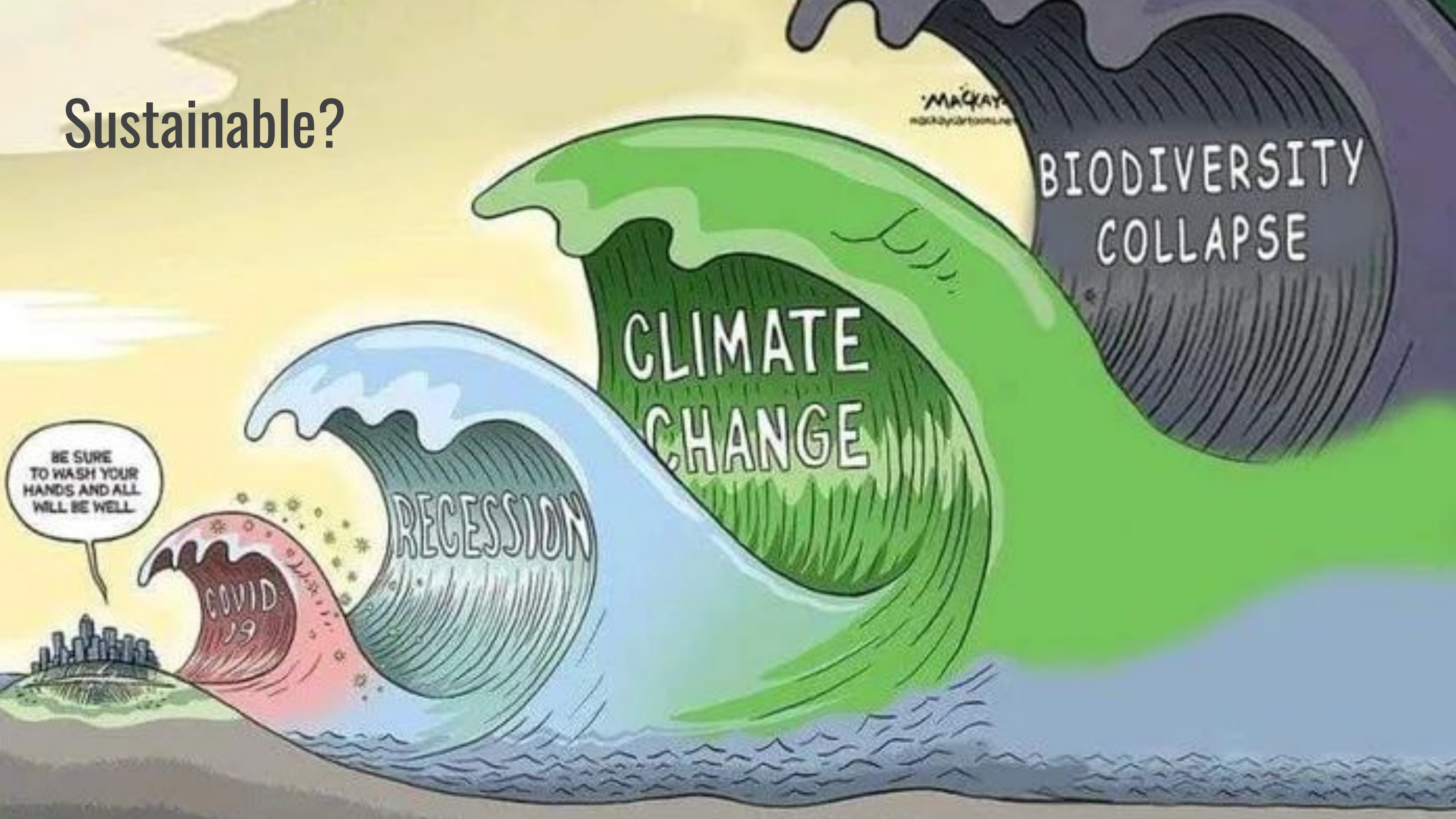
AI for Sustainable Earth Sciences

Gustau Camps-Valls
Image Processing Laboratory
Universitat de València

http://isp.uv.es @isp_uv_es gustau.camps@uv.es

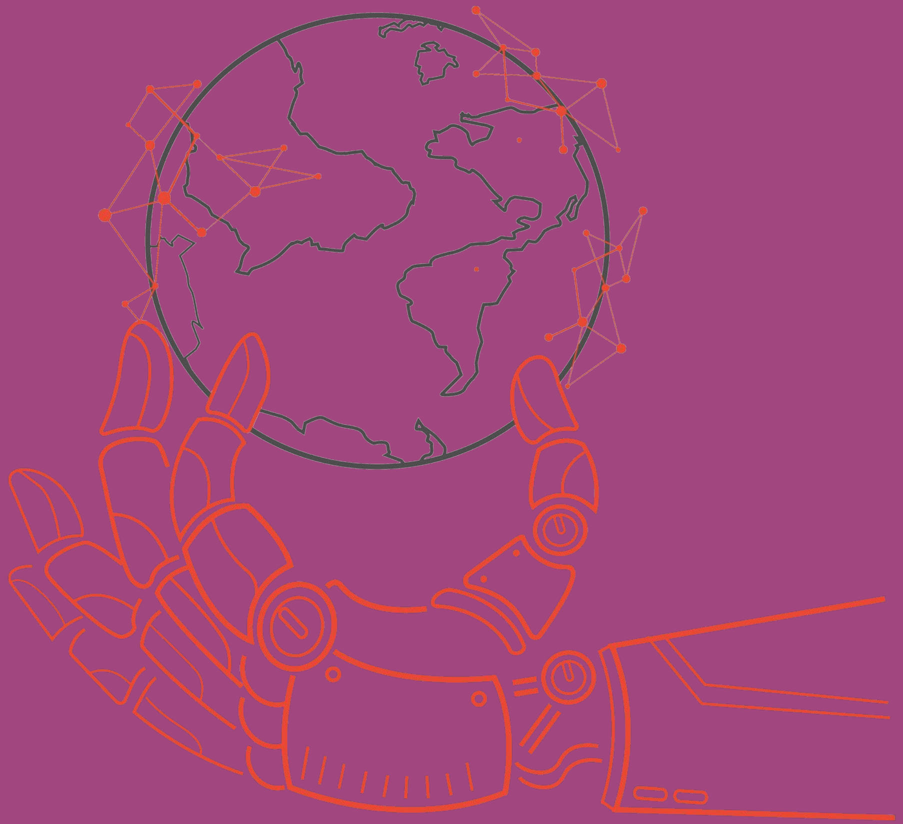
Sustainability …

Sustainable?



SUSTAINABLE DEVELOPMENT GOALS

AI for SDGs?



AI can provide ...

- Better **weather prediction**, and better climate projections
- Better **impact assessment** and extreme event detection
- Better **forecasting models on land, agriculture, water bodies and air quality**
- Deeper **understanding** of the relations between humans and the planet
- **Resources allocation & optimization**:
  - power consumption,
  - location of solar panels,
  - quantify emissions for fitted carbon budget

AI for SDGs

nature COMMUNICATIONS

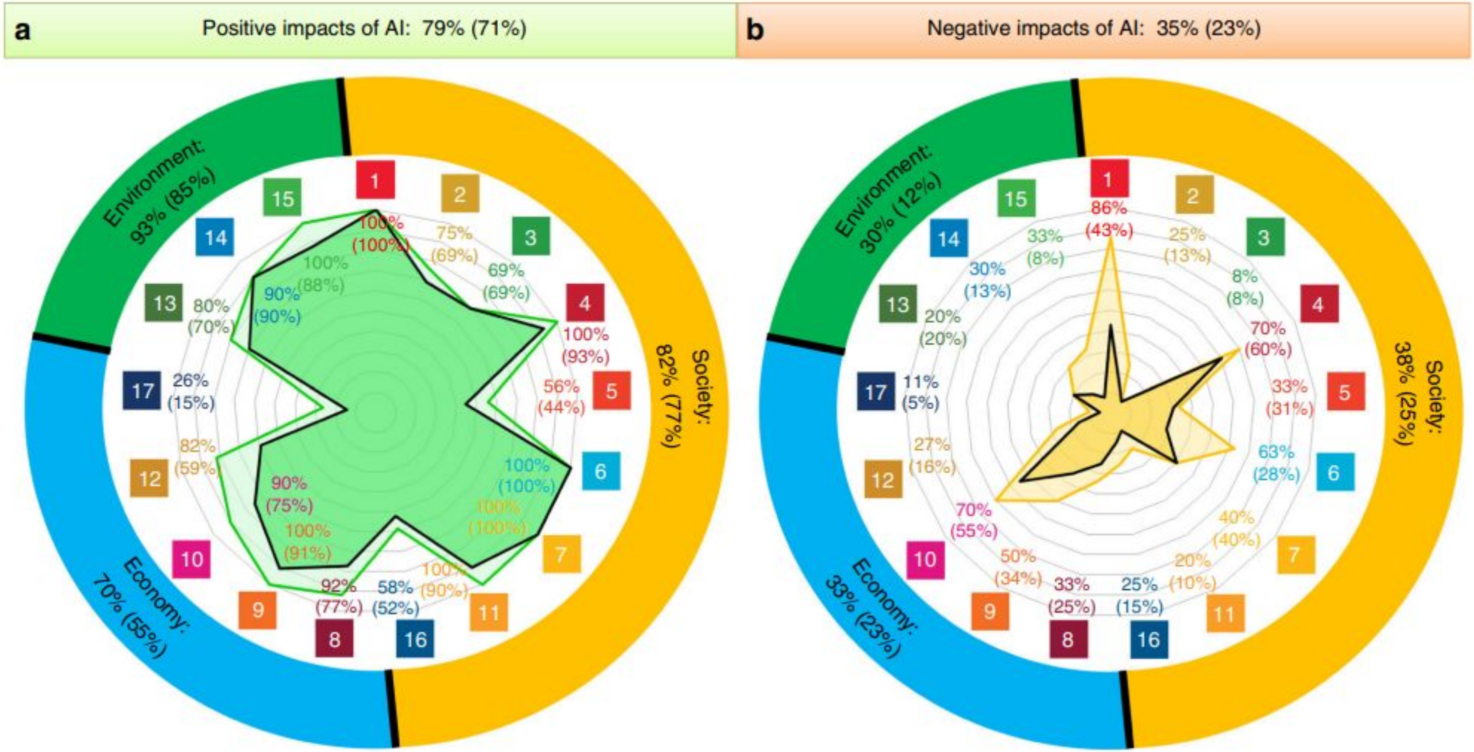
PERSPECTIVE

https://doi.org/10.1038/s41467-019-14108-y OPEN

The role of artificial intelligence in achieving the Sustainable Development Goals

Ricardo Vinuesa [1*], Hossein Azizpour [2], Iolanda Leite[2], Madeline Balaam[3], Virginia Dignum[4], Sami Domisch [5], Anna Felländer[6], Simone Daniela Langhans[7,8], Max Tegmark[9] & Francesco Fuso Nerini [10*]

AI for SDGs

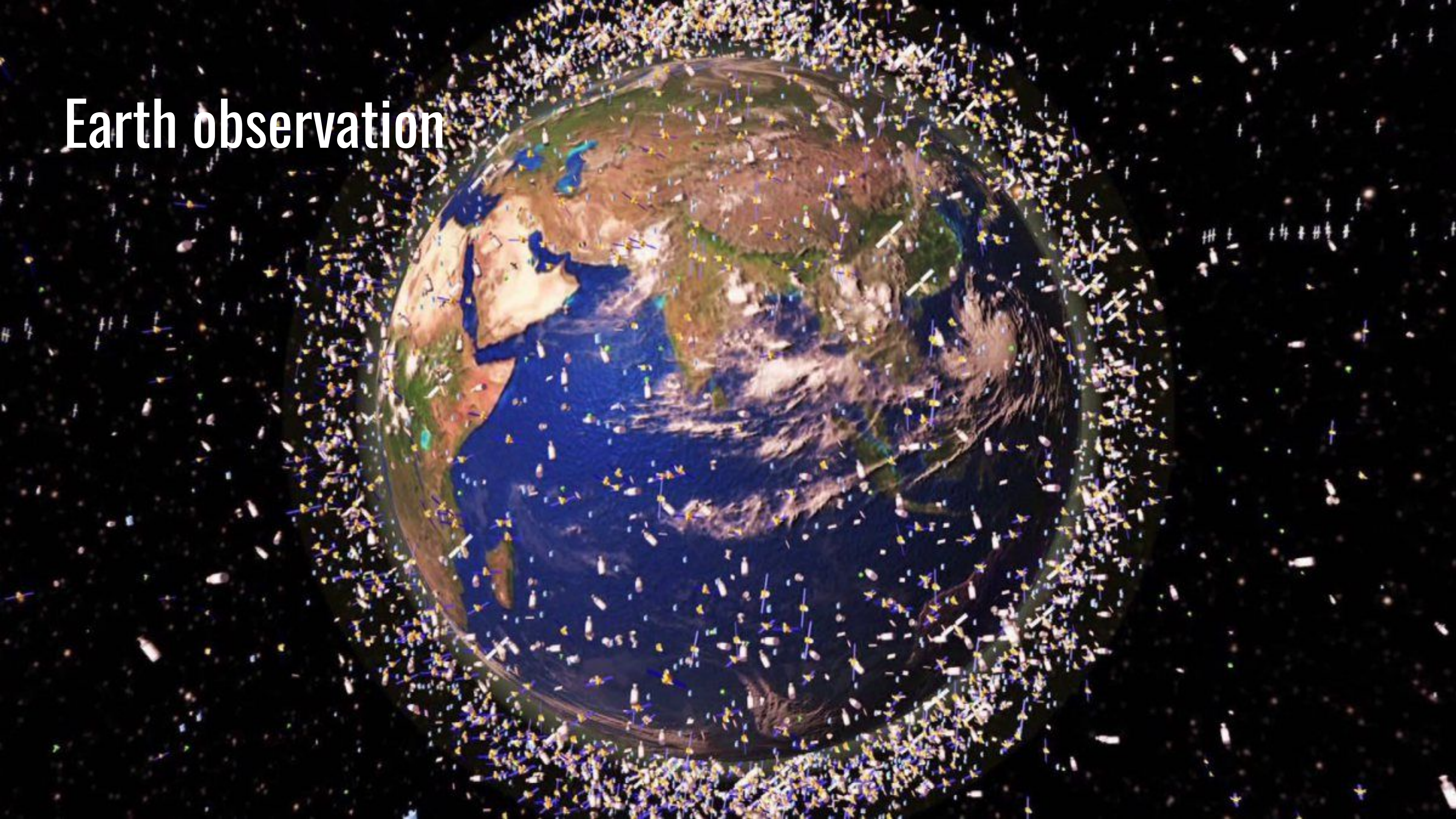

a
Positive impacts of AI: 79% (71%)
b
Negative impacts of AI: 35% (23%)
Environment: 93% (85%)
Society: 82% (77%)
Economy: 70% (55%)
Environment: 30% (12%)
Society: 38% (25%)
Economy: 33% (23%)

AI for Good

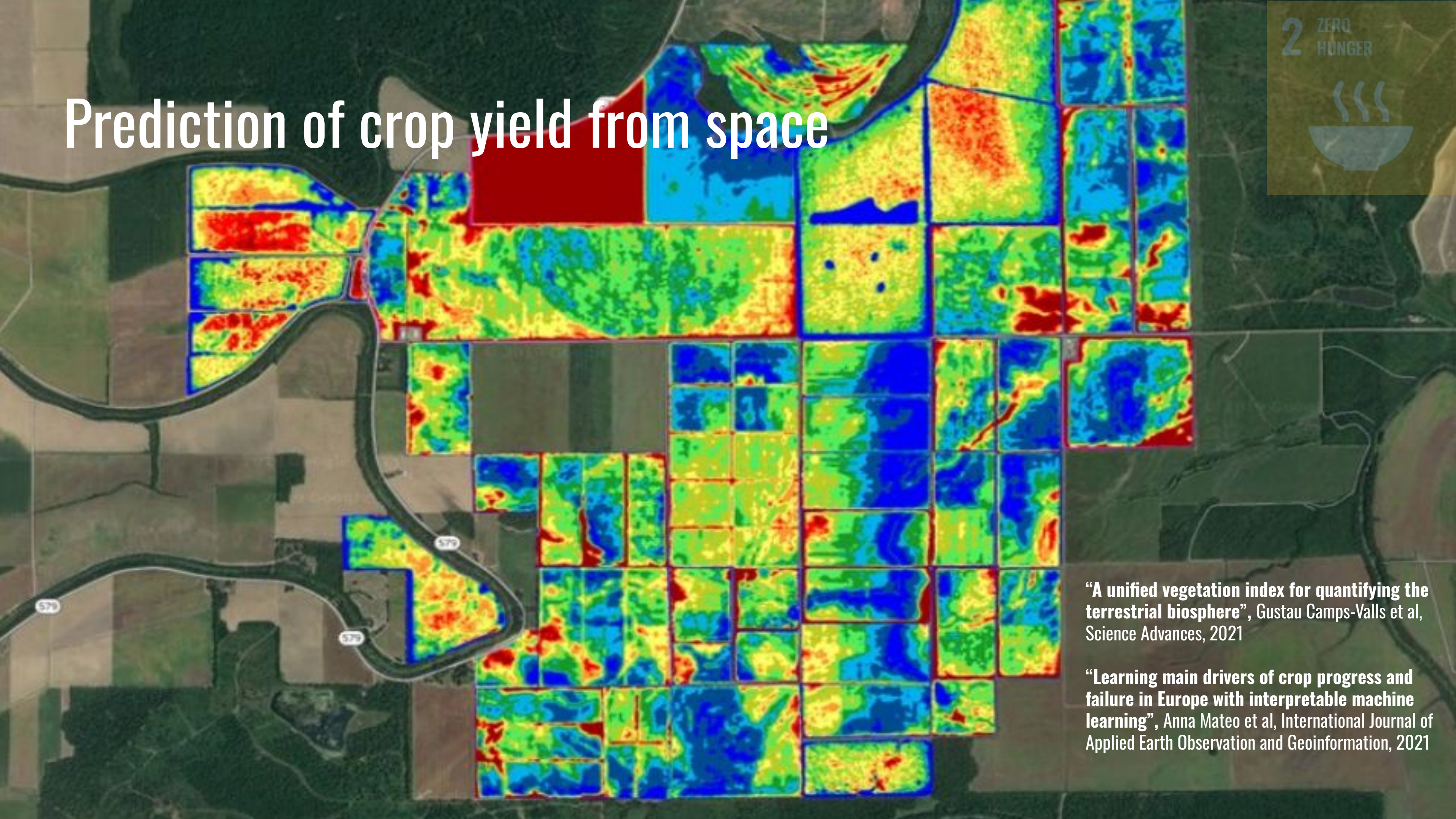

AI for Good
Neural Network
AI-powered networking community platform
aiforgood.itu.int
38 UN PARTNERS
ITU

Earth science

Earth observation



Prediction of crop yield from space



"A unified vegetation index for quantifying the terrestrial biosphere", Gustau Camps-Valls et al, Science Advances, 2021

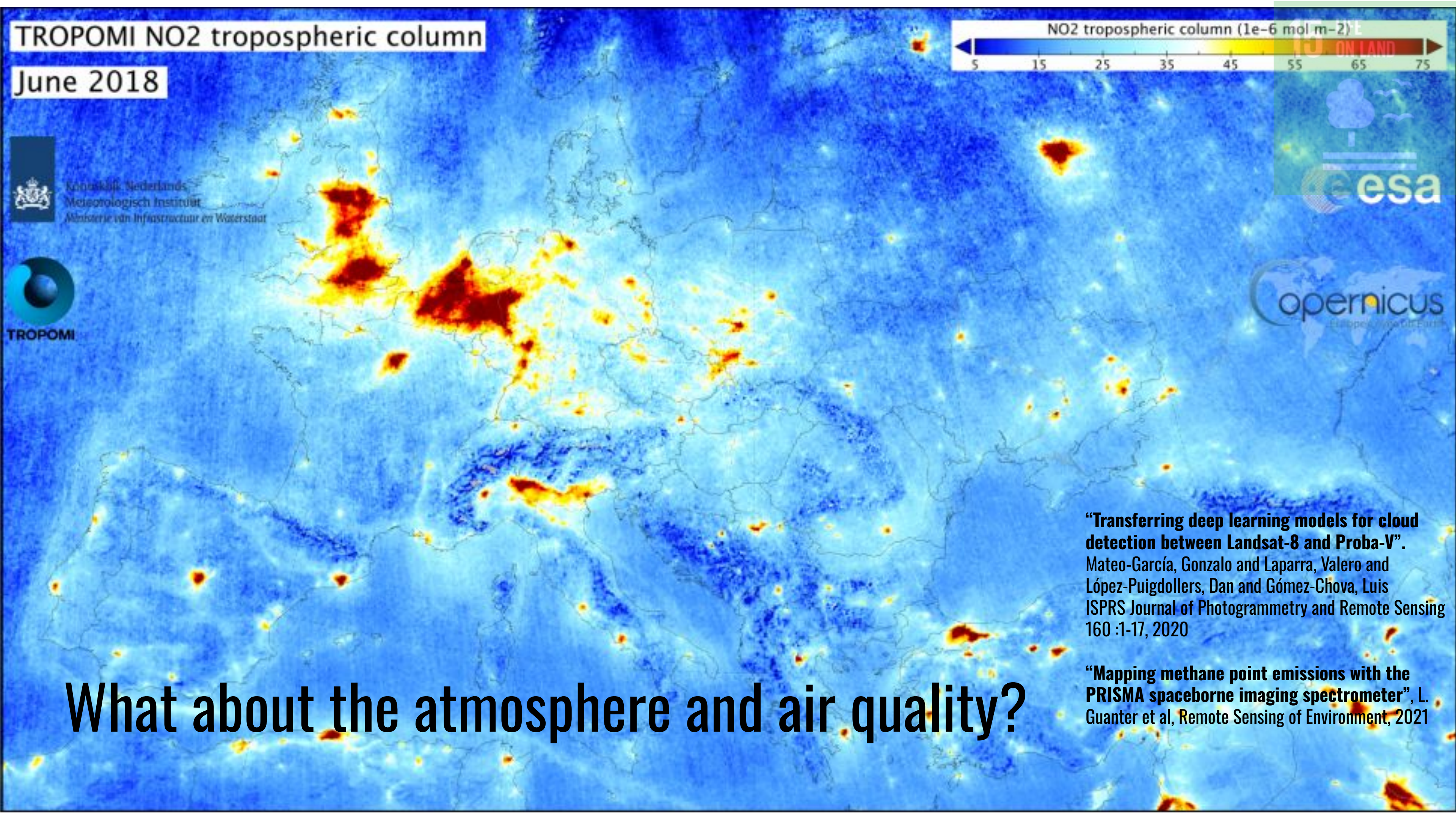
"Learning main drivers of crop progress and failure in Europe with interpretable machine learning", Anna Mateo et al, International Journal of Applied Earth Observation and Geoinformation, 2021

Coastlines, water bodies and oceans?

"Learning Relevant Features of Optical Water Types" Blix, K. and Ruescas, A. and Johnson, E. and Camps-Valls, G. IEEE Geoscience and Remote Sensing Letters, 2022

"Estimation of Oceanic Particulate Organic Carbon with Machine Learning" Sauzède, R and Johnson, J Emmanuel and Claustre, H and Camps-Valls, G and Ruescas, AB. ISPRS Annals of the Photogrammetry, 2 :949--956, 2020

"Predicting regional coastal sea level changes with machine learning", V Nieves, C. Radin & G. Camps-Valls, Scientific Reports, 2021



What about the atmosphere and air quality?

"Transferring deep learning models for cloud detection between Landsat-8 and Proba-V". Mateo-García, Gonzalo and Laparra, Valero and López-Puigdollers, Dan and Gómez-Chova, Luis ISPRS Journal of Photogrammetry and Remote Sensing 160 :1-17, 2020

"Mapping methane point emissions with the PRISMA spaceborne imaging spectrometer", L. Guanter et al, Remote Sensing of Environment, 2021

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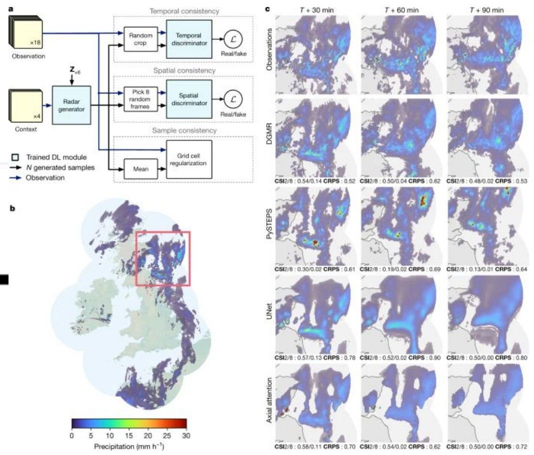
Article | Open Access | Published: 31 March 2021

Towards global flood mapping onboard low cost satellites with machine learning

Gonzalo Mateo-Garcia, Joshua Veitch-Michaelis, Lewis Smith, Silviu Vlad Oprea, Guy Schumann, Yarin Gal, Atılım Güneş Baydin & Dietmar Backes

Scientific Reports **11**, Article number: 7249 (2021) | Cite this article

13k Accesses | **31** Citations | **97** Altmetric | Metrics



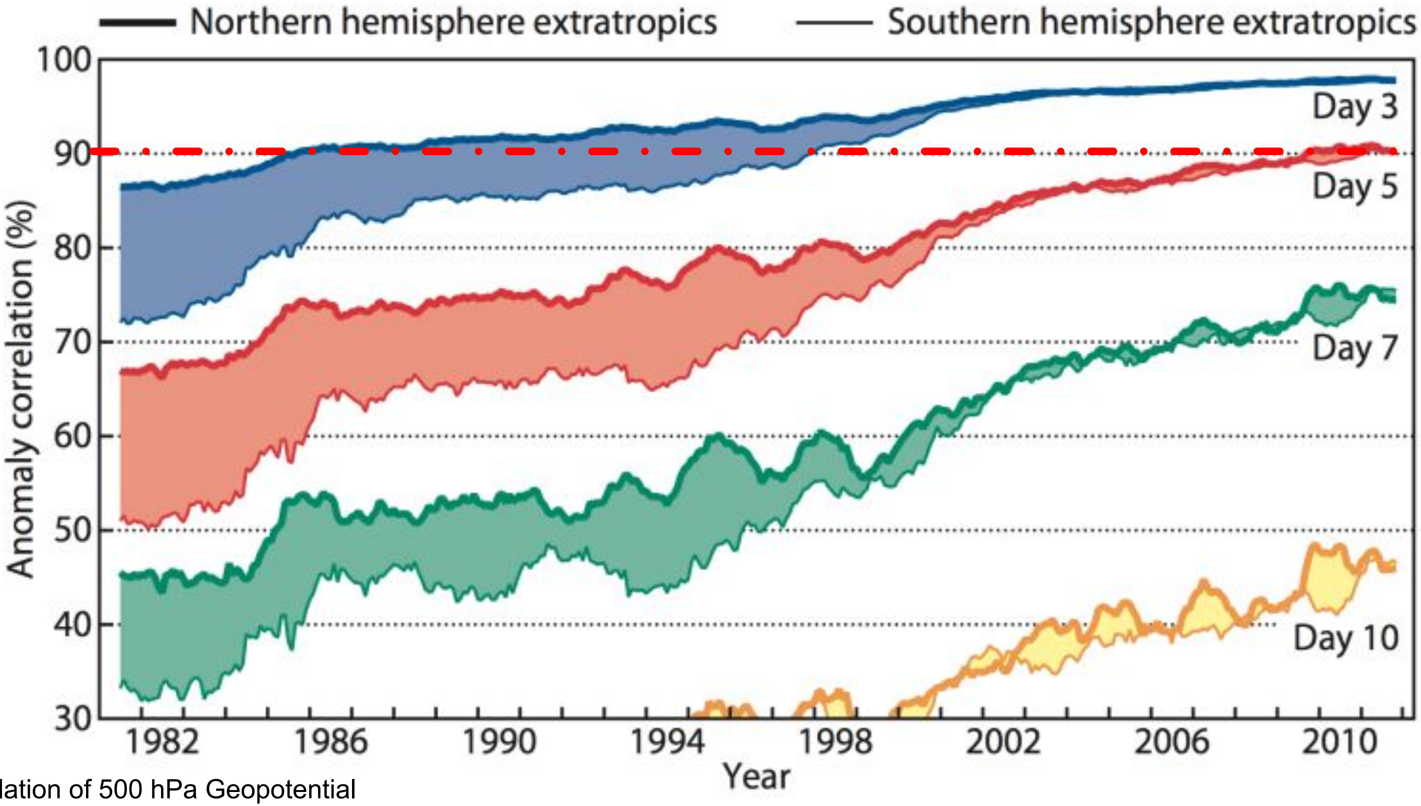
Article | Open Access | Published: 29 September 2021

Skilful precipitation nowcasting using deep generative models of radar

Suman Ravuri, Karel Lenc, Matthew Willson, Dmitry Kangin, Remi Lam, Piotr Mirowski, Megan Fitzsimons, Maria Athanassiadou, Sheleem Kashem, Sam Madge, Rachel Prudden, Amol Mandhane, Aidan Clark, Andrew Brock, Karen Simonyan, Raia Hadsell, Niall Robinson, Ellen Clancy, Alberto Arribas & Shakir Mohamed ✉

Nature **597**, 672–677 (2021) | Cite this article

Better forecasts...

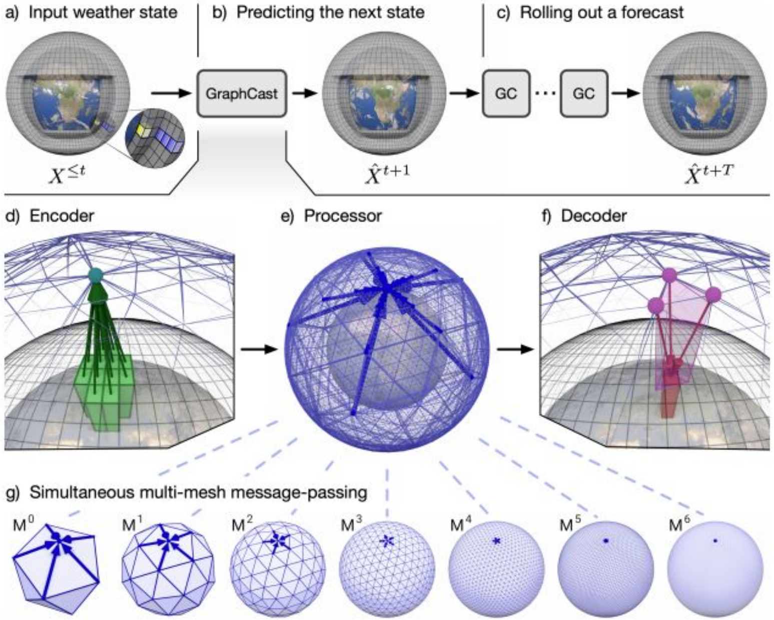


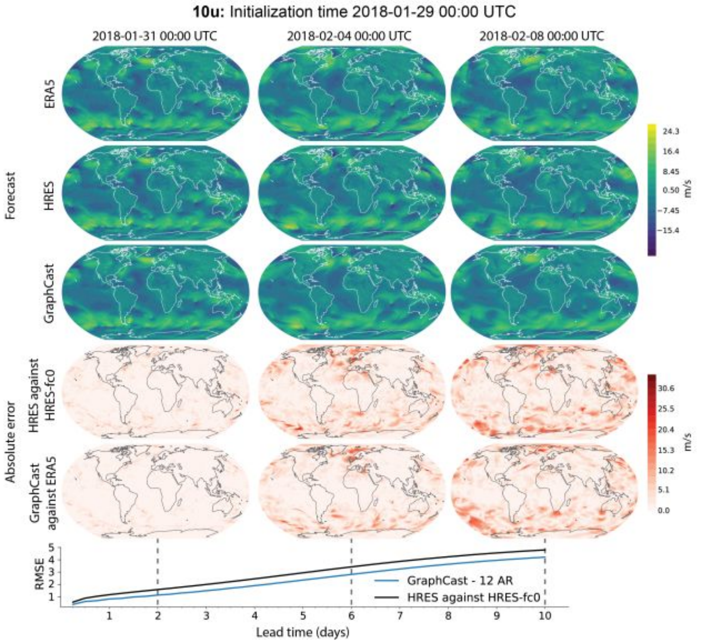
Anomaly correlation of 500 hPa Geopotential

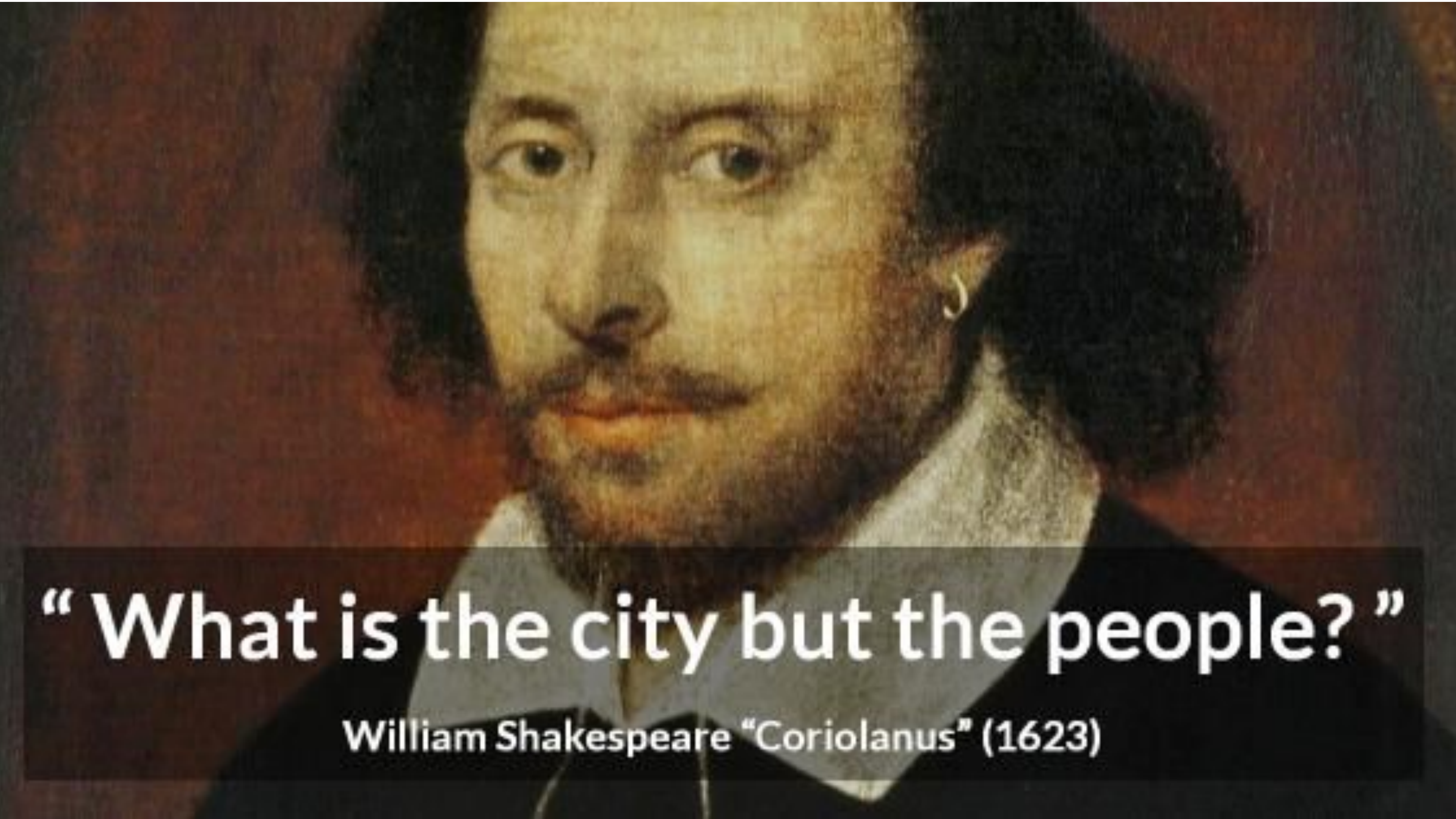
GraphCast: Learning skillful medium-range global weather forecasting

Remi Lam[*,1], Alvaro Sanchez-Gonzalez[*,1], Matthew Willson[*,1], Peter Wirnsberger[*,1], Meire Fortunato[*,1], Alexander Pritzel[*,1], Suman Ravuri[1], Timo Ewalds[1], Ferran Alet[1], Zach Eaton-Rosen[1], Weihua Hu[1], Alexander Merose[2], Stephan Hoyer[2], George Holland[1], Jacklynn Stott[1], Oriol Vinyals[1], Shakir Mohamed[1] and Peter Battaglia[1]

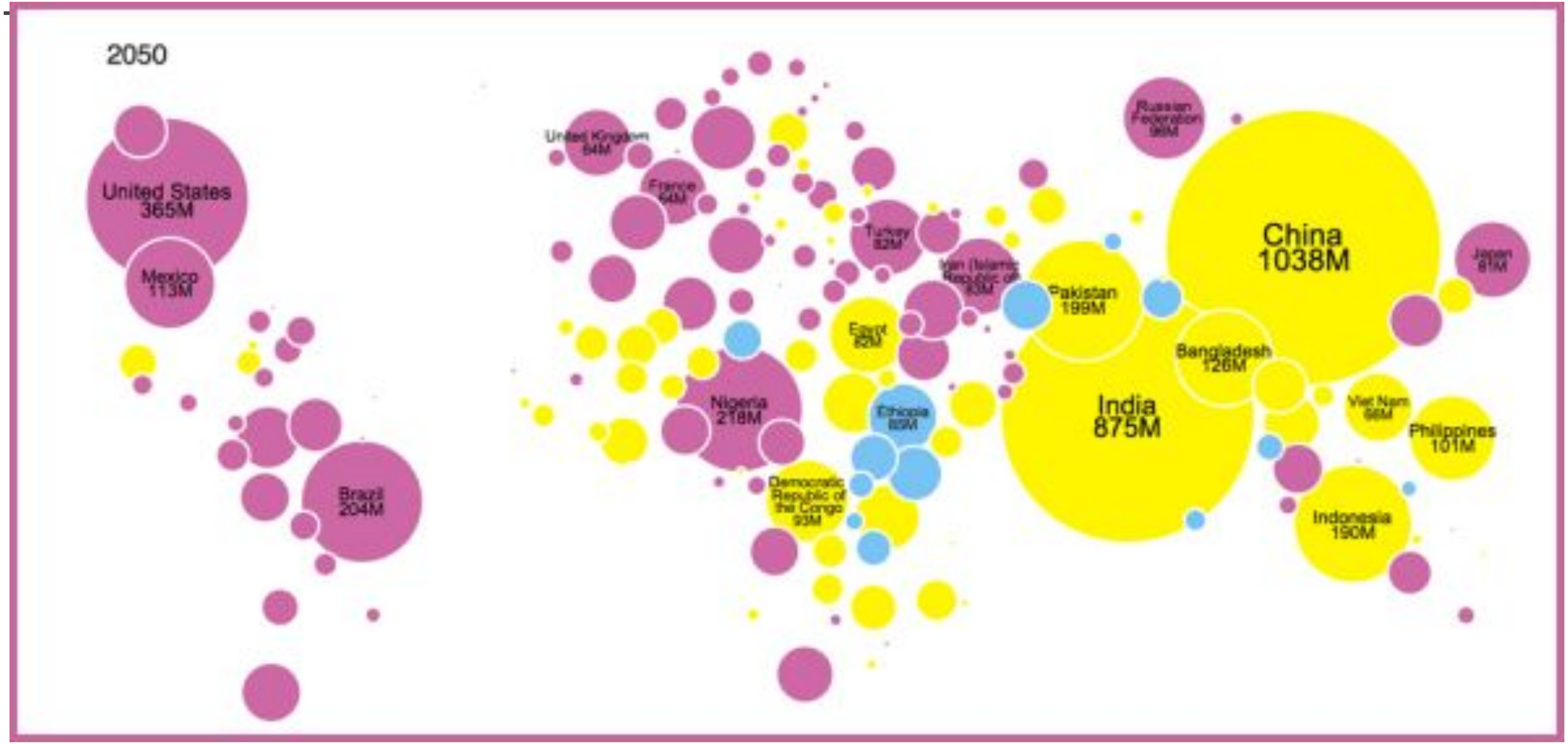
[*]equal contribution, [1]DeepMind, [2]Google






“ What is the city but the people? ”
William Shakespeare “Coriolanus” (1623)

By 2050, 70% Of The World's Population Will Be Urban



DL for the city - climate change mitigation & adaptation

DL for urban sustainability

- DL may catalyze food, health, water & energy services to the population
- DL+EO unique to monitor cities with high spatial and temporal resolution
- DL exploits data to accurately estimate key SDG urban indicators: air quality, energy fluxes, urbanization, poverty, ...

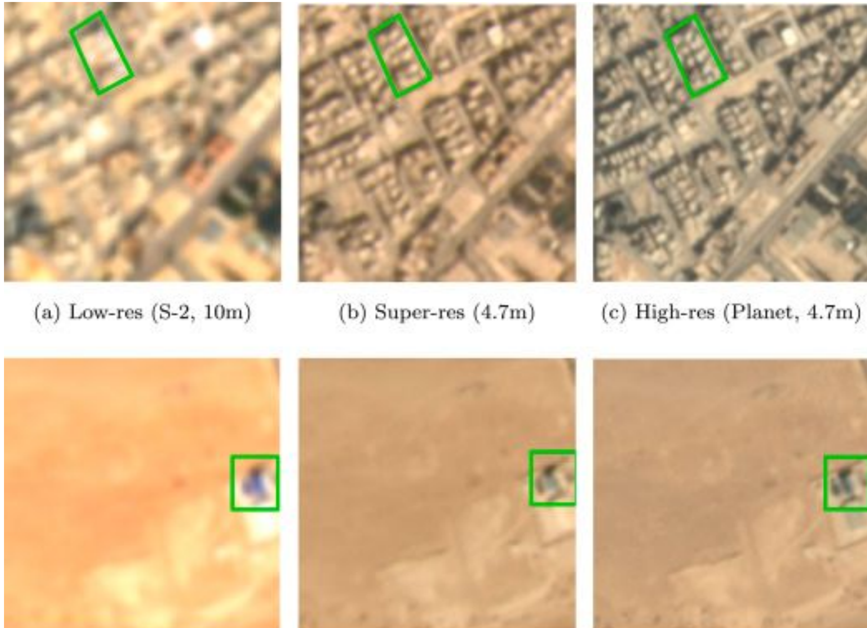
ELSEVIER

ISPRS Journal of Photogrammetry and Remote Sensing

Volume 195, January 2023, Pages 1-13

Multi-spectral multi-image super-resolution of Sentinel-2 with radiometric consistency losses and its effect on building delineation

Muhammed T. Razzak [a], Gonzalo Mateo-García [b], Gurvan Lecuyer [c], Luis Gómez-Chova [b], Yarin Gal [a], Freddie Kalaitzis [a]



(a) Low-res (S-2, 10m) (b) Super-res (4.7m) (c) High-res (Planet, 4.7m)

DL for climate change mitigation


Contents lists available at ScienceDirect
Landscape and Urban Planning
journal homepage: www.elsevier.com/locate/landurbplan

Research Paper

Roofpedia: Automatic mapping of green and solar roofs for an open roofscape registry and evaluation of urban sustainability

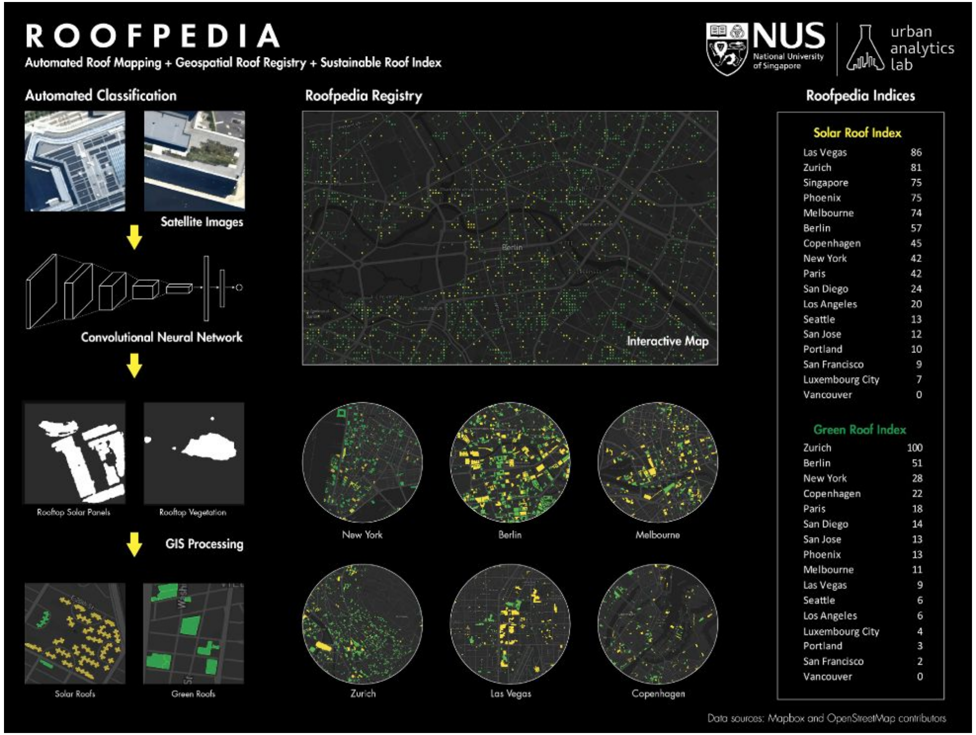
Abraham Noah Wu[a,1], Filip Biljecki[a,b,*,2]

[a] Department of Architecture, National University of Singapore, Singapore
[b] Department of Real Estate, National University of Singapore, Singapore

HIGHLIGHTS

- There is a lack of open data on urban rooftop typology and current use of roofs.
- A deep learning and GIS workflow to map and quantify green and solar roofs.
- A generated dataset that covers 17 cities, scalable to include more locations.
- An index to benchmark the proliferation of green and solar roofs in cities.

GRAPHICAL ABSTRACT



"Roofpedia: Automatic mapping of green and solar roofs for an open roofscape registry and evaluation of urban sustainability."
Wu, Abraham Noah, and Filip Biljecki. Landscape and Urban Planning 214 (2021): 104167.

DL for climate change mitigation

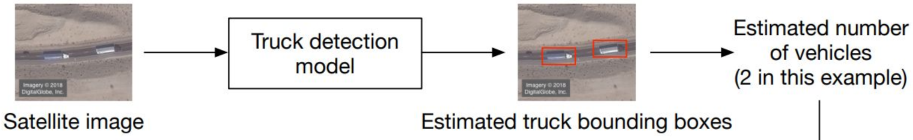
Truck Traffic Monitoring with Satellite Images

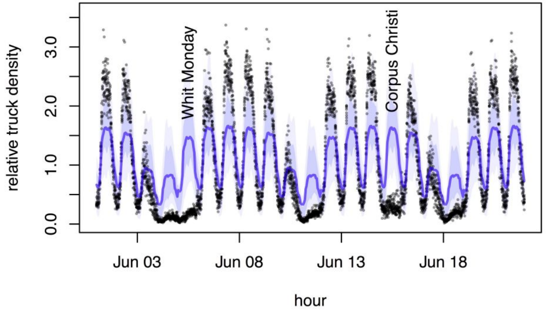
Lynn H. Kaack[1, 2], George H. Chen[3], and M. Granger Morgan[1]

[1]Department of Engineering and Public Policy, Carnegie Mellon University
[2]Energy Politics Group, ETH Zürich
[3]Heinz College of Information Systems and Public Policy, Carnegie Mellon University

Abstract

The road freight sector is responsible for a large and growing share of greenhouse gas emissions, but reliable data on the amount of freight that is moved on roads in many parts of the world are scarce. Many low- and middle-income countries have limited ground-based traffic monitoring and freight surveying activities. In this proof of concept, we show that we can use an object detection network to count trucks in satellite images and predict average annual daily truck traffic from those counts. We describe a complete model, test the uncertainty of the estimation, and discuss the transfer to developing countries.





"Truck traffic monitoring with satellite images." Kaack, Lynn H., George H. Chen, and M. Granger Morgan. Proceedings of the 2nd ACM SIGCAS Conference on Computing and Sustainable Societies. 2019.

DL for climate change adaptation

PHILOSOPHICAL TRANSACTIONS OF THE ROYAL SOCIETY A

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Opinion piece

Can deep learning beat numerical weather prediction?

M. G. Schultz, C. Betancourt, B. Gong, F. Kleinert, M. Langguth, L. H. Leufen, A. Mozaffari and S. Stadtler

Published: 15 February 2021 | https:

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Towards global flood mapping onboard low cost satellites with machine learning

Gonzalo Mateo-Garcia, Joshua Veitch-Michaelis, Lewis Smith, Silviu Vlad Oprea, Guy Schumann, Yarin Gal, Atılım Güneş Baydin & Dietmar Backes

Scientific Reports 11, Article number: 7249 (2021) | Cite this article

3105 Accesses | 66 Altmetric | Metrics

1520 IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 45, NO. 6, JUNE 2007

Satellite Image Analysis for Disaster and Crisis-Management Support

Stefan Voigt, Thomas Kemper, Torsten Riedlinger, Ralph Kiefl, Klaas Scholte, and Harald Mehl

***Abstract*—This paper describes how multisource satellite data and efficient image analysis may successfully be used to conduct rapid-mapping tasks in the domain of disaster and crisis-management support. The German Aerospace Center (DLR) has set up a dedicated crosscutting service, which is the so-called**

event has improved substantially. There are several factors which have lead to this fact. First of all, ground pixel spacing of civil Earth-observation systems has developed to the meter domain for optical and radar systems and to the decameter

Behavior, wealth and health

DL for wealth, energy & activity analysis

Poverty Prediction with Public Landsat 7 Satellite Imagery and Machine Learning

Anthony Perez
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Stefano Ermon
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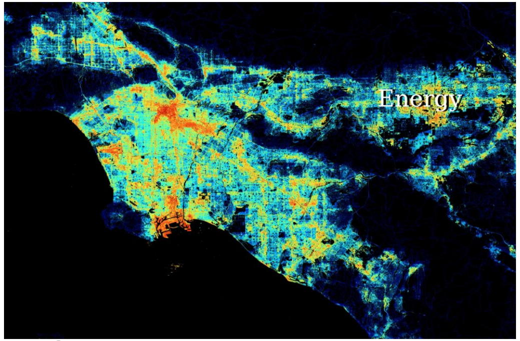
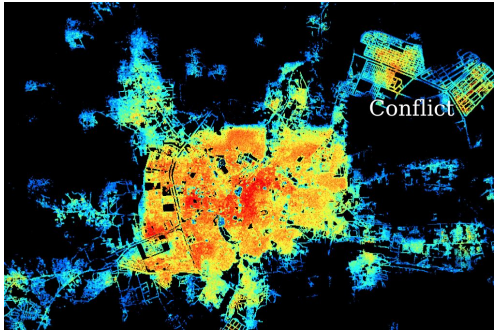
ermon@cs.stanford.edu

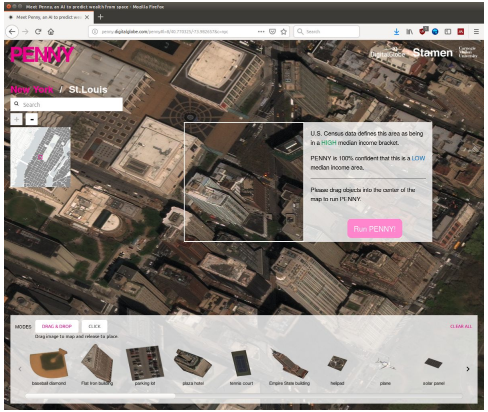
Model	Mean Train r^2	Mean Test r^2	Aggregate Residual r^2
Nightlights / GBT	0.63	0.66	1.0
VGG-F, RGB / ridge	0.71	0.64	0.69
VGG-F, 9 Band / ridge	0.68	0.63	0.70
ResNet-18, 9 Band / ridge	0.69	0.64	0.73
ResNet-34, 9 Band / ridge	0.70	0.65	0.74
Jean et al. [8]	0.53	0.54	0.76

"Poverty prediction with public Landsat 7 satellite imagery and machine learning." Perez, Anthony, et al. arXiv:1711.03654 (2017).





NASA's black marble – https://blackmarble.gsfc.nasa.gov/

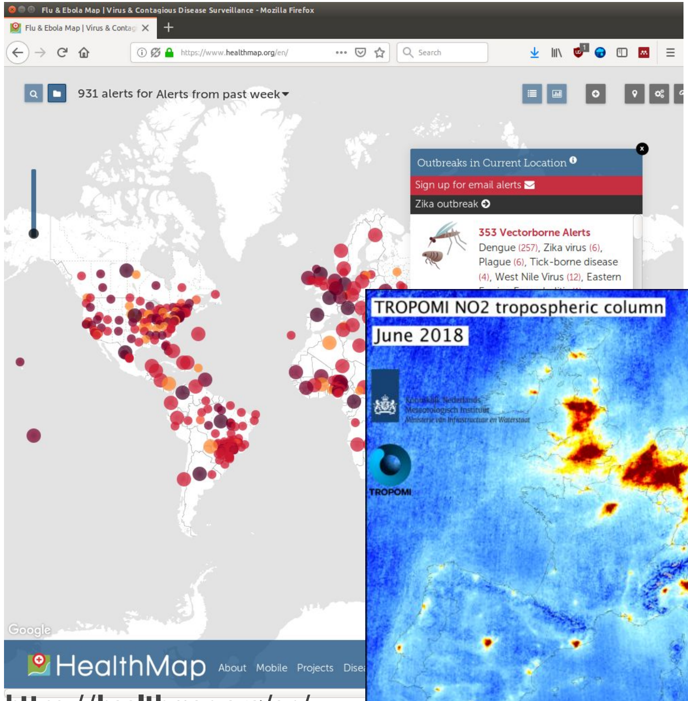


Global wealth map
http://penny.digitalglobe.com

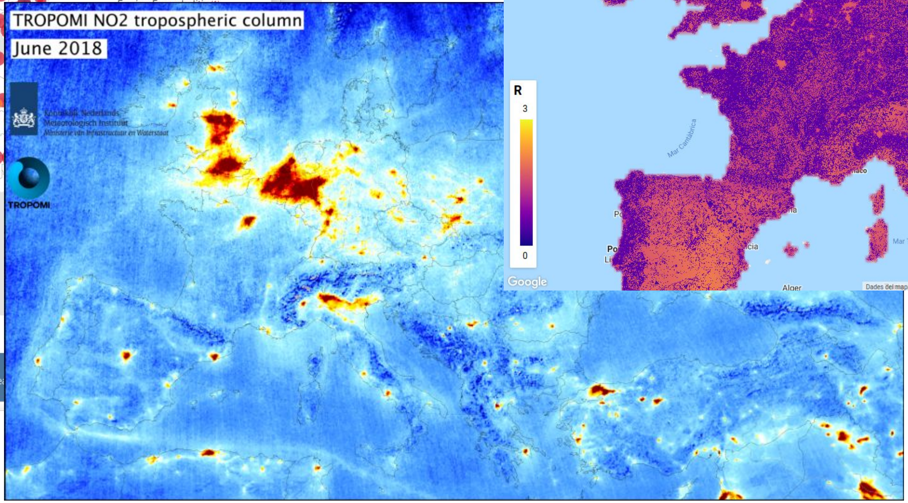
DL for health analysis

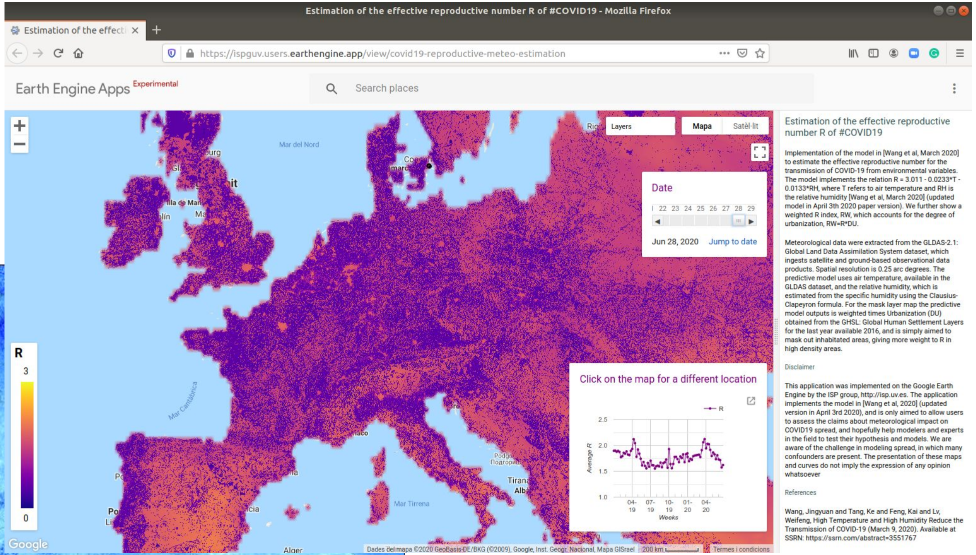
3 GOOD HEALTH AND WELL-BEING

https://ispguv.users.earthengine.app/view/covid19-reproductive-meteo-estimation

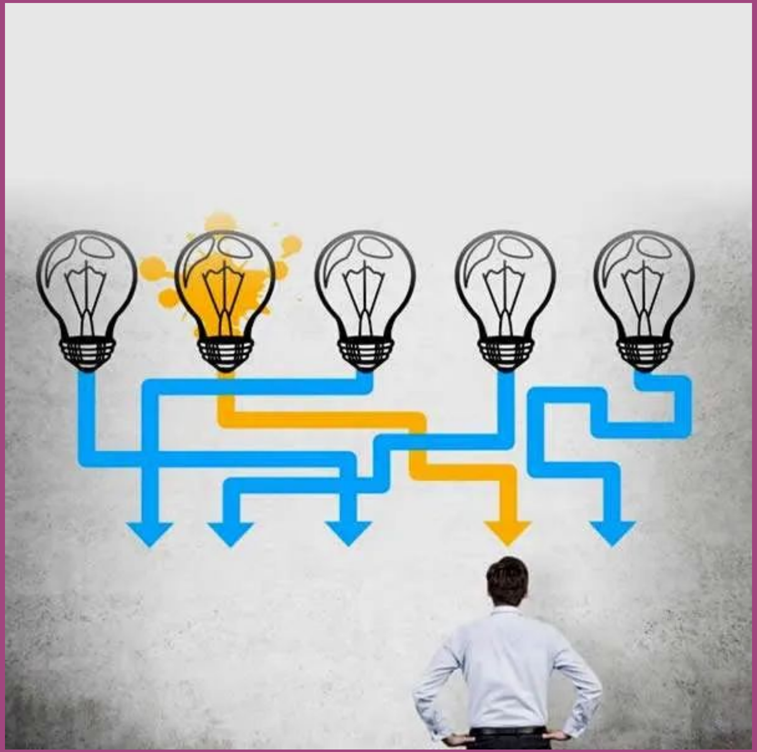


https://healthmap.org/en/





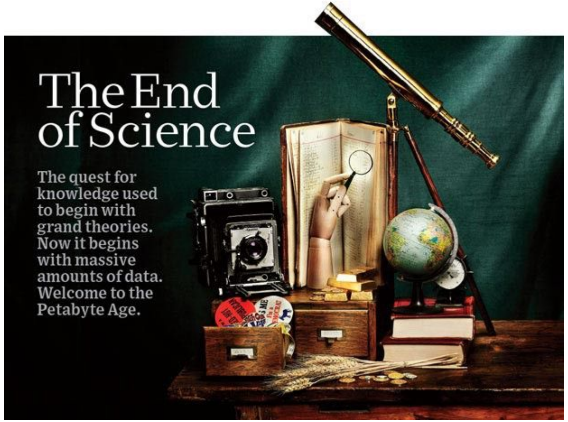
AI … problem solved?



AI promises to transform scientific discovery …

Deep learning challenges

- **Do Models respect Physics Laws?**
- **What did the ML model learn?**
- **Do they get cause-effect relations?**




The New York Times

Opinion

OP-ED CONTRIBUTORS

Eight (No, Nine!) Problems With Big Data

By Gary Marcus and Ernest Davis


nature International weekly journal of science

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Archive > Volume 538 > Issue 7623 > News Feature > Article

NATURE | NEWS FEATURE

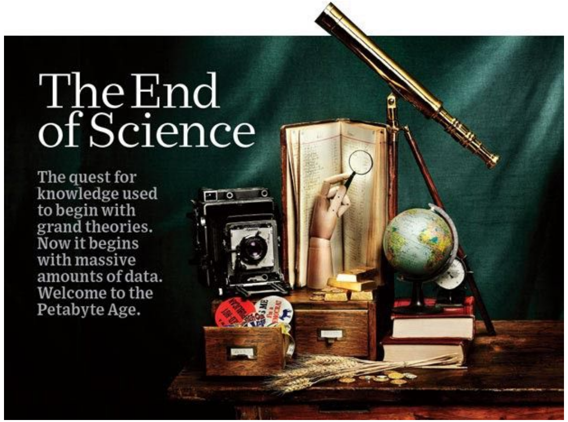
Can we open the black box of AI?

Artificial intelligence is everywhere. But before scientists trust it, they first need t
understand how machines learn.

Davide Castelvecchi

Deep learning challenges

- Do Models respect Physics Laws? **Physics-aware ML**
- What did the ML model learn? **Explainable AI**
- Do they get cause-effect relations? **Causal inference**




The New York Times

Opinion

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Eight (No, Nine!) Problems With Big Data

By Gary Marcus and Ernest Davis


nature International weekly journal of science

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NATURE | NEWS FEATURE

Can we open the black box of AI?

Artificial intelligence is everywhere. But before scientists trust it, they first need t understand how machines learn.

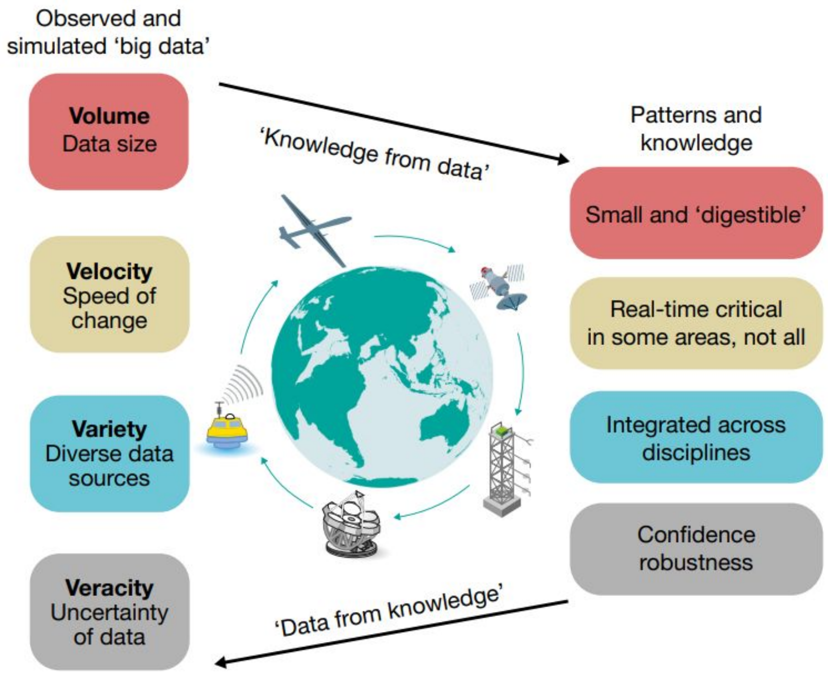
Davide Castelvecchi

Machine learning

$$F(X) = y$$

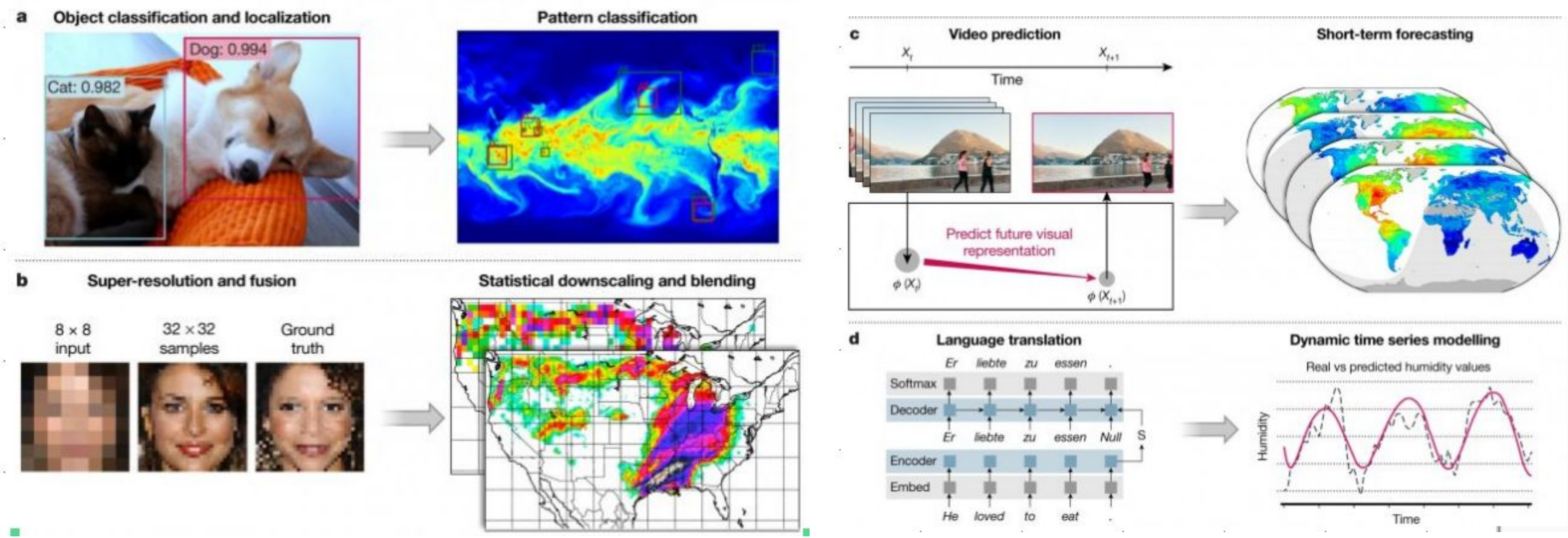
Why does machine learning work?

- Regression, classification, clustering, …
- Deals well with heterogeneous spatio-temporal multidim. big data
- Can incorporate inductive priors by new losses & architectures
- Now a democratized commodity tool



Reichstein, Camps-Valls et al, Nature, 2019
Camps-Valls, Tuia, Xiang, Reichstein. Wiley & Sons book, 2021

And don't forget analogies!



Reichstein, Camps-Valls et al, Nature, 2019

Camps-Valls, Tuia, Xiang, Reichstein. Wiley & Sons book, 2021

Machine learning for the Earth sciences

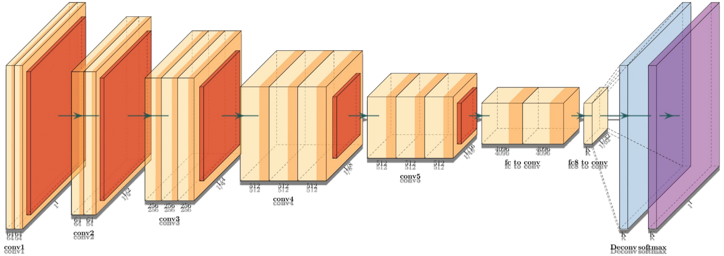
PERSPECTIVE

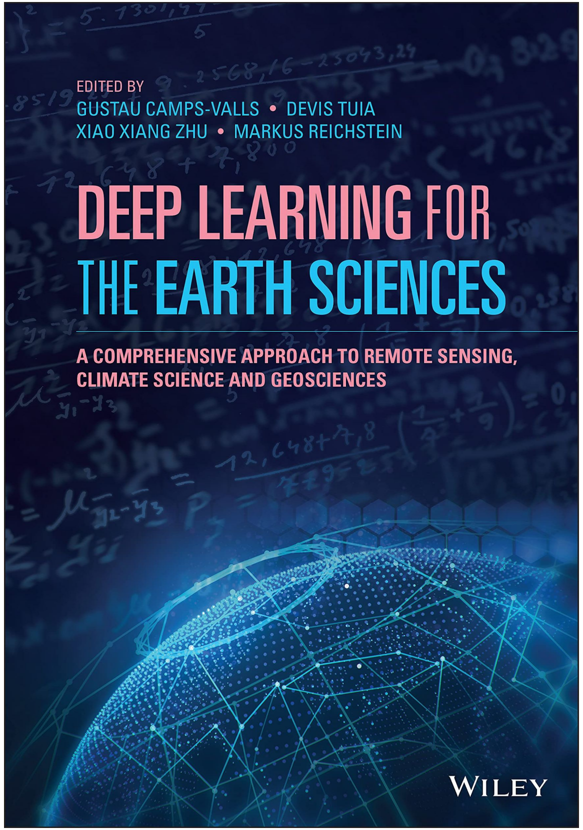
https://doi.org/10.1038/s41586-019-0912-1

Deep learning and process understanding for data-driven Earth system science

Markus Reichstein[1,2]*, Gustau Camps-Valls[3], Bjorn Stevens[4], Martin Jung[1], Joachim Denzler[2,5], Nuno Carvalhais[1,6] & Prabhat[7]

Machine learning approaches are increasingly used to extract patterns and insights from the ever-increasing stream of geospatial data, but current approaches may not be optimal when system behaviour is dominated by spatial or temporal context. Here, rather than amending classical machine learning, we argue that these contextual cues should be used as part of deep learning (an approach that is able to extract spatio-temporal features automatically) to gain further process understanding of Earth system science problems, improving the predictive ability of seasonal forecasting and modelling of long-range spatial connections across multiple timescales, for example. The next step will be a hybrid modelling approach, coupling physical process models with the versatility of data-driven machine learning.





Reichstein, Camps-Valls et al, Nature, 2019

Camps-Valls & Bruzzone. Wiley & Sons book, 2012

Camps-Valls, Tuia, Xiang, Reichstein. Wiley & Sons book, 2021

ML needs domain knowledge

$$F\left(X, \begin{array}{l} u = \frac{1}{2\mu}\frac{\partial p}{\partial x}y^2 + Ay + B \\ w = \frac{1}{2\mu}\frac{\partial p}{\partial z}y^2 + Cy + D \end{array}\right) = y$$

* physics-aware ML, aka physics-guided, physics-informed, physics-constrained, science-guided, ...

Living in the ML-Physics interplay

A — Data-model blending
- Joint Gaussian processes
- Distribution regression

B — Surrogate modeling
- Gaussian processes
- Bayesian optimization

C — Learning to parameterize
- Variational inference
- Monte Carlo, Gibbs

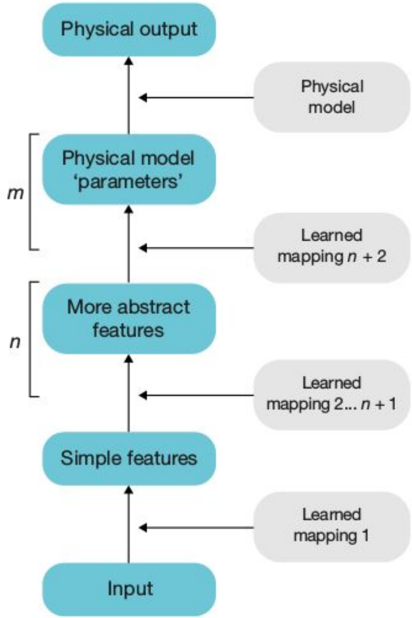
D — Learning physics
- Sparse regression
- Latent force models

"Living in the Physics - Machine Learning Interplay for Earth Observation"
Camps-Valls et al. AAAI Fall Series 2020 Symposium on Physics-guided AI for Accelerating Scientific Discovery, 2020. arxiv.org/abs/2010.09031

A- Hybrid machine learning

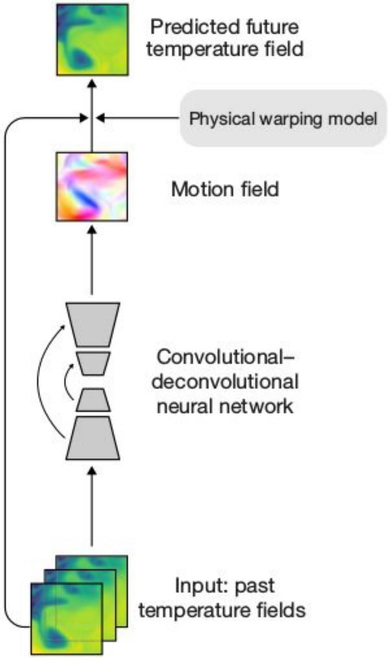
- ML that learns laws of physics (e.g. model-data consistency, mass and energy conservation)

A: "Physisizing" a deep learning architecture by adding one or several physical layers after the multilayer neural network



"Deep learning and process understanding for data-driven Earth System Science"
Reichstein, Camps-Valls et al. Nature, 2019.

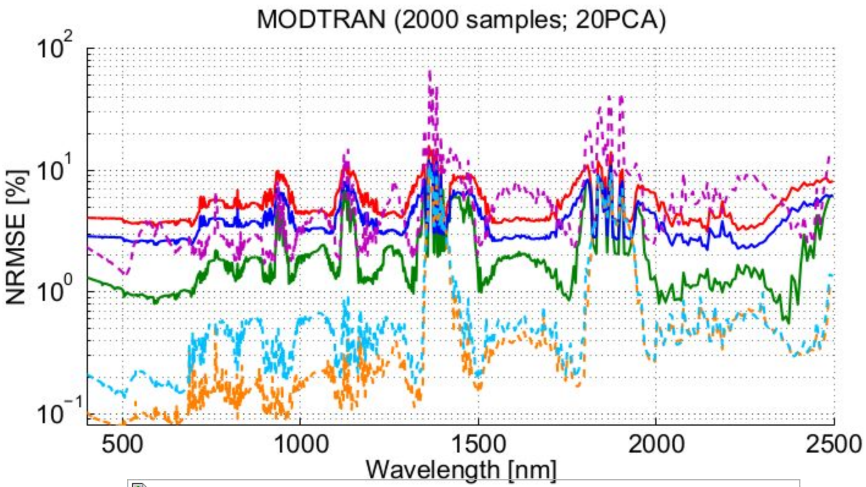
B: A motion field is learned with a convolutional-deconvolutional net, and the motion field is further processed with a physical model

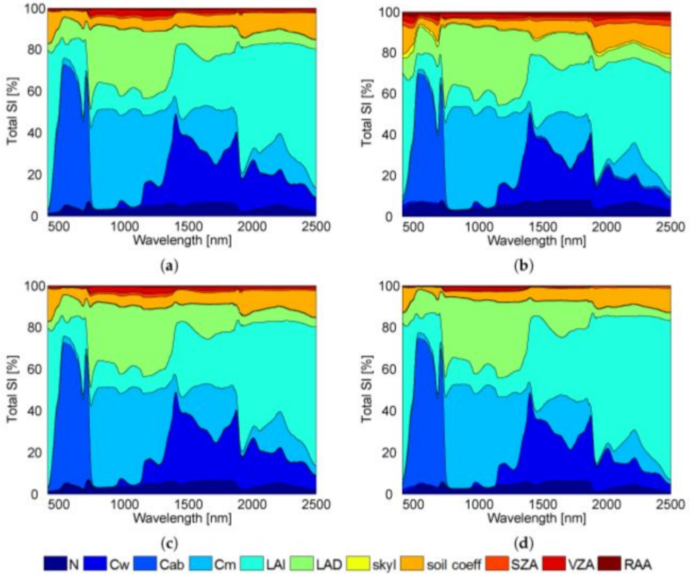


"Deep Learning for Physical Processes: Incorporating Prior Scientific Knowledge".
de Bezenac, Pajot, & Gallinari, arXiv:1711.07970 (2017).

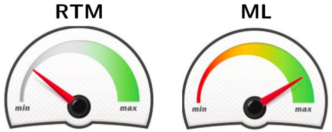
GitHub **https://github.com/DL4ES/DL4ES**

B- Emulating complex codes





[“Emulation of Leaf, Canopy and Atmosphere Radiative Transfer Models for Fast Global Sensitivity Analysis”,](#)
Verrelst, Camps-Valls et al Remote Sensing of Environment, 2016
[“Emulation as an accurate alternative to interpolation in sampling radiative transfer codes”,](#)
Vicent and Camps-Valls, IEEE Journal Sel. Topics Rem. Sens, Apps. 2018



2.3–24.5 s/pix	0.1–1.3 ms/pix
0%	RMSE = 0.1 – 5%

GitHub https://github.com/dhsvendsen/AMOGAPE

C- Learn parametrizations with variational inference

Springer Link

Published: 08 June 2021

Inference over radiative transfer models using variational and expectation maximization methods

Daniel Heestermans Svendsen, Daniel Hernández-Lobato, Luca Martino, Valero Laparra, Álvaro Moreno-Martínez & Gustau Camps-Valls

Machine Learning (2021) | Cite this article

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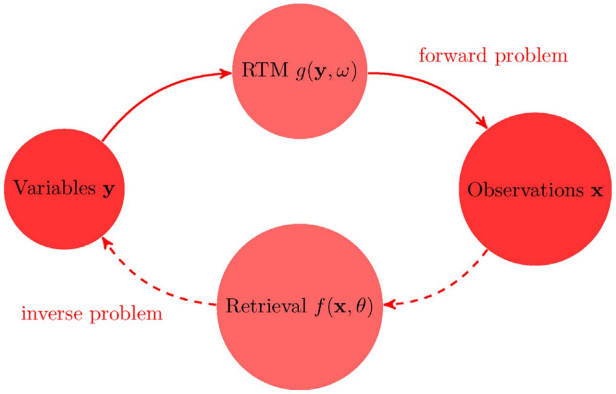
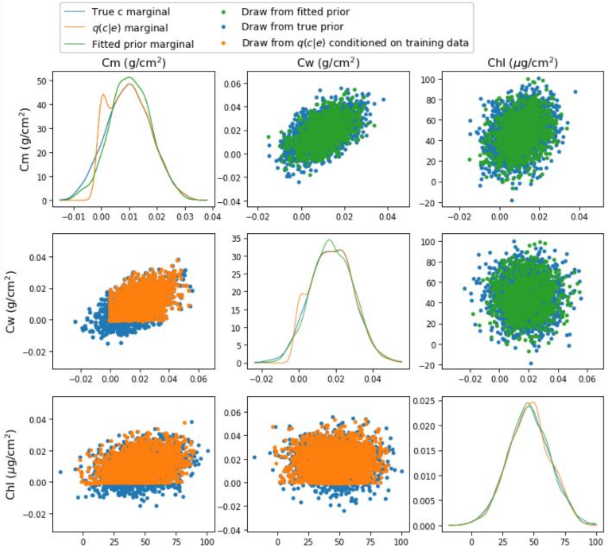
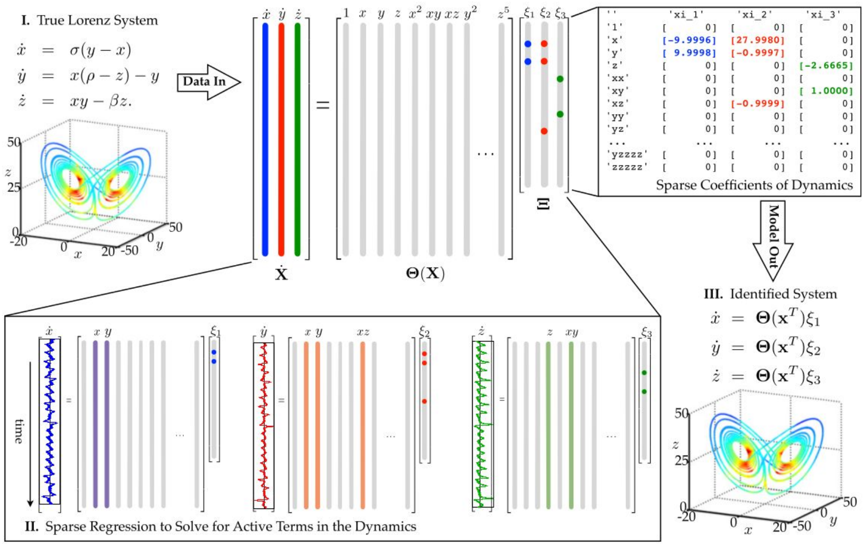
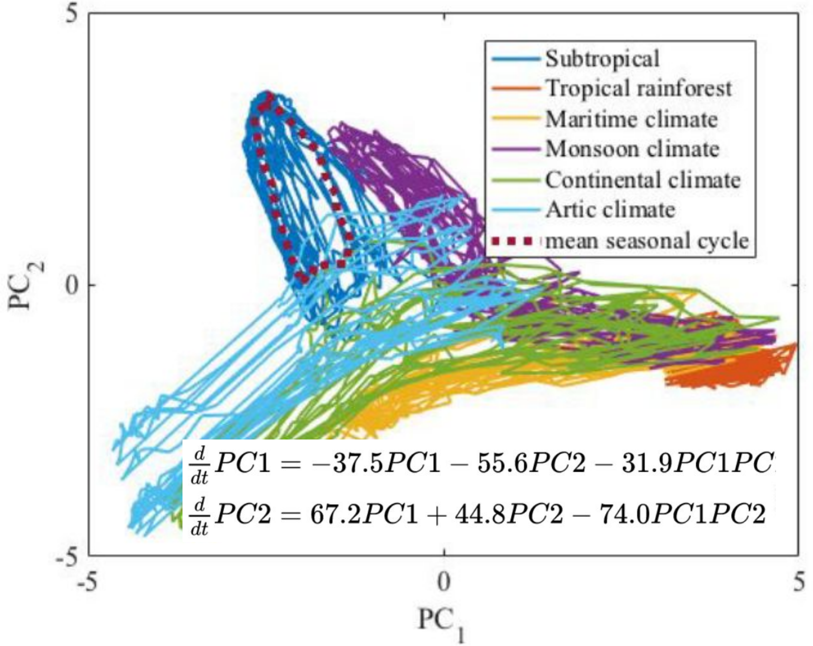




D- Discover equations from data

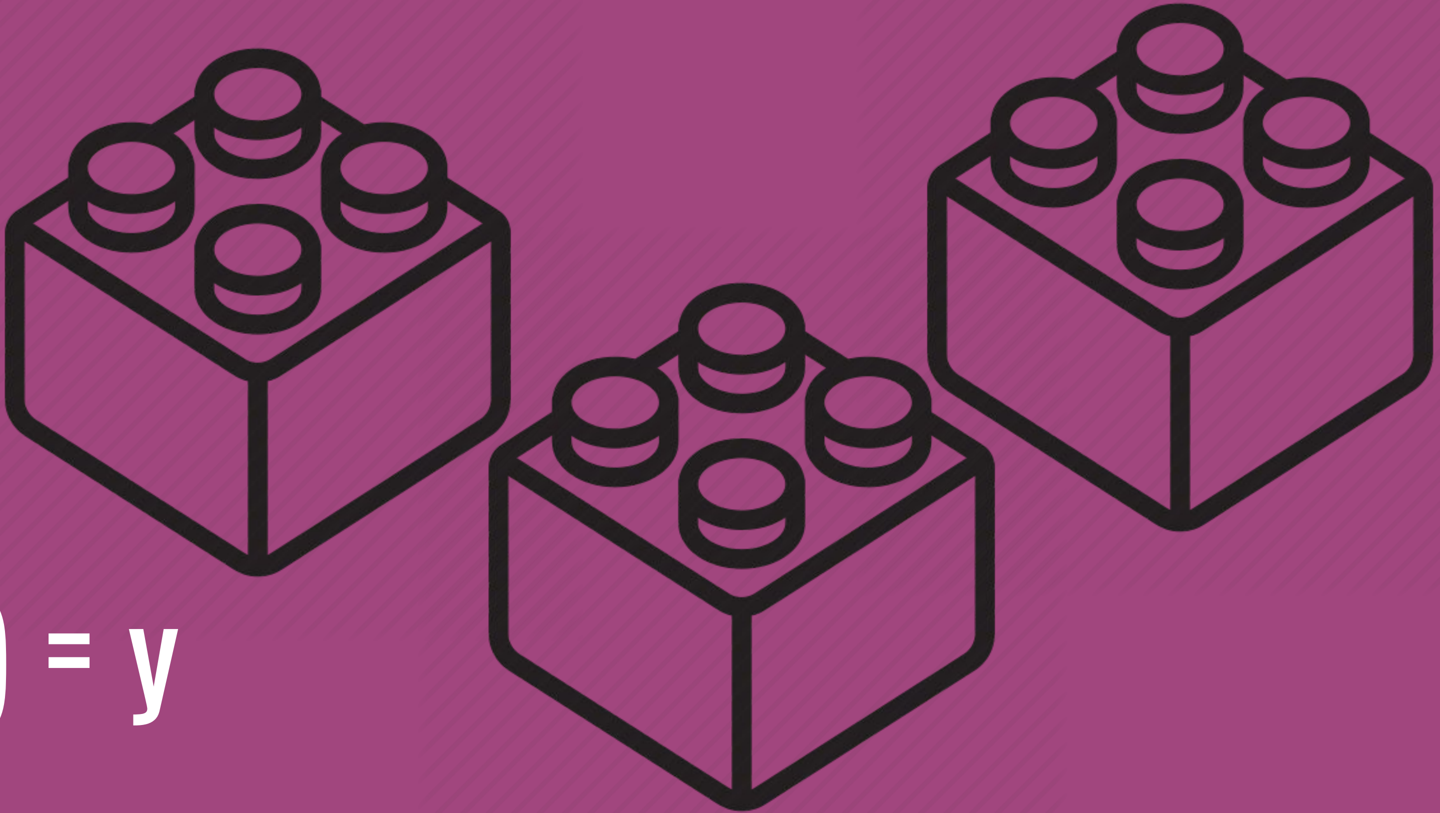




"Discovering governing equations from data by sparse identification of nonlinear dynamical systems" Brunton, Proctor, Kutz, PNAS 2016
"Discovering Differential Equations from Earth Observation Data" Adsuara, J.E.; Camps-Valls, G.; Reichstein, M. and Mahecha, M. IGARSS 2020

GitHub **https://github.com/dhsvendsen/sample4Acause**

DL decisions should be *explainable* and *accountable*

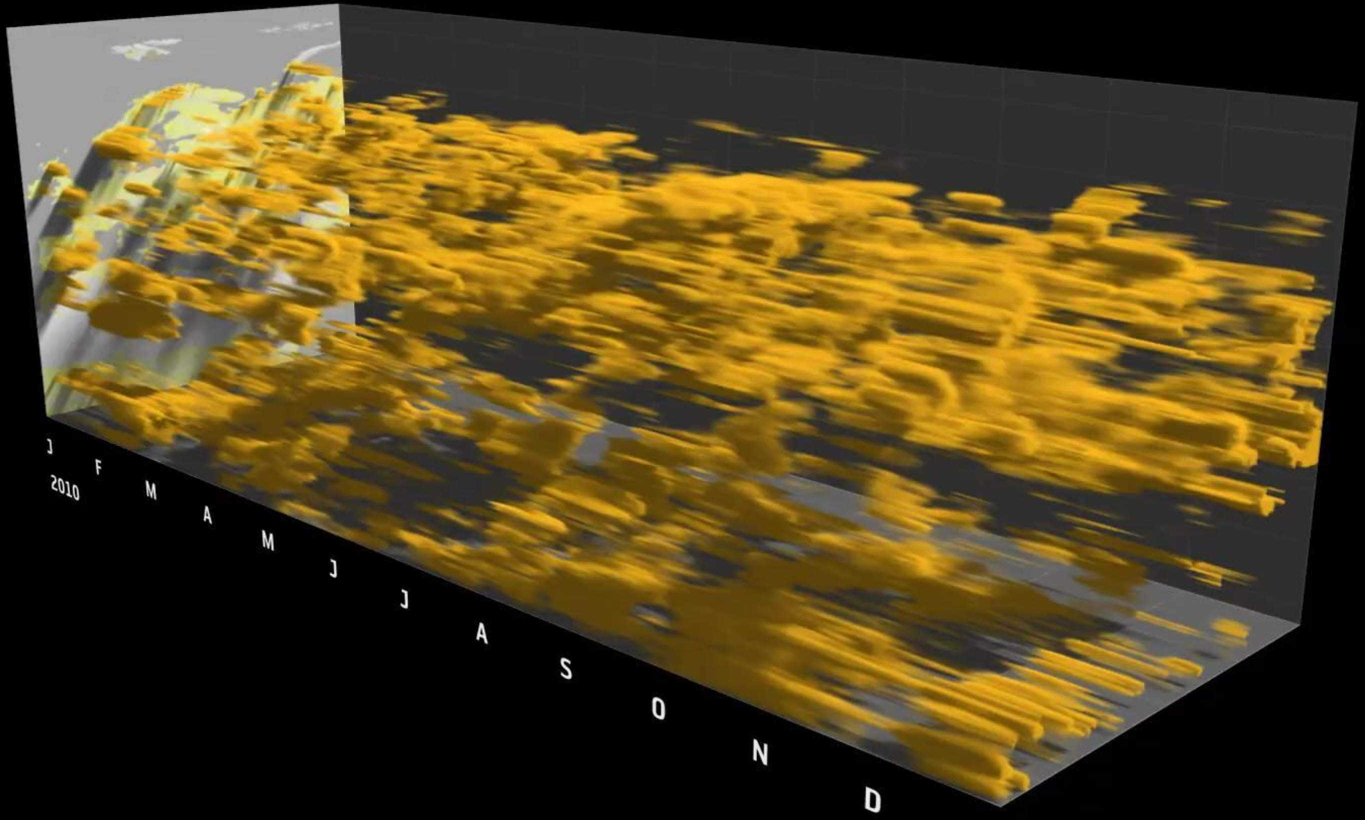


F(X) = y

A full family of XAI

Methods	HSI	ANN	Mechansim		
CAM with global average pooling [41], [90]	✗	✓	Decomposition	Saliency	Perceptive Interpretability
+ Grad-CAM [42] generalizes CAM, utilizing gradient	✓	✓			
+ Guided Grad-CAM and Feature Occlusion [67]	✗	✓			
+ Respond CAM [43]	✗	✓			
+ Multi-layer CAM [91]	✗	✓			
LRP (Layer-wise Relevance Propagation) [13], [52]	✗	N.A.			
+ Image classifications. PASCAL VOC 2009 etc [44]	✗	✓			
+ Audio classification. AudioMNIST [46]	✗	✓			
+ LRP on DeepLight. fMRI data from Human Connectome Project [47]	✗	✓			
+ LRP on CNN and on BoW(bag of words)/SVM [48]	✗	✓			
+ LRP on compressed domain action recognition algorithm [49]	✗	✗			
+ LRP on video deep learning, *selective relevance method* [51]	✗	✓			
+ BiLRP [50]	✗	✓			
DeepLIFT [56]	✗	✓			
Prediction Difference Analysis [57]	✗	✓			
Slot Activation Vectors [40]	✗	✓			
PRM (Peak Response Mapping) [58]	✗	✓			
LIME (Local Interpretable Model-agnostic Explanations) [14]	✓	✓	Sensitivity		
+ MUSE with LIME [84]	✓	✓			
+ Guidelinebased Additive eXplanation optimizes complexity, similar to LIME [92]	✓	✓			
# Also listed elsewhere: [55], [68], [70], [93]	N.A.	N.A.			
Others. Also listed elsewhere: [94]	N.A.	N.A.	Others		
+ Direct output labels. Training NN via multiple instance learning [64]	✗	✓			
+ Image corruption and testing Region of Interest statistically [65]	✗	✓			
+ Attention map with autofocus convolutional layer [66]	✗	✓			
DeconvNet [71]	✗	✓	Inversion	Signal	
Inverting representation with natural image prior [72]	✗	✓			
Inversion using CNN [73]	✗	✓			
Guided backpropagation [74], [90]	✗	✓			
Activation maximization/optimization [37]	✗	✓	Optimization		
+ Activation maximization on DBN (Deep Belief Network) [75]	✗	✓			
+ Activation maximization, multifaceted feature visualization [76]	✗	✓			
Visualization via regularized optimization [77]	✗	✓			
Semantic dictionary [38]	✗	✓			
Decision trees	N.A.	N.A.	Verbal		
Propositional logic, rule-based [81]	✗	✗			
Sparse decision list [82]	✗	✗			
Decision sets, rule sets [83], [84]	✓	✗			
Encoder-generator framework [85]	✗	✓			
Filter Attribute Probability Density Function [86]	✗	✗			
MUSE (Model Understanding through Subspace Explanations) [84]	✓	✓			

"A Survey on Explainable Artificial Intelligence(XAI): towards Medical XAI", Tjoa 2019
"Advancing Deep Learning For Earth Sciences: From Hybrid Modeling To Interpretability", Camps-Valls, G. and Reichstein, M. and Zhu, Z. and Tuia, D. IEEE IGARSS (2020)



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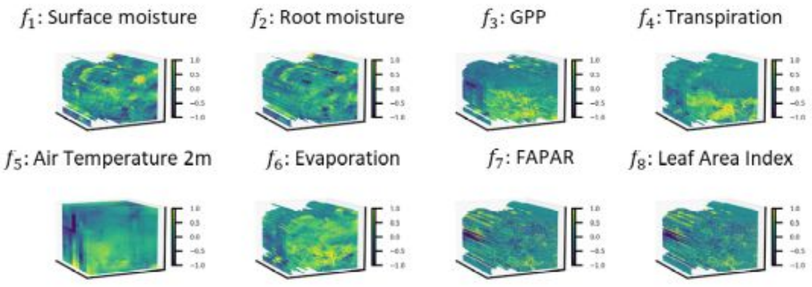
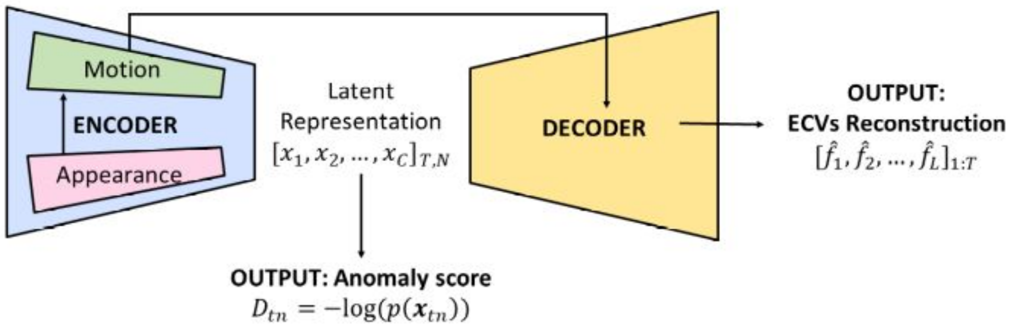
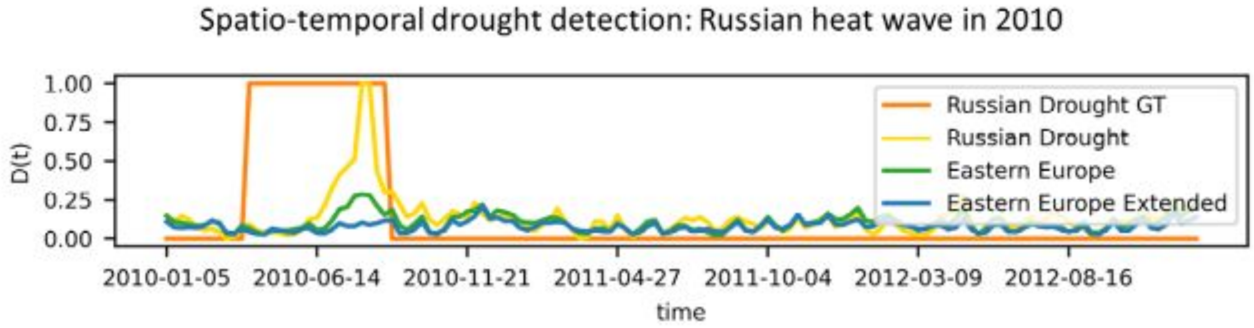
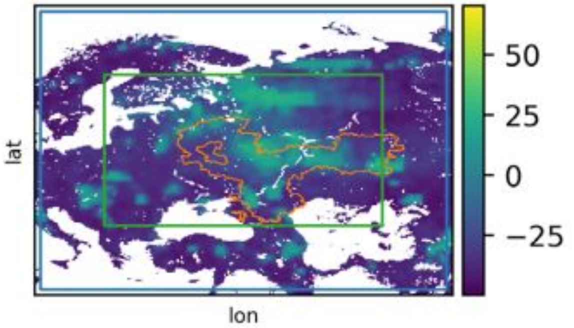
1- Explaining droughts with XAI



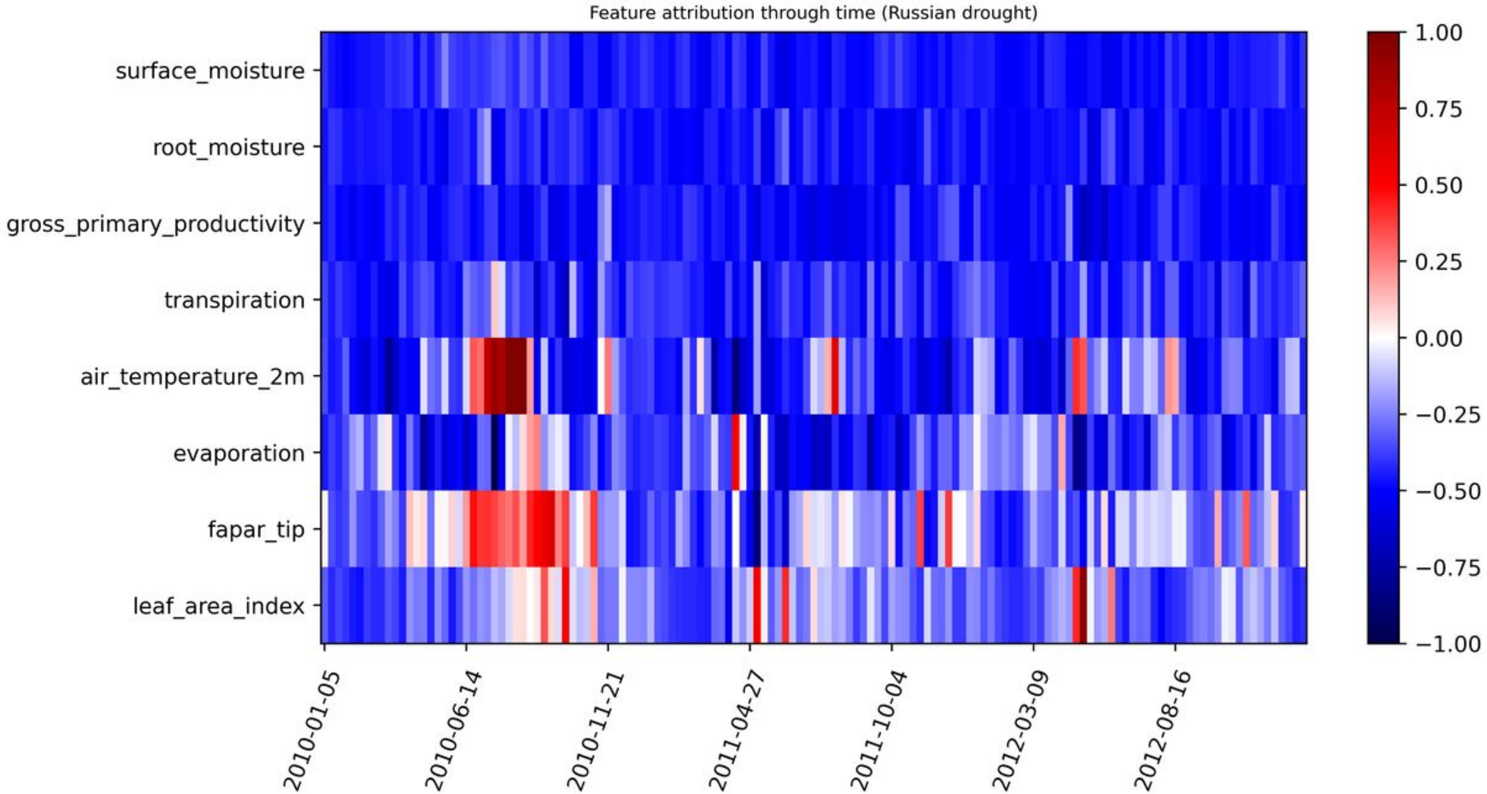






Spatio-Temporal Gaussianization Flows for Extreme Event Detection. Miguel-Ángel Fernández-Torres and J. Emmanuel Johnson and María Piles and Gustau Camps-Valls
EGU General Assembly, Geophysical Research Abstracts, Online, 19-30 April 2021

1- Explaining droughts with XAI



“Spatio-Temporal Gaussianization Flows for Extreme Event Detection”. Miguel-Ángel Fernández-Torres and J. Emmanuel Johnson and María Piles and Gustau Camps-Valls
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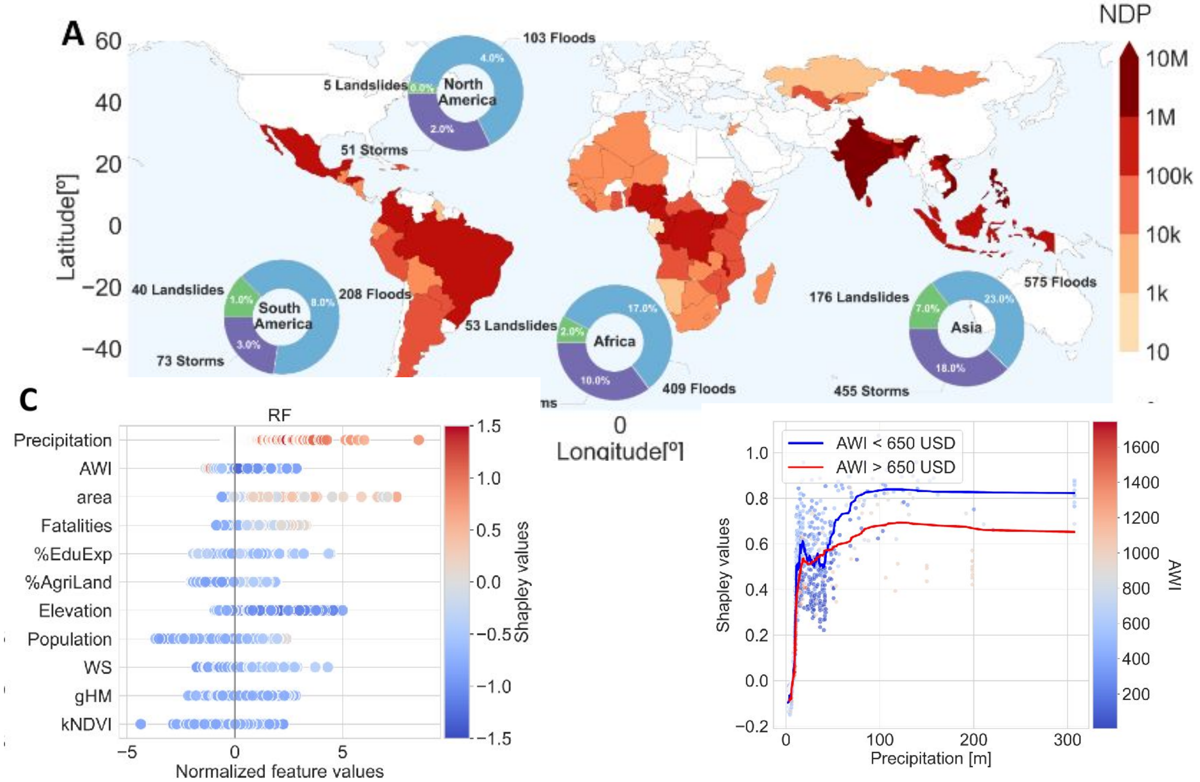
2- XAI explains climate-induced migrations

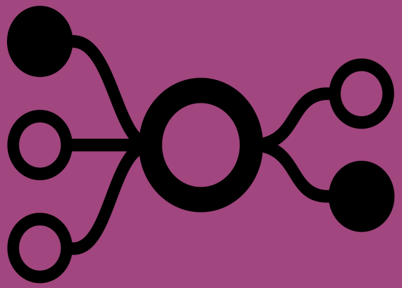
- Large, harmonized, global database of disaster-induced movements in the presence of floods, storms & landslides
- RF is accurate
- SHAP: displacements attributed to the combo of poor household conditions & intense precipitation



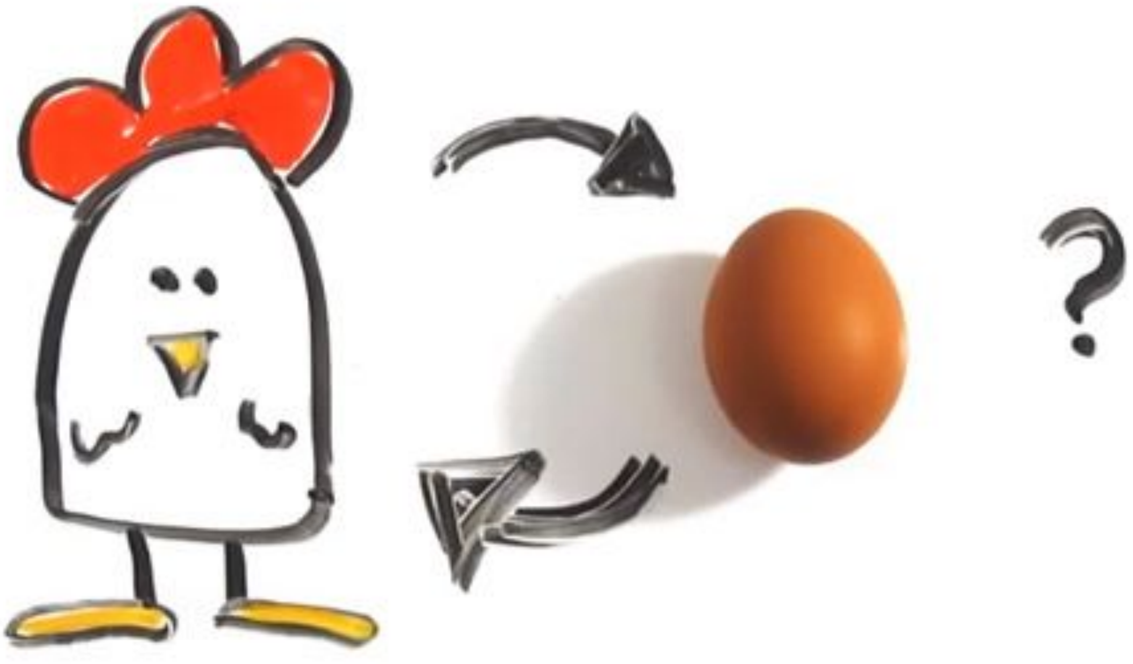
“Exploring interactions between societal context and natural hazards on human population displacement”. M. Ronco, JM Tárraga, M Piles and Gustau Camps-Valls, Nature Comms. 2023

DL needs to be *causal*

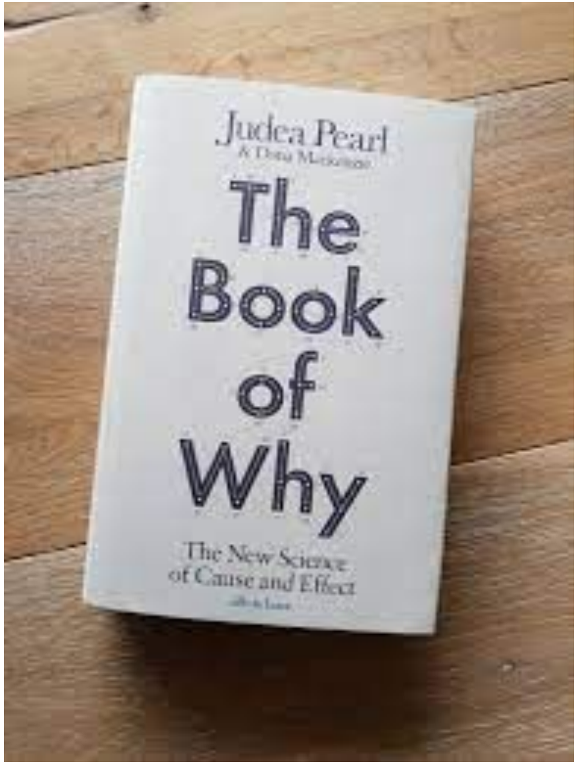
$$F(X,Y) =$$

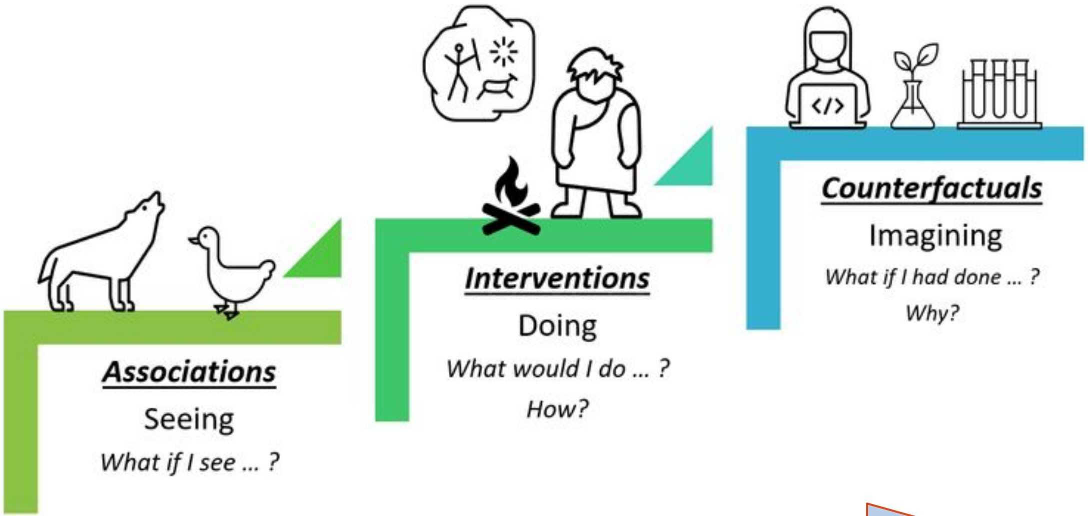


Causal inference



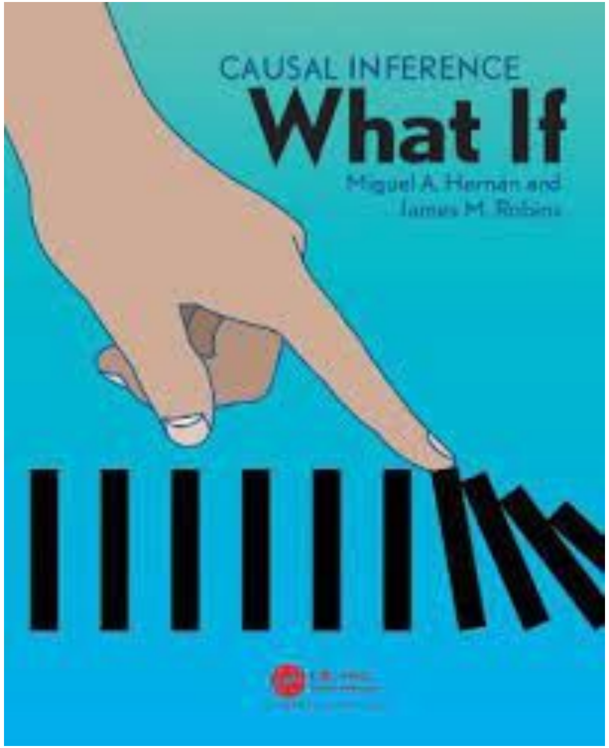
The rungs of inference …

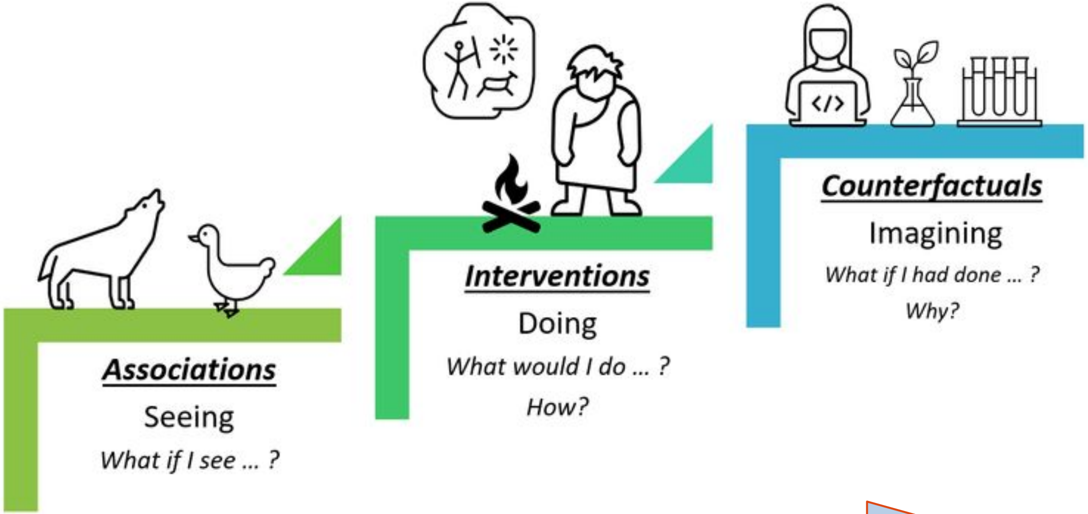




Deep learning world Interaction world Scenarios world

The rungs of inference ...





Deep learning world Interaction world Scenarios world

Causality & Disasters

Understanding Disasters *is about* answering causal queries

- **Causal inference:** draw conclusions about causal relations
- **Causal discovery:** learn relations from data & assumptions
- **Cause-effect estimation:** quantify impacts of interventions

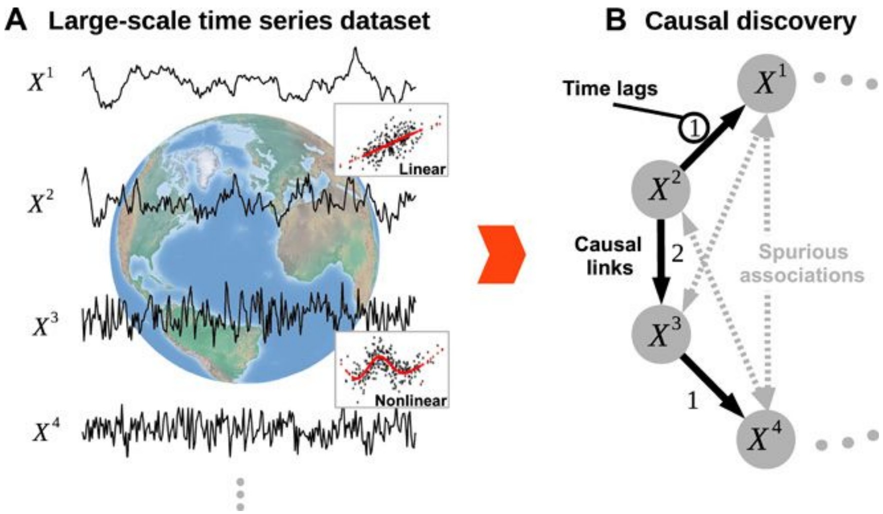
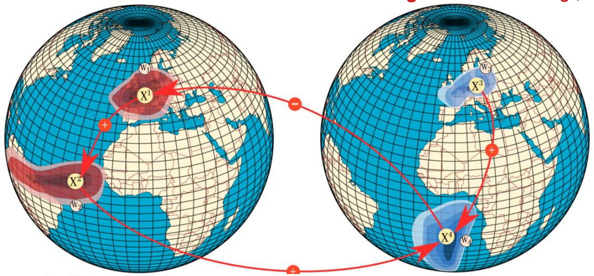


Image credits: Jakob Runge, 2019



Causal discovery from data

nature COMMUNICATIONS

PERSPECTIVE

https://doi.org/10.1038/s41467-019-10105-3 OPEN

Inferring causation from time series in Earth system sciences

Jakob Runge[1,2], Sebastian Bathiany[3,4], Erik Bollt[5], Gustau Camps-Valls[6], Dim Coumou[7,8], Ethan Deyle[9], Clark Glymour[10], Marlene Kretschmer[8], Miguel D. Mahecha[11], Jordi Muñoz-Marí[6], Egbert H. van Nes[4], Jonas Peters[12], Rick Quax[13,14], Markus Reichstein[11], Marten Scheffer[4], Bernhard Schölkopf[15], Peter Spirtes[10], George Sugihara[9], Jie Sun[5,16], Kun Zhang[10] & Jakob Zscheischler[17,18,19]

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Technical Review | Published: 27 June 2023

Causal inference for time series

Jakob Runge, Andreas Gerhardus, Gherardo Varando, Veronika Eyring & Gustau Camps-Valls

Nature Reviews Earth & Environment (2023) | Cite this article

IEE

Causal Inference in Geoscience and Remote Sensing From Observational Data

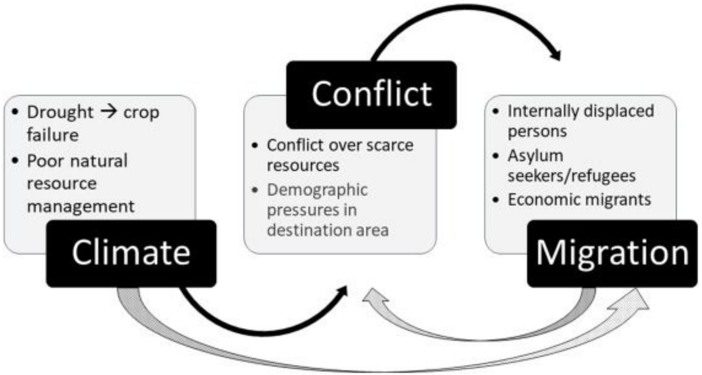
Adrián Pérez-Suay, Member, IEEE, and Gustau Camps-Valls, Fellow, IEEE

Abstract—Establishing causal relations between random variables from observational data is perhaps the most important challenge in today's science. In remote sensing and geosciences, this is of special relevance to better understand the earth's system and the complex interactions between the governing processes.

with societal, economical, and environmental challenges, such as climate change [2], [3]. There is an urgent need for tools that help us to observe and study the earth system. Nowadays, machine learning and signal processing play a crucial role in

"Inferring causation from time series with perspectives in Earth system sciences", Runge, Bathiany, Bollt, Camps-Valls, et al. Nat Comm., 2019
"Causal Inference in Geoscience and Remote Sensing from Observational Data," Pérez-Suay and Camps-Valls, IEEE Trans. Geosc. Rem. Sens, 2018
"CauseMe: An online system for benchmarking causal inference methods," Muñoz-Marí, Mateo, Runge, Camps-Valls. In preparation (2019). **CauseMe: http://causeme.uv.es**

1- Learning drivers of displacement



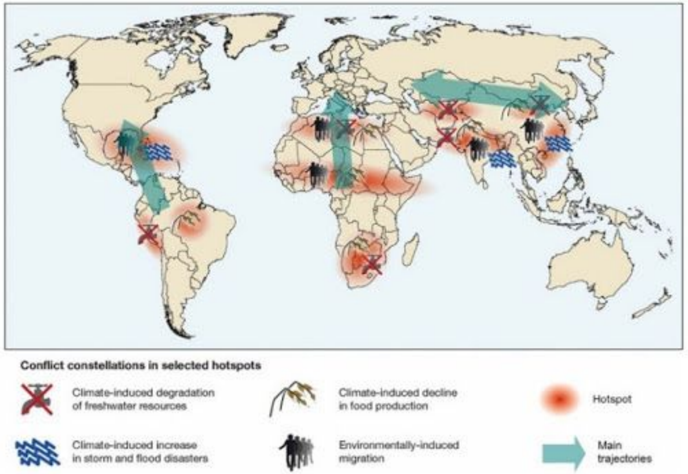


Fig. 11.1 A map of conflict and migration induced by environmental stressors (source: German Advisory Council on Global Change WBGU (2007): Climate Change as a Security Risk arrows added by UNU-EHS)

nature climate change

Comment | Published: 26 November 2019

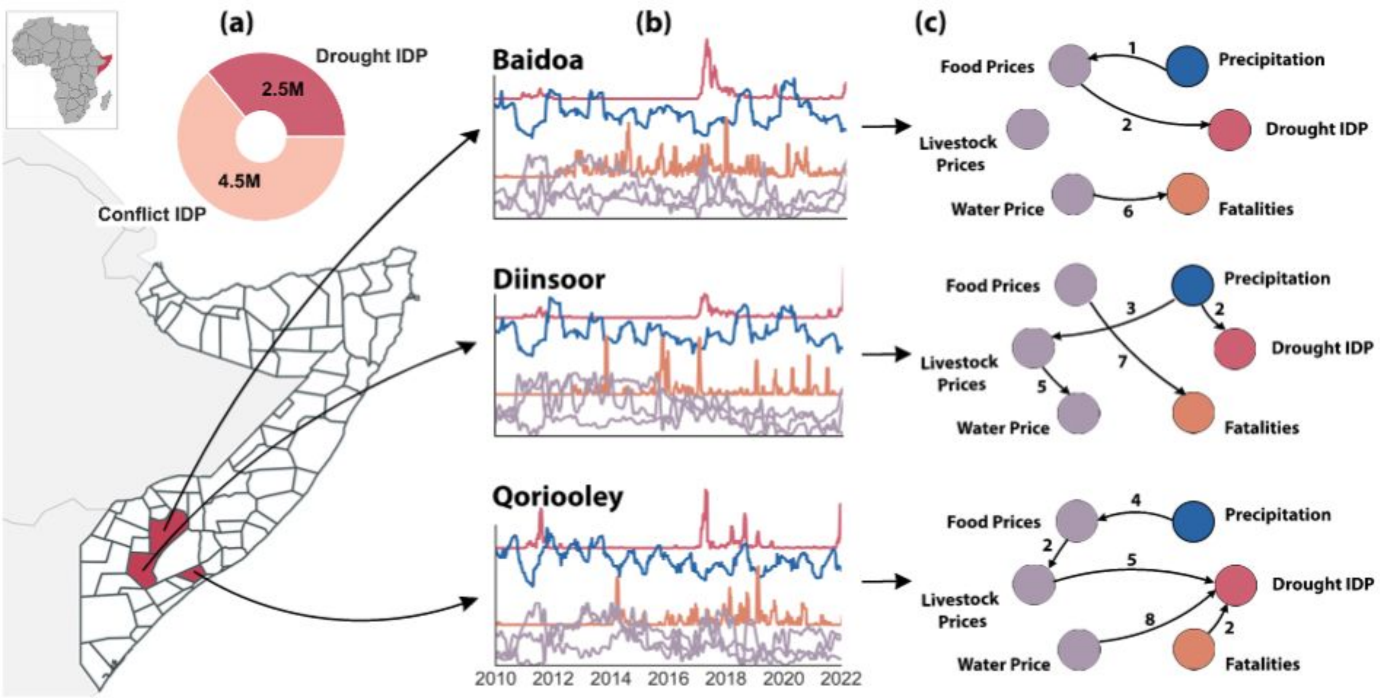
Climate migration myths

Ingrid Boas, Carol Farbotko, [...] Mike Hulme

Nature Climate Change **9**, 901–903(2019) | Cite this article

476 Accesses | **114** Altmetric | Metrics

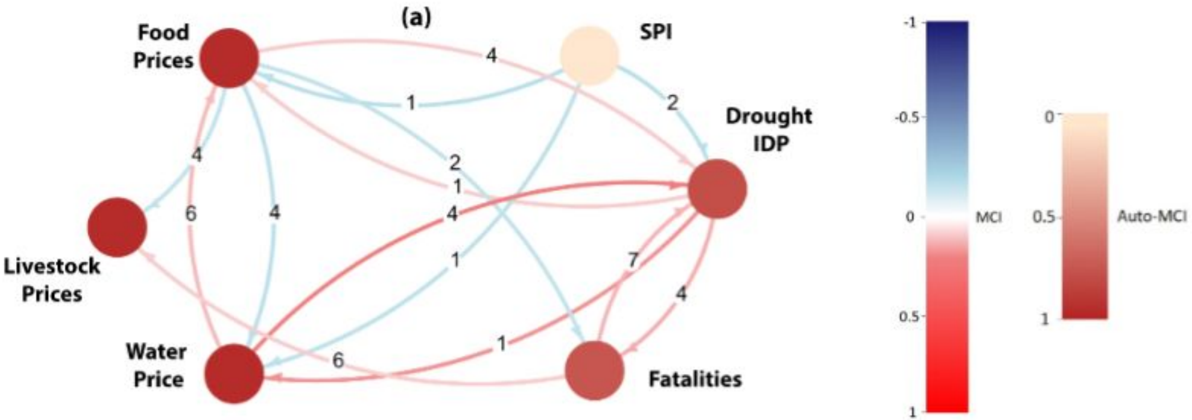
1- Learning drivers of displacement



"Causal discovery of drought-induced human displacement drivers", Tarraga, Piles, Sevillano, Muñoz, Ronco, Camps-Valls, et al. *Submited*, 2023

1- Learning drivers of displacement

Variable	Source	Spatial Resolution	Temporal Resolution
Mean Precipitation	CHIRPS (Chris et al., 2015)	0.05º	Daily
Median NDVI	MODIS TERRA (Didan and Huete, 2015)	1 km	Daily
Mean LST	MODIS TERRA (Wan et al., 2015)	1 km	Daily
Violent Conflict	ACLED (Clionadh et al., 2010)	Geolocated Event	Hourly
Local Market Prices	FSNAU (FSNAU, 2021)	District	Monthly
Drought Displacement	UNHCR PRMN (UNHCR Somalia ID)	District	Weekly
Somalia Districts	UNDP (UNDP)	District	Static
Livelihood Zones	FEWS NET (Fews Net)	Sub-national	Static



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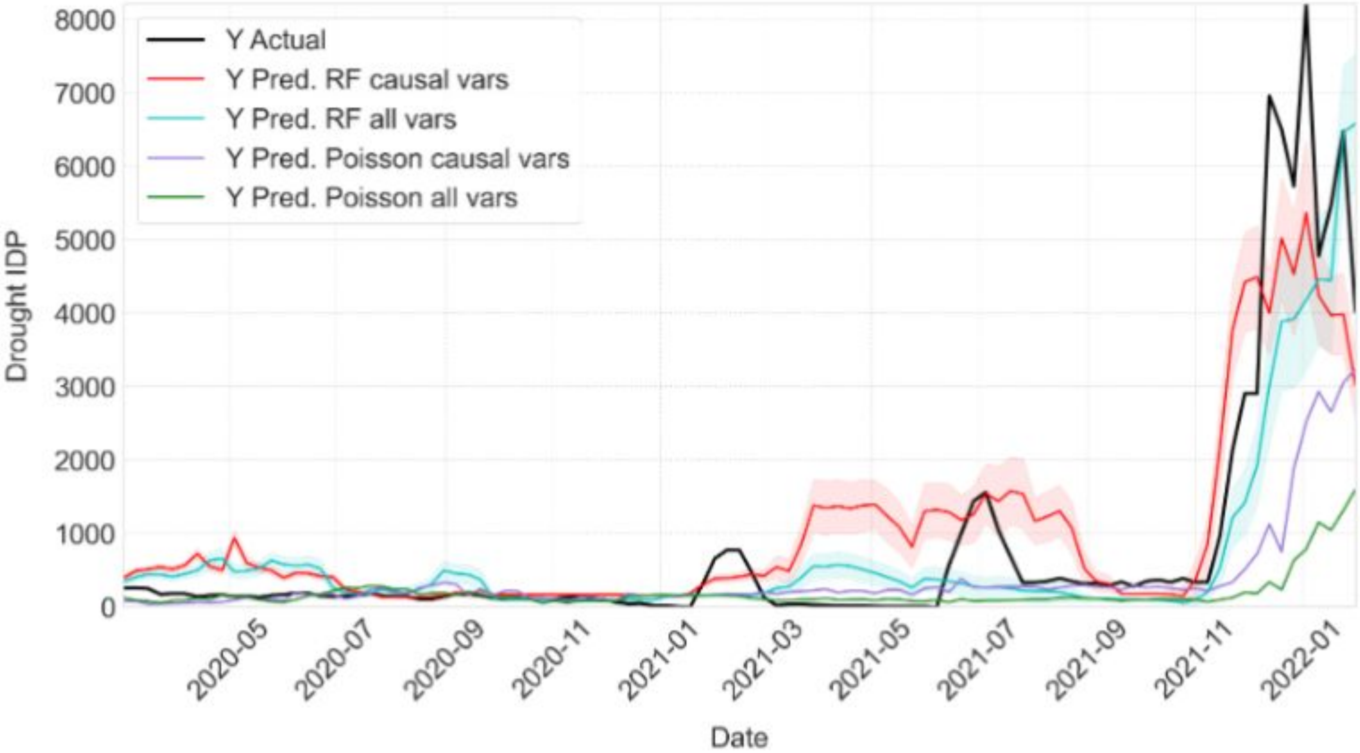
1- Learning drivers of displacement



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Activities Firefox Web Browser abr 13 09:25

CauseMe - A platform to ×

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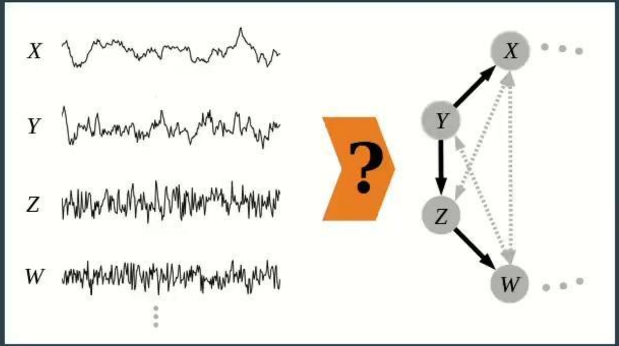
CAUSEME (BETA)

HOME DATA AND MODELS METHODS RANKING HOWTO TERMS PROFILE LOGOUT

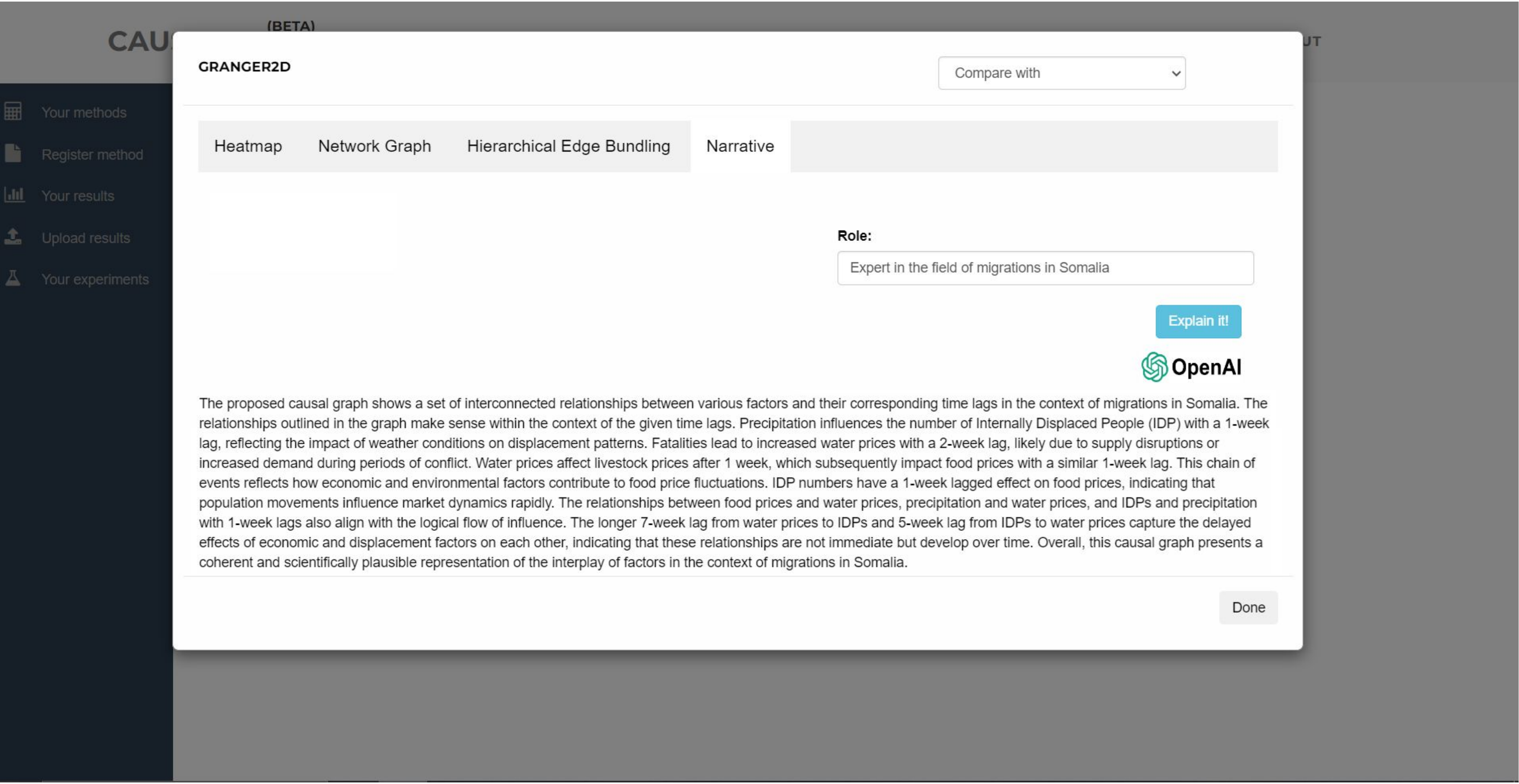


CAUSEME

A platform to benchmark causal discovery methods

CAUSAL DISCOVERY

Detecting causal associations in time series datasets is a key challenge for novel insights into complex dynamical systems such


CAU
(BETA)
UT
Your methods
Register method
Your results
Upload results
Your experiments
GRANGER2D
Compare with
Heatmap
Network Graph
Hierarchical Edge Bundling
Narrative
Role:
Expert in the field of migrations in Somalia
Explain it!
OpenAI
The proposed causal graph shows a set of interconnected relationships between various factors and their corresponding time lags in the context of migrations in Somalia. The relationships outlined in the graph make sense within the context of the given time lags. Precipitation influences the number of Internally Displaced People (IDP) with a 1-week lag, reflecting the impact of weather conditions on displacement patterns. Fatalities lead to increased water prices with a 2-week lag, likely due to supply disruptions or increased demand during periods of conflict. Water prices affect livestock prices after 1 week, which subsequently impact food prices with a similar 1-week lag. This chain of events reflects how economic and environmental factors contribute to food price fluctuations. IDP numbers have a 1-week lagged effect on food prices, indicating that population movements influence market dynamics rapidly. The relationships between food prices and water prices, precipitation and water prices, and IDPs and precipitation with 1-week lags also align with the logical flow of influence. The longer 7-week lag from water prices to IDPs and 5-week lag from IDPs to water prices capture the delayed effects of economic and displacement factors on each other, indicating that these relationships are not immediate but develop over time. Overall, this causal graph presents a coherent and scientifically plausible representation of the interplay of factors in the context of migrations in Somalia.
Done

2- Impact on food insecurity

"A total of 6.5 million people face acute food insecurity amid the driest conditions in 40 years(...) A total of 1.84 million children under 5 face acute malnutrition. (...) over 1.5 million drought-driven displacements since the start of the climate crisis."

World Food Programme, Jan 2023

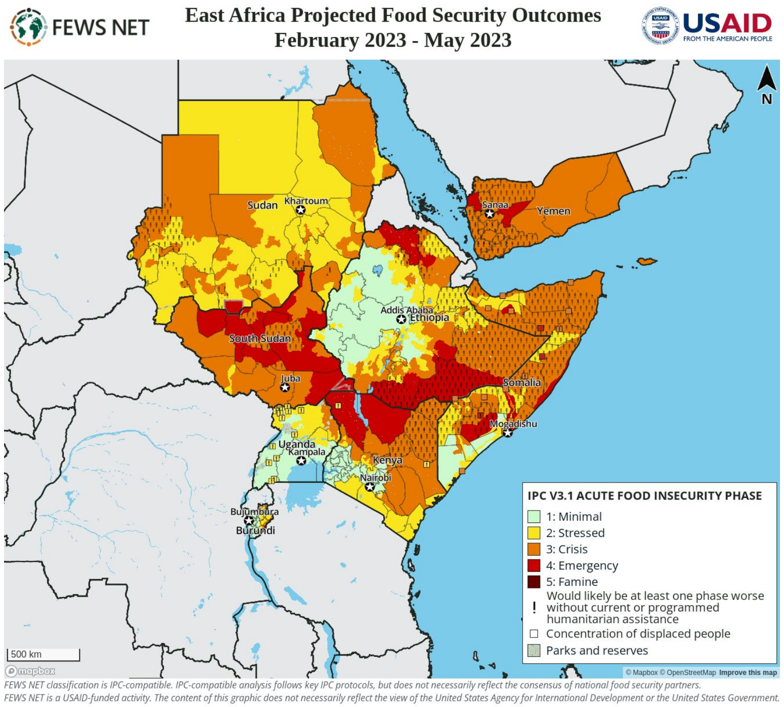
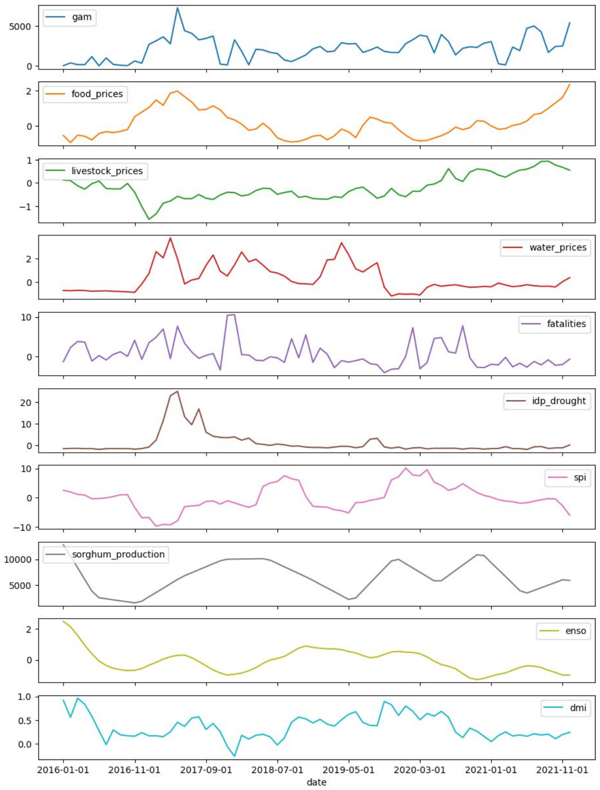


Image credits to: FEWS NET, https://fews.net

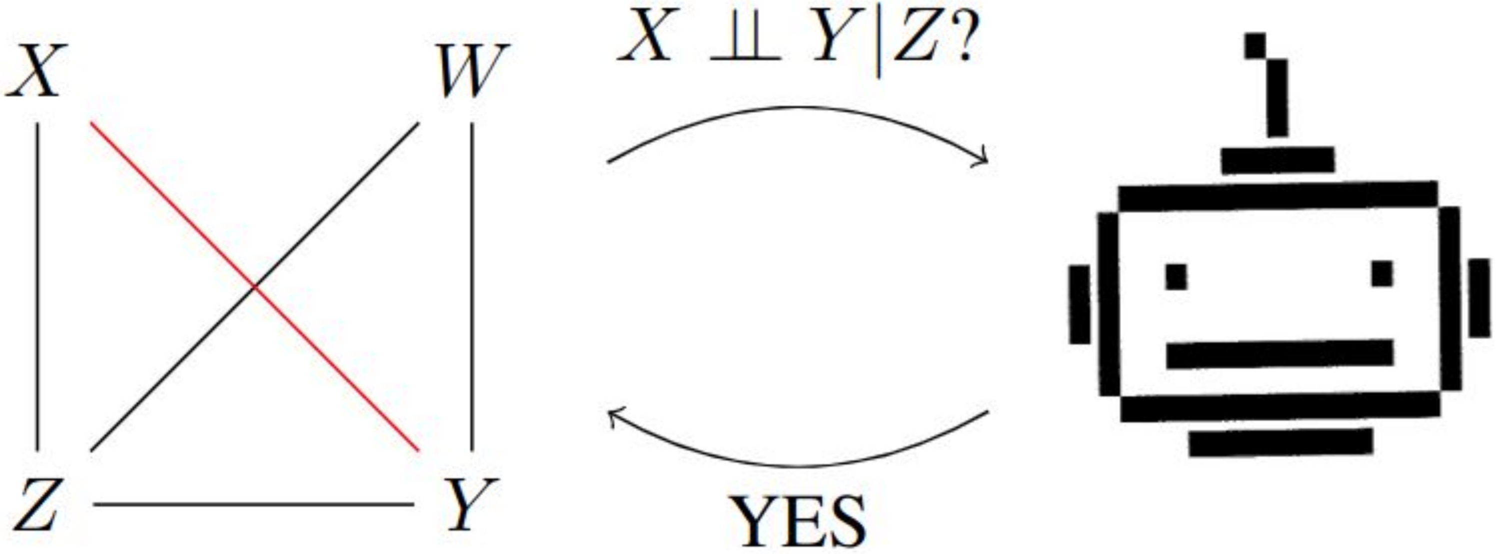
2- Impact on food insecurity

- Monthly data
- 2016 - 2021
- 37 districts
- N~70
- Market/food/livestock/water prices, displaced people, fatalities, climate variables, humanitarian aid
- Target: malnutrition

Baidoa District



2- chatGPT for Constrained-Based Causal Discovery



"Large Language Models for Constrained-Based Causal Discovery" K-H Cohrs, G. Varando, G. Camps-Valls, AAAI 2024

2- chatGPT for Constrained-Based Causal Discovery

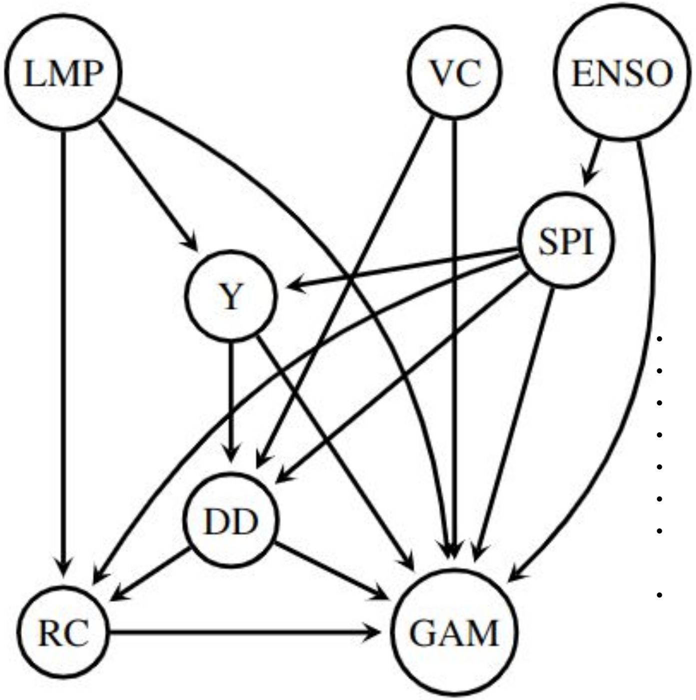
Persona specification
Instructions
Context
Variables description
CI Statement question
Response template

```
system: You are a helpful expert in {field}
and willing to answer questions.

system: You will be asked to provide your
best guess and your uncertainty on the
statistical independence between two
variables potentially conditioned on a set
of variables. Your answer should not be
based on data or observations but on
available knowledge. Even when unsure or
uncertain, provide your best guess (YES or
NO) and the probability that your guess is
correct. Answer only in the required format.

user: {context} Consider the following
variables:
{variables list and description}
is {x} independent of {y} given {z}?

system: Work out the answer in a
step-by-step way to be as sure as possible
that you have the right answer. After
explaining your reasoning, provide the
answer in the following form: [<ANSWER>
(<PROBABILITY>)] where ANSWER is either YES
or NO and PROBABILITY is a percentage
between 0\% and 100\%.
YES stands for "{x} is independent of {y}
given {z}"  and NO stands for "{x} is not
independent of {y} given {z}".

For example [NO (50%)] or [YES (50%)].
```

“Large Language Models for Constrained-Based Causal Discovery” K-H Cohrs, G. Varando, G. Camps-Valls, AAAI 2024

2- chatGPT for Constrained-Based Causal Discovery

- Find traces of causal reasoning in model's answers
- Promising, alternative avenue for automated causality
- Useful for fast response, scarce data regimes



- El Niño Southern Oscillation (ENSO)
- Standardized Precipitation Index (SPI)
- Fatalities due to conflicts (VC)
- Local market prices (LMP)
- Sorghum yield production (Y)
- Drought-induced IDP (DD)
- People receiving cash from humanitarian aid (RC)
- Global Acute Malnutrition (GAM).

"Large Language Models for Constrained-Based Causal Discovery" K-H Cohrs, G. Varando, G. Camps-Valls, AAAI 2024

Outlook

Take-home messages

- All models are wrong, some are useful → Physics-informed AI!
- Prediction is not enough → Explainable AI!
- You can be right for the wrong reason → Causality!

On the quest for “Educated AI”

http://isp.uv.es @isp_uv_es gustau.camps@uv.es