Only one of these is not a climate simulation.

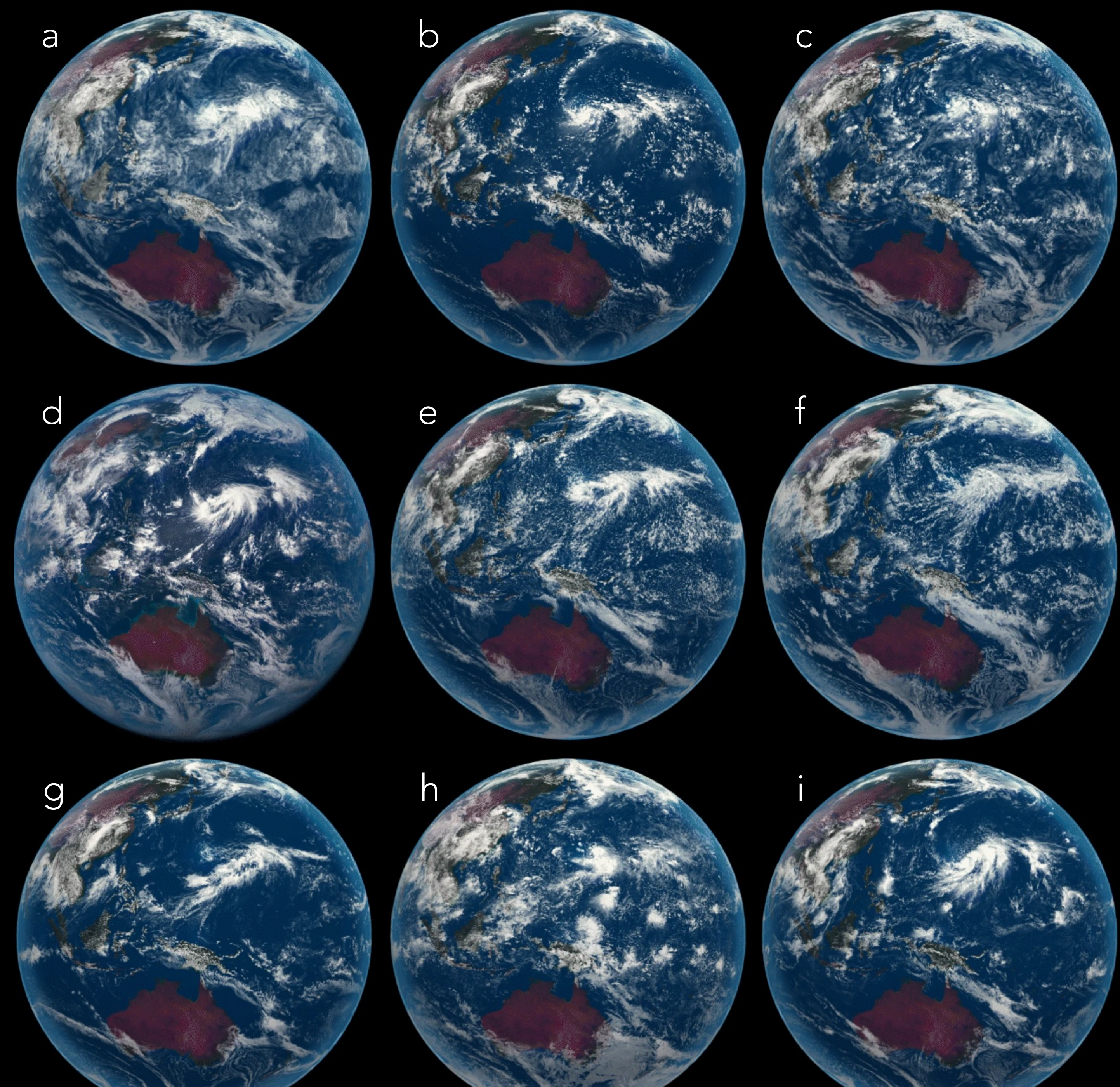
Which is the "real" photo of Earth?

To submit a guess, scan the QR code!

OR

1. Go to vevox.app
2. 156-136-777

TUDelft



Stevens et al, 2019

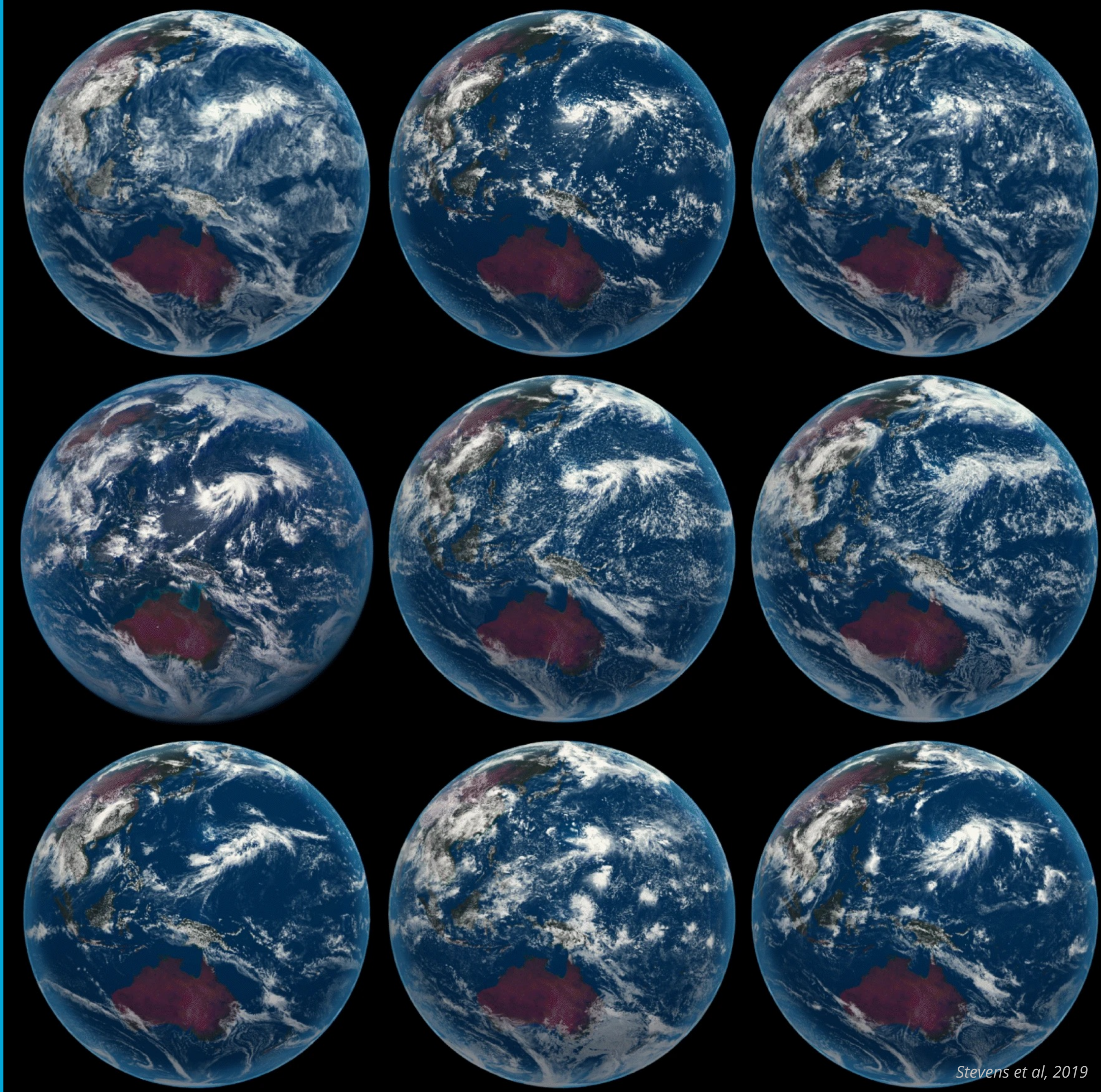
Climate Action Flagship :

Machine Learning for Regional Climate

Machine Learning for Understanding Climate Physics

Geet George (GRS) & Jing Sun (INSY)

TU Delft



Stevens et al, 2019

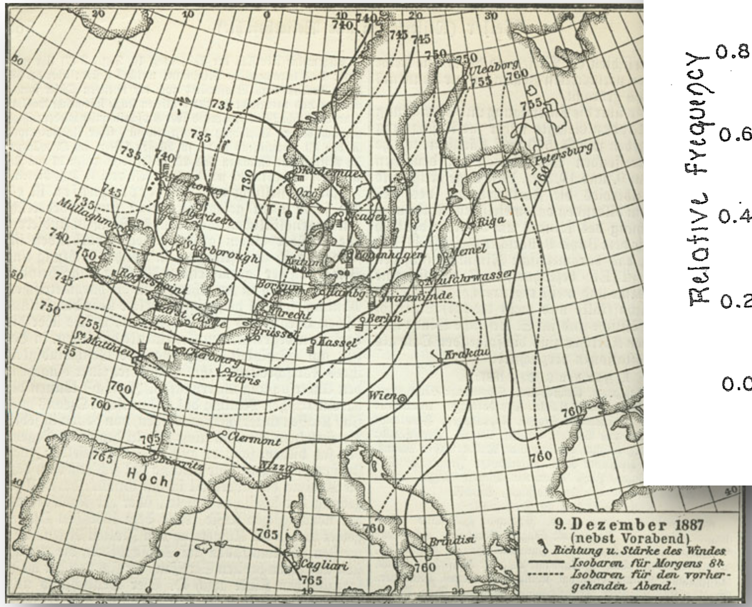
It's very difficult to make predictions especially about the future…

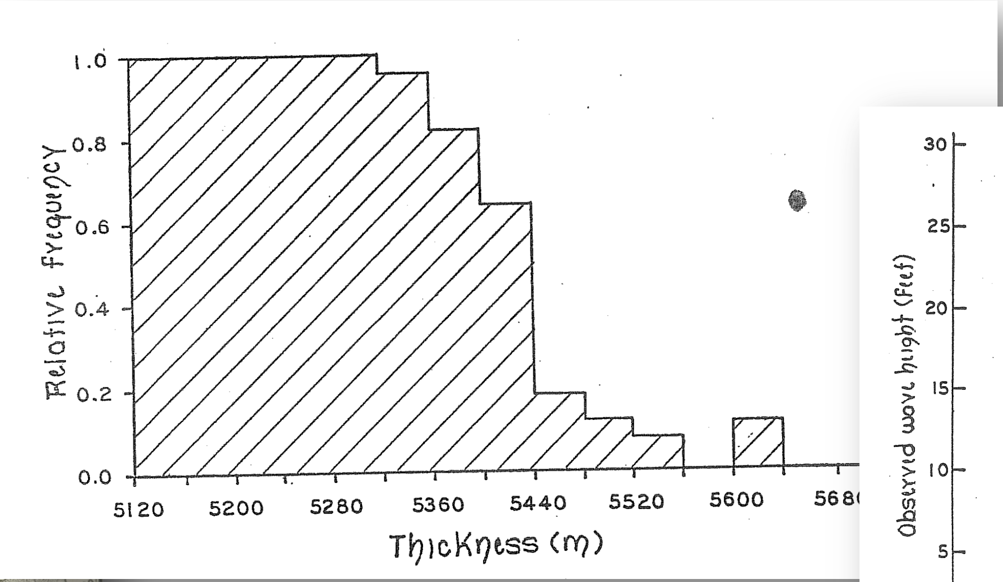
Global surface temperature change relative to 1850–1900

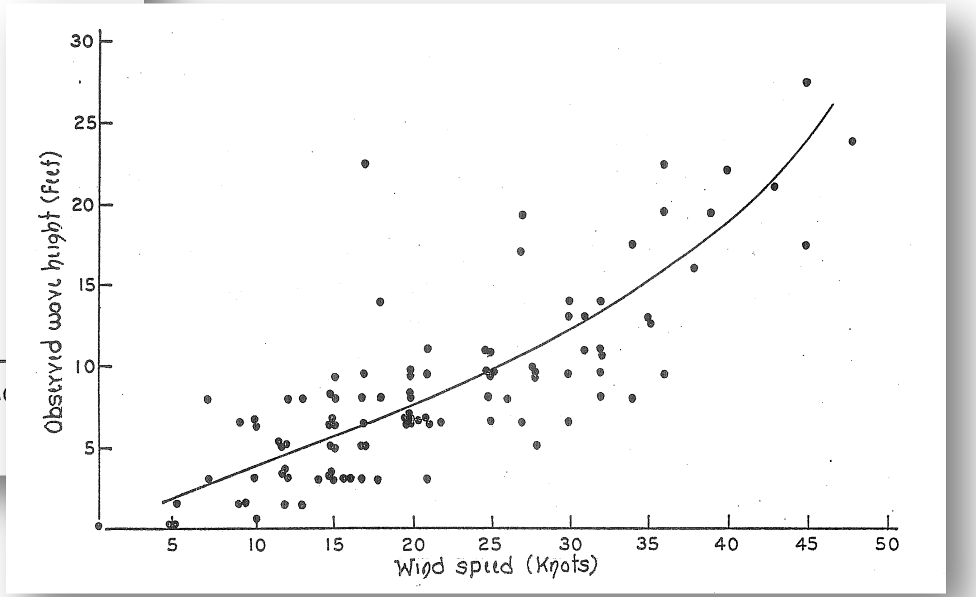
Opening inspired from Gettelman et al, 2022

A hundred years ago, what did we do?

Look at historical patterns & make a statistical prediction!



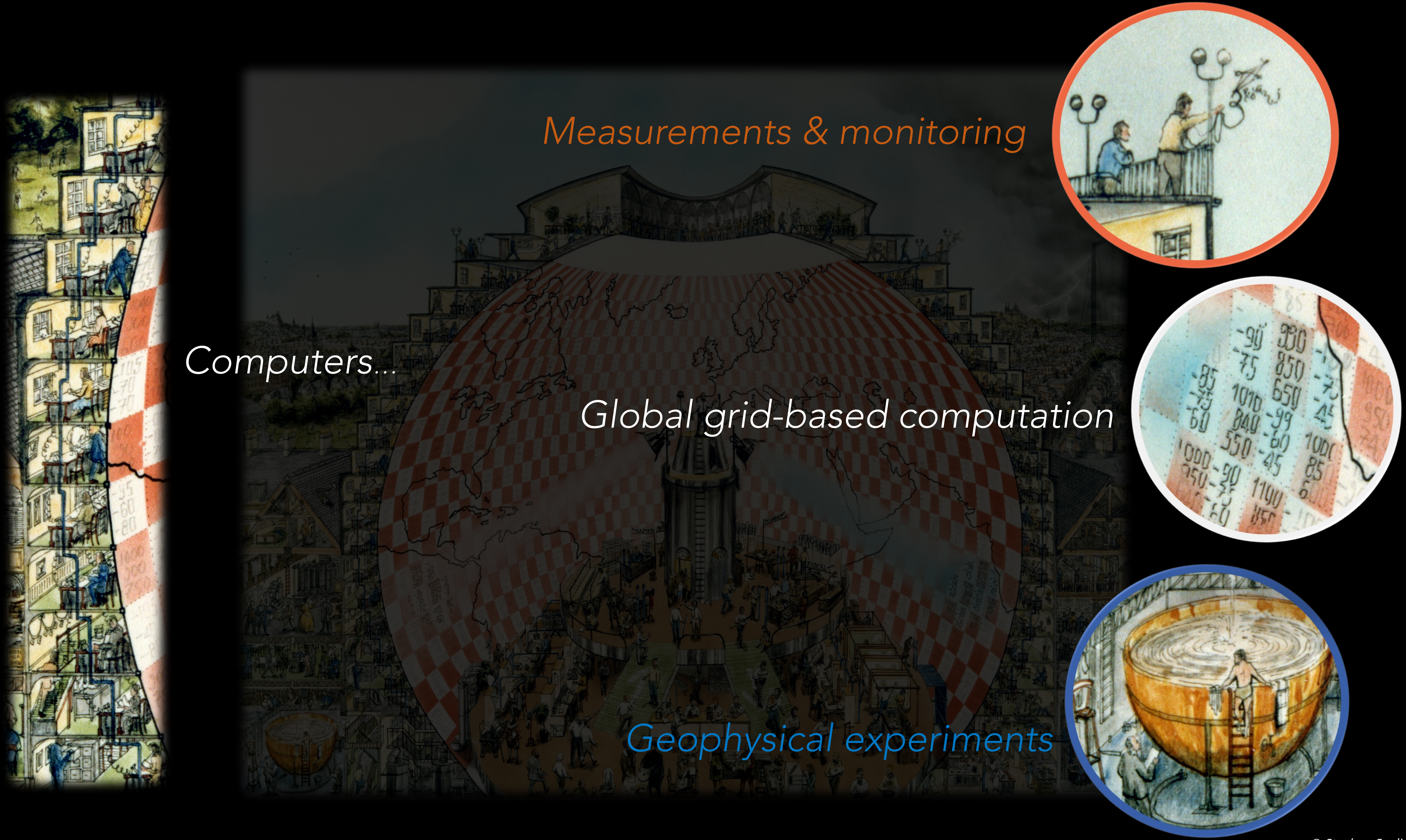


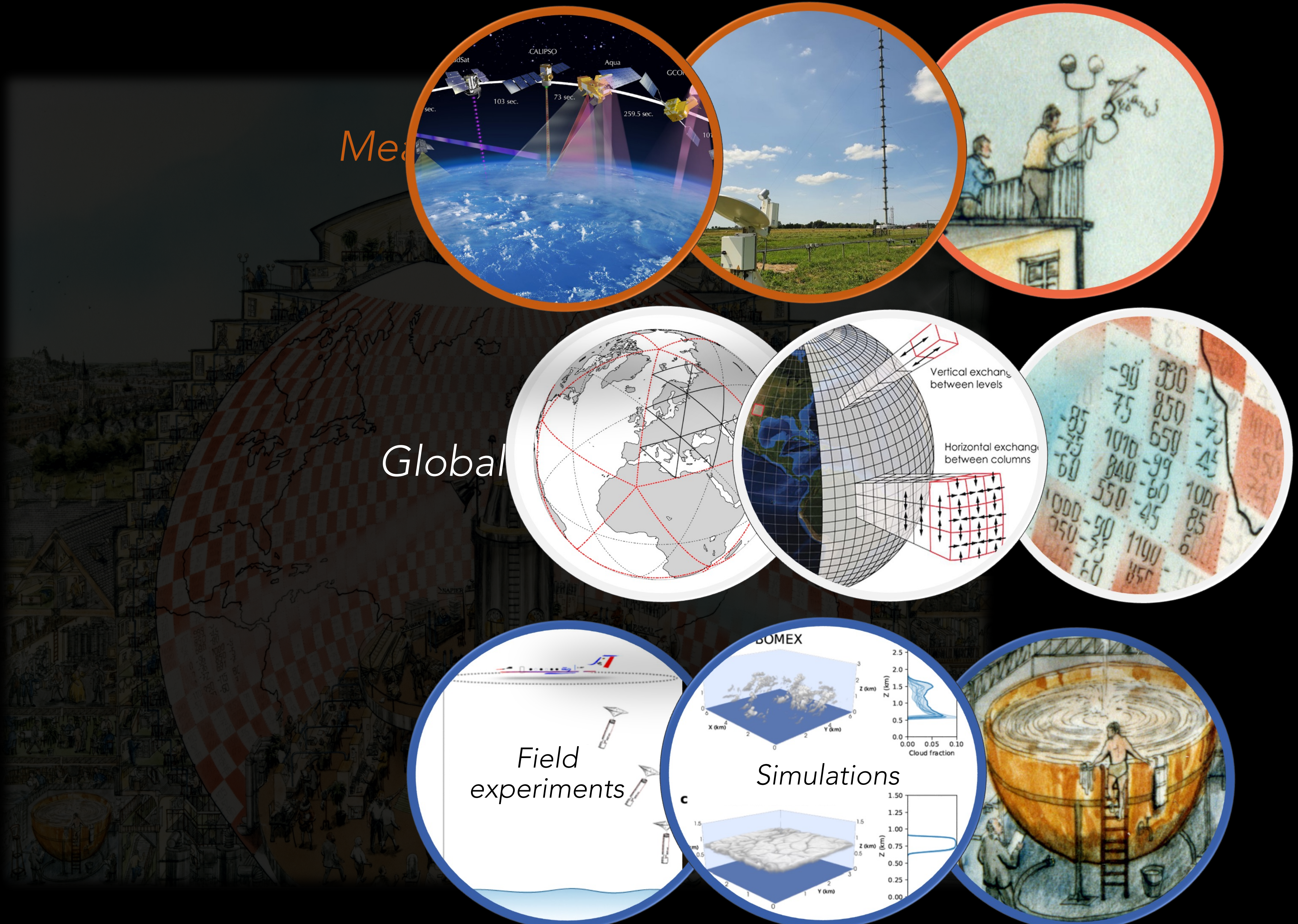


Murphy & Katz, 1982

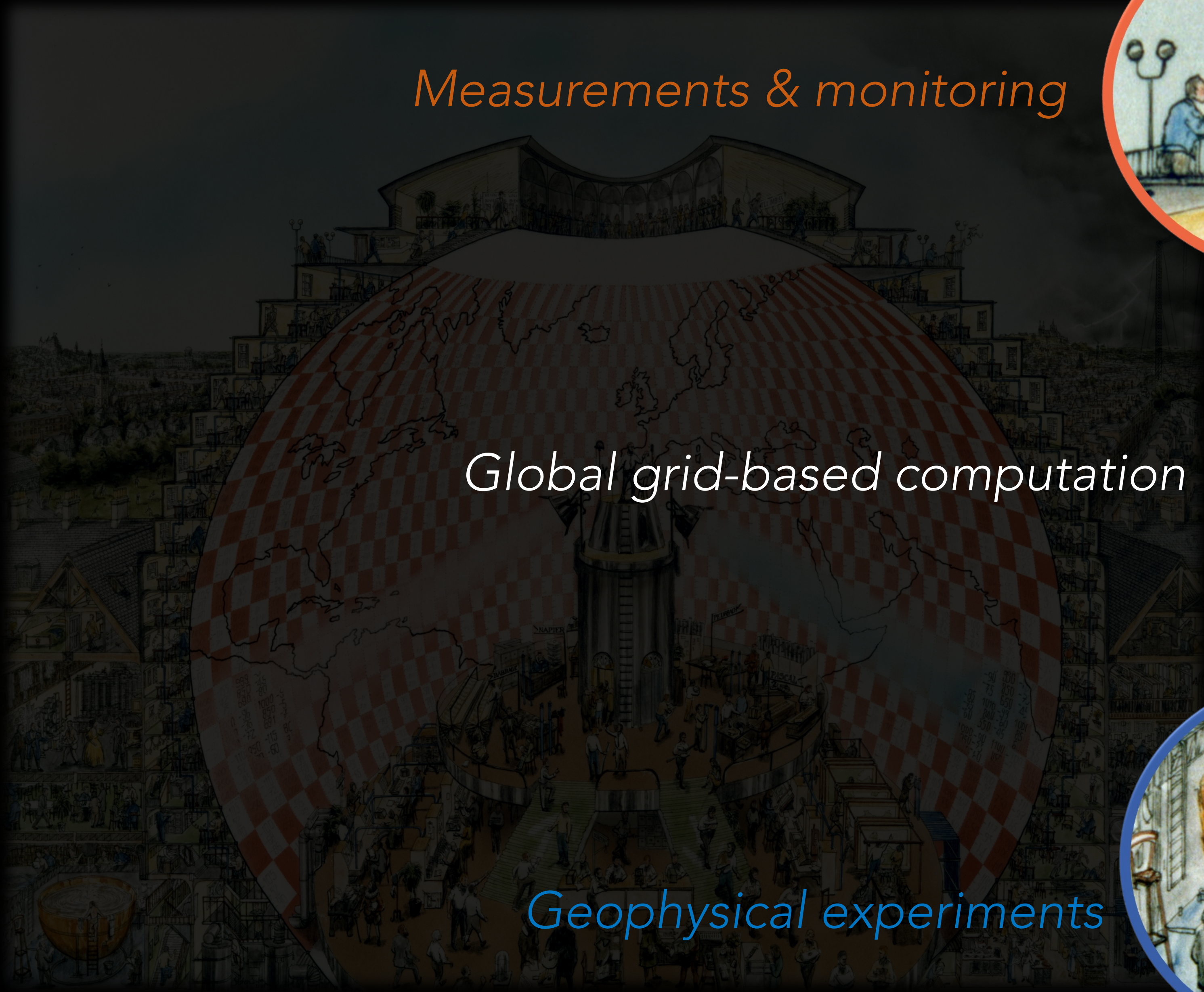
"… may one play with a fantasy?
Imagine a large hall like a theatre…"

- Richardson (1922)


Measurements & monitoring
Computers...
Global grid-based computation
Geophysical experiments



Images adapted from : George et al, 2023, CliMA (Caltech), ICON Model (MPIM, DWD), Kotamarthi R et al, 2021, A-Train (NASA JPL), Ruisdael Observatory

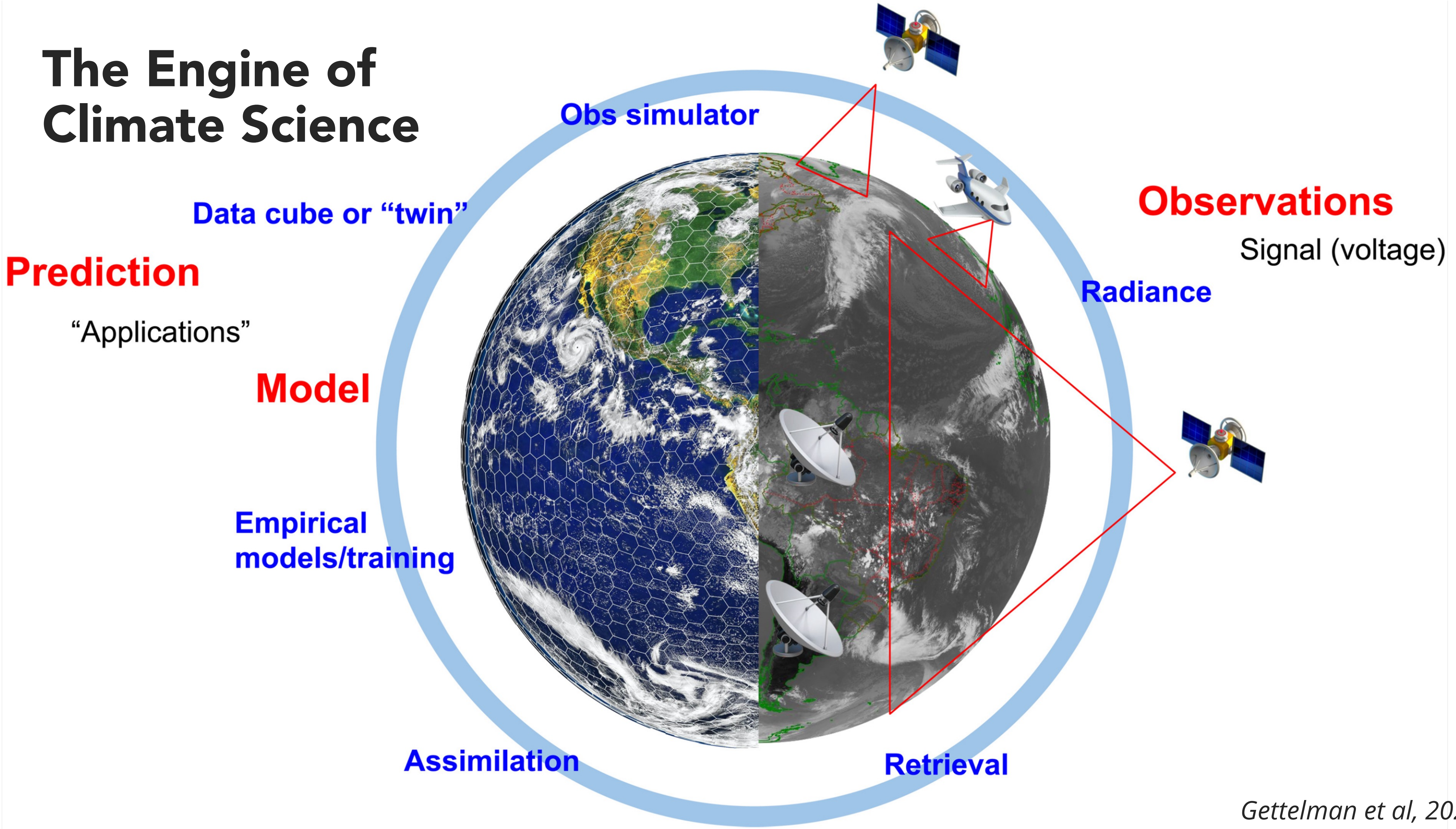


Measurements & monitoring

Global grid-based computation

Geophysical experiments

The Engine of Climate Science



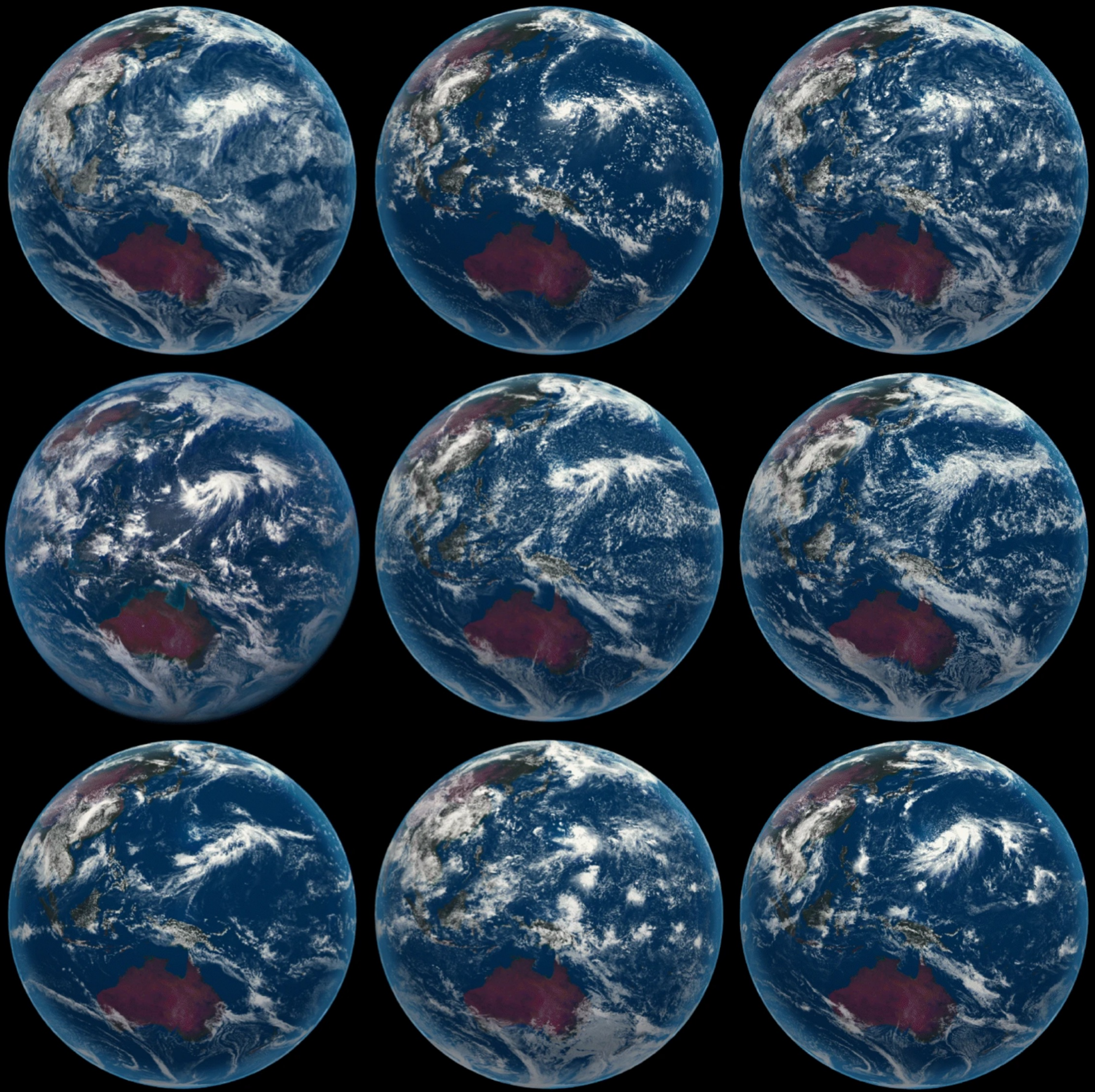
Gettelman et al, 2022

High-resolution climate models, e.g. DYAMOND, NextGEMS, etc.

Stevens et al, 2019

Coupling components of the Earth system

Hohenegger et al, 2022



Larger-domain simulations in limited-area models like LES

Schulz et al, 2023

Hypercube ensembles of simulations to study phase-space

Jansson et al, 2023

Stevens et al, 2019

Increasingly sophisticated space-borne instrumentation

Growing network of surface-based observations

Autonomous measurements on land and in ocean

Image credit: ESA

Big Data Challenge

The 4 Vs

AI ?

> 100 petabytes of data

> 5 petabytes / year

10 Hz data collection

Widely different sources

Errors & inconsistencies

Reichstein et al, 2019

Climatic Research Questions in Our Flagship

With ML

Patterns: Detecting and studying patterns in climate science

Physics: Data-driven understanding of climate physics, as opposed to pure theory-driven

Predictions: Forecasting weather and climate across different scales, including how subsystems, such as ice sheet and sea level, will respond to climate change

When we talk about **AI**, what are we talking about?

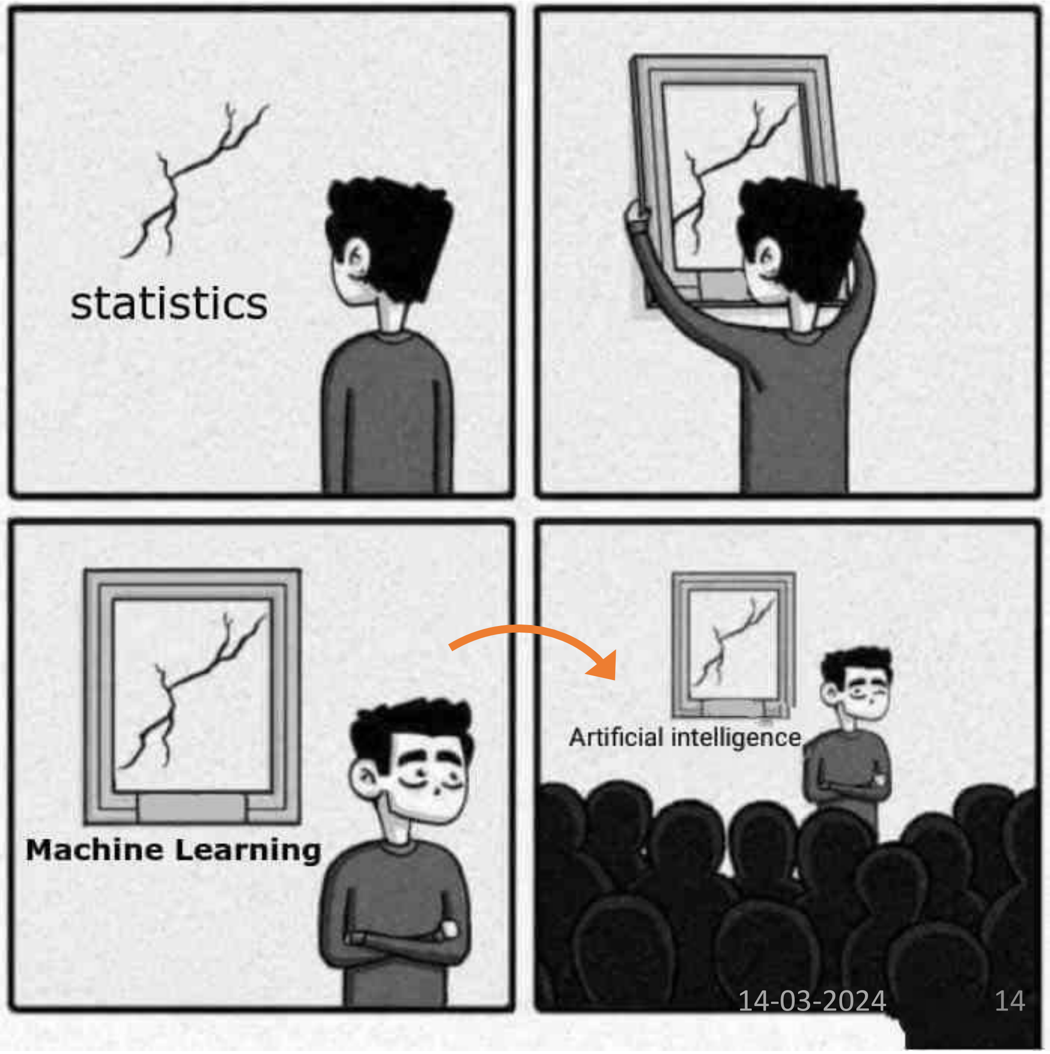
Artificial Intelligence

-- Alan Turing (1950)

"Computing Machinery and Intelligence "

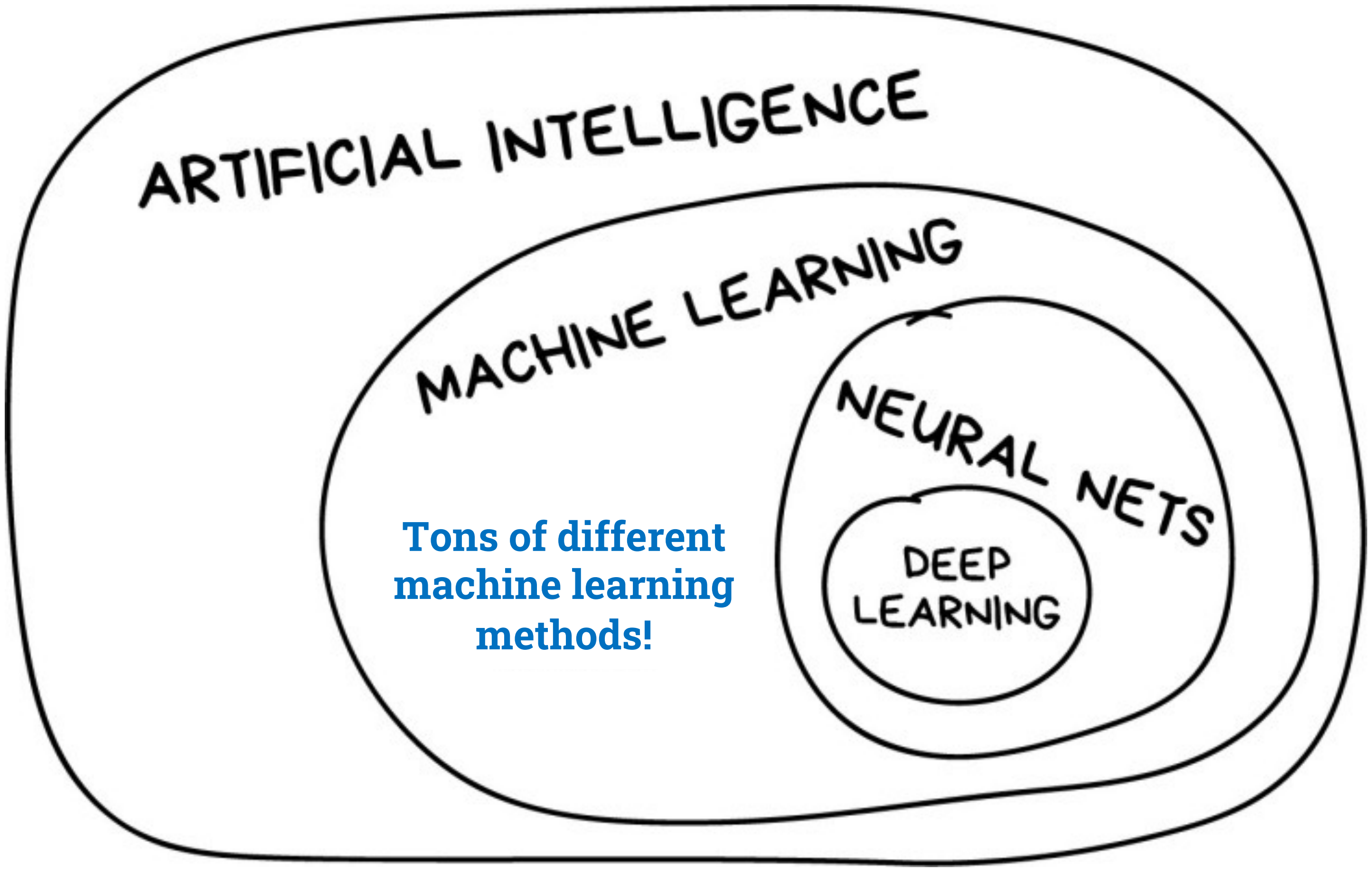
Even at the official opening of the academic year 2024-2025 at TU Delft, the theme was "**Enter the Age of AI**".

Who brought AI to the center of attention?



TU Delft

“Enter the Age of AI” – TU Delft

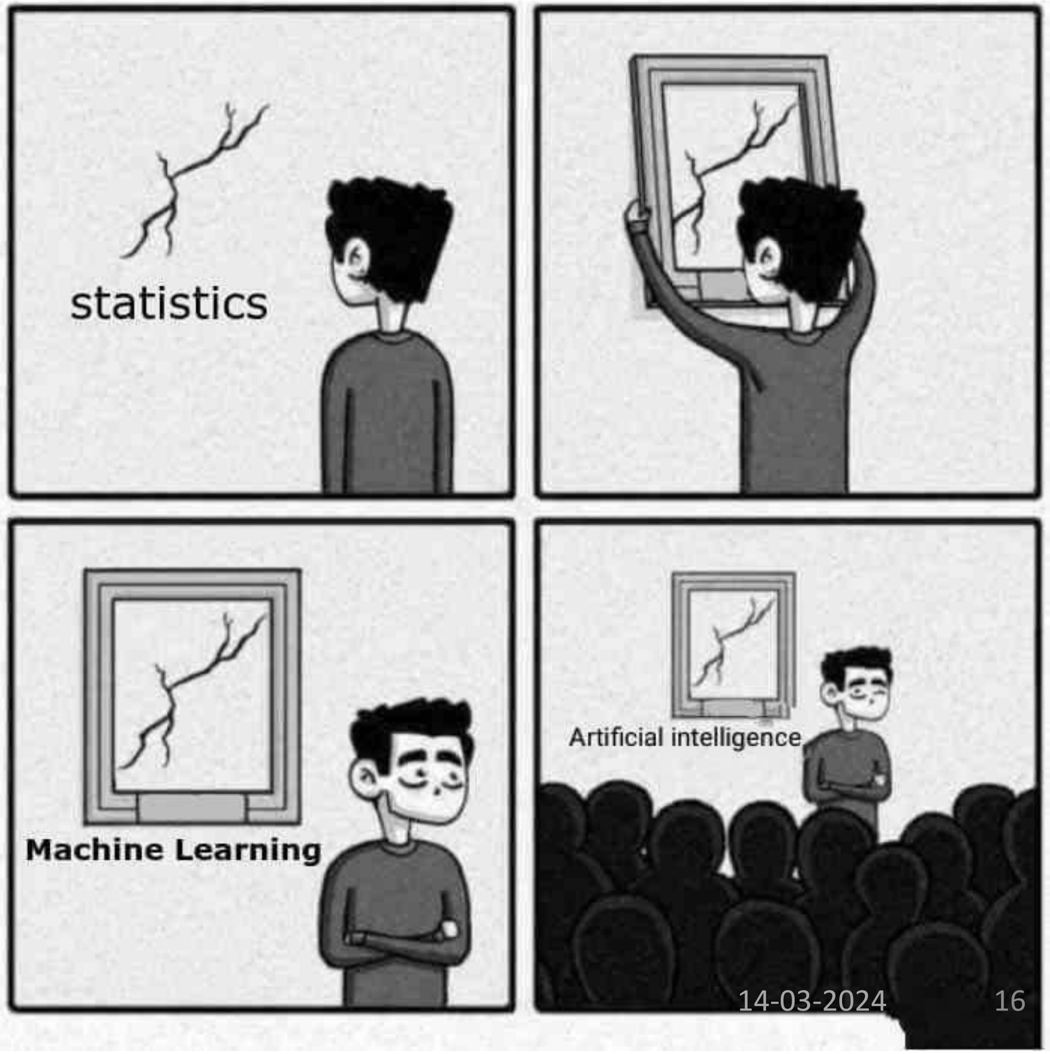


Tons of different machine learning methods!

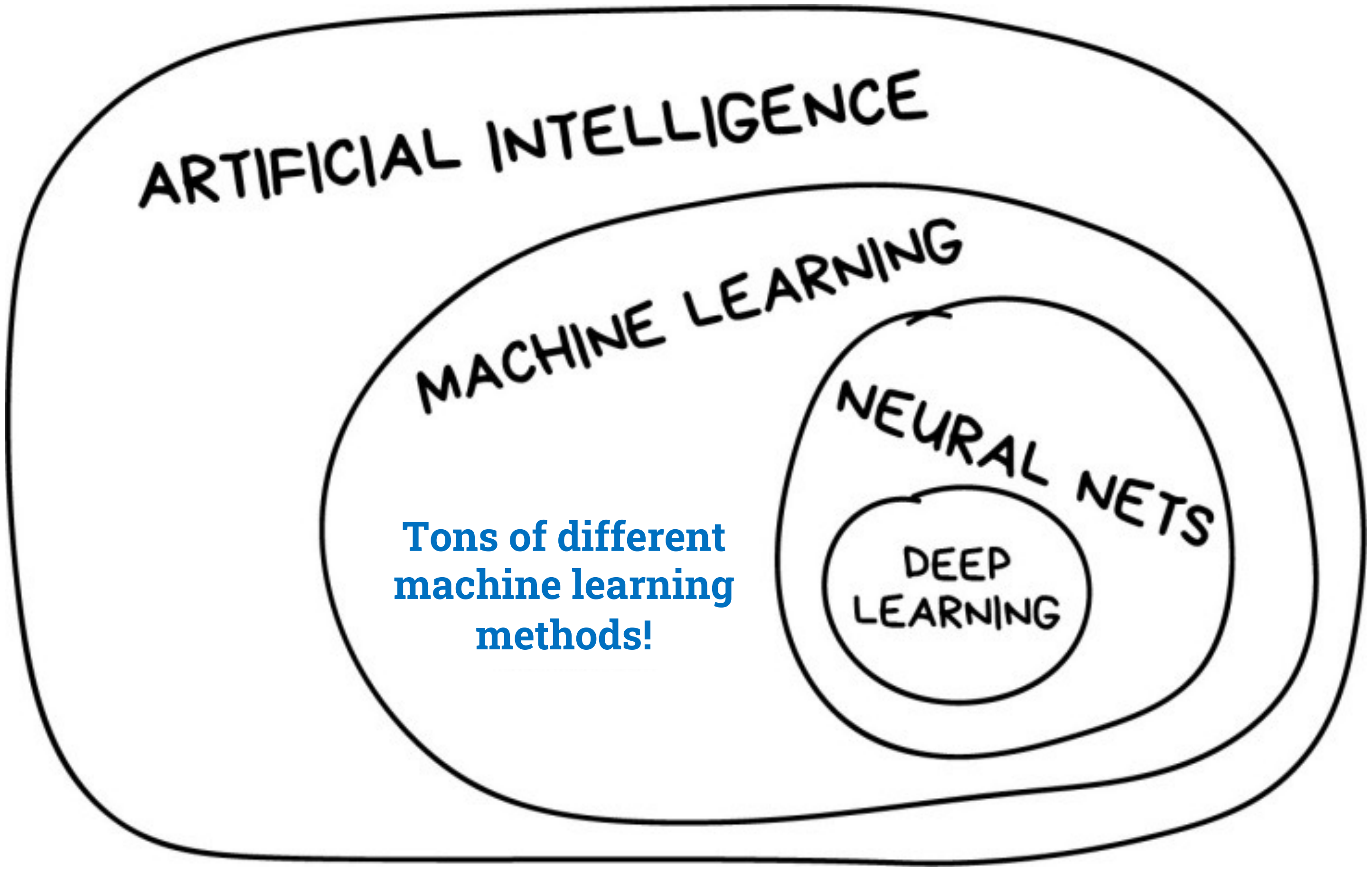
When we talk about **ML**, what are we talking about?

In 1959, Arthur Samuel described ML as the “field of study that **gives computers the ability** to **learn without being explicitly programmed**”.

Or you may call it Statistical Learning



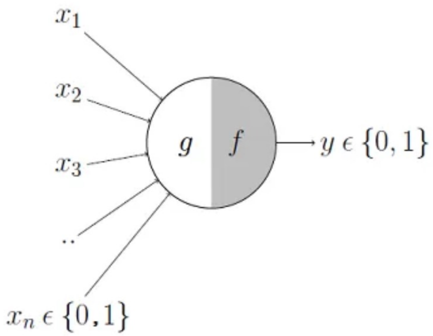
“Enter the Age of AI” – TU Delft



Warren McCulloch & Walter Pitts

“A Logical Calculus of Ideas Immanent in Nervous Activity” (1943):

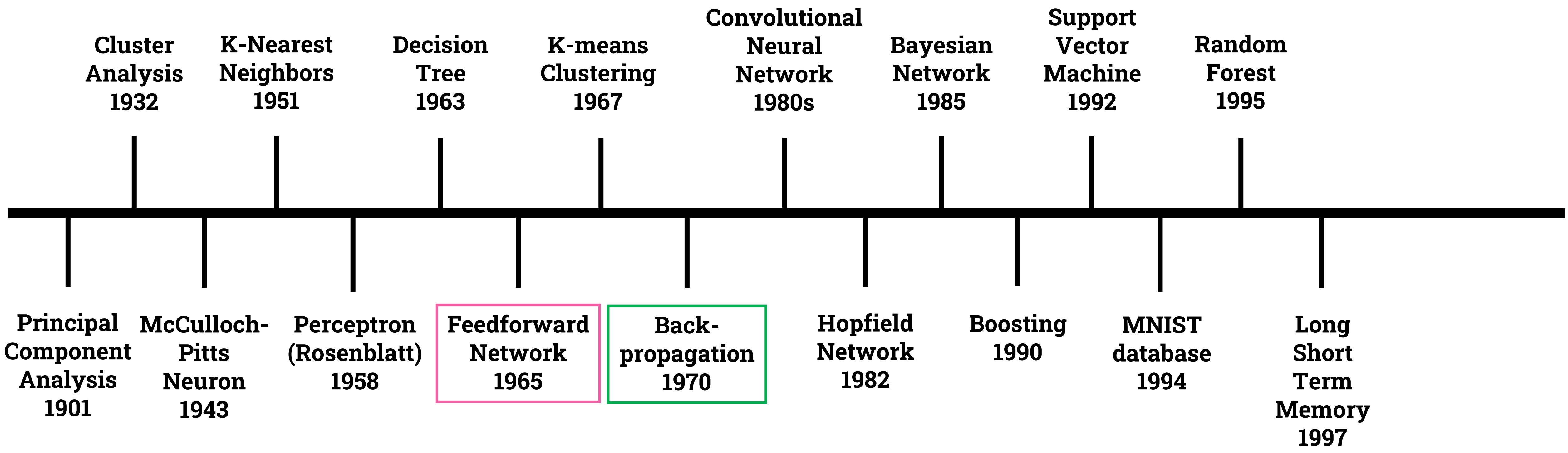
The first mathematical model of a neural network.

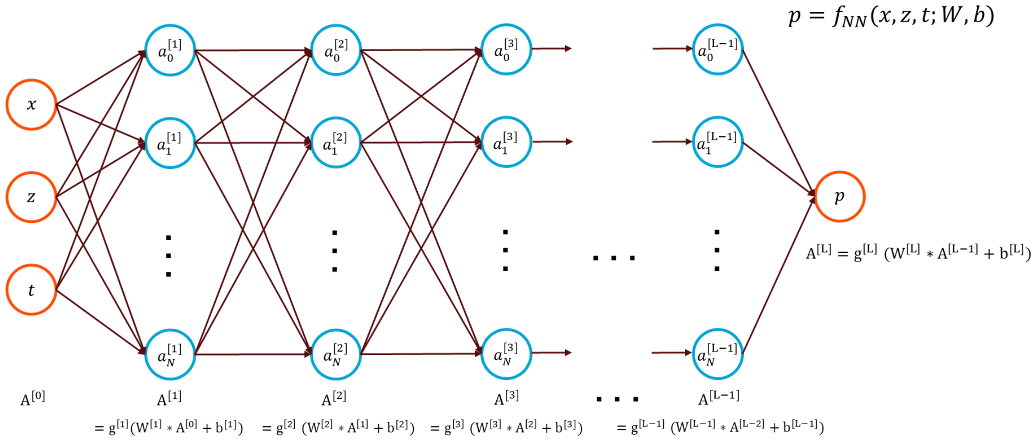


Milestones in ML

- Principal Component Analysis 1901
- Cluster Analysis 1932
- McCulloch-Pitts Neuron 1943
- K-Nearest Neighbors 1951
- Perceptron (Rosenblatt) 1958
- Decision Tree 1963
- Feedforward Network 1965
- K-means Clustering 1967
- Back-propagation 1970
- Convolutional Neural Network 1980s
- Hopfield Network 1982
- Bayesian Network 1985
- Boosting 1990
- Support Vector Machine 1992
- MNIST database 1994
- Random Forest 1995
- Long Short Term Memory 1997

Milestones in ML





A Deep Neural Network

Forward propagation

Initial W, b

Input x, z, t

Prediction p

Loss calculation

Target $\hat{p}$

Update W, b

Backward propagation

$$L = \frac{1}{D} \sum_{i=1}^{D} (p^{(i)} - \hat{p}^{(i)})^{2}$$

D : size of the training data set
$p^{(i)}$: prediction from the NN of the i^{th} data point
$\hat{p}^{(i)}$: desired output of the i^{th} data point

TU Delft

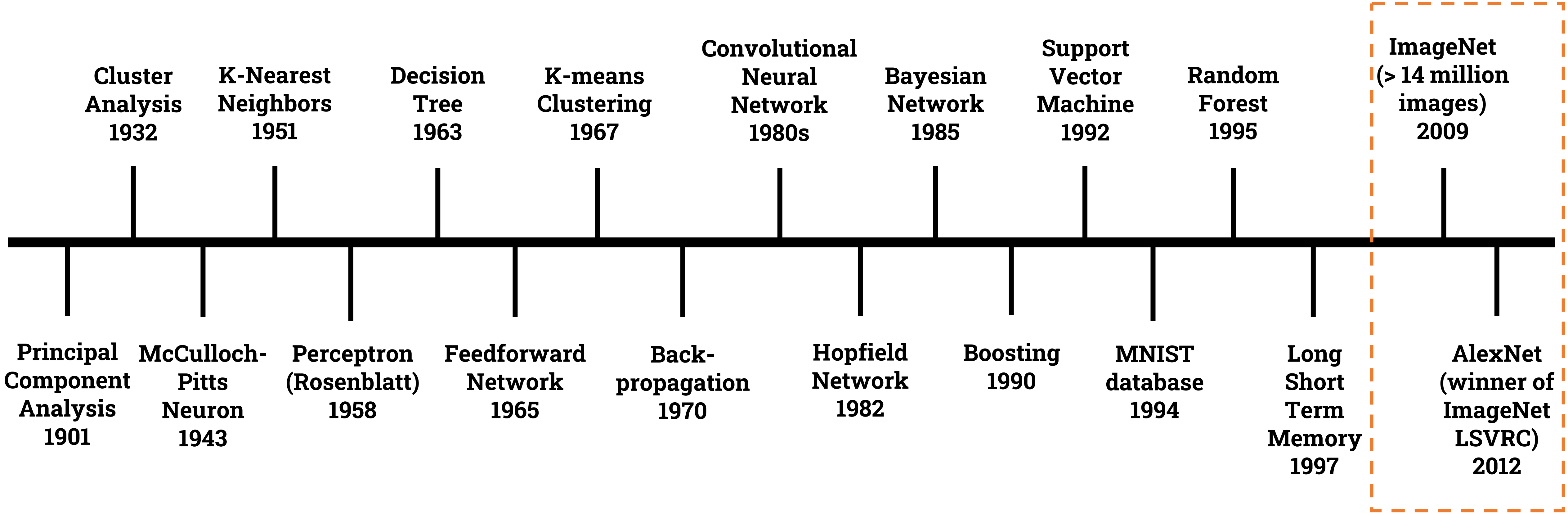
Milestones in ML

- Principal Component Analysis 1901
- Cluster Analysis 1932
- McCulloch-Pitts Neuron 1943
- K-Nearest Neighbors 1951
- Perceptron (Rosenblatt) 1958
- Decision Tree 1963
- Feedforward Network 1965
- K-means Clustering 1967
- Back-propagation 1970
- Convolutional Neural Network 1980s
- Hopfield Network 1982
- Bayesian Network 1985
- Boosting 1990
- Support Vector Machine 1992
- MNIST database 1994
- Random Forest 1995
- Long Short Term Memory 1997

Computation Limitation…

TUDelft

Milestones in ML



"Enter the Age of **Deep Learning**!"
(or **AI Boom**!)

Milestones in DL ∈ ML

NeurIPS
https://papers.nips.cc › paper › 7181-attention-is-all-yo...
Attention is All you Need
by A Vaswani · 2017 · Cited by 111587 — We propose a based solely onan attention mechanism, dispensing wit

https://openai.com/

OpenAI

ImageNet (> 14 million images) 2009

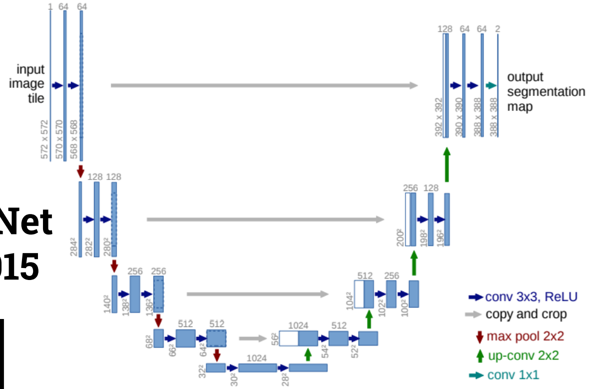
AlexNet (winner of ImageNet LSVRC) 2012

VGG 2014

FCN (Fully Convolutional Network) 2014

GAN (Generative Adversarial Networks) 2014

U-Net 2015



Diffusion Model 2015

ResNet 2016

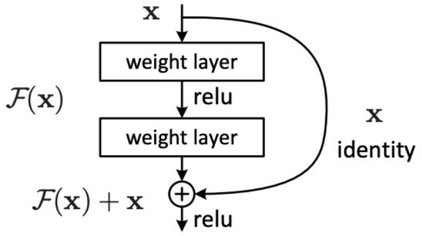
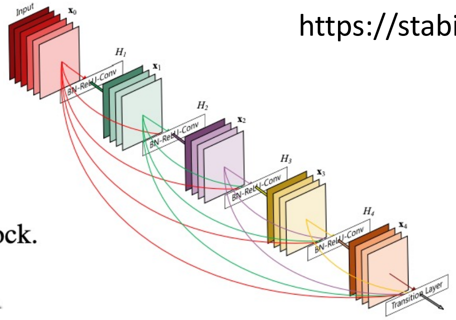


Figure 2. Residual learning: a building block.

Transformer 2017

DenseNet 2017



GPT-1 2018

GPT-2 2019

GPT-3 2020

DALL-E 2021

GPT-3.5 DALL-E2 2022

GPT-4 DALL-E3 2023

The real party…

stability.ai

https://stability.ai/

Stable Diffusion 2022

Sora 2024

NeurIPS
https://papers.nips.cc › paper › 5423-generative-ad
Generative Adversarial Nets
by I Goodfellow · 2014 · Cited by 65246 — We propose generative models via adversarial nets, in which we si

The Computer Vision Foundation
https://www.cv-foundation.org › papers › He_De..
Deep Residual Learning for Image Recognition
by K He · 2016 · Cited by 208219 — Deeper neural networks are mor present a residual learning framework to ease the training of networ

TU Delft

References

- Pearson, K. 1901. "On Lines and Planes of Closest Fit to Systems of Points in Space". Philosophical Magazine. 2 (11): 559–572.
- Driver, H.E. and Kroeber, A.L., 1932. Quantitative expression of cultural relationships (Vol. 31, No. 4). Berkeley: University of California Press.
- McCulloch, W.S. and Pitts, W., 1943. A logical calculus of the ideas immanent in nervous activity. The bulletin of mathematical biophysics, 5, pp.115-133.
- Fix, Evelyn; Hodges, Joseph L. 1951. Discriminatory Analysis. Nonparametric Discrimination: Consistency Properties. USAF School of Aviation Medicine, Randolph Field, Texas
- Rosenblatt, F., 1958. The perceptron: a probabilistic model for information storage and organization in the brain. Psychological review, 65(6), p.386.
- Morgan, J.N. and Sonquist, J.A., 1963. Problems in the analysis of survey data, and a proposal. Journal of the American statistical association, 58(302), pp.415-434.
- MacQueen, J., 1967, June. Some methods for classification and analysis of multivariate observations. In Proceedings of the fifth Berkeley symposium on mathematical statistics and probability (Vol. 1, No. 14, pp. 281-297).
- Linnainmaa, S., 1970. The representation of the cumulative rounding error of an algorithm as a Taylor expansion of the local rounding errors (Doctoral dissertation, Master's Thesis (in Finnish), Univ. Helsinki).
- Fukushima, K., 1980. Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. Biological cybernetics, 36(4), pp.193-202.
- Hopfield, J.J., 1982. Neural networks and physical systems with emergent collective computational abilities. Proceedings of the national academy of sciences, 79(8), pp.2554-2558.
- Pearl, J., 1985, August. Bayesian netwcrks: A model of self-activated memory for evidential reasoning. In Proceedings of the 7th conference of the Cognitive Science Society, University of California, Irvine, CA, USA (pp. 15-17).
- LeCun, Y., Boser, B., Denker, J., Henderson, D., Howard, R., Hubbard, W. and Jackel, L., 1989. Handwritten digit recognition with a back-propagation network. Advances in neural information processing systems, 2.
- Schapire, R.E., 1990. The strength of weak learnability. Machine learning, 5, pp.197-227.
- Boser, B.E., Guyon, I.M. and Vapnik, V.N., 1992, July. A training algorithm for optimal margin classifiers. In Proceedings of the fifth annual workshop on Computational learning theory (pp. 144-152).
- Bottou, L., Cortes, C., Denker, J.S., Drucker, H., Guyon, I., Jackel, L.D., LeCun, Y., Muller, U.A., Sackinger, E., Simard, P. and Vapnik, V., 1994, October. Comparison of classifier methods: a case study in handwritten digit recognition. In Proceedings of the 12th IAPR International Conference on Pattern Recognition, Vol. 3-Conference C: Signal Processing (Cat. No. 94CH3440-5) (Vol. 2, pp. 77-82). IEEE.
- Ho, T.K., 1995, August. Random decision forests. In Proceedings of 3rd international conference on document analysis and recognition (Vol. 1, pp. 278-282). IEEE.
- Hochreiter, S. and Schmidhuber, J., 1997. Long short-term memory. Neural computation, 9(8), pp.1735-1780.

TU Delft

References

- Deng, J., Dong, W., Socher, R., Li, L.J., Li, K. and Fei-Fei, L., 2009, June. Imagenet: A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition (pp. 248-255). IEEE.
- Krizhevsky, A., Sutskever, I. and Hinton, G.E., 2012. Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 25.
- Simonyan, K. and Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.
- Long, J., Shelhamer, E. and Darrell, T., 2015. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3431-3440).
- Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. and Bengio, Y., 2014. Generative adversarial nets. Advances in neural information processing systems, 27.
- Ronneberger, O., Fischer, P. and Brox, T., 2015. U-net: Convolutional networks for biomedical image segmentation. In Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18 (pp. 234-241). Springer International Publishing.
- Sohl-Dickstein, J., Weiss, E., Maheswaranathan, N. and Ganguli, S., 2015, June. Deep unsupervised learning using nonequilibrium thermodynamics. In International conference on machine learning (pp. 2256-2265). PMLR.
- He, K., Zhang, X., Ren, S. and Sun, J., 2016. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).
- Huang, G., Liu, Z., Van Der Maaten, L. and Weinberger, K.Q., 2017. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4700-4708).
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł. and Polosukhin, I., 2017. Attention is all you need. Advances in neural information processing systems, 30.

"Opportunities and Risks"

"Though foundation models are based on standard deep learning and transfer learning, **their scale results in new emergent capabilities**, and their effectiveness across so many tasks incentivizes homogenization. Homogenization provides powerful leverage but demands caution, as the defects of the foundation model are inherited by all the adapted models downstream. Despite the impending widespread deployment of foundation models, **we currently lack a clear understanding of how they work, when they fail, and what they are even capable of due to their emergent properties**. To tackle these questions, we believe much of the critical research on foundation models will require deep interdisciplinary collaboration commensurate with their fundamentally sociotechnical nature."

Greater Power (of the AI),
Greater Responsibility (for the AI researchers).

Center for Research on Foundation Models
Stanford University Human-Centered Artificial Intelligence

On the Opportunities and Risks of Foundation Models

Download the report.

114 AI researchers

Authors: Rishi Bommasani*, Drew A. Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S. Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, Erik Brynjolfsson, Shyamal Buch, Dallas Card, Rodrigo Castellon, Niladri Chatterji, Annie Chen, Kathleen Creel, Jared Quincy Davis, Dora Demszky, Chris Donahue, Moussa Doumbouya, Esin Durmus, Stefano Ermon, John Etchemendy, Kawin Ethayarajh, Li Fei-Fei, Chelsea Finn, Trevor Gale, Lauren Gillespie, Karan Goel, Noah Goodman, Shelby Grossman, Neel Guha, Tatsunori Hashimoto, Peter Henderson, John Hewitt, Daniel E. Ho, Jenny Hong, Kyle Hsu, Jing Huang, Thomas Icard, Saahil Jain, Dan Jurafsky, Pratyusha Kalluri, Siddharth Karamcheti, Geoff Keeling, Fereshte Khani, Omar Khattab, Pang Wei Kohd, Mark Krass, Ranjay Krishna, Rohith Kuditipudi, Ananya Kumar, Faisal Ladhak, Mina Lee, Tony Lee, Jure Leskovec, Isabelle Levent, Xiang Lisa Li, Xuechen Li, Tengyu Ma, Ali Malik, Christopher D. Manning, Suvir Mirchandani, Eric Mitchell, Zanele Munyikwa, Suraj Nair, Avanika Narayan, Deepak Narayanan, Ben Newman, Allen Nie, Juan Carlos Niebles, Hamed Nilforoshan, Julian Nyarko, Giray Ogut, Laurel Orr, Isabel Papadimitriou, Joon Sung Park, Chris Piech, Eva Portelance, Christopher Potts, Aditi Raghunathan, Rob Reich, Hongyu Ren, Frieda Rong, Yusuf Roohani, Camilo Ruiz, Jack Ryan, Christopher Ré, Dorsa Sadigh, Shiori Sagawa, Keshav Santhanam, Andy Shih, Krishnan Srinivasan, Alex Tamkin, Rohan Taori, Armin W. Thomas, Florian Tramèr, Rose E. Wang, William Wang , Bohan Wu, Jiajun Wu, Yuhuai Wu, Sang Michael Xie, Michihiro Yasunaga, Jiaxuan You, Matei Zaharia, Michael Zhang, Tianyi Zhang, Xikun Zhang, Yuhui Zhang, Lucia Zheng, Kaitlyn Zhou, Percy Liang*

TU Delft

Bommasani, Rishi, et al., 2021. On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*.

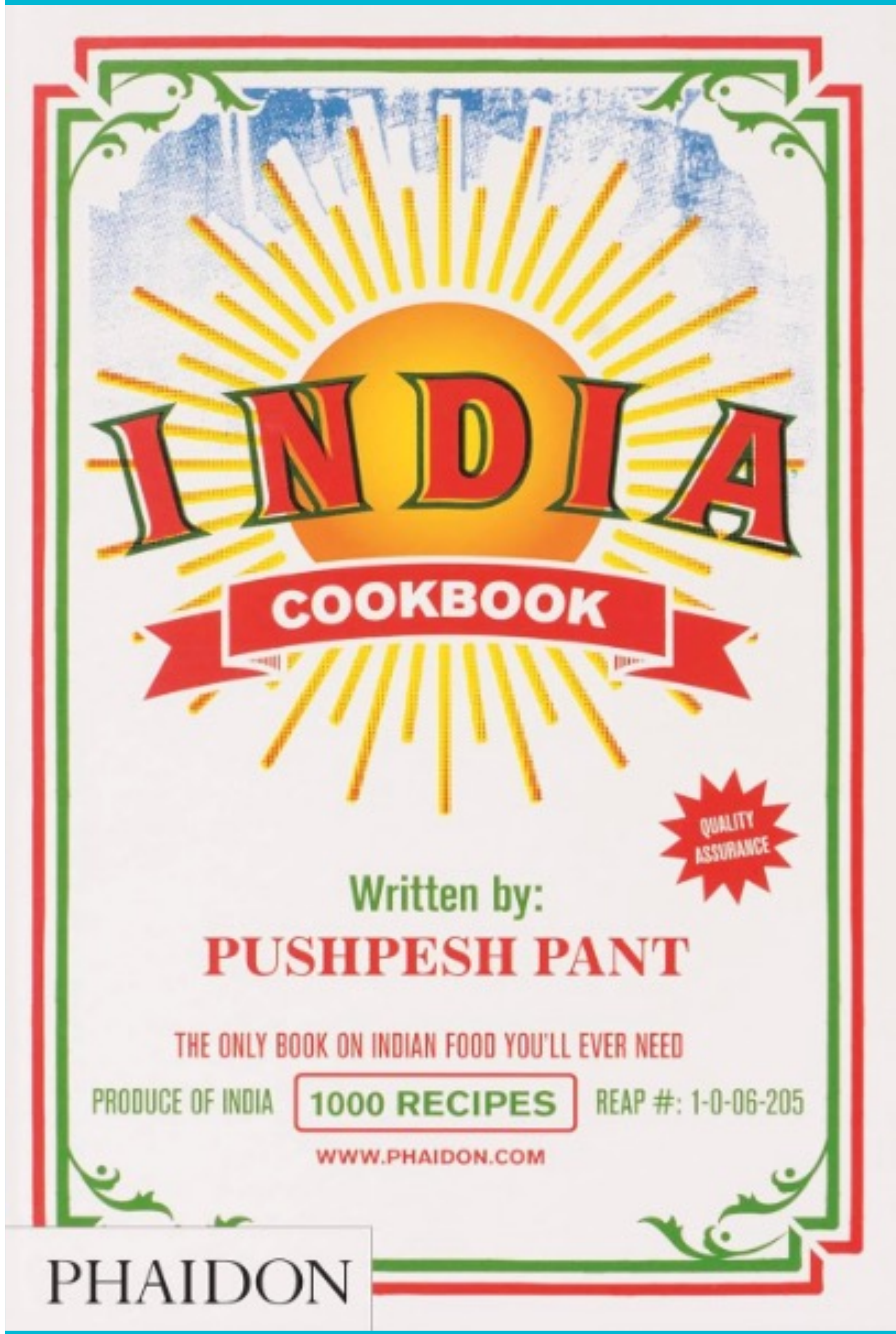
Where is the Solution to My Task!

This is like teaching someone Chinese to cook Indian food;

you have 1,000 successful recipes from experts' experiences beforehand,

but you never foresee what you will actually serve at the table in the end.

You do get lucky in some cases where "transplanting" simply works!



TU Delft

https://www.amazon.nl/India-Cookbook-Pushpesh-Pant/dp/0714859028

What are the correct connections based on your intuition?

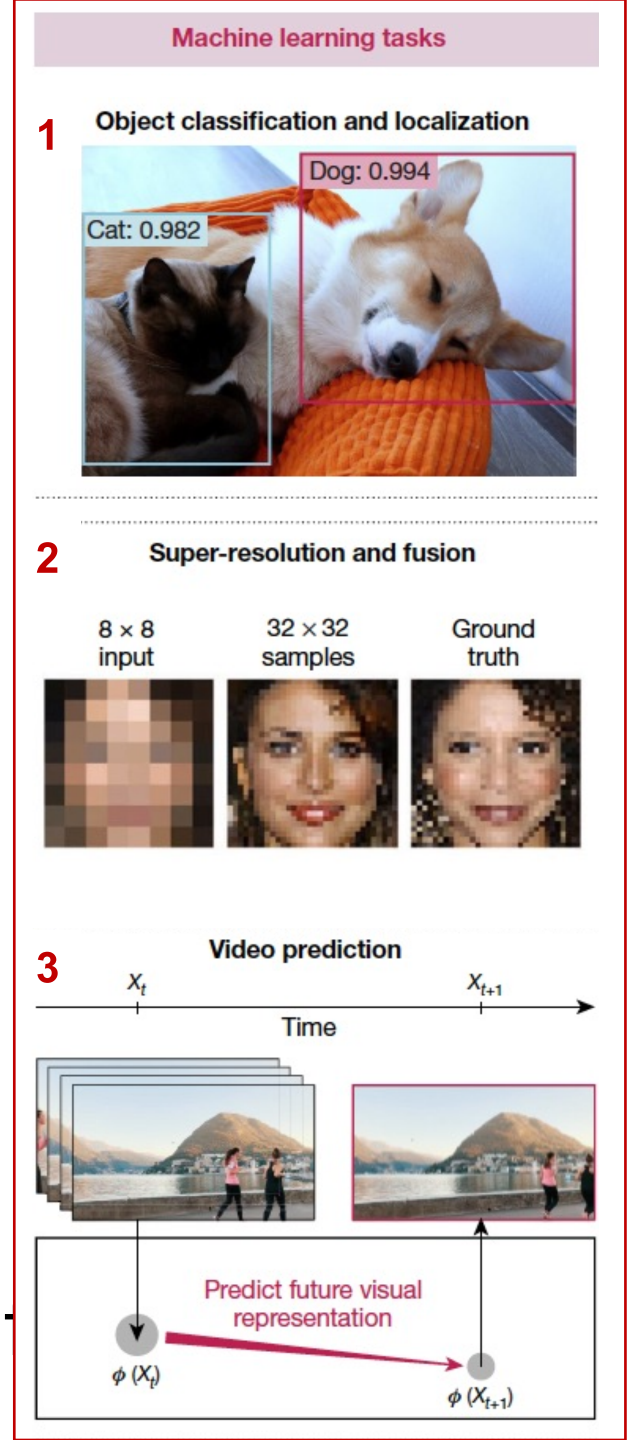
Give your answer:

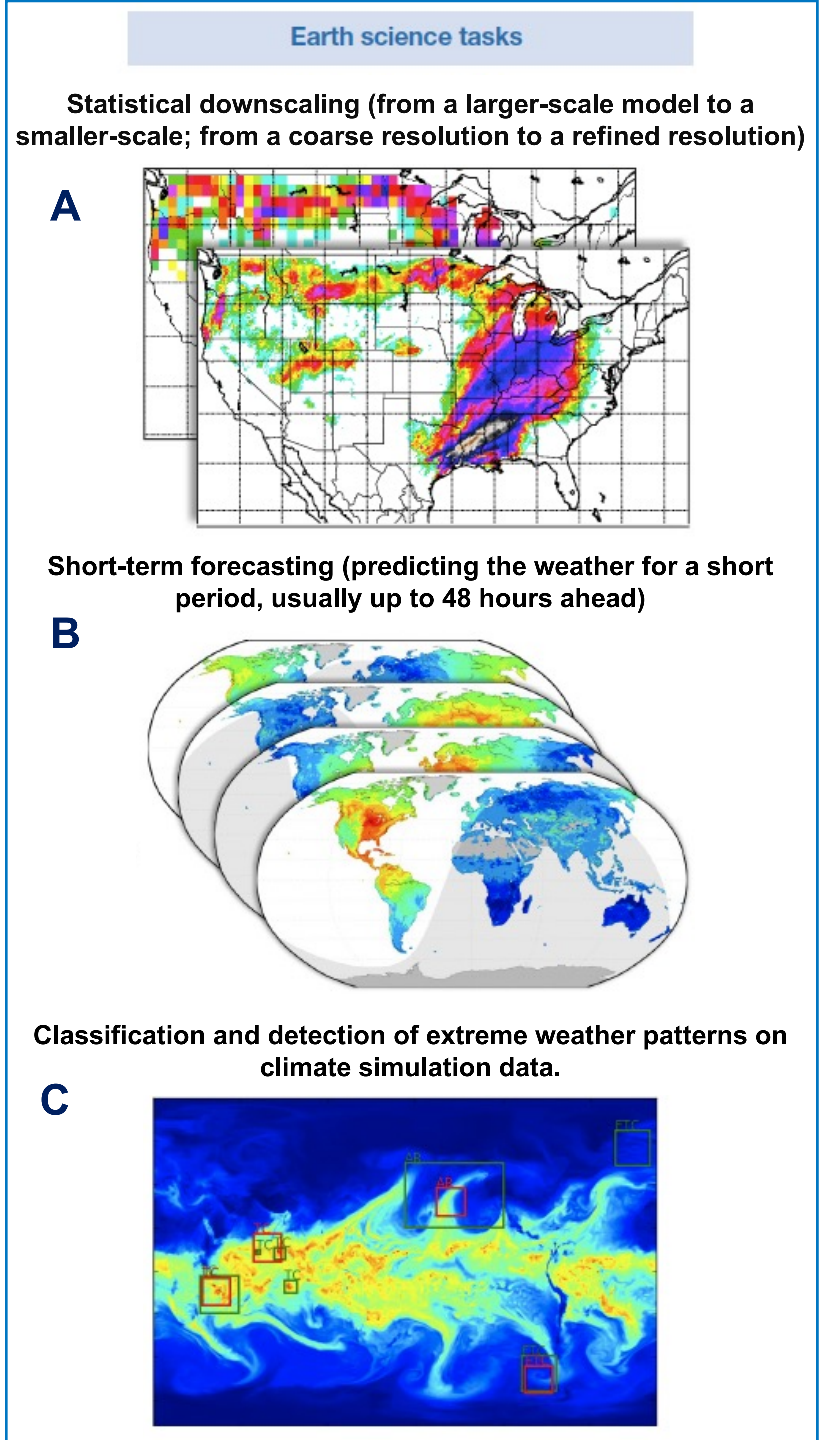
Scan the QR Code!

OR

1. Go to vevox.app
2. 156-136-777

Left panels: AI tasks in **computer vision.**





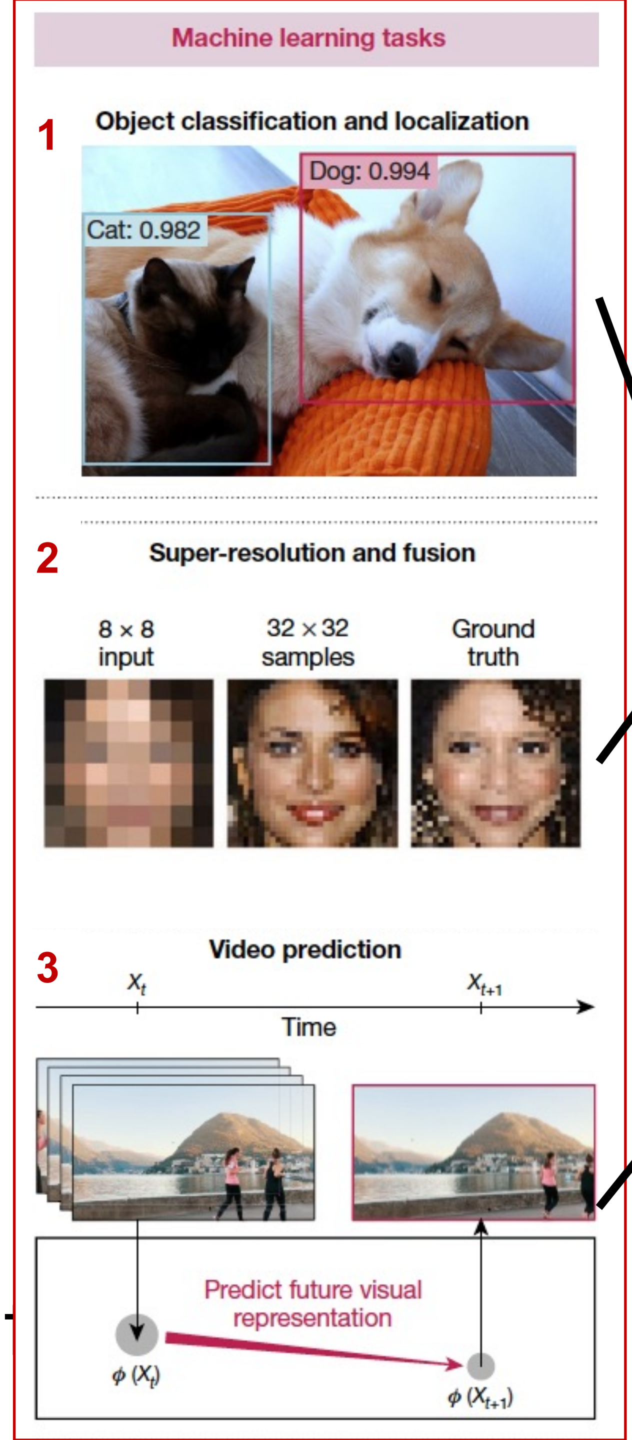
Right panels: **geoscientific problems** to which the same AI techniques can be applied.

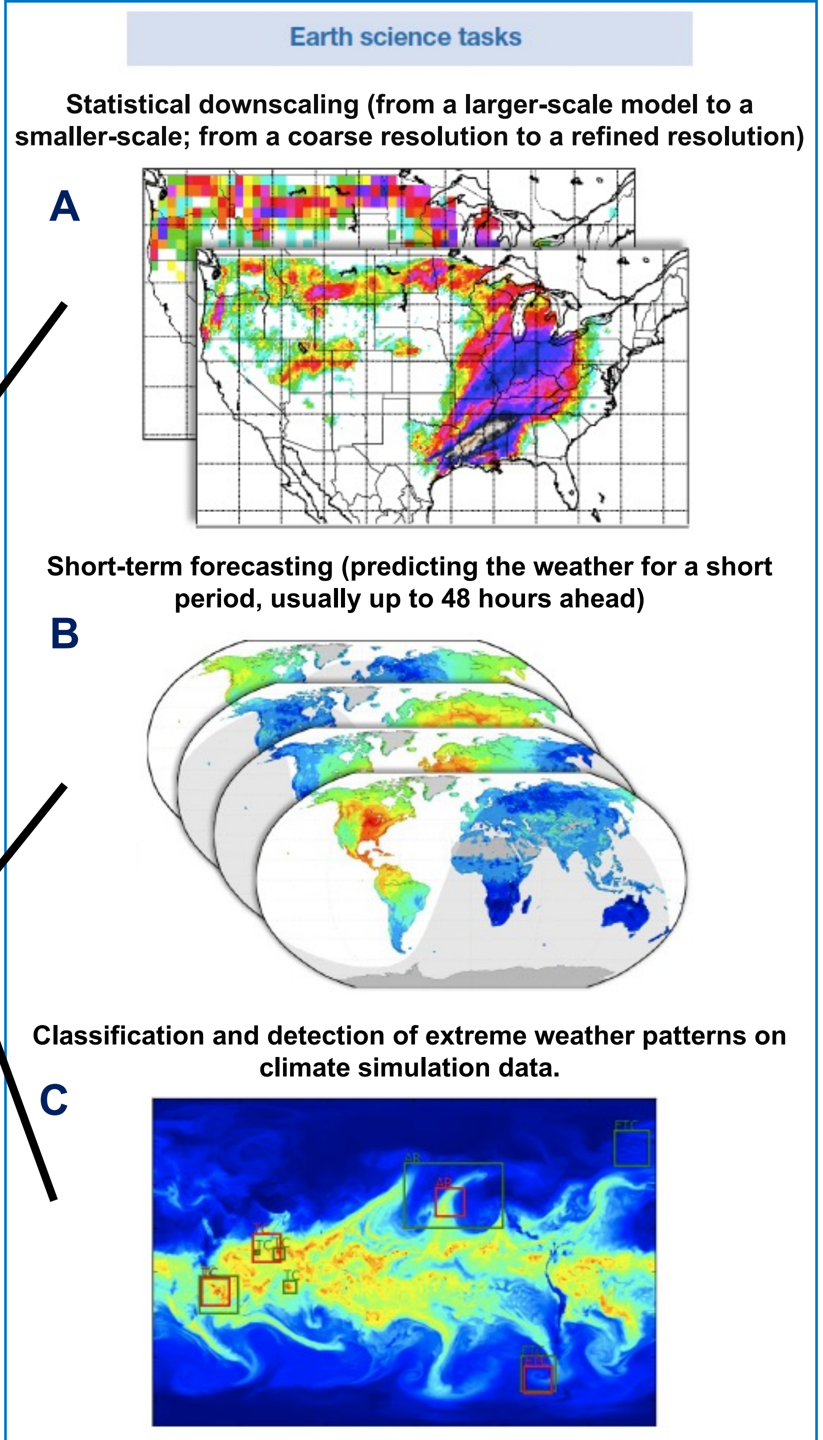
Scan the QR Code!

OR

1. Go to vevox.app
2. 156-136-777

Left panels: AI tasks in **computer vision.**



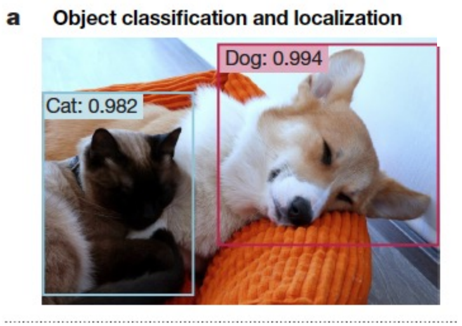


Right panels: **geoscientific problems** to which the same AI techniques can be applied.

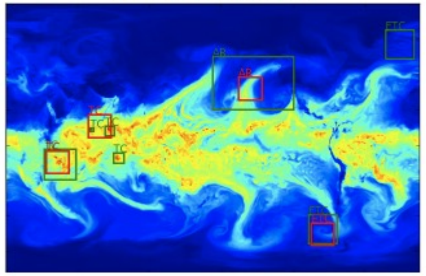
Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N. and Prabhat, F., 2019. Deep learning and process understanding for data-driven Earth system science. *Nature*, *566*(7743), pp.195-204.

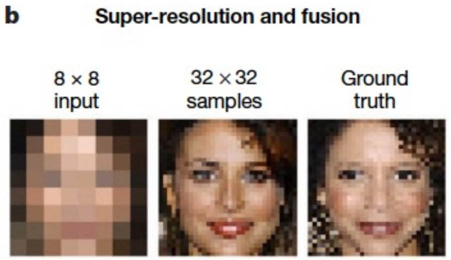
Case Studies

With ML
- Patterns
- Physics
- Predictions

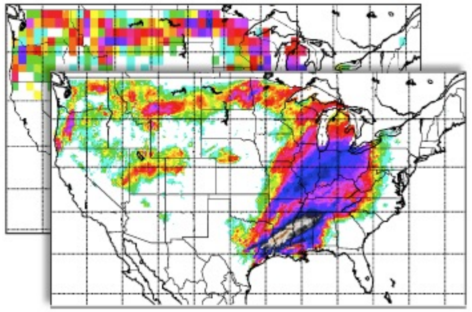


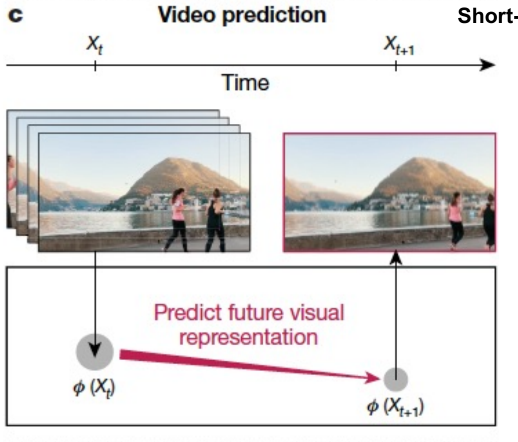
Classification and detection of extreme weather patterns on climate simulation data.



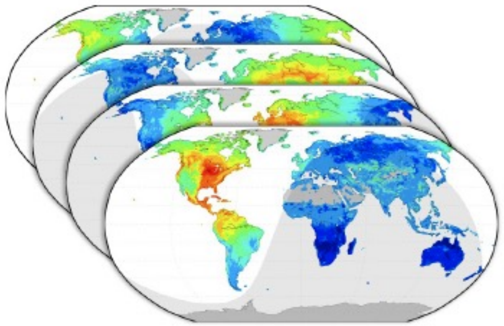


Statistical downscaling (from a larger-scale model to a smaller-scale; from a coarse resolution to a refined resolution)



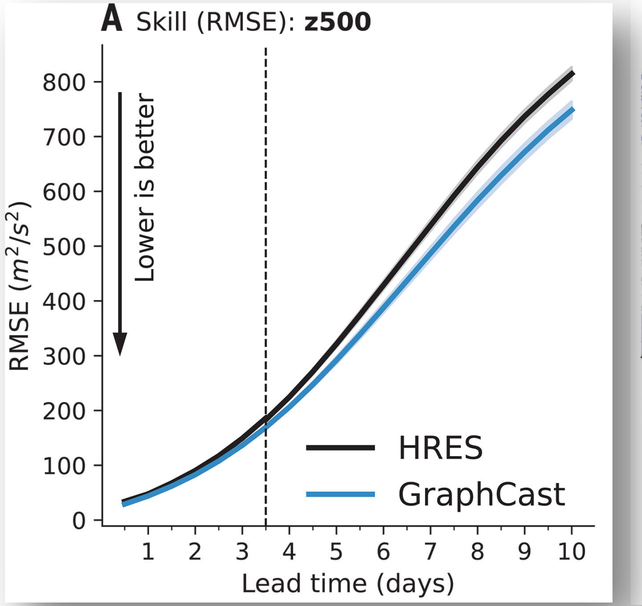


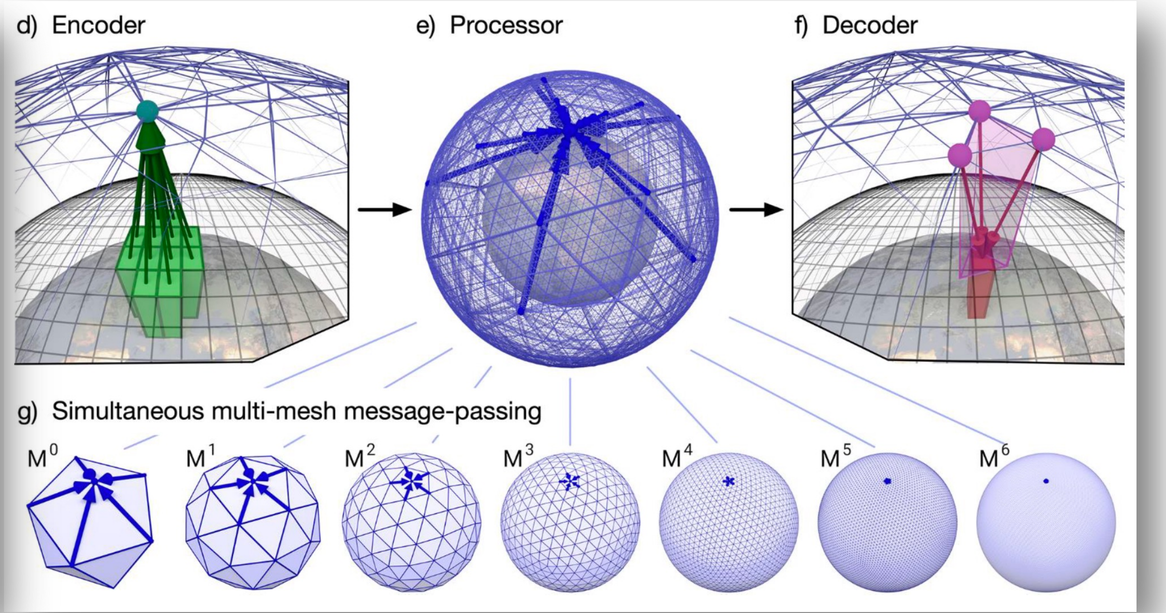
Short-term forecasting (predicting the weather for a short period, usually up to 48 hours ahead)



Recent developments in AI-Climate

"Data"-driven weather forecasts *(early work by Düben & Bauer, 2018 and Weyn et al, 2019)*





Graphcast (Google), Lam et al, 2023

Similar approaches, differing AI strategies

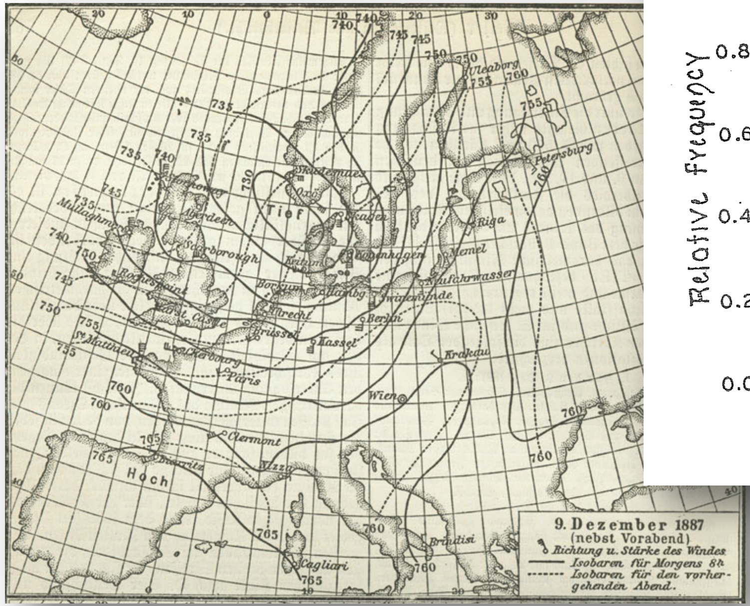
Fourcastnet (NVIDIA), FuXi (Fudan Uni), PanguWeather (Huawei), Keisler (2022)

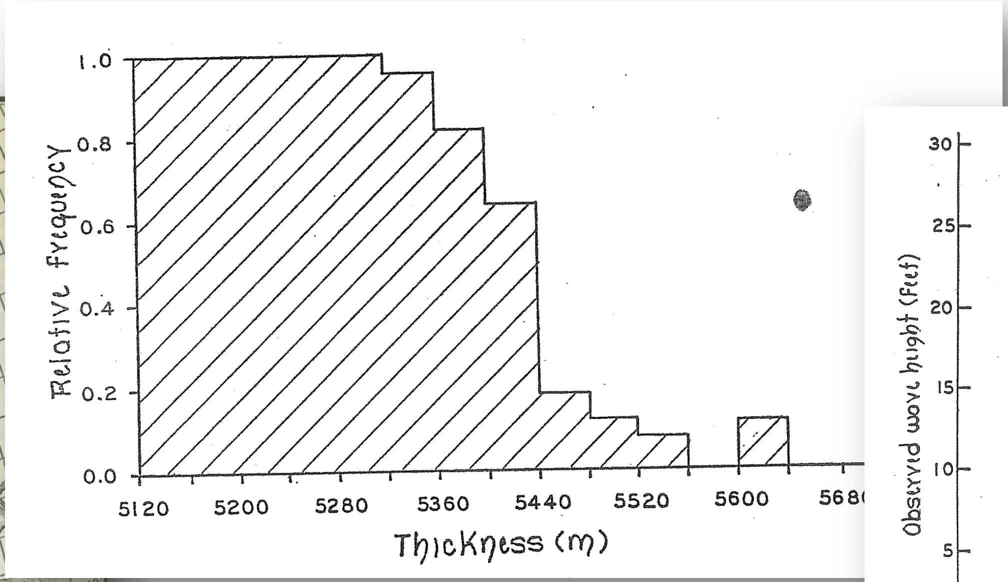
TUDelft

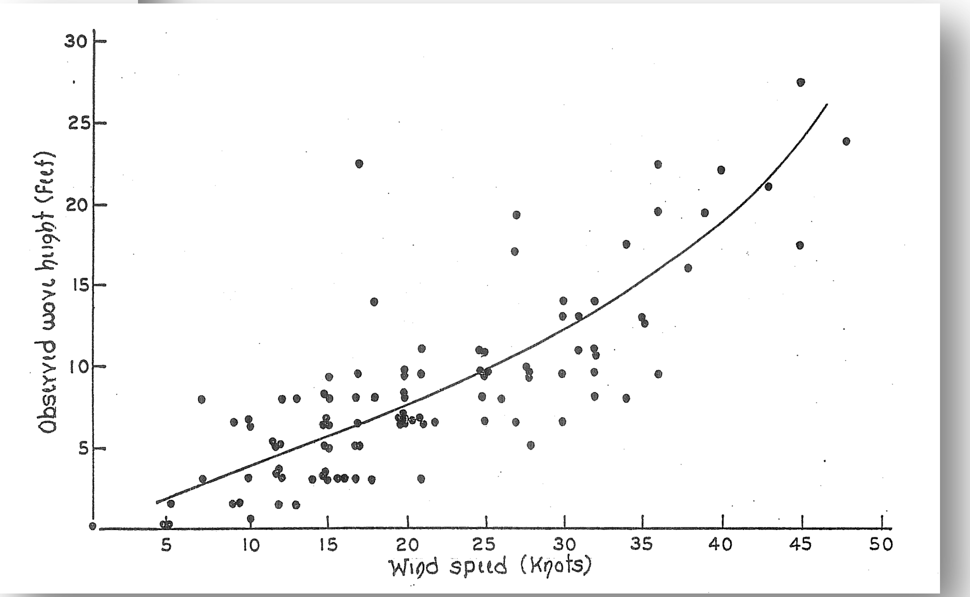
Lam et al, 2023

A hundred years ago, what did we do?

Look at historical patterns & make a statistical prediction!



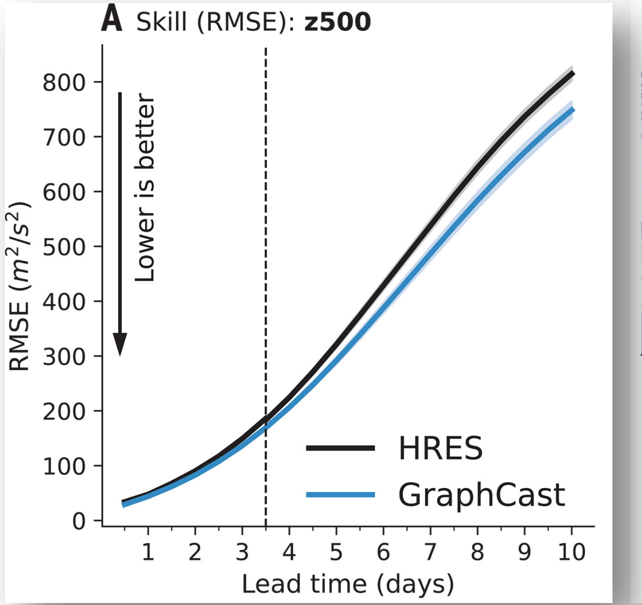


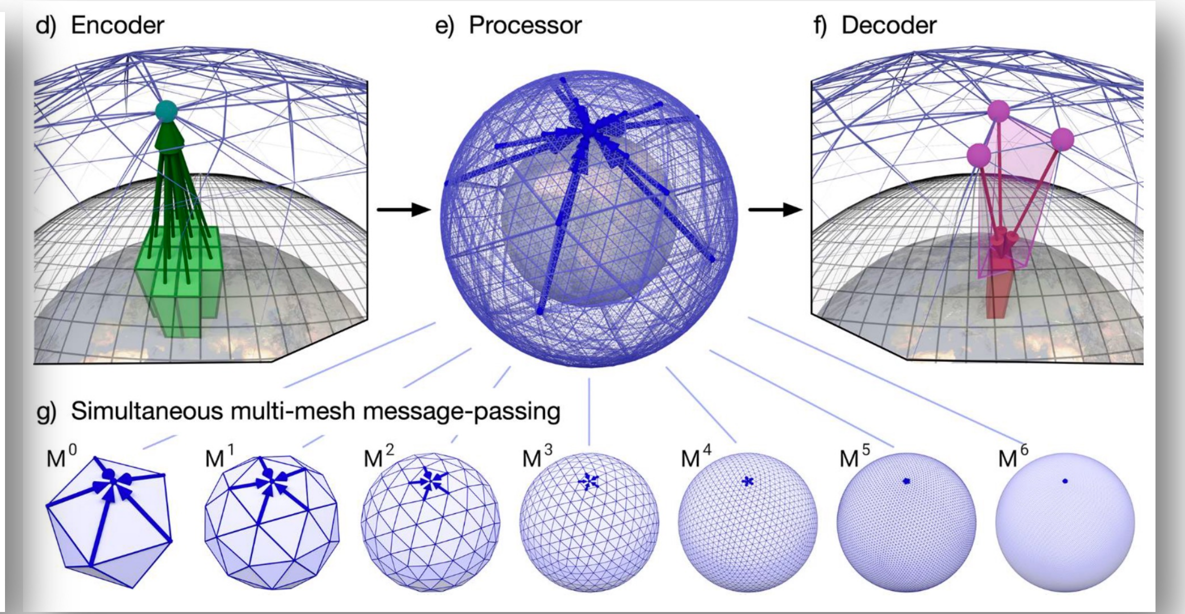


Murphy & Katz, 1982

Recent developments in AI-Climate

"Data"-driven weather forecasts *(early work by Düben & Bauer, 2018 and Weyn et al, 2019)*





Graphcast (Google),
Lam et al, 2023

Similar approaches, differing AI strategies

Fourcastnet (NVIDIA),
FuXi (Fudan Uni),
PanguWeather (Huawei),
Keisler (2022)

TU Delft

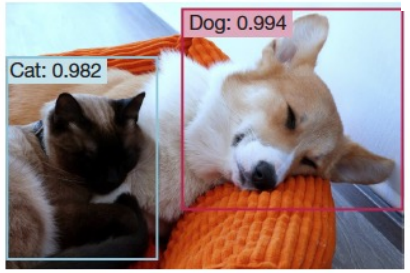
Lam et al, 2023

Case Studies

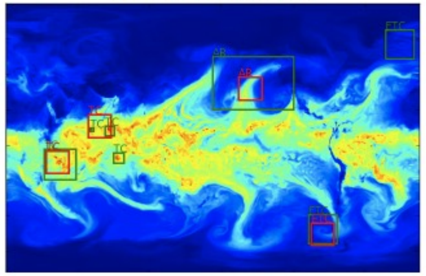
With ML

- Patterns
- Physics
- Predictions

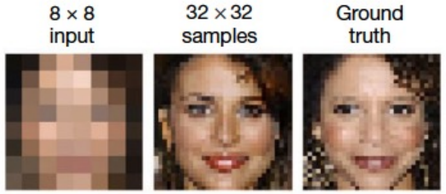
a Object classification and localization



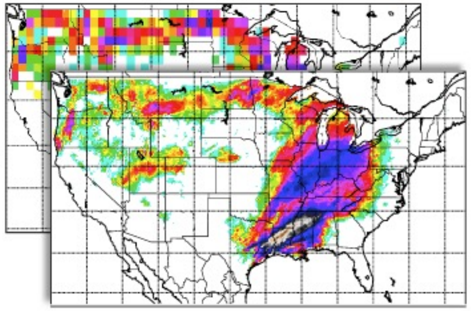
Classification and detection of extreme weather patterns on climate simulation data.



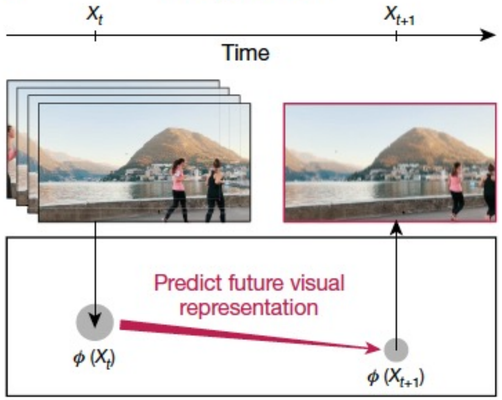
b Super-resolution and fusion



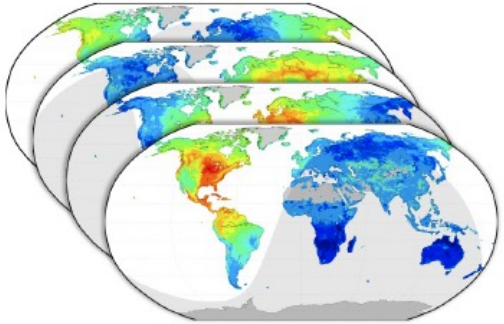
Statistical downscaling (from a larger-scale model to a smaller-scale; from a coarse resolution to a refined resolution)



c Video prediction

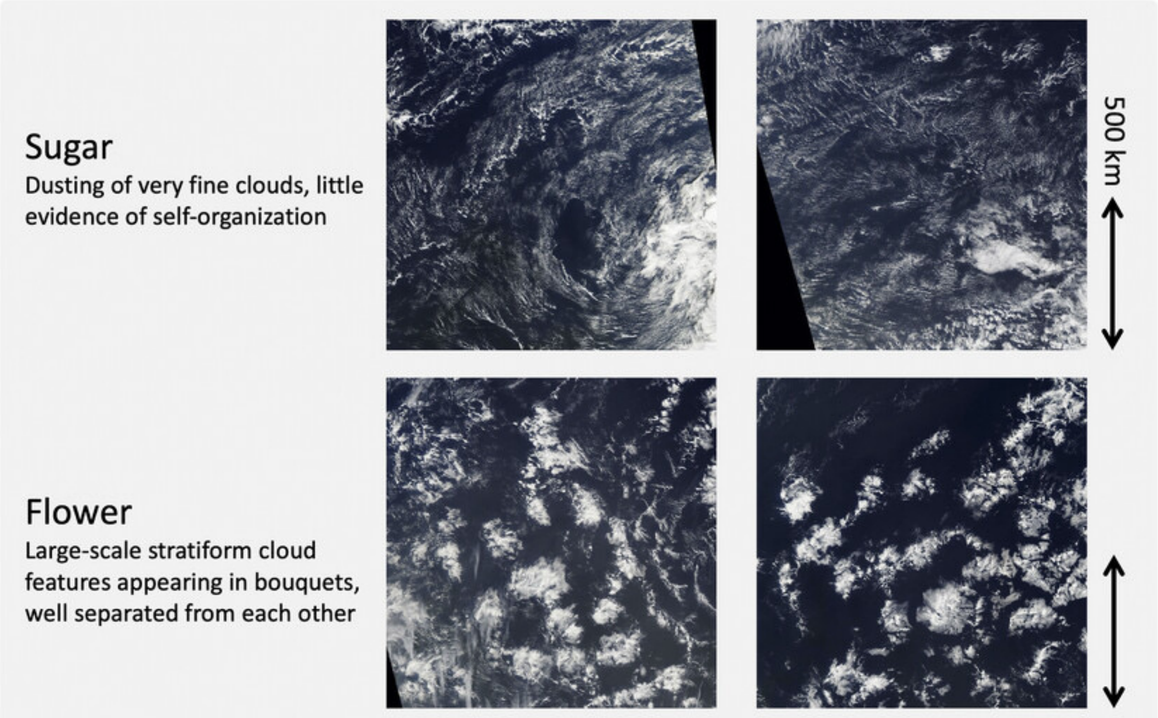


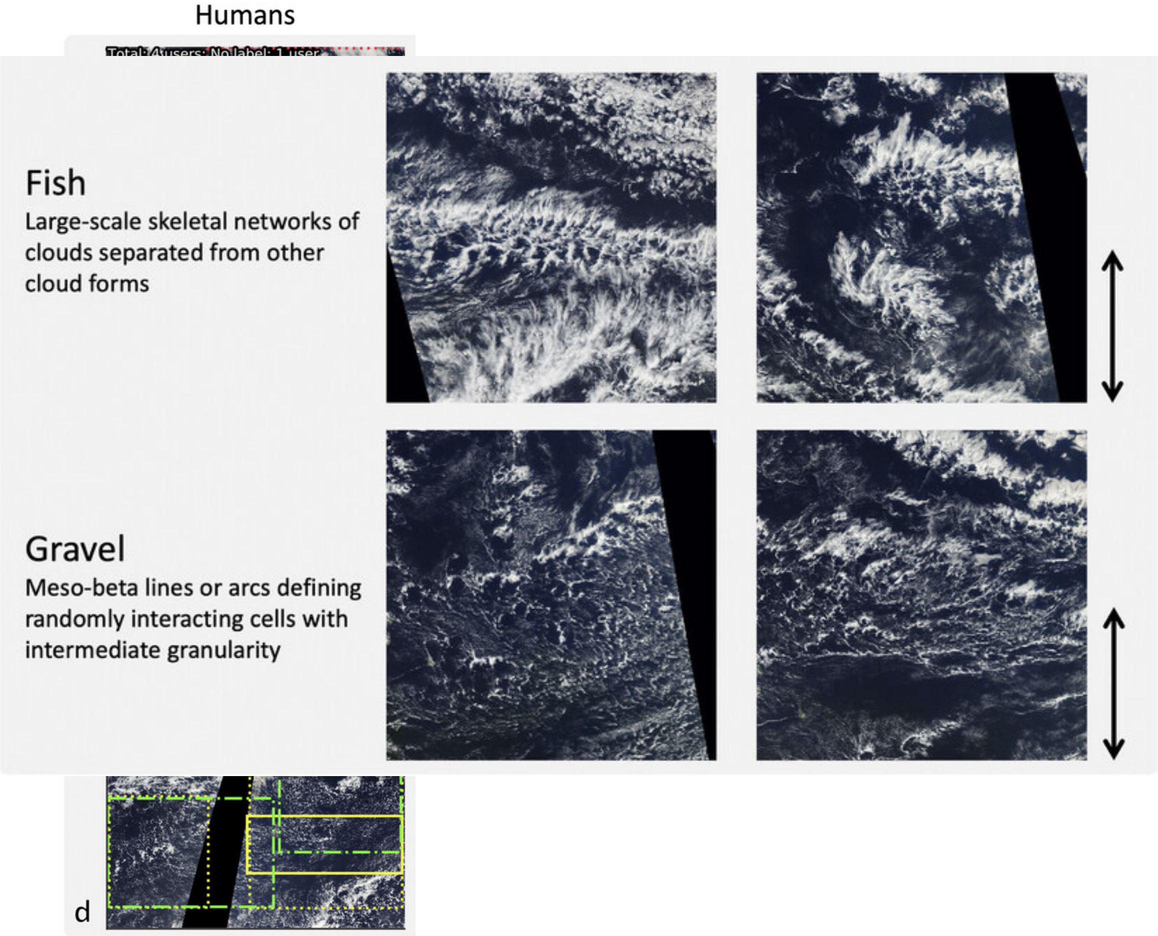
Short-term forecasting (predicting the weather for a short period, usually up to 48 hours ahead)



Patterns

Detect Cloud Organization Patterns





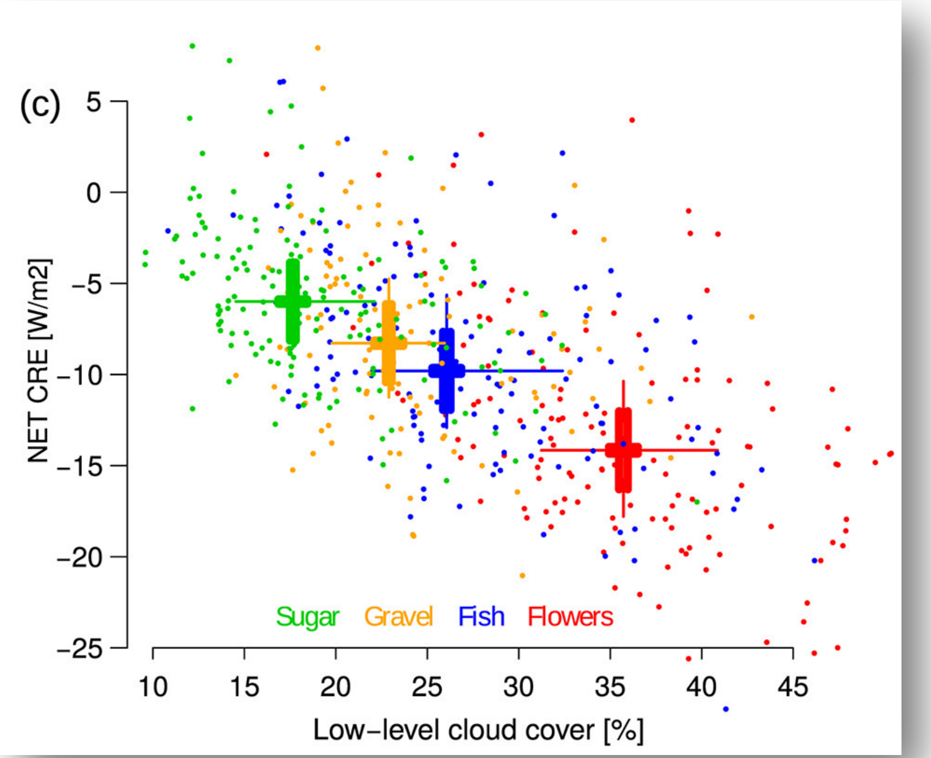
Object detection: RetinaNet

Segmentation: UNet

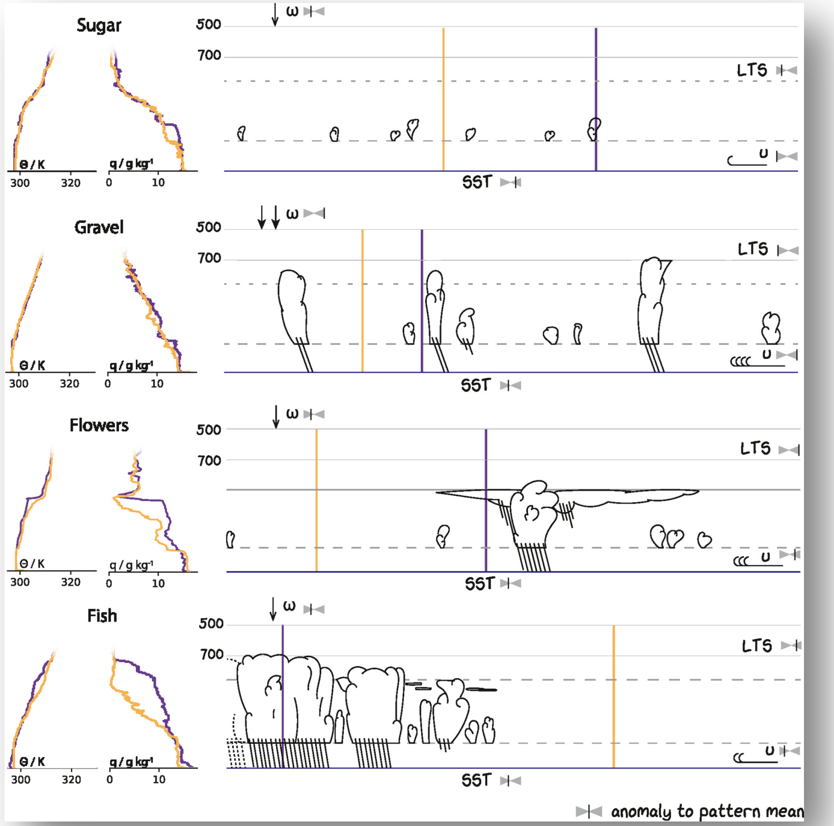
Rasp et al, 2020, Stevens et al, 2019, Schulz et al, 2021

Detect Cloud Organization Patterns

Patterns



Radiative effects of these patterns



Distinguishing physics of these patterns

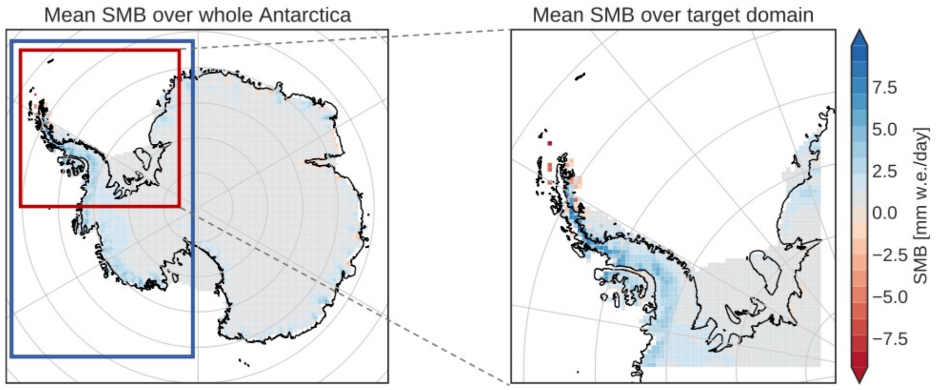
TU Delft

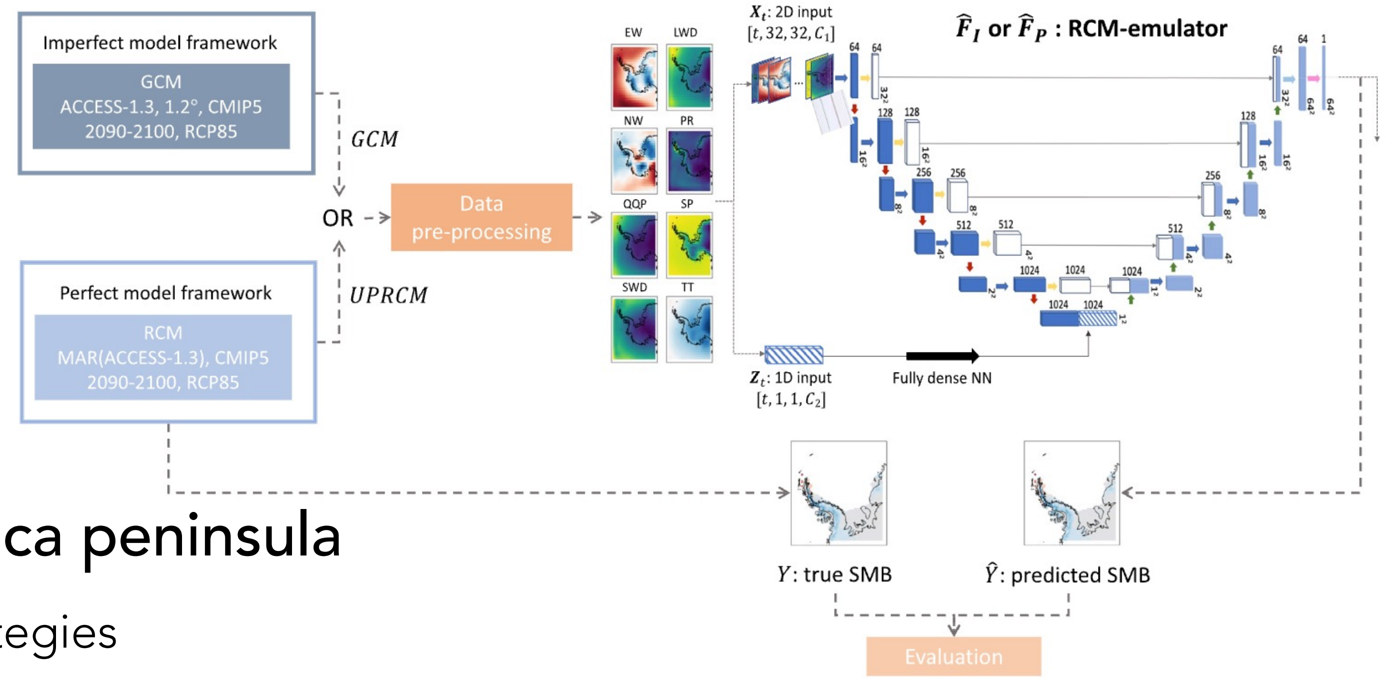
Bony et al, 2020, Schulz et al, 2021

Downscaling: Global to Regional Climate Model

Physics

Data-driven emulator instead of a dynamical model





Surface Mass Balance over Antarctica peninsula

U-Net architecture: Two different training strategies

Perfect (blind to global) and Imperfect (can see global-regional coupling)

Near-instantaneous predictions instead of several weeks on a supercomputer!

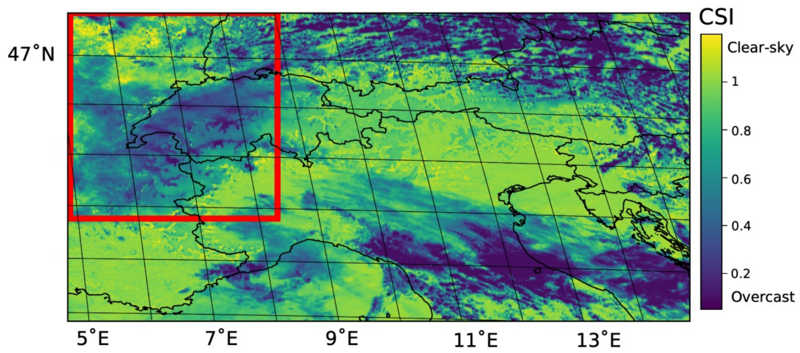
TU Delft

***van der Meer, Marijn, Sophie de Roda Husman, and Stef Lhermitte**. "Deep learning regional climate model emulators: A comparison of two downscaling training frameworks." JAMES 15.6 (2023): e2022MS003593.*

Short-term weather forecasting (Nowcasting)

Predictions

Intra-day solar forecast with deep learning – Enhancing solar energy



Clear-sky irradiances from satellite data

Deterministic & probabilistic for large-scale vs noisy dynamics

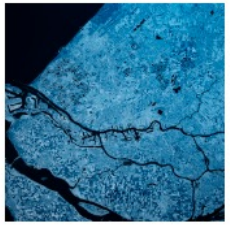
Performance & accuracy!

A. Carpentieri, D. Folinia, J. Leinonen, and A. Meyer. *"Extended intraday solar forecast horizons with deep generative models" submitted, preprint on arXiv*

Visions of the Climate Action Flagship

Flagship project

Machine Learning for Regional Climate



Climate models are the primary tools used for generating projections of climate change under different future socio- economic scenarios and provide key input for regional decision making for a future climate resilient society. However, due to the large range of spatial and temporal scales and huge number of processes being modelled, these climate models are extremely computationally expensive to run, analyze and interpret using traditional tools and methods. Therefore, there is great interest in how machine learning (ML) might help to improve regional climate projections, especially with novel ML methodologies that are interpretable, show physical consistency, allow assimilation of observations and models across different scales, and that can handle complex and uncertain data. On the application side, these ML techniques should contribute potentially to the improvement of regional projections for the Dutch delta, where downscaling of global circulation models and uncertainties in circulation patterns are some of the main challenges.

Flagship team

Geet George
Angela Meyer
Franziska Glassmeier
Riccardo Riva
Pier Siebesma
Marcel Reinders
Jing Sun (Academic Career Tracker)

Improving regional climate projections

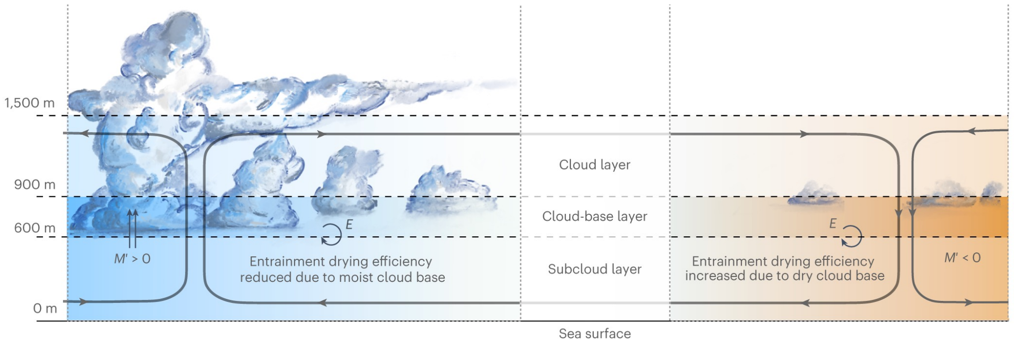
Downscaling global models

Uncertainties in circulation patterns

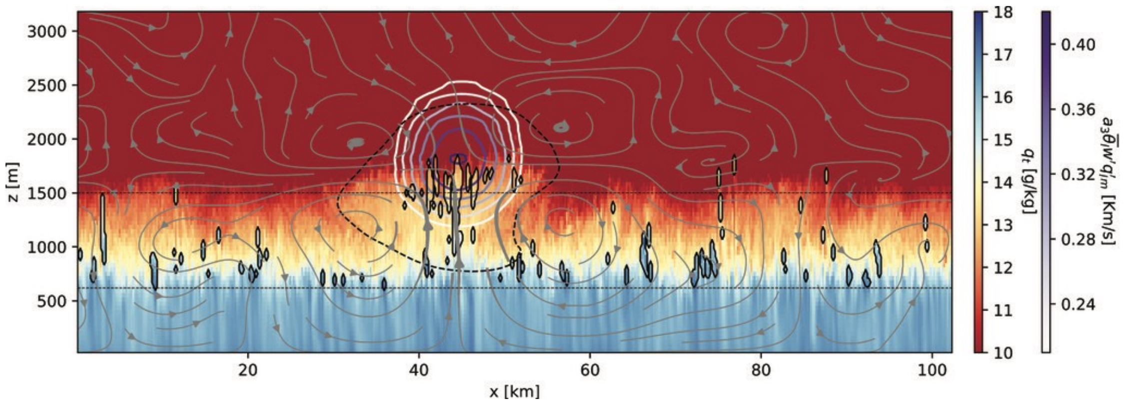
We showcase a few projects and ideas…

AI for Data Enhancement
Understanding clouds-circulations coupling

Circulations in measurements



Circulations in models

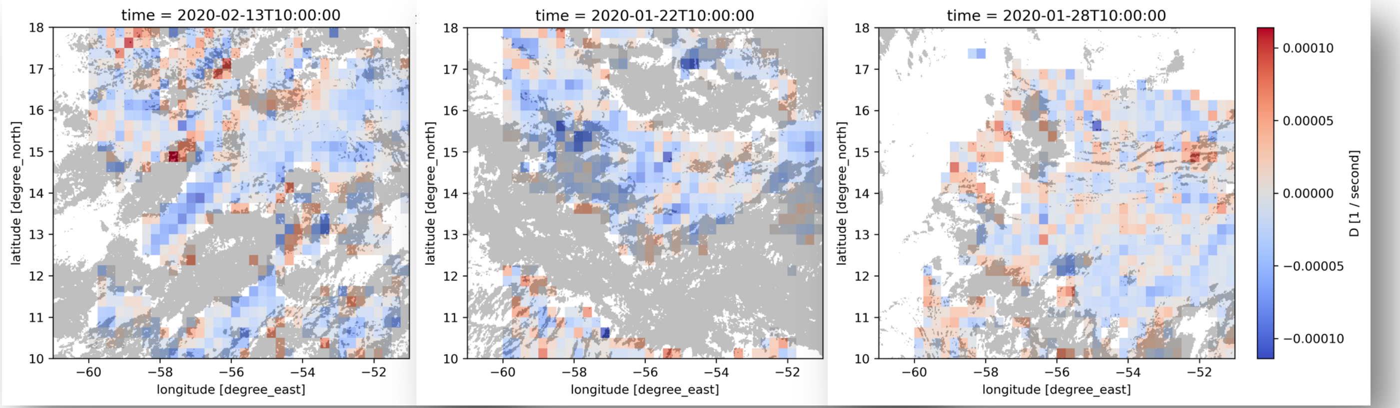


Uncertainties in understanding of circulations

Satellites can provide large data to help

Data-gaps & coarse-resolution

Gap-filling & increasing SnR with deep learning



TU Delft

George et al, 2023, Janssens et al, 2023

AI for Physics in Data
Physical interpretations from raw data

Synergistic use of observations to understand physical processes

Assumptions hidden in retrievals of physical quantities

AI works with raw, native data: Look for stable hypervolumes in raw-data space

TU Delft

Image courtesy: Ruisdael

Sea Level + ML

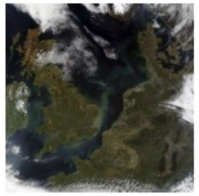
Riccardo Riva (Sea Level Change) and **Jing Sun** (ML) are collaboratively supervising a PhD project focusing the following research questions:

- Can we quantify mass changes in freshwater reservoirs from satellite altimetry observations over the oceans?
- How can we use machine learning techniques to detect slow and large-scale signals due to geophysical processes?

Riva, R., 2022. A novel reconstruction of sea level sources from satellite altimetry. NWO. Use of space infrastructure for Earth observation and planetary research (GO).

Flagship project

Regional Sea Level Rise



Sea level rise is one of the main effects of climate change that the Netherlands faces. While coastal engineers and policymakers need accurate regional sea level projections, our physical understanding of how the circulation in deep oceans impacts sea level in shallow seas like the North Sea, and hence our ability to model this, is still limited. We will address this issue by studying the connections between sea level change on ocean basin scales and coastal scales, as well as the underlying dynamical processes in the ocean driving them, for present-day and for future climates. Possible approaches include the development and application of high-resolution numerical models and sophisticated analyses of observations.

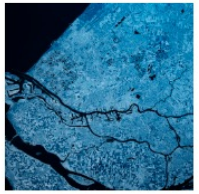
Flagship team

Caroline Katsman
Riccardo Riva
Renske Gelderloos (Academic Career Tracker)

In-Theme Collaboration

Flagship project

Machine Learning for Regional Climate



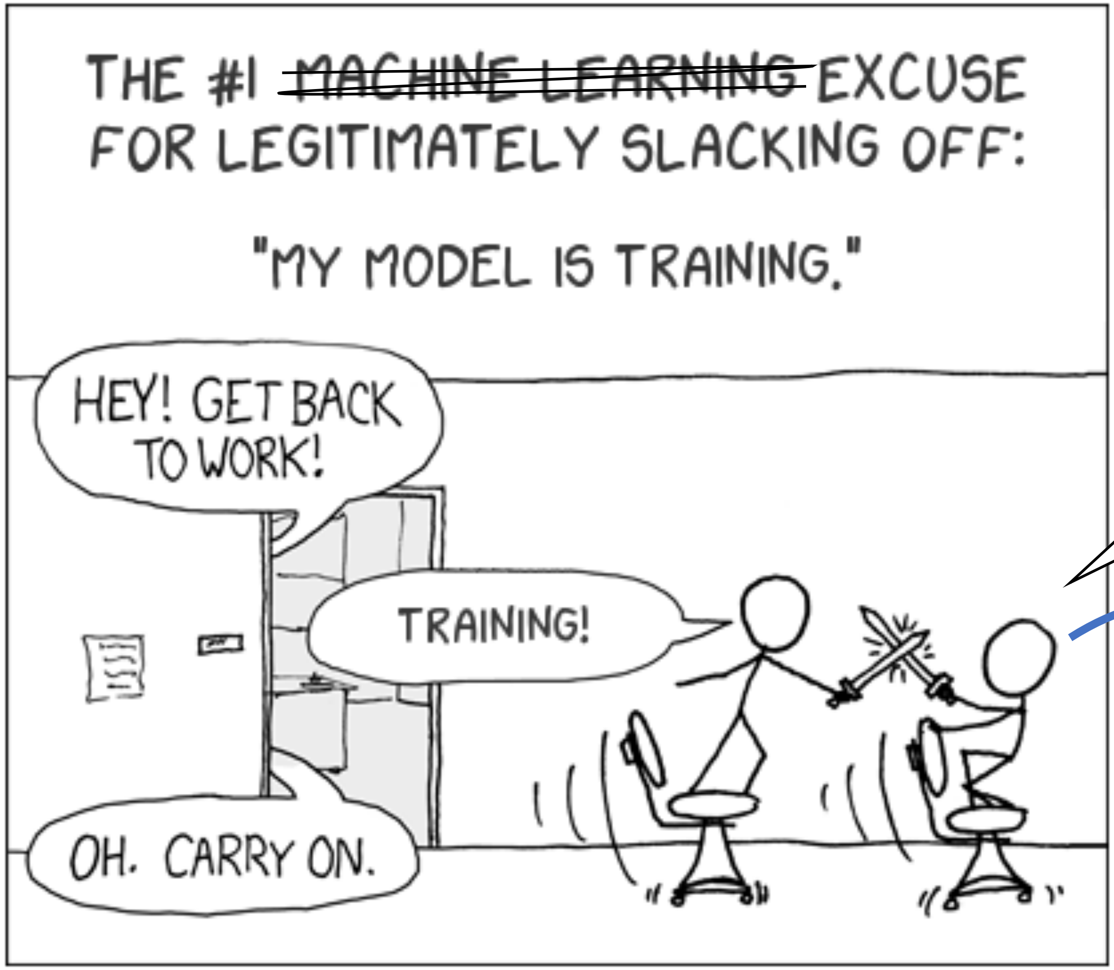
Climate models are the primary tools used for generating projections of climate change under different future socio- economic scenarios and provide key input for regional decision making for a future climate resilient society. However, due to the large range of spatial and temporal scales and huge number of processes being modelled, these climate models are extremely computationally expensive to run, analyze and interpret using traditional tools and methods. Therefore, there is great interest in how machine learning (ML) might help to improve regional climate projections, especially with novel ML methodologies that are interpretable, show physical consistency, allow assimilation of observations and models across different scales, and that can handle complex and uncertain data. On the application side, these ML techniques should contribute potentially to the improvement of regional projections for the Dutch delta, where downscaling of global circulation models and uncertainties in circulation patterns are some of the main challenges.

Flagship team

Geet George
Angela Meyer
Franziska Glassmeier
Riccardo Riva
Pier Siebesma
Marcel Reinders
Jing Sun (Academic Career Tracker)

Larger Model! Bigger Data!

DEEP LEARNING



Out of the house! It should be Machine AND Deep Learning!

THE MACHINE LEARNING

Challenges in AI

Climate is Climate!

- Interpretability
- Physics Consistency
- Uncertainty Quantification
- Computational Efficiency

A poor Netflix recommendation ruins a movie night;
a poor climate decision-making dims the future's light.

Trustworthy AI

Electricity Consumption: **ChatGPT = 17,000 US household users**

-- THE NEW YORKER

https://www.newyorker.com/news/daily-comment/the-obscene-energy-demands-of-ai

The comparison was based on ChatGPT responding to 200 million requests per day, and the average U.S. household consuming 29 kilowatt-hours daily.

Computation

Traditional mechanical computation

Computation

~70 years ago…

Machine computation

Image Courtesy: LUMI

Traditional statistical learning

Data

Today!

Deep learning

Bedankt voor uw aandacht!
Thanks for your attention!

Dr. Geet George
G.George@tudelft.nl
Office 2.22, Building 23
Department of Geoscience and Remote Sensing

Dr. Jing Sun
Jing.Sun@tudelft.nl
Office 6.E.100, Building 28
Department of Intelligent Systems