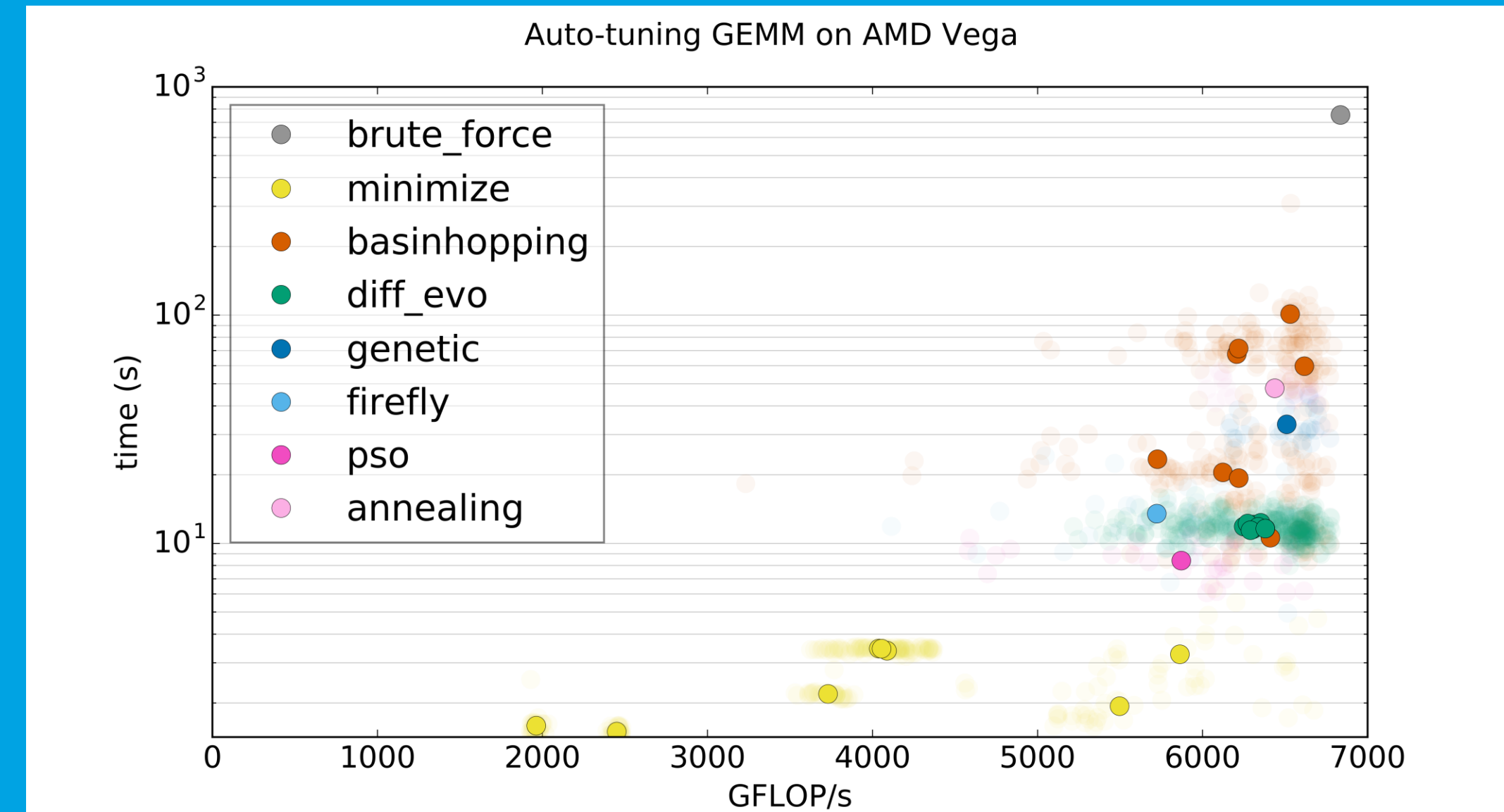


Optimized GPU code requires that you get all the details exactly right:

- Mapping of the problem to threads and thread blocks
- Thread block dimensions
- Data layouts in the different memories
- Tiling factors
- Loop unrolling factors
- How to overlap computation and communication
- ...

Problem:

Creates a very large and discontinuous search space



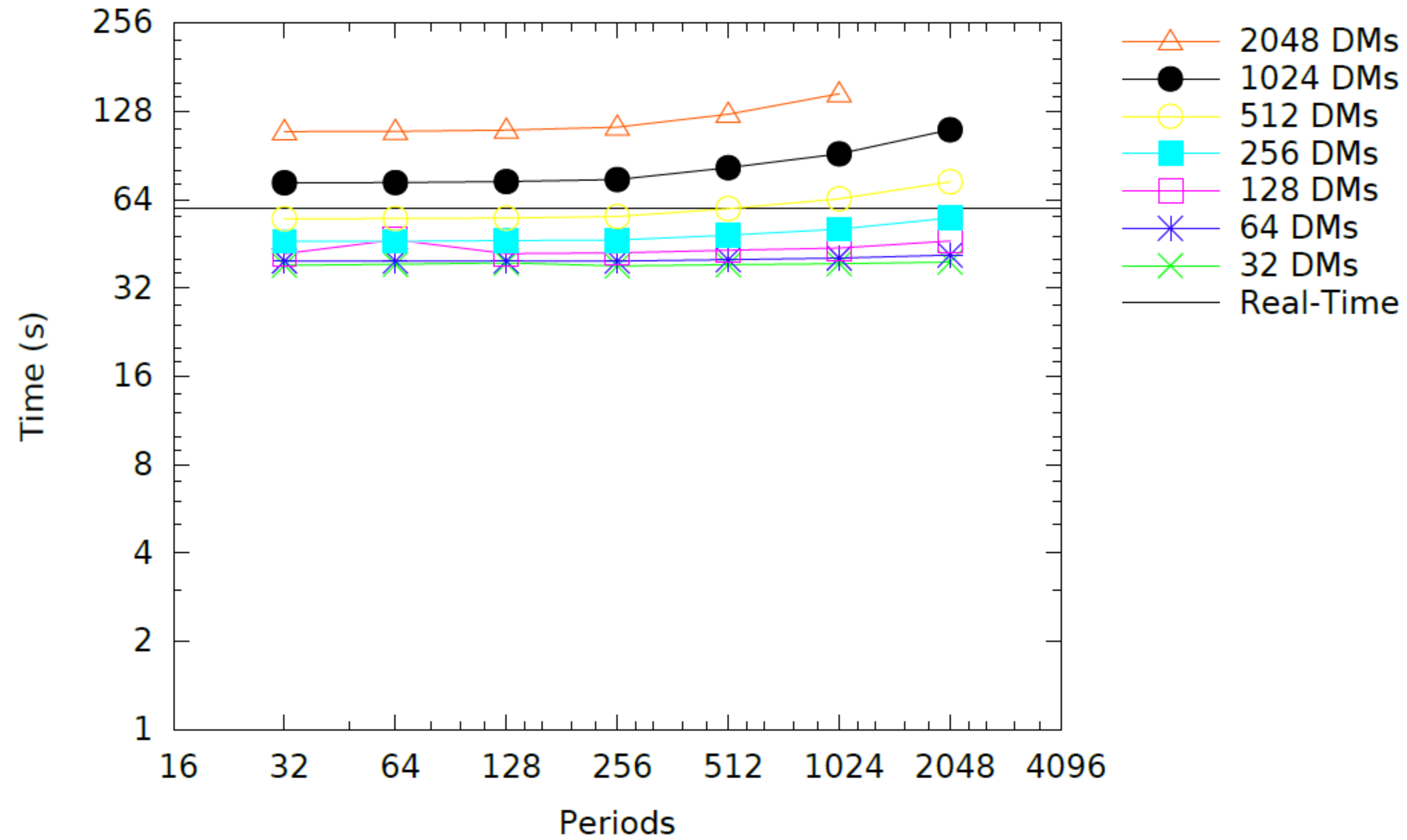
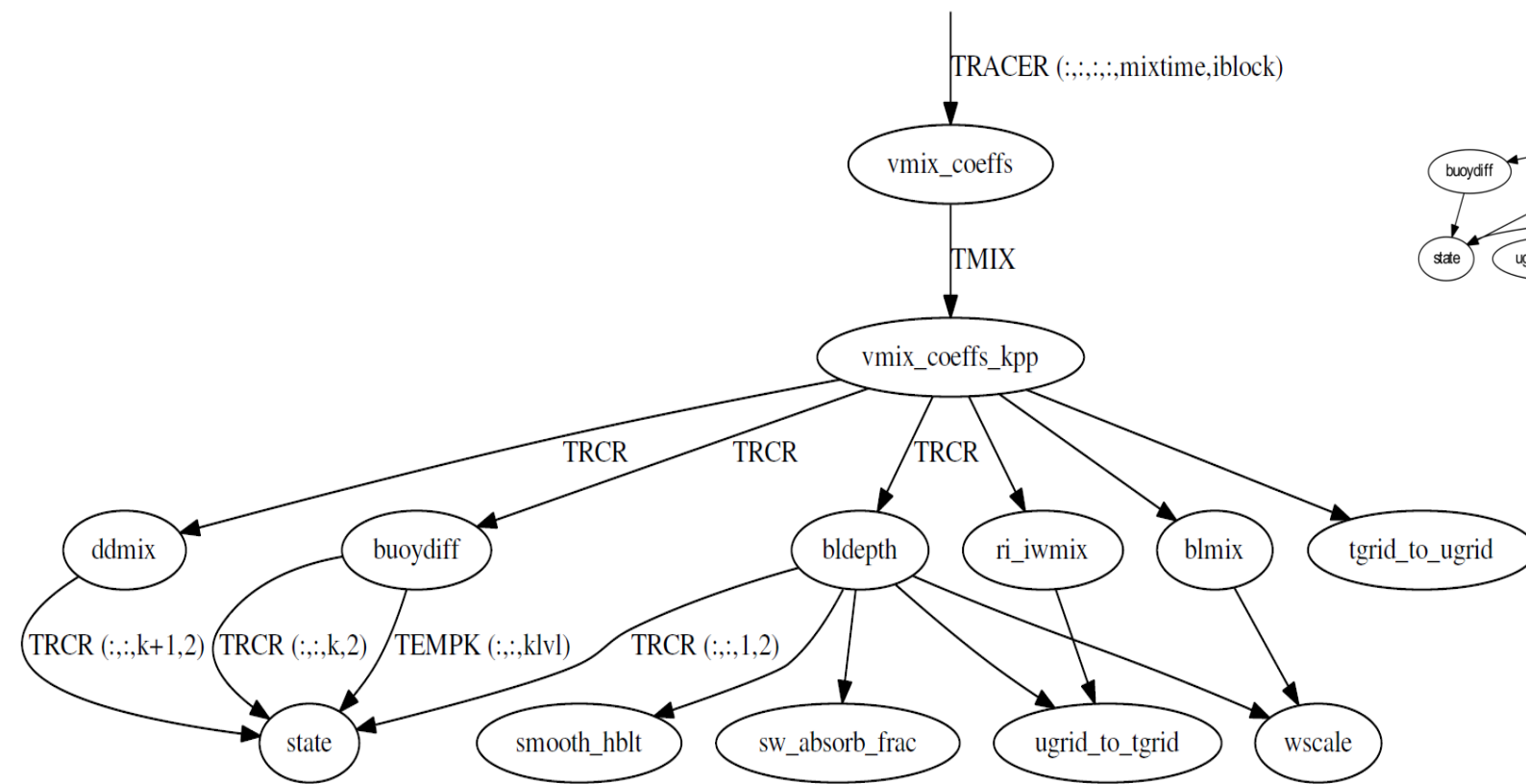


Fig. 5. Pipeline performance for the AMD HD7970, SKA1 scenario.

Marver

source code analysis



transformation

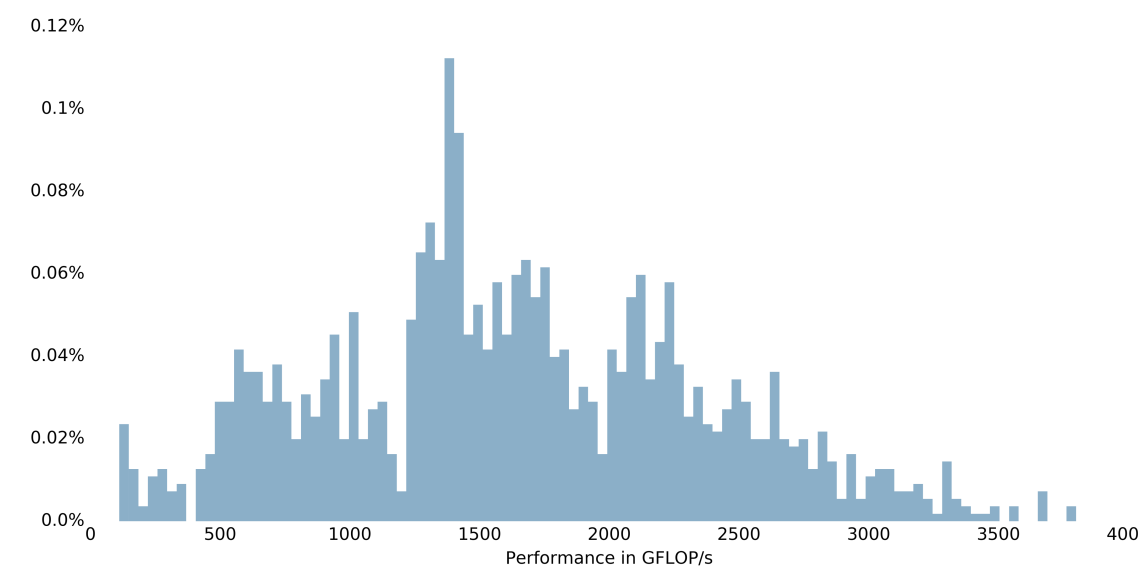
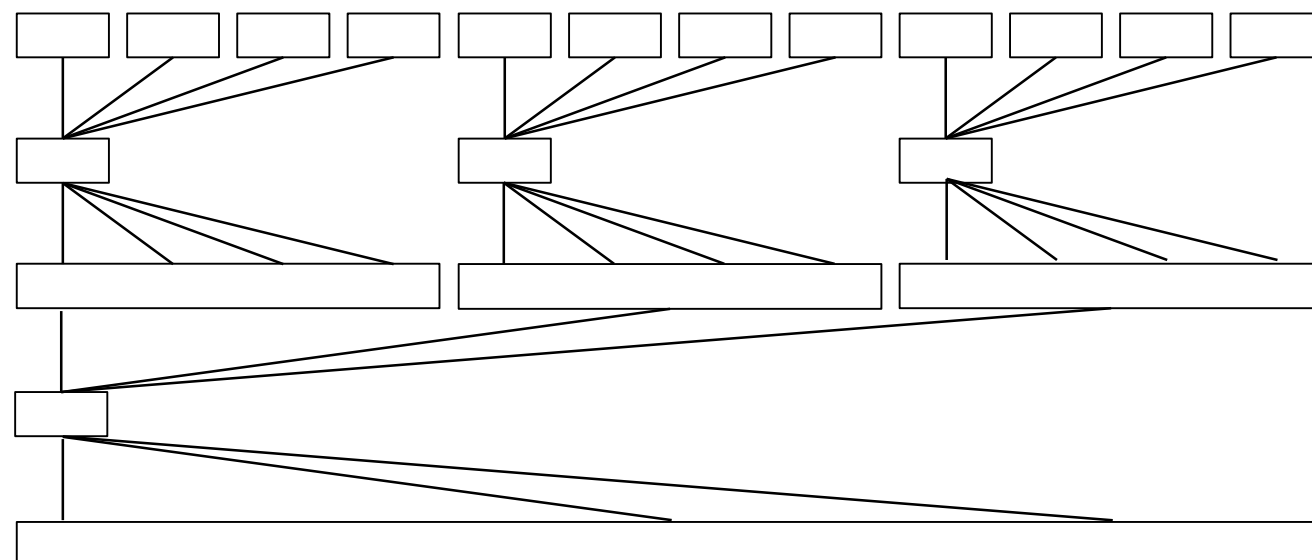


source-to-source translation

```
VVC(:, :, k) = merge(WORK2, c0,
                    (k < KMU(:, :, bid)))
```

```
VVC(i, j, k) = ((k < KMU(i, j, bid)) ?
                WORK2 : c0);
```

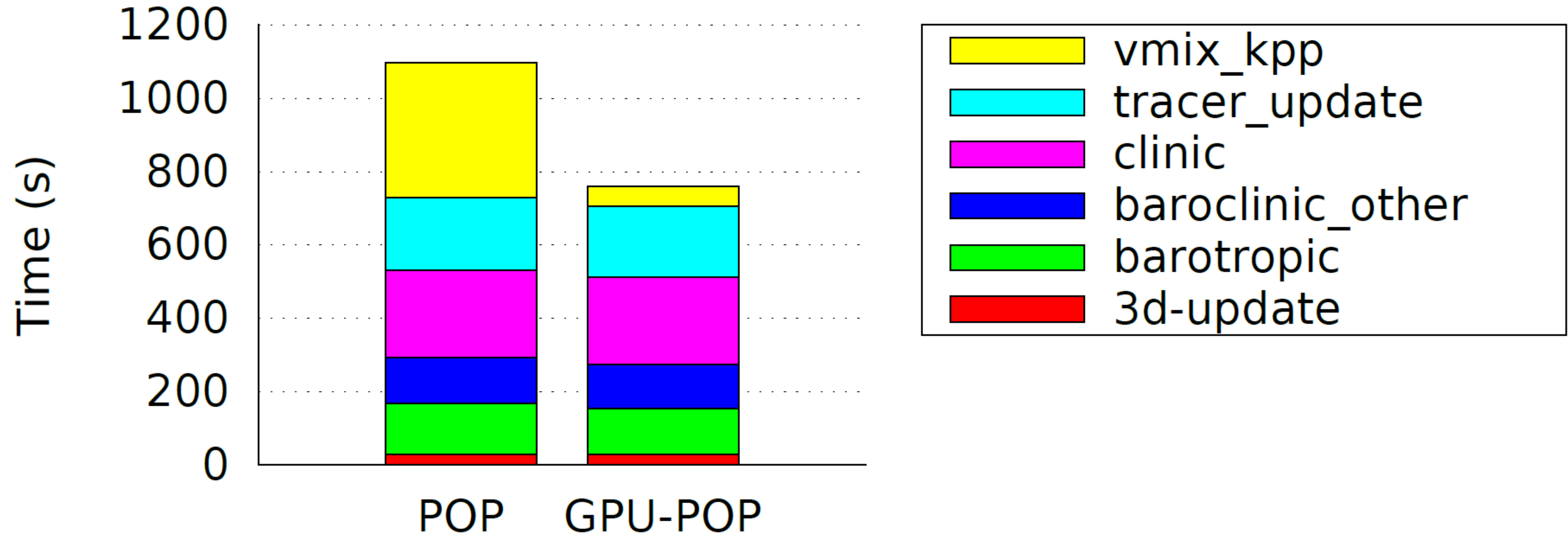
Kernel tuner



```
kernel_string = """
__global__ void vector_add(float *c, float *a, float *b,
int n) {
    int i = blockIdx.x * block_size_x + threadIdx.x;
    if (i < n) {
        c[i] = a[i] + b[i];
    }
}"""
```

```
n = numpy.int32(1e7)
a = numpy.random.randn(n).astype(numpy.float32)
b = numpy.random.randn(n).astype(numpy.float32)
c = numpy.zeros_like(b)
args = [c, a, b, n]
params = {"block_size_x" : 512 }
```

```
answer = kernel_tuner.run_kernel("vector_add",
kernel_string, n, args, params)
assert numpy.allclose(answer[0], a+b, atol=1e-8)
```



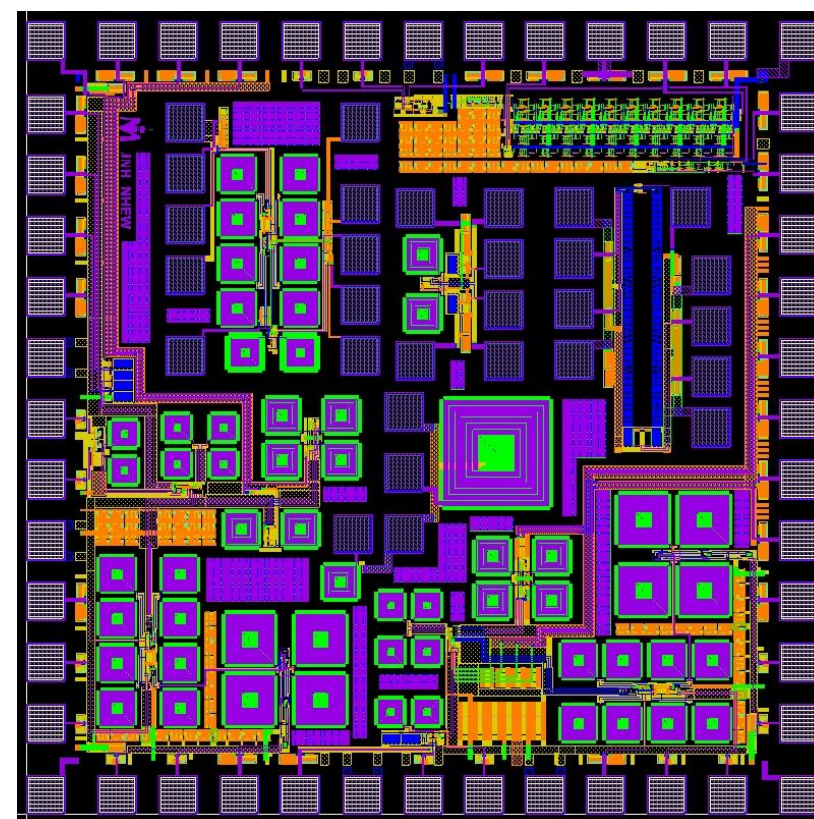
Reconfigurable circuit (no instruction set!)

Very low latency

Built in floating point operations

CPU on FPGA board (high bandwidth)

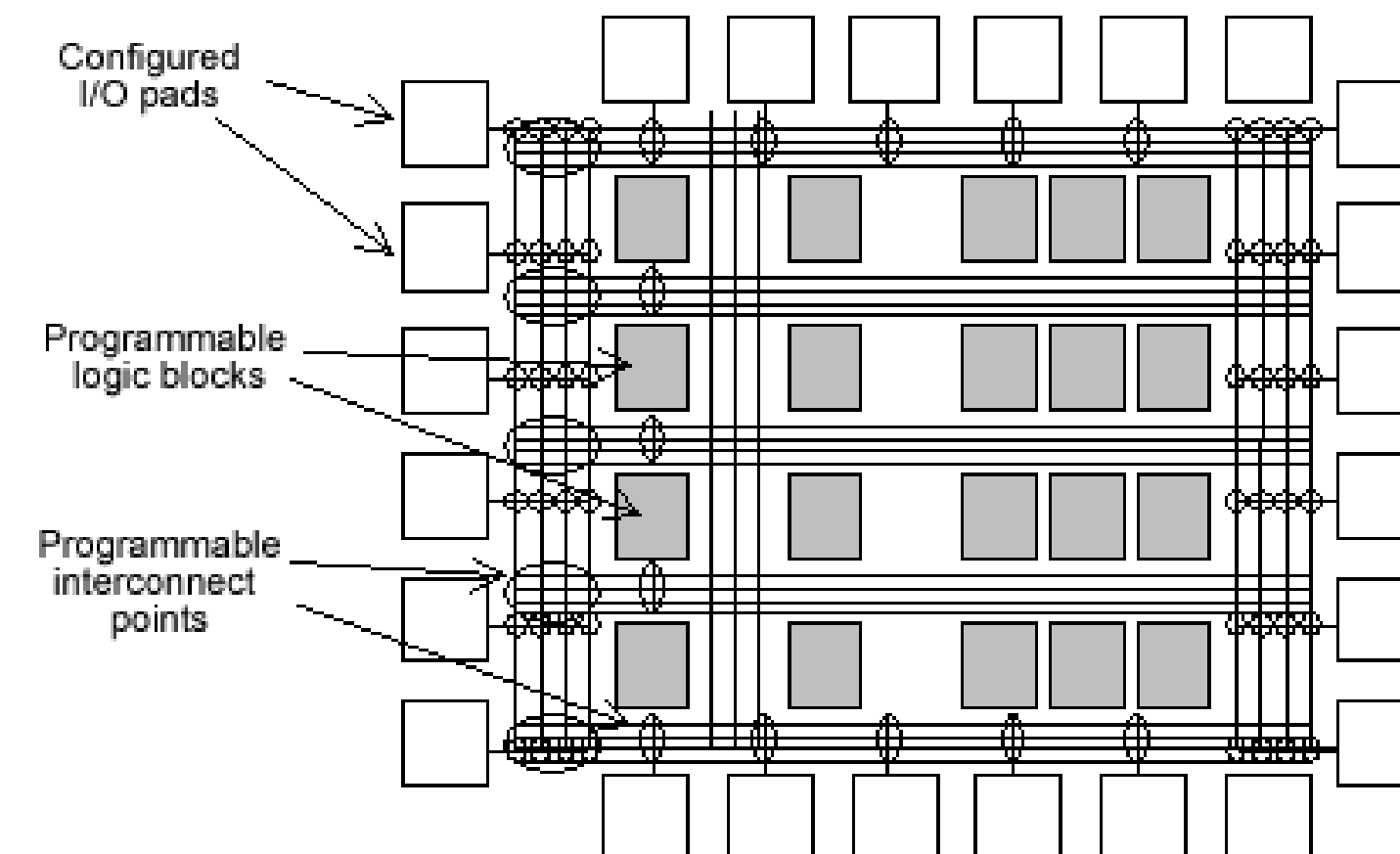
Gigabit Ethernet on board



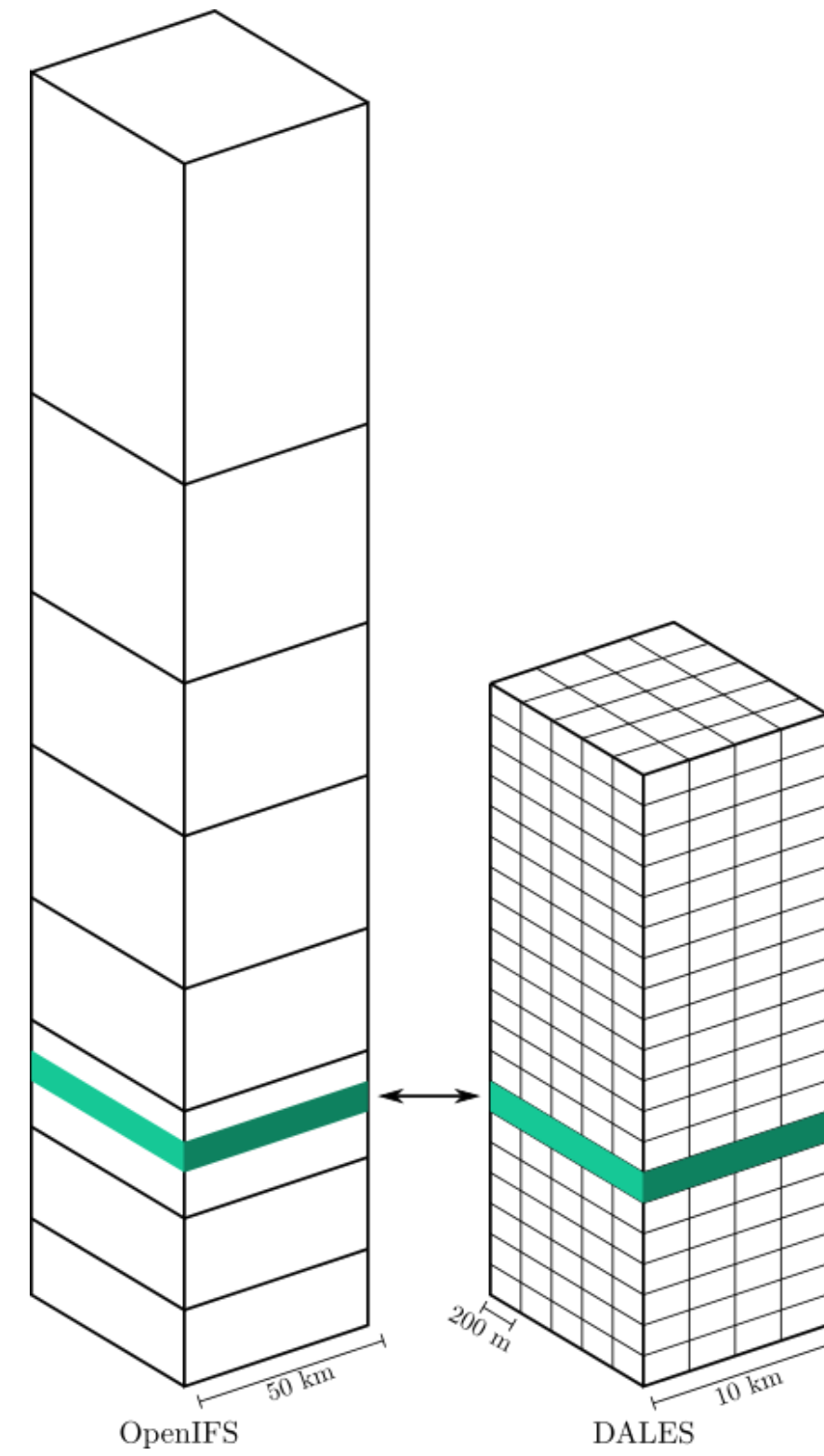
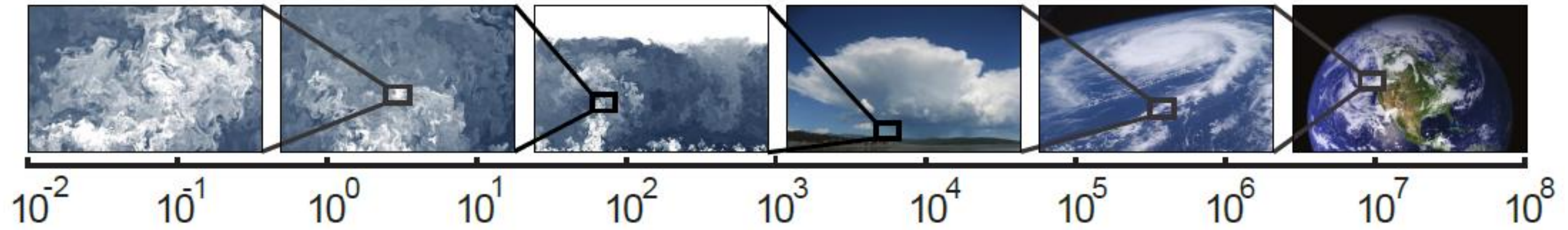
Compute kernel



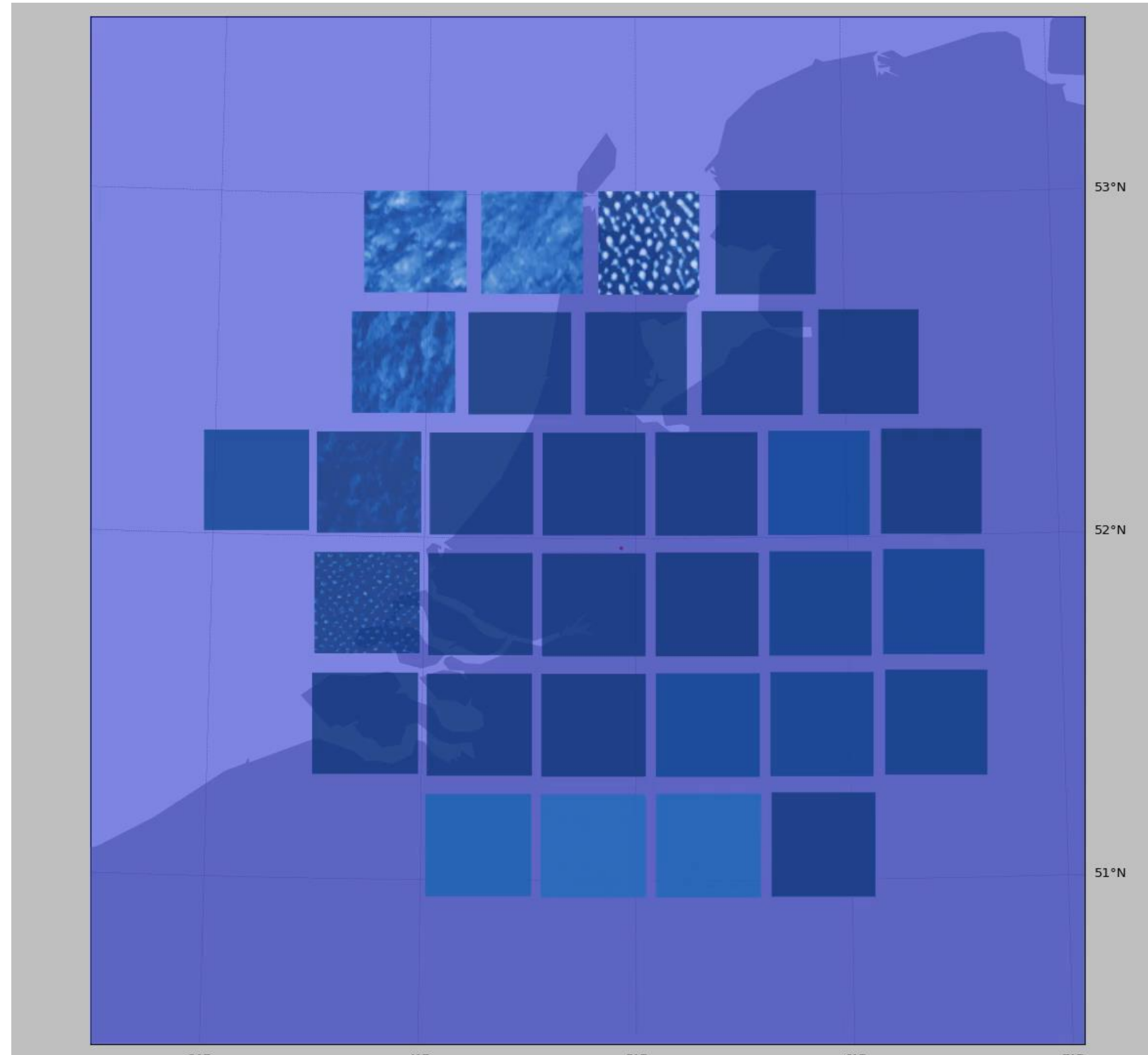
8-20 hrs



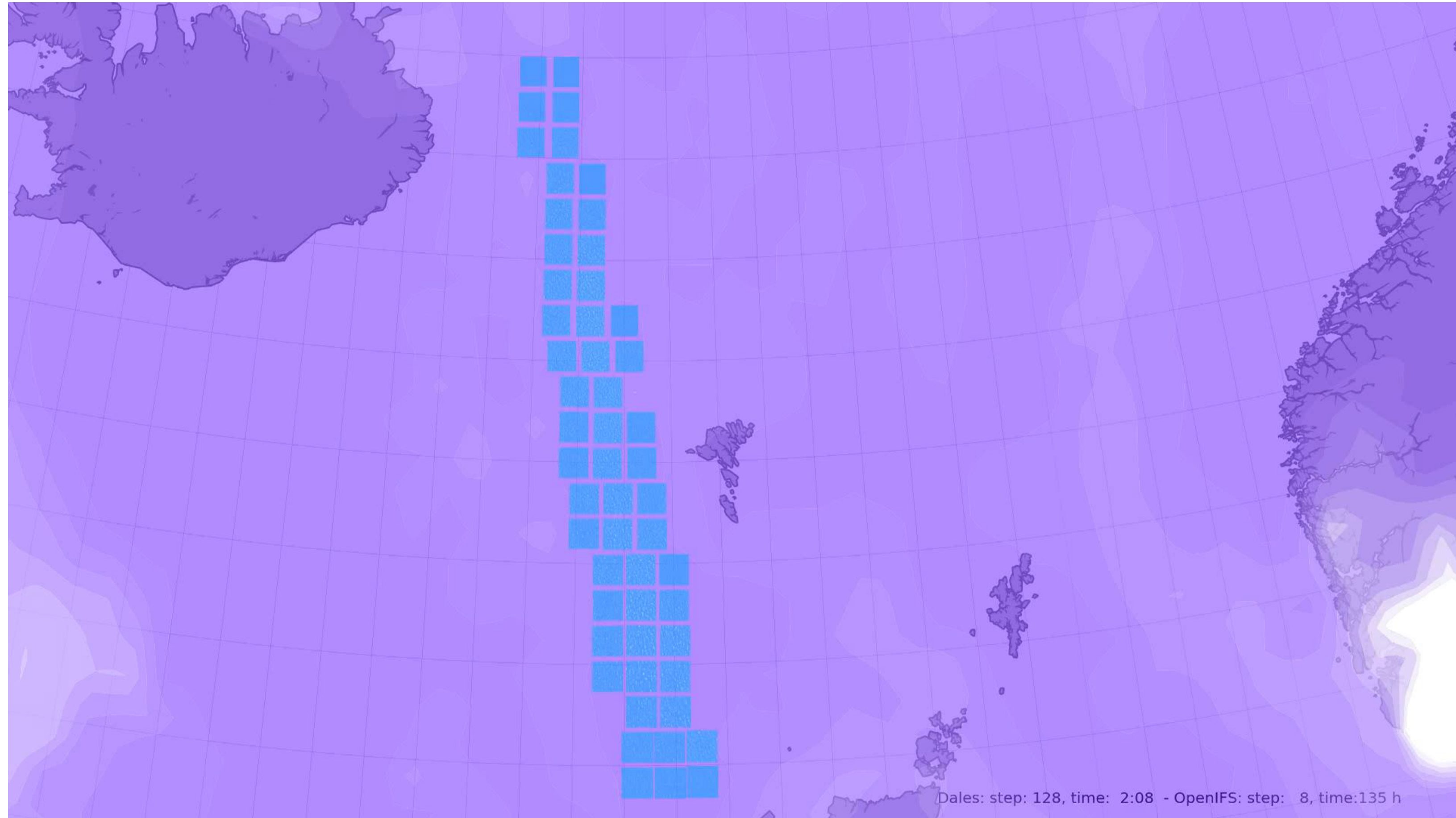
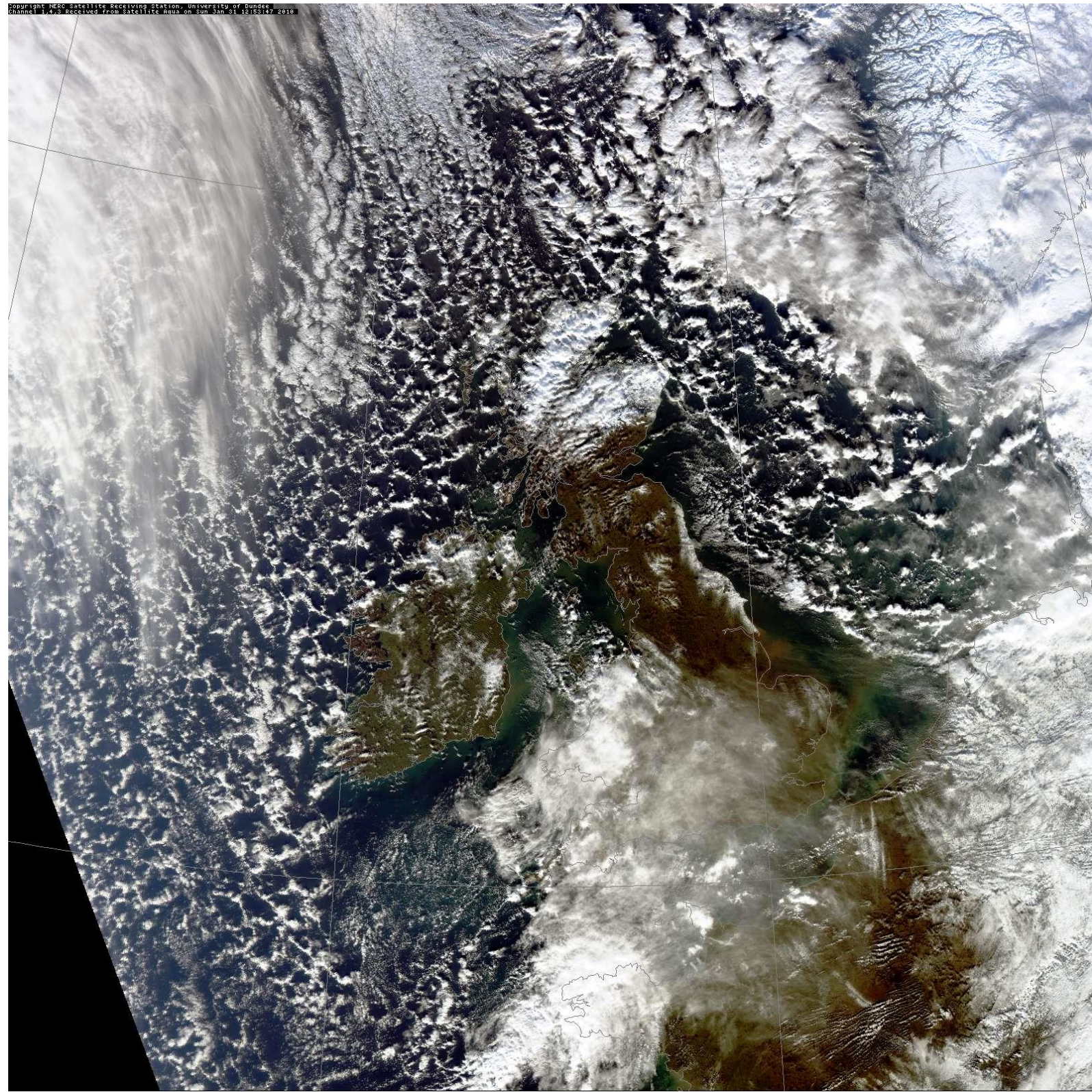
Superparameterization, downscaling and machine learning



Project output: Cloud-resolving climate models

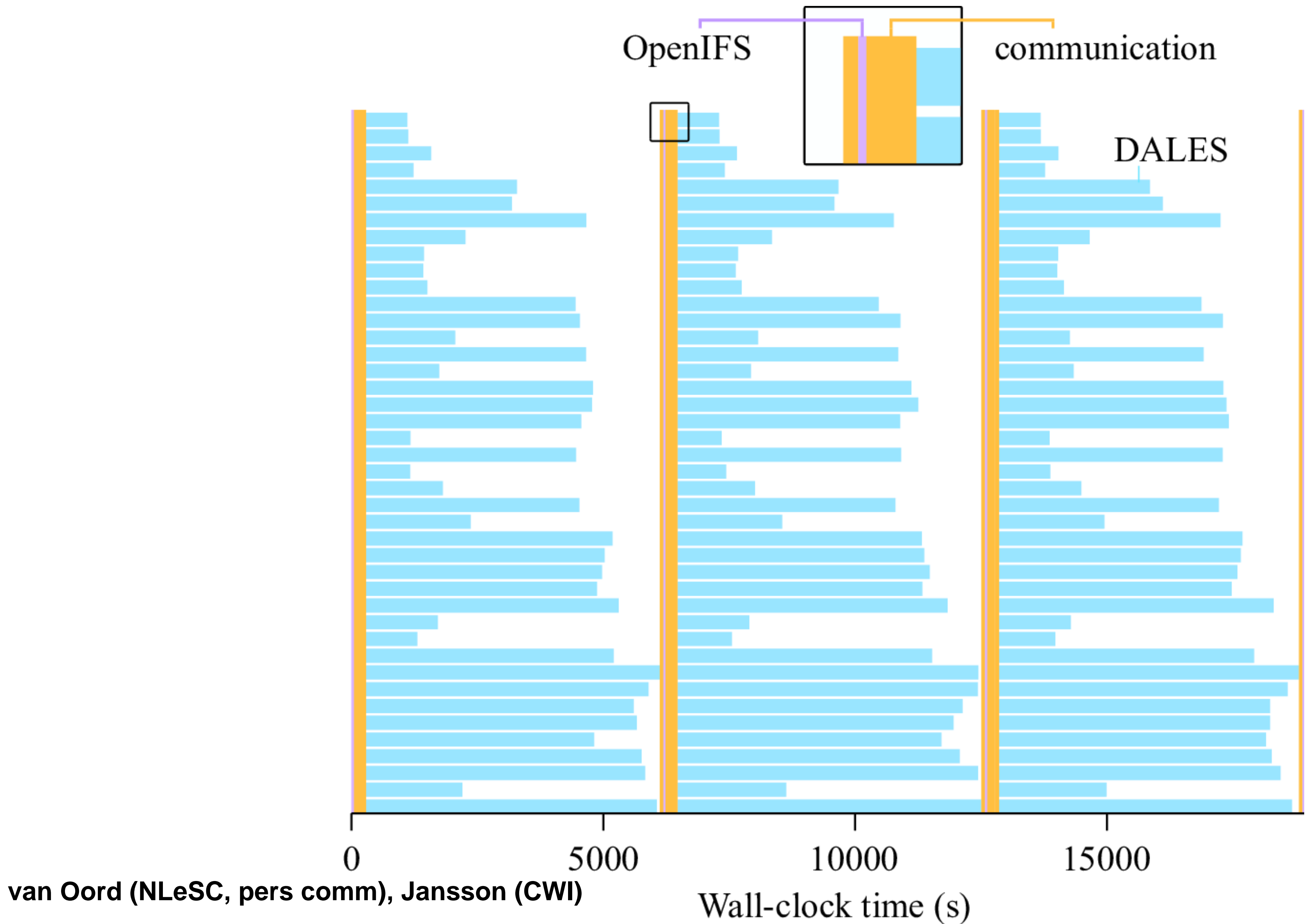


van Oord (NLeSC, pers comm), Jansson (CWI)



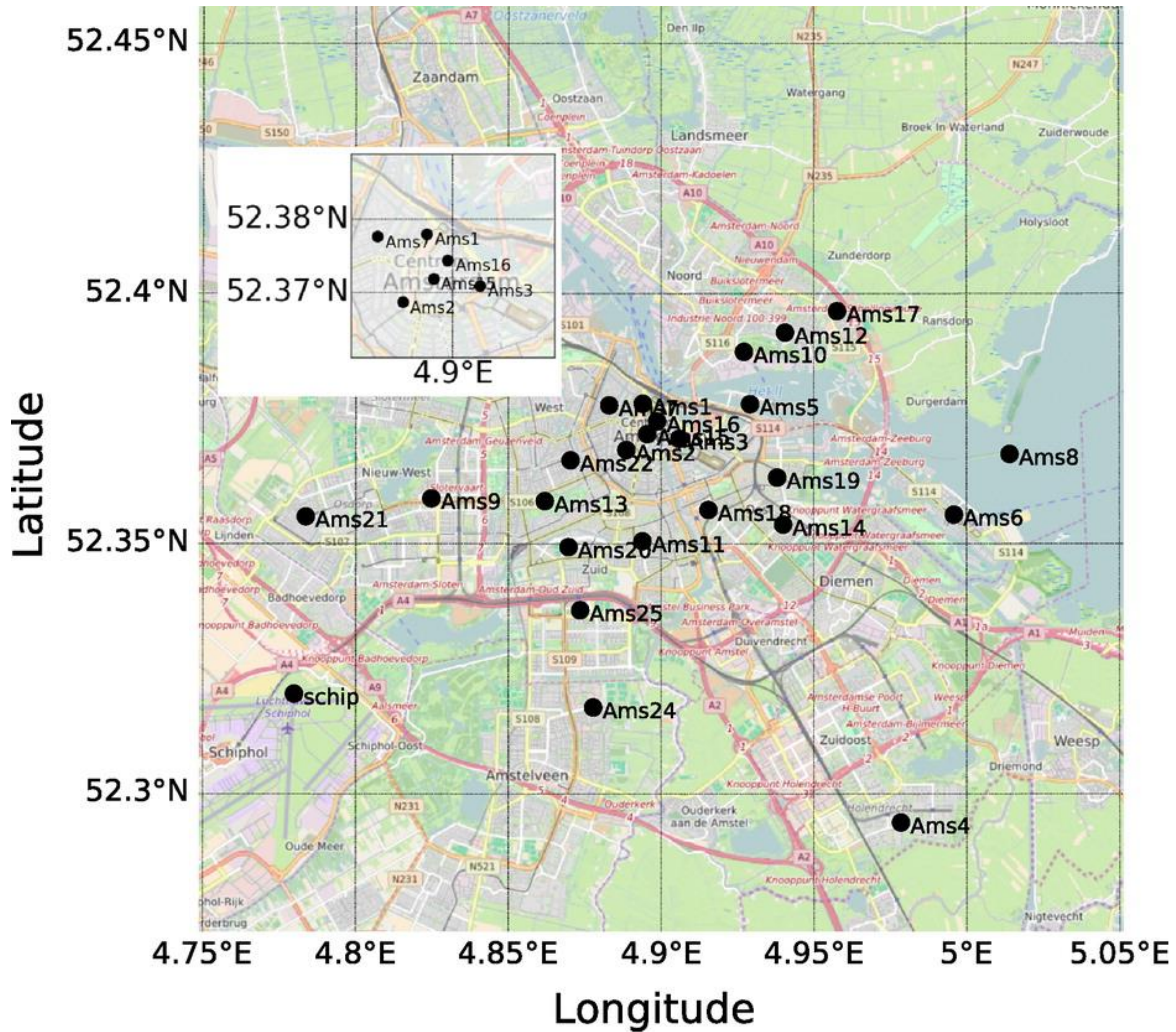
van Oord (NLeSC, pers comm), Jansson (CWI)

Load balancing OpenIFS and DALES



Computing and data challenge: nowcasting and short term forecasting at local scale





Downscaling

Daily forecasts

WRF3.5 + urban module (SLUCM)

48 hour runs, 24 hour spin-up

Domain 1: 12.5km

default setup

Domain 2: 2.5km

default setup

Domain 3: 500m

hi-res landuse,

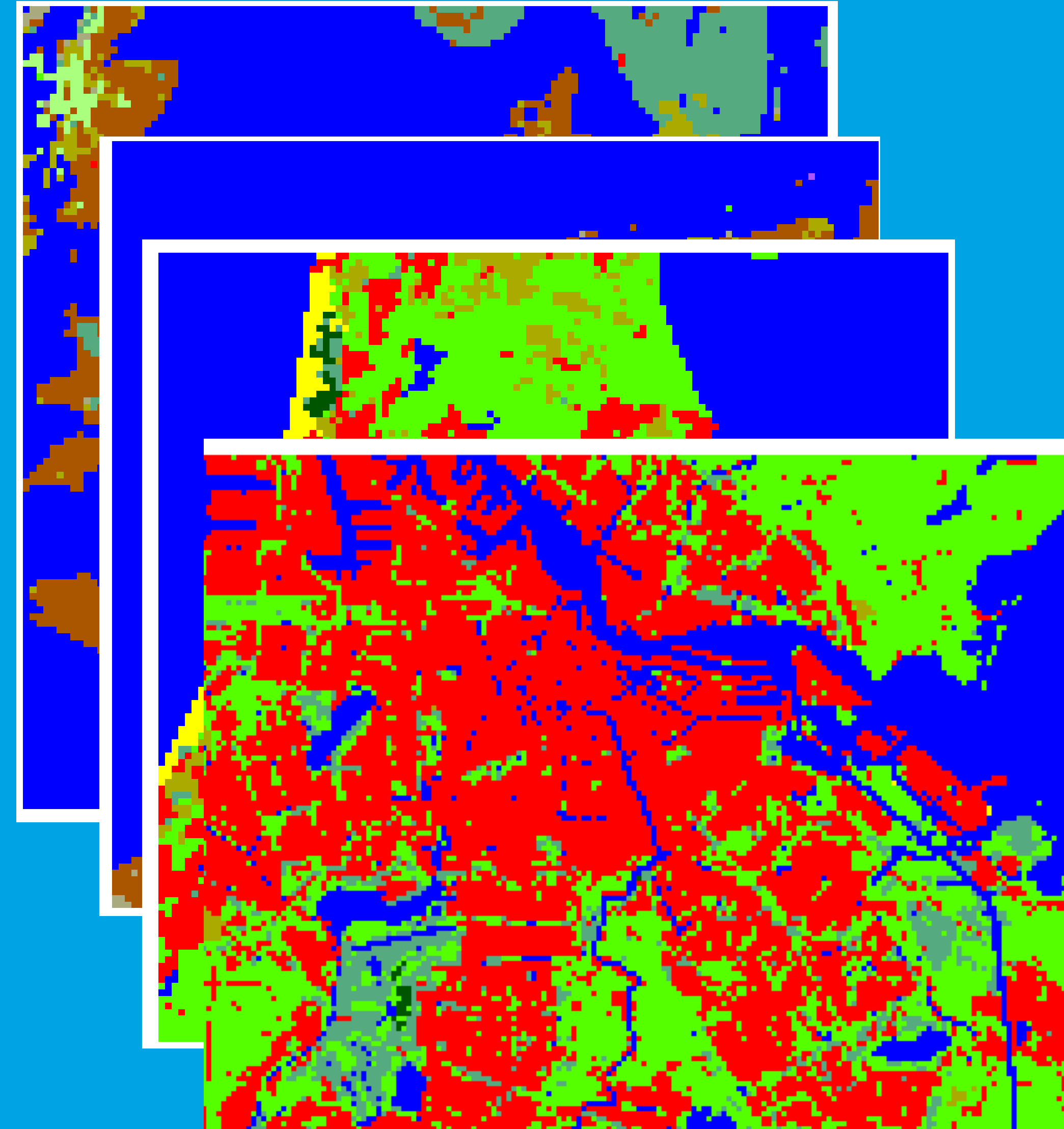
Rijkswaterstaat river temperatures

Domain 4: 100m

Rijkswaterstaat river temperatures,

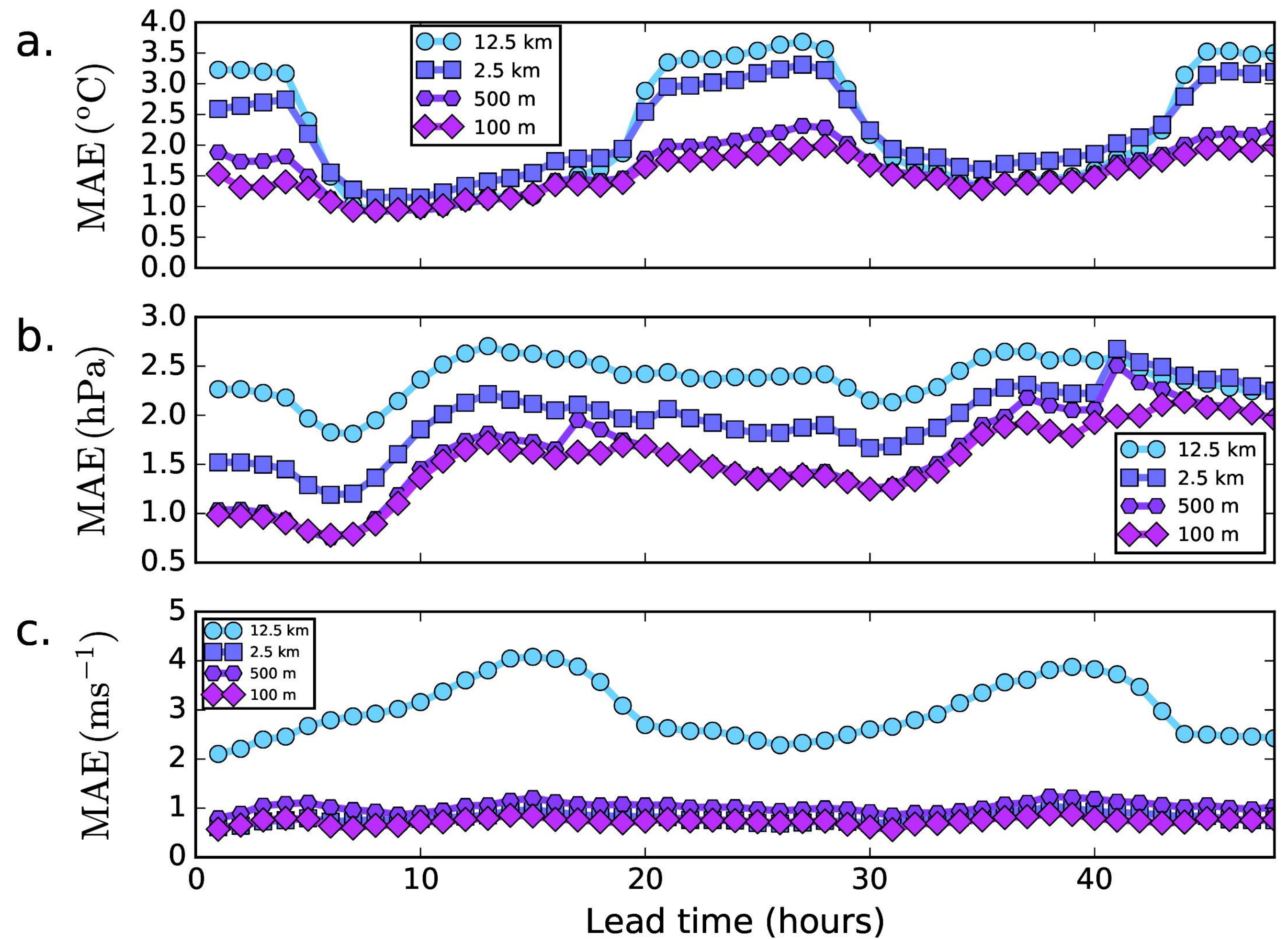
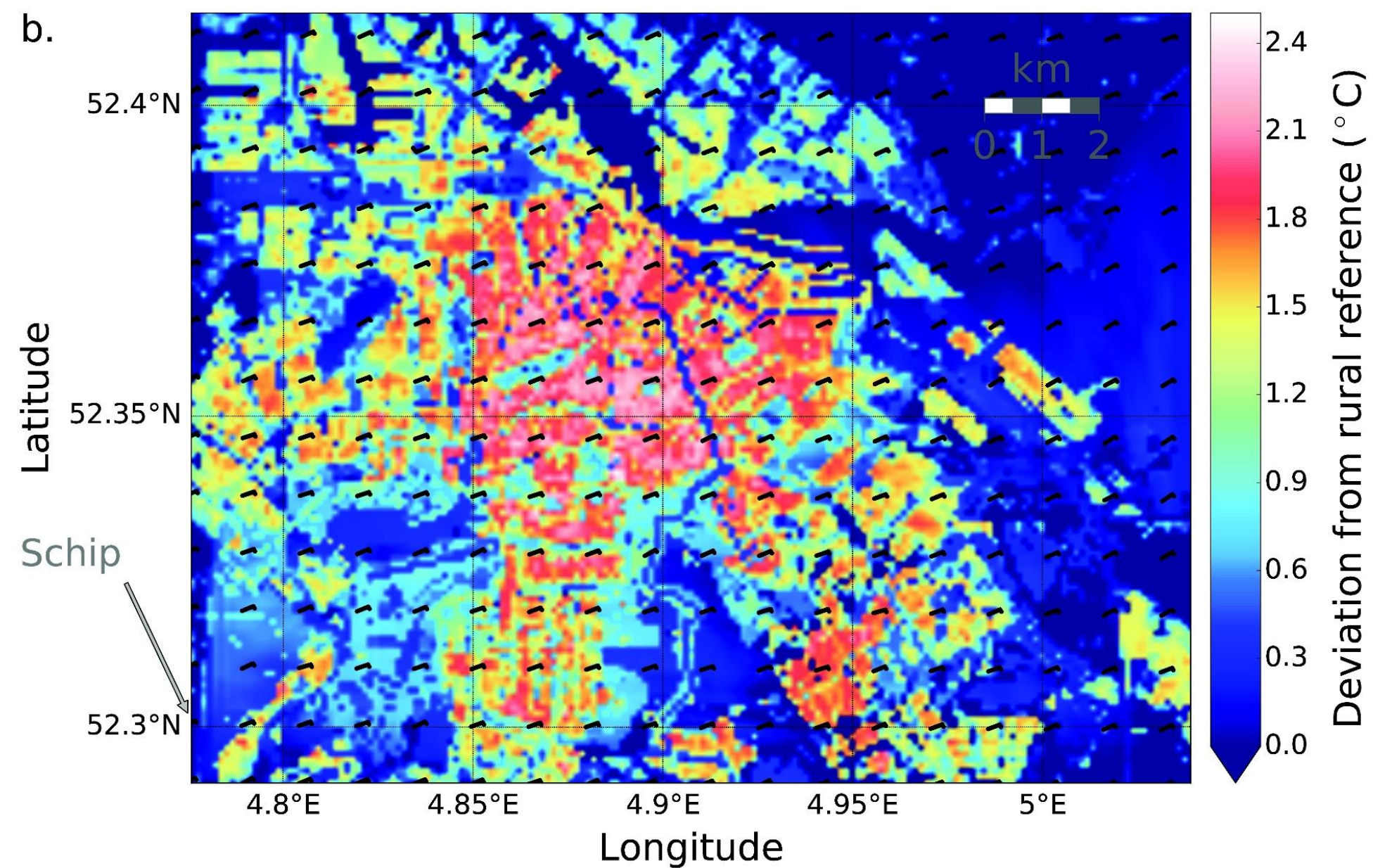
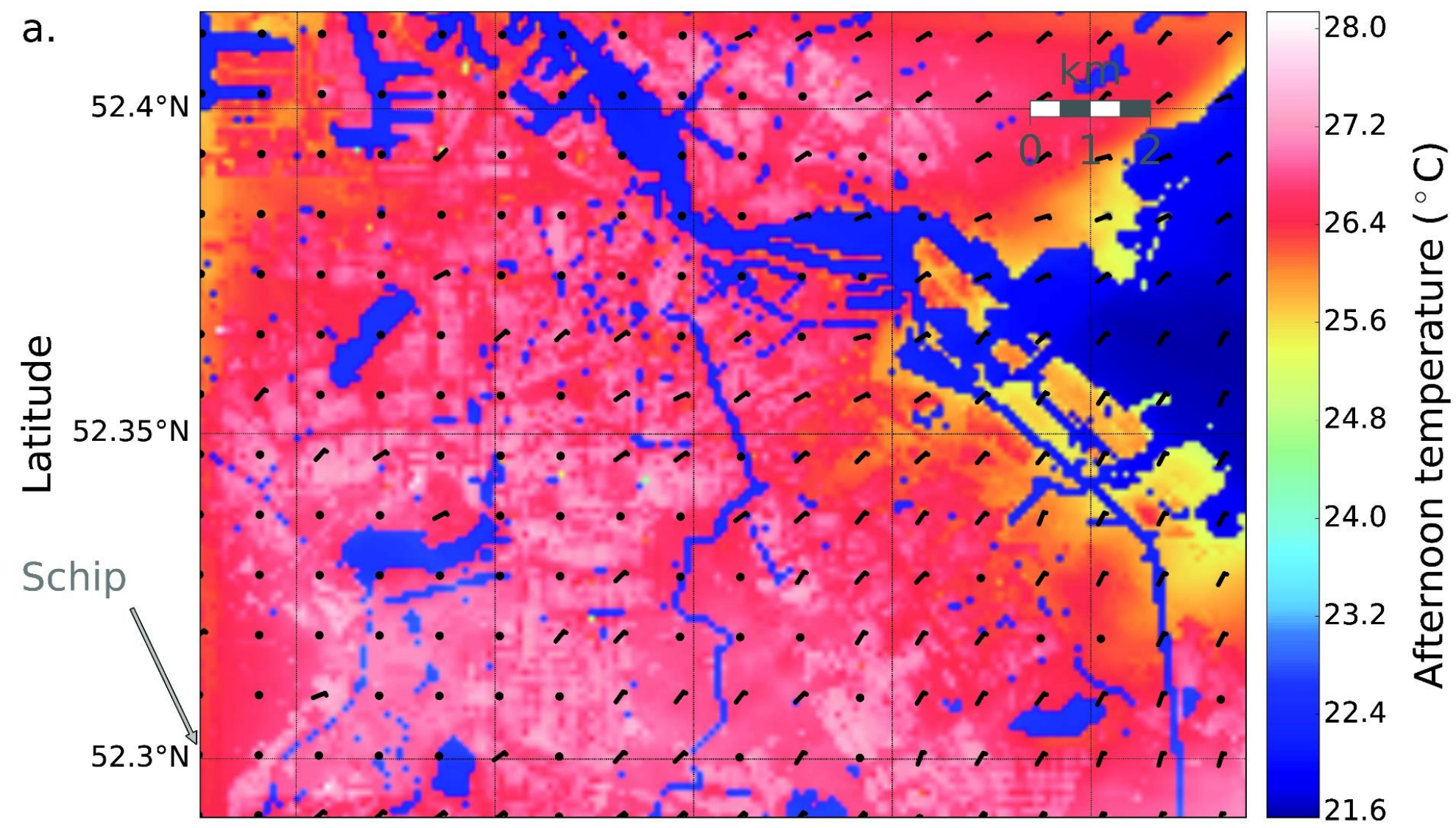
TOP10NL, satellite imagery, AHN2

(height map), CBS data



Attema et al, IEEE eScience, 2015

Short range weather forecasting at street level



Vector of model parameters, computable θ_c (e.g. high res models) and non-computable θ_n

$$\theta = (\theta_c, \theta_n)$$

θ in parameterization schemes of climate model (ζ), that forms a map parameterized by time t , that takes the parameters θ to the state variables x . *And state variables are related to observables y*

$$x(t) = \zeta(\theta, t)$$

$$y(t) = \kappa(x(t))$$

Actual observation (\tilde{y}) and observable mismatch (note, y depends on θ , but \tilde{y} does not, so mismatch can be used to learn θ) :

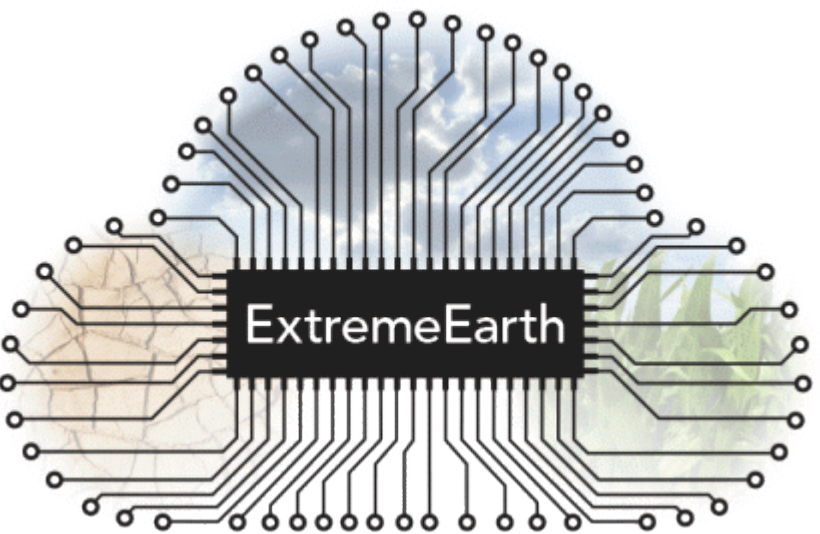
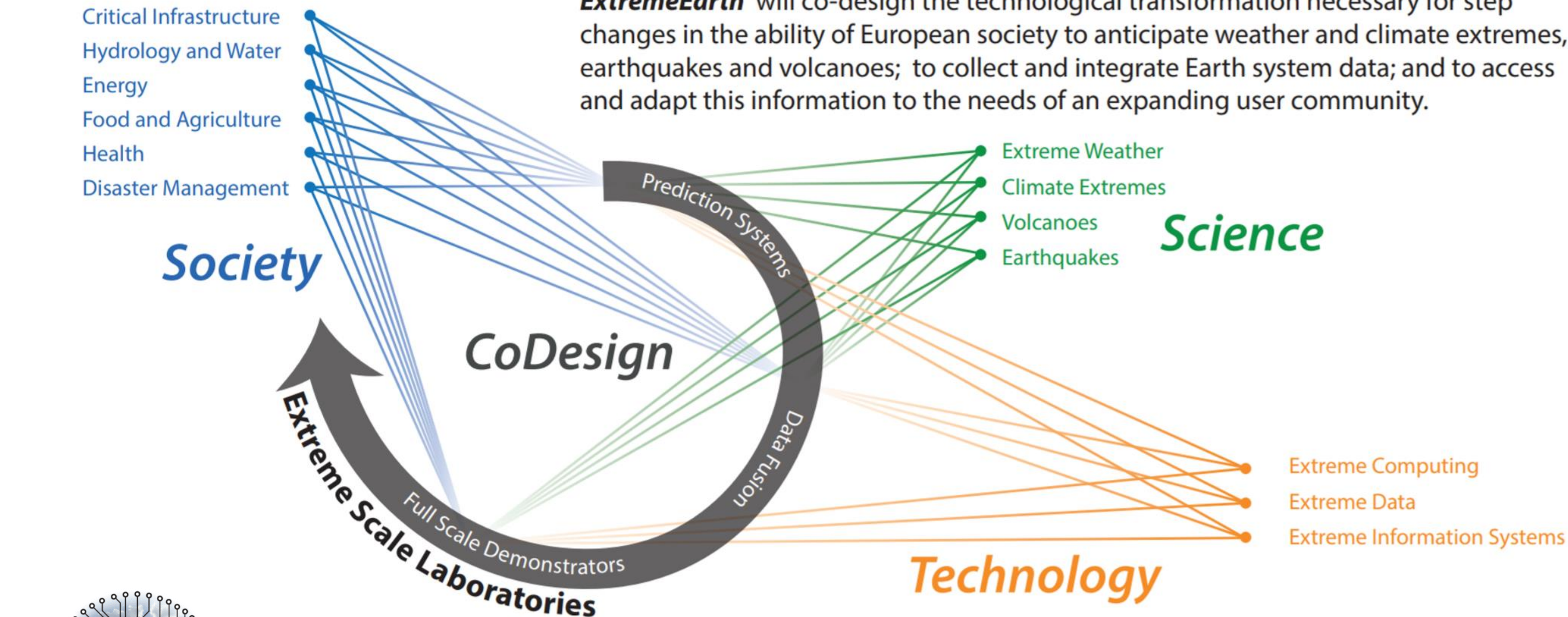
$$J_0 = \frac{1}{2} \| \langle f(y) \rangle_T - \langle f(\tilde{y}) \rangle_T \|_{\Sigma_y}^2$$

High-resolution simulations nested in a climate model may be viewed as a time-dependent map C from the state variables x of the climate model to simulated state variable \tilde{z} . The variable z in the climate model depends on all parameters θ and again the mismatch can be used to learn the non computable parameters (a similar cost function can be defined as for y),

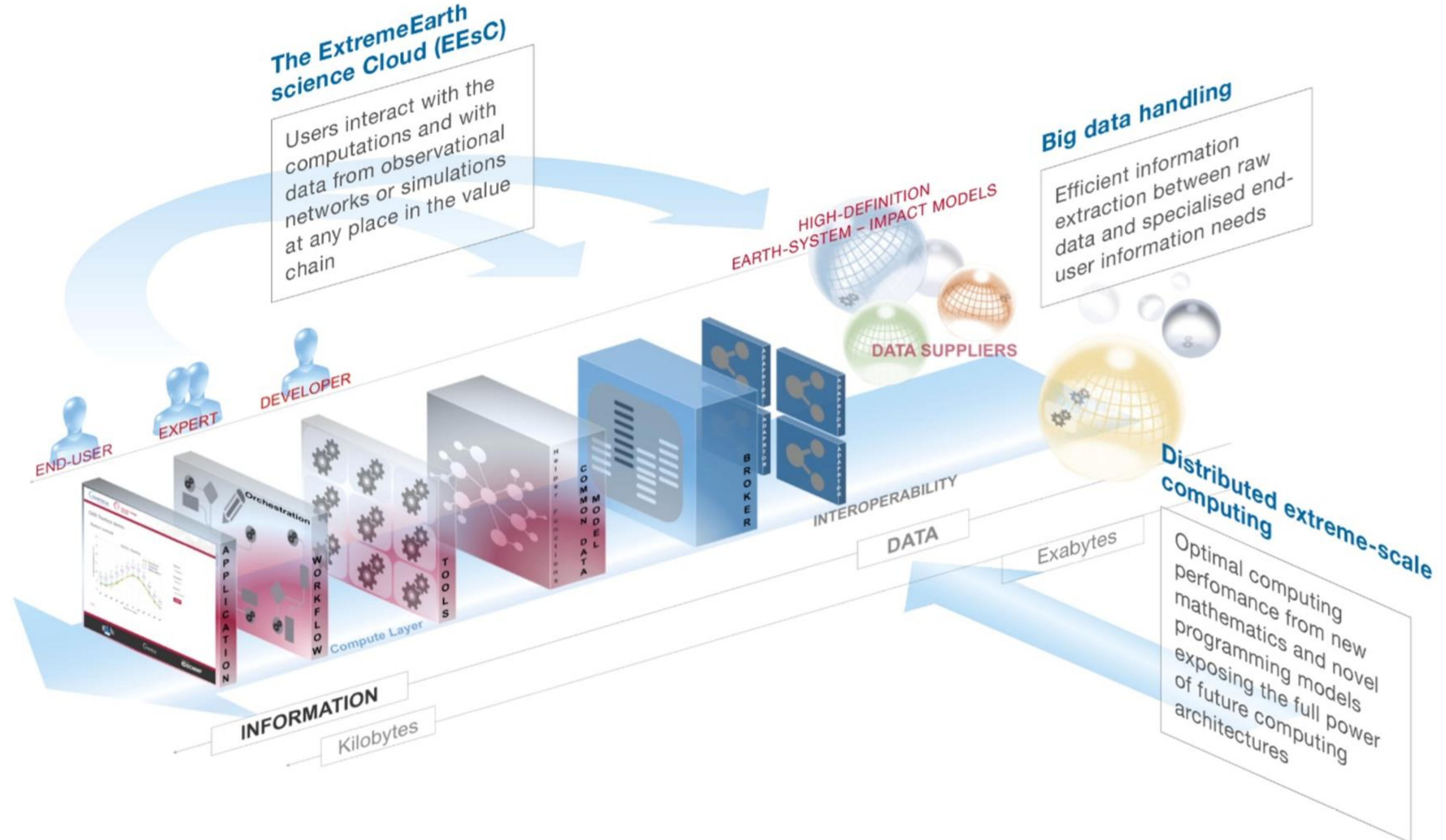
$$\tilde{z}(t) = C(\theta_n, t; x)$$

$$z(t) = s(\theta, t; x)$$

ExtremeEarth will co-design the technological transformation necessary for step changes in the ability of European society to anticipate weather and climate extremes, earthquakes and volcanoes; to collect and integrate Earth system data; and to access and adapt this information to the needs of an expanding user community.



What e-infrastructure does it take?



A step-change in domain-specific, distributed high-performance computing for the simulation and prediction of Earth-system extremes.

A step-change in domain-specific, distributed big data handling for the simulation and prediction of Earth-system extremes, and for exploring the full range of information from simulations and observation

User interaction enabled by a domain-specific, integrated information system towards the ExtremeEarth science Cloud (EEsC)