Machine learning to represent atmospheric sub-grid processes in climate models

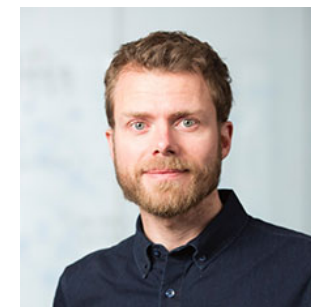Stephan Rasp   *LMU Munich*

Mike Pritchard   *UC Irvine*
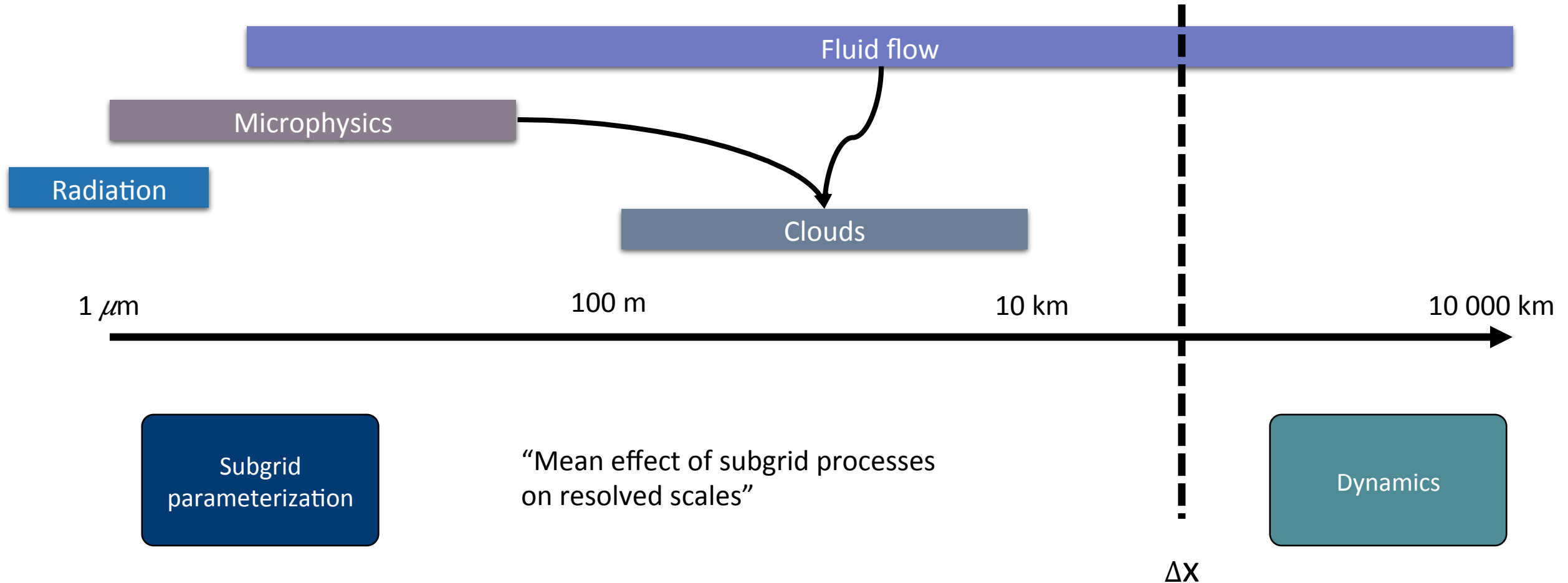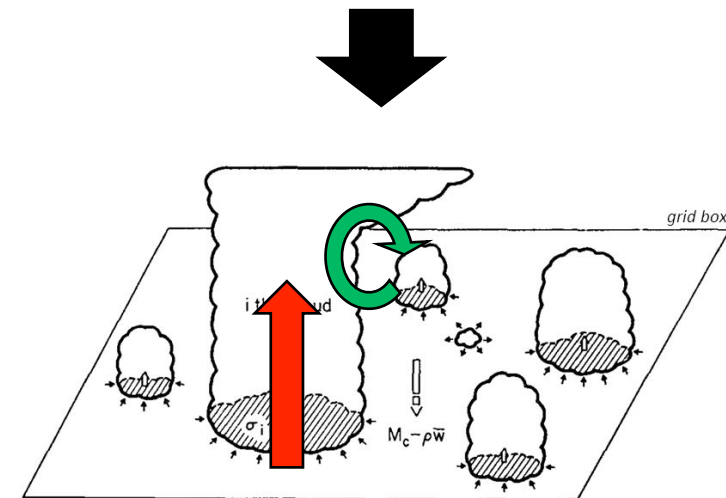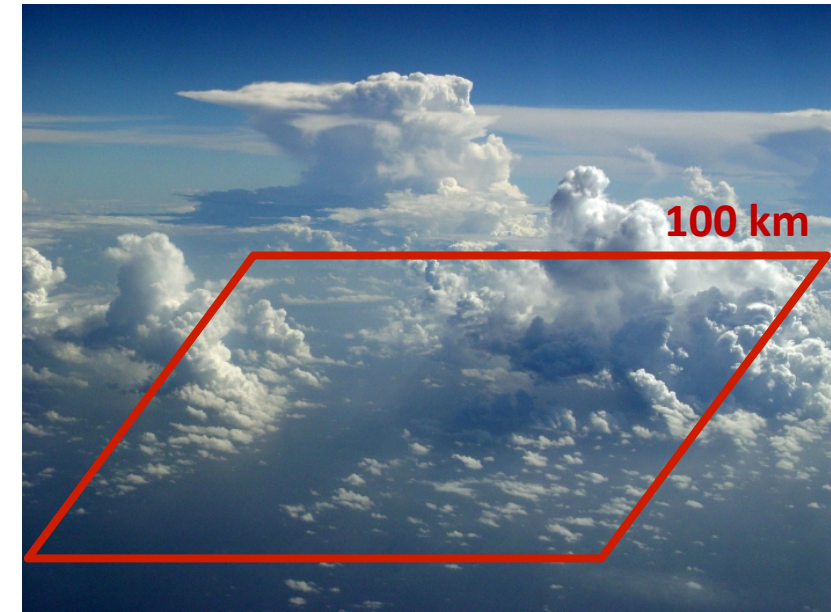
Pierre Gentine   *Columbia University*

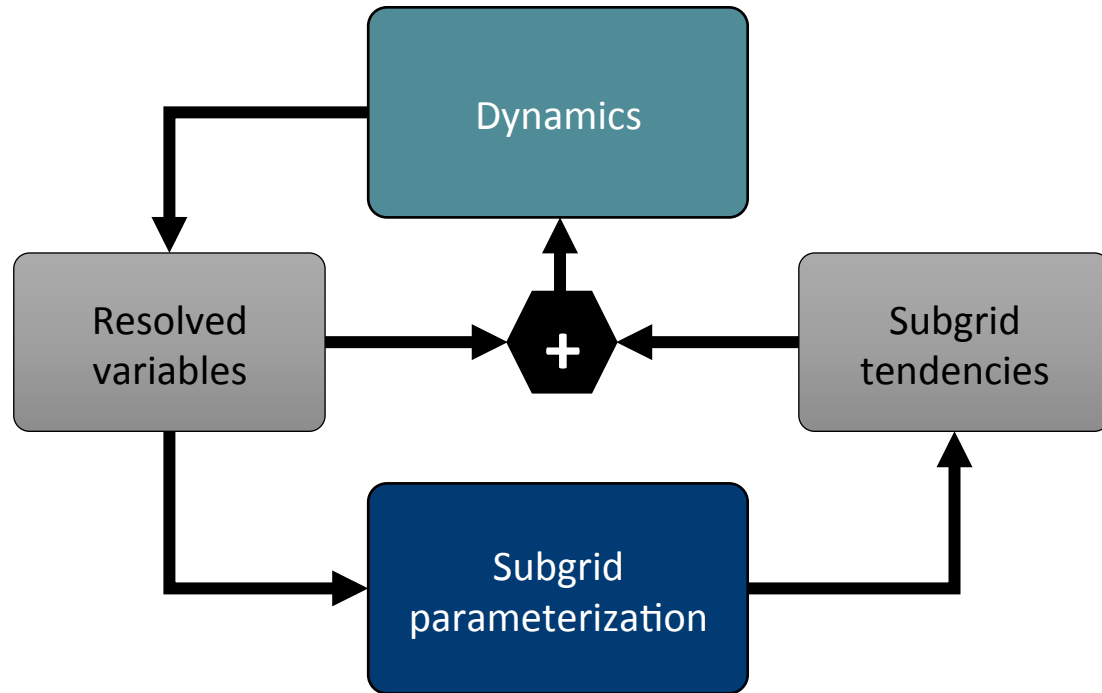# The sub-grid parameterization problem

Goal of atmospheric modeling

Represent the physical processes in the atmosphere as accurately as possible.

Fluid flow

Microphysics

Radiation

Clouds

1 μm   100 m   10 km   10 000 km

Subgrid parameterization

"Mean effect of subgrid processes on resolved scales"

Dynamics

ΔX

# Traditional parameterization development

Growing frustration with state of climate modeling

Carbon Dioxide and Climate: A Scientific Assessment

Report of an Ad Hoc Study Group on Carbon Dioxide and Climate
Woods Hole, Massachusetts
July 23–27, 1979
to the
Climate Research Board
Assembly of Mathematical and Physical Sciences
National Research Council

Jule G. Charney, Massachusetts Institute of Technology, *Chairman*
Akio Arakawa, University of California, Los Angeles
D. James Baker, University of Washington
Bert Bolin, University of Stockholm
Robert E. Dickinson, National Center for Atmospheric Research
Richard M. Goody, Harvard University
Cecil E. Leith, National Center for Atmospheric Research
Henry M. Stommel, Woods Hole Oceanographic Institution
Carl I. Wunsch, Massachusetts Institute of Technology

but they do not appear to be so strong as the positive moisture feedback. We estimate the most probable global warming for a doubling of CO_2 to be near 3°C with a probable error of ± 1.5°C. Our estimate is based primarily on our
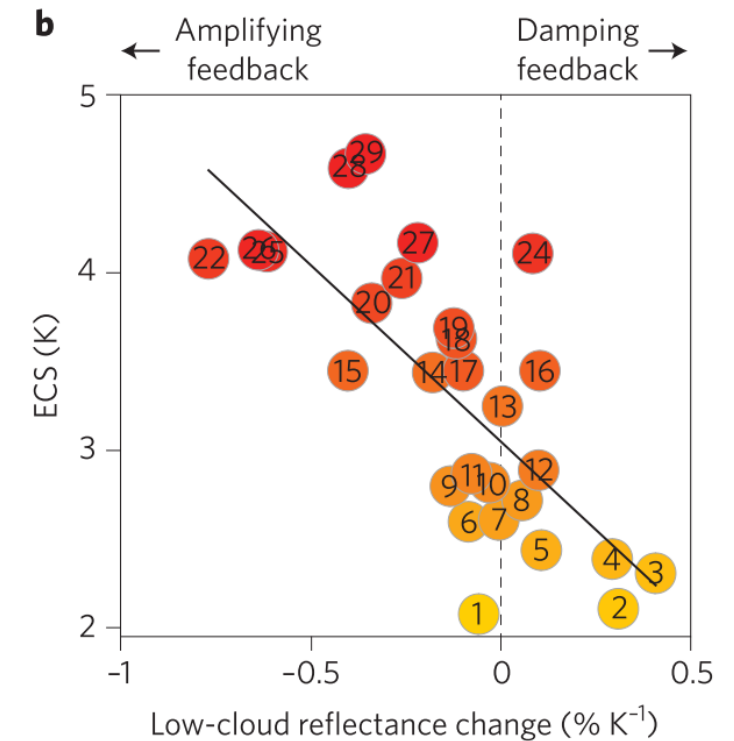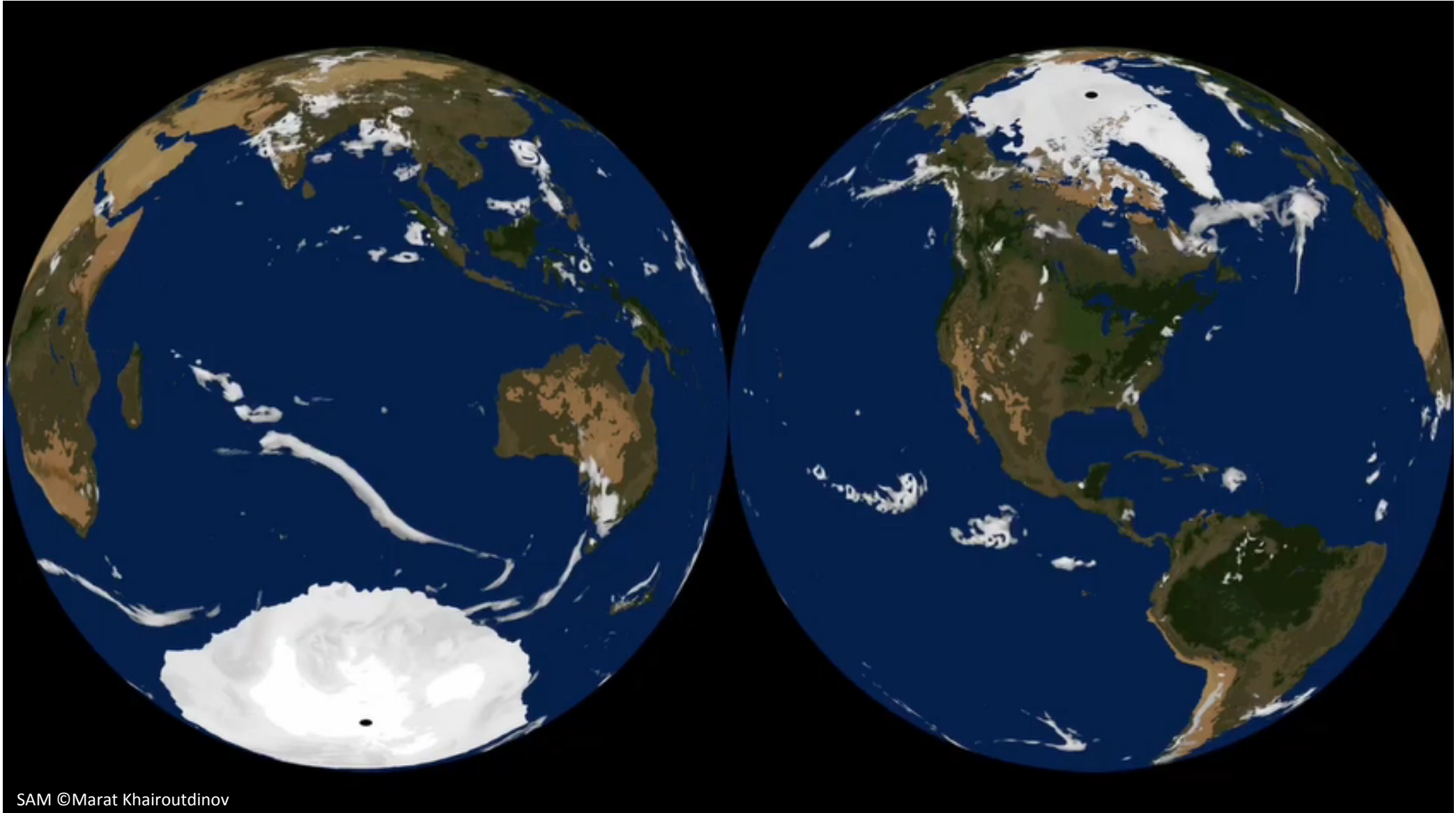

"Most uncertainty caused by representation of subgrid clouds"
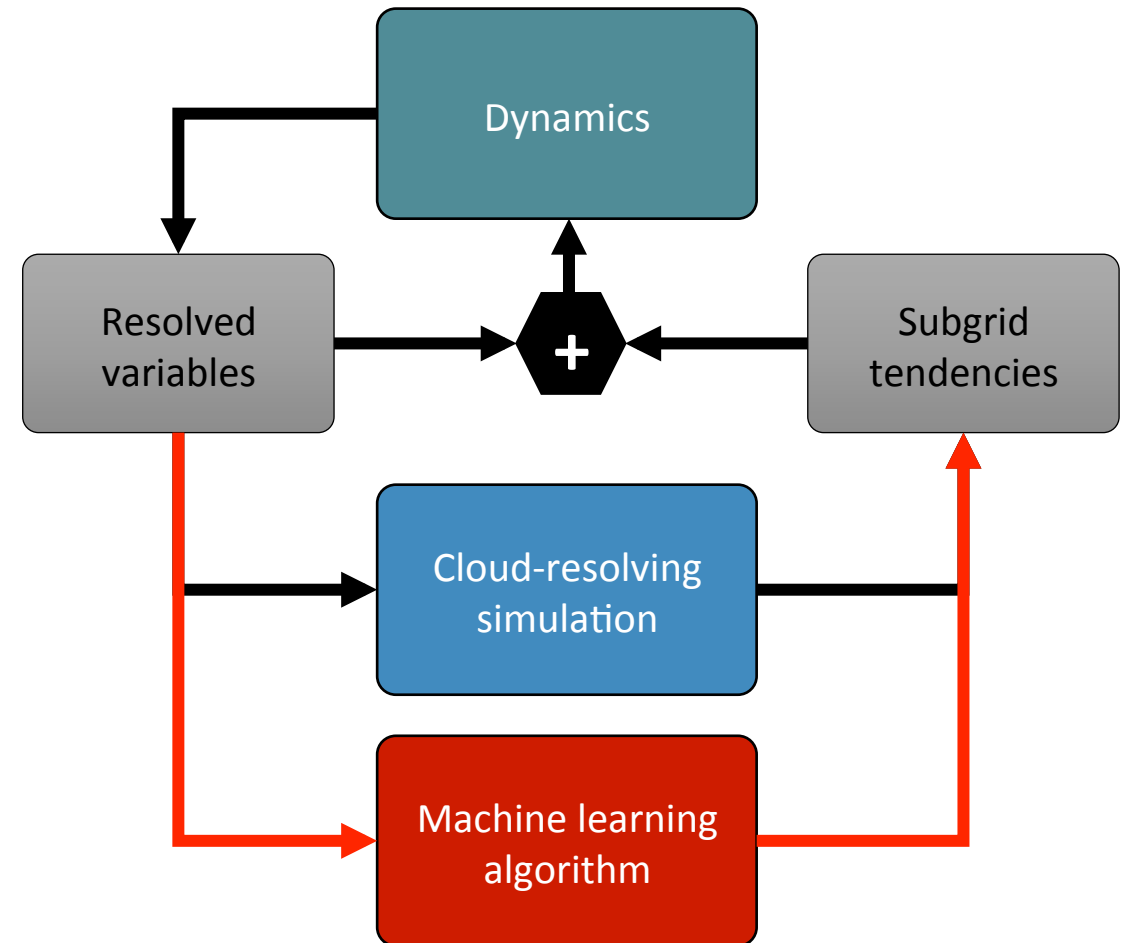
Schneider *et al.,* 2017. *Nature Climate Char*

Global cloud resolving simulations

SAM ©Marat Khairoutdinov

Building a machine learning parameterization

The plan

1. Run a cloud-resolving training simulation
2. Train an efficient machine learning algorithm
3. Replace the original GCM parameterization

Rasp, S., Pritchard, M. and Gentine, P., 2018. *Deep learning to represent sub-grid processes in climate models*. PNAS.

Gentine, P., Pritchard, M., Rasp, S., Reinaudi, G. and Yacalis, G., 2018. *Could machine learning break the convection parameterization deadlock?* GRL.

What is a neural network?

a_l

Hidden layers

Target from
data

Resolved
Variables
$T(z)$, $Q{\downarrow}v(z)$,
$P{\downarrow}S$, SHF,
LHF, $SOLIN$

Subgrid
tendencies

$\Delta T{\downarrow}conv+ra$
$d(z)$, Δ
$Q{\downarrow}conv(z)$,
$4{\times}F{\downarrow}rad$,
$Prec$

```python
inp = Input(shape=(feature_shape,))
# First hidden layer
x = Dense(hidden_layers[0], kernel_regularizer=l2)(inp)
x = act_layer(activation)(x)

if len(hidden_layers) > 1:
    for h in hidden_layers[1:]:
        x = Dense(h, kernel_regularizer=l2)(x)
        x = act_layer(activation)(x)

# Output layer
x = Dense(target_shape, activation='linear', kernel_regularizer=l2)(x)
```
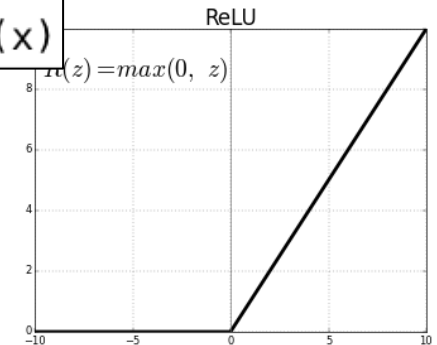
$a{\downarrow}i = \sum{\uparrow}{\blacksquare} w{\downarrow}i,j\ x{\downarrow}j + b{\downarrow}$

Activation function:
$g(a)=\max(0, a)$

ReLU

$r(z)=max(0, z)$

8

6

4

2

0

−10   −5   0   5   10

How well does the neural network do?
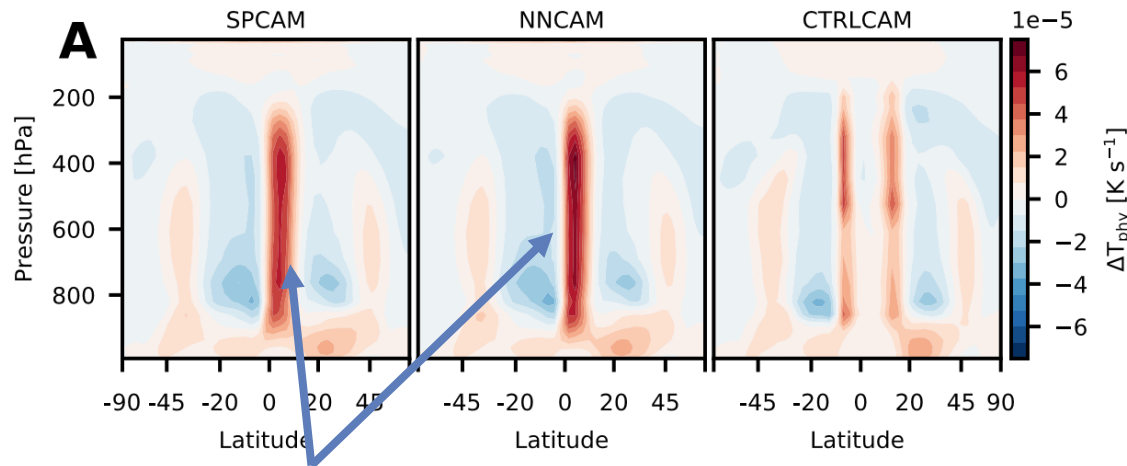
Good agreement
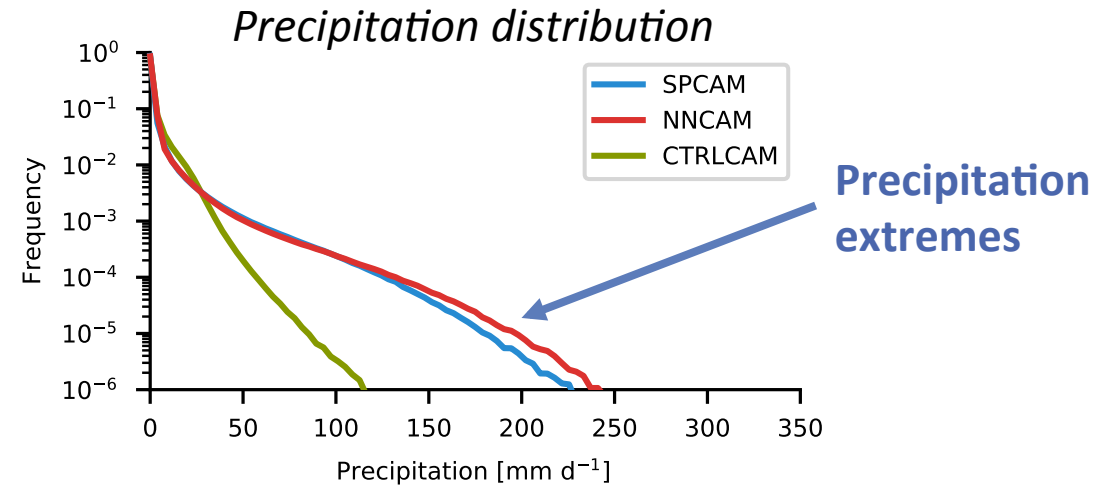
No outliers!

Column moist static energy conservation

Precipitation distribution

Precipitation extremes
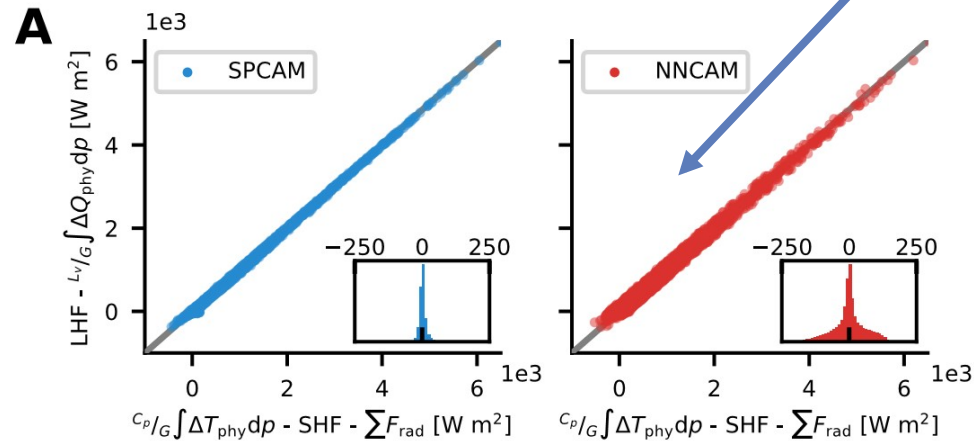
Mean climate and key aspects of variability are reproduced.

Neural network is significantly faster (40x) than cloud-resolving reference.

Energy is approximately conserved.

But neural network has trouble extrapolating to new climates.

2018: Machine learning parameterizations

Deep learning to represent subgrid processes in climate models

Stephan Rasp[a,b,1], Michael S. Pritchard[b], and Pierre Gentine[c,d]

[a]Meteorological Institute, Ludwig-Maximilian-University, 80333 Munich, Germany; [b]Department of Earth System Science, University of California, Irvine, CA 92697; [c]Department of Earth and Environmental Engineering, Earth Institute, Columbia University, New York, NY 10027; and [d]Data Science Institute, Columbia University, New York, NY 10027
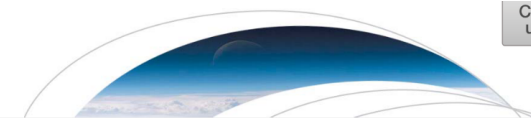
Geophysical Research Letters

Prognostic Validation of a Neural Network Unified Physics Parameterization

Key Points:
- A neural network-based unified trained on imulation el

N. D. Brenowitz[1] and C. S. Bretherton[1]

[1]Department of Atmospheric Sciences, University of Washington, Seattle, WA, USA

Journal of Advances in Modeling Earth Systems

Using Machine Learning to Parameterize Moist Convection: Potential for Modeling of Climate, Climate Change, and Extreme Events

Key Points:
- Random-forest parameterization of convection gives accurate GCM simulations of climate and precipitation extremes in idealized tests
- Climate change captured when

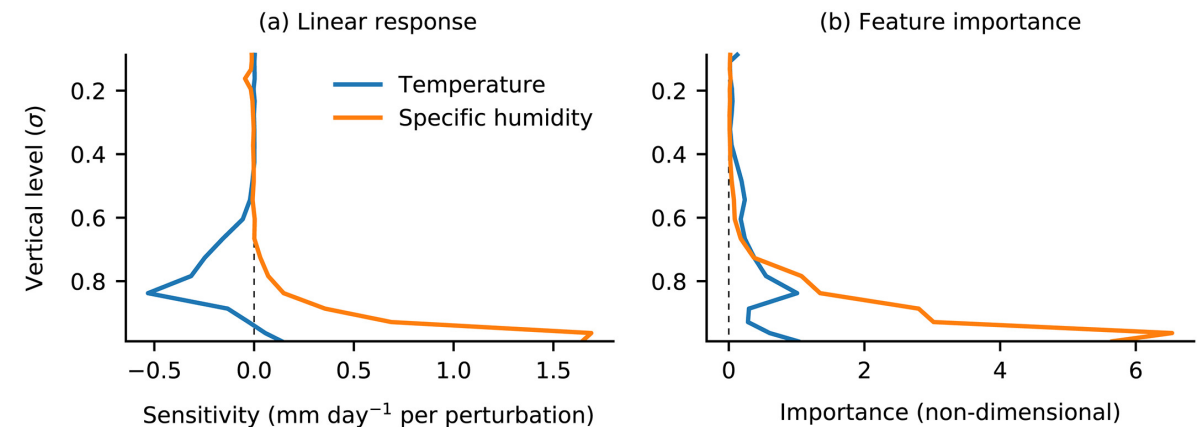Paul A. O'Gorman[1] and John G. Dwyer[1]

[1]Department of Earth, Atmospheric and Planetary Sciences, Massachusetts Institute of Technology, Cambridge, MA, USA

O'Gorman and Dwyer: Random forest

- ML algorithm: Random forest
  - Ensemble of binary decision trees
  - Predictions are means over subsets from training data
- Compared to neural networks
  - Advantages: Physical constraints from training data conserved, potentially better for small sample sizes
  - Disadvantages: Less (potential) predictive power, struggle with very large data amounts

$$P(c|f) = \sum_{1}^{n} P_n(c|f)$$
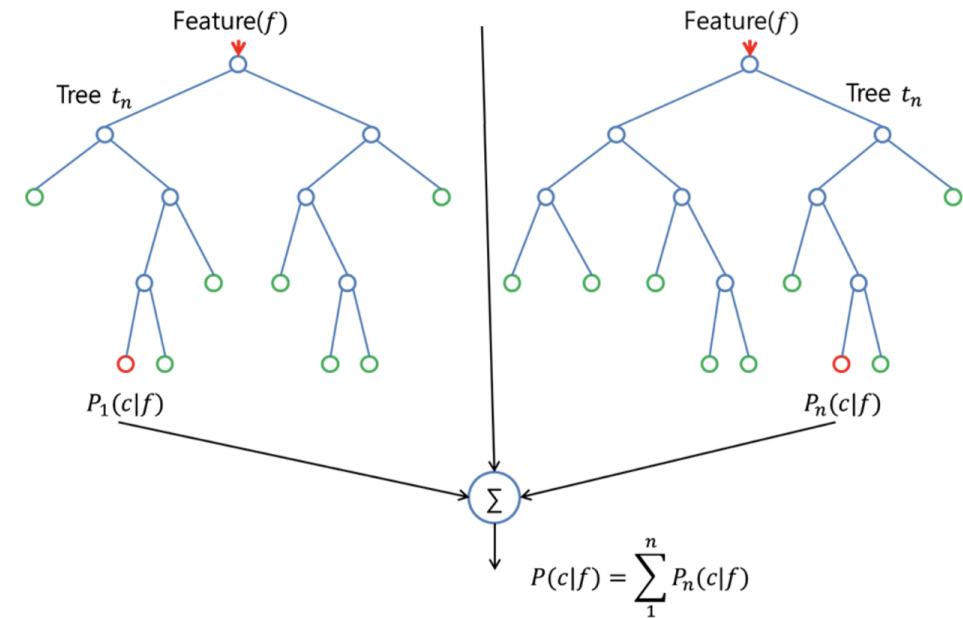
Machine learning is only a gray box!

(a) Linear response

(b) Feature importance

O'Gorman and Dwyer, 2018. JAMES.

Key challenges for machine learning parameterizations

#1: Stability

How can we make sure a ML parameterization is stable when coupled to the dynamics?

#2: Physical constraints

How can we enforce conservation laws and positivity constraints?

#3: Generalization

How bad are neural networks at generalizing in a realistic climate?

How can we enhance the generalization capabilities?
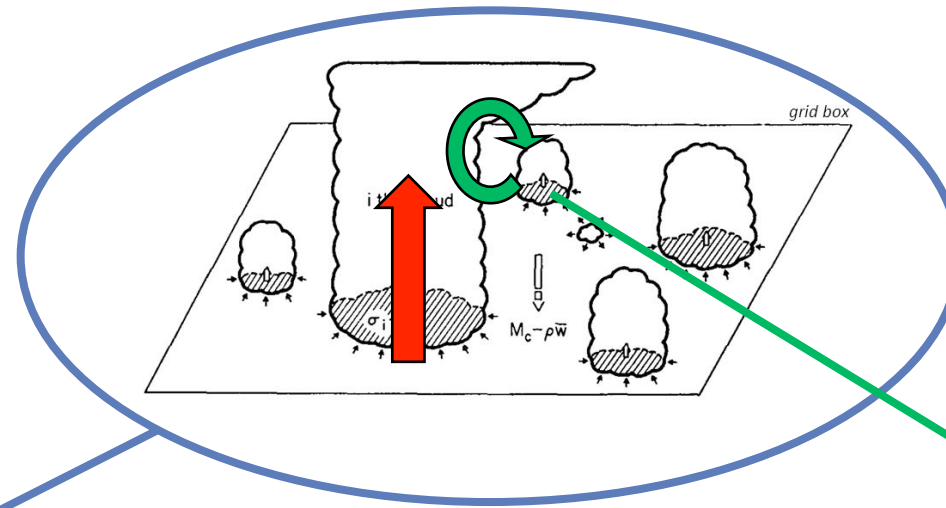
#4: Stochasticity

How do we deal with chaos in training data?

Can we build a stochastic ML parameterization?

#5: Tuning

How can we fix biases after the offline training stage?

Data-driven parameterization development

One algorithm to rule them all

- Captures process interactions

- No heuristic biases

Learn in existing framework

- Respect known physics

- More interpretable

"How to best combine physical reasoning and available data?"