

Atmospheric AI/ML for Radiological Emergencies

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October 24, 2022



Briefing for the Fall 2022 RAMP Meeting



Presentation Outline

- Brief introduction to the National Atmospheric Release Advisory Center
- Machine Learning and AI for Atmospheric Applications
- Deeper dive into rapid hazard predictions

The National Atmospheric Release Advisory Center



<https://narac.llnl.gov/home>



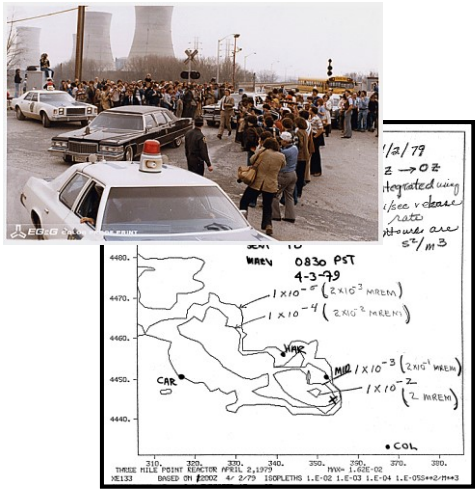
A screenshot of the NARAC website. The browser address bar shows 'https://narac.llnl.gov/home'. The website header includes the Lawrence Livermore National Laboratory logo and the NARAC name. A navigation menu has links for Home, About, Products, Tools, and Research and Development. The main banner features the NARAC logo over a photo of three people in a control room. Below the banner, a text box states: 'Providing expertise and tools to predict and map the spread of hazardous material accidentally or intentionally released into the atmosphere'. To the right of this text is a video player titled 'NARAC Overview' showing a building. The video player controls show a play button, a progress bar at 0:07 / 13:33, and a YouTube logo. Below the video player, the text reads: 'NARAC is a national support and resource center for emergency planning, real-time assessment, emergency response, and detailed studies of atmospheric releases of nuclear, radiological, chemical, biological, and hazardous natural materials. Located at the Department of Energy/National Nuclear Security Administration's (DOE/NNSA) Lawrence Livermore National Laboratory (LLNL), NARAC provides timely and accurate plume predictions to aid emergency preparedness and response efforts in protecting the public and the environment. Since 1979, NARAC has provided support for numerous accidents or potential incidents, and celebrated its 40th anniversary in 2019.'

NARAC provides expertise and tools to predict and map the spread of hazardous material released into the atmosphere

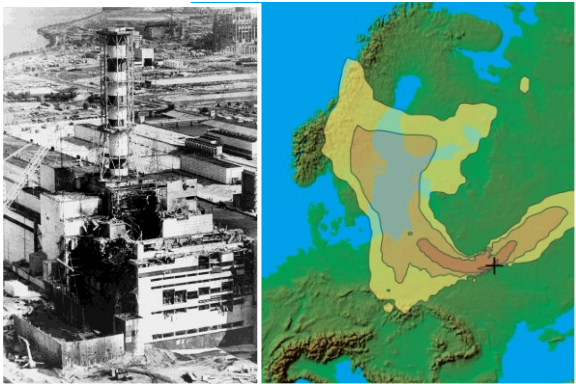


Four decades of NARAC response

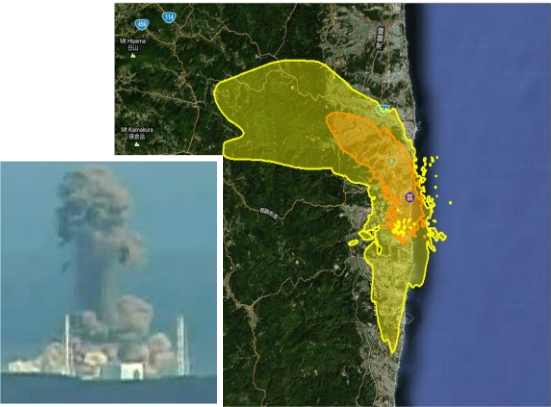
1979
Three Mile
Island
nuclear
power plant,
Harrisburg,
PA, USA



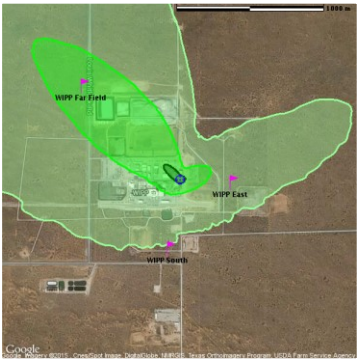
1986
Chernobyl
nuclear
power plant
accident,
USSR



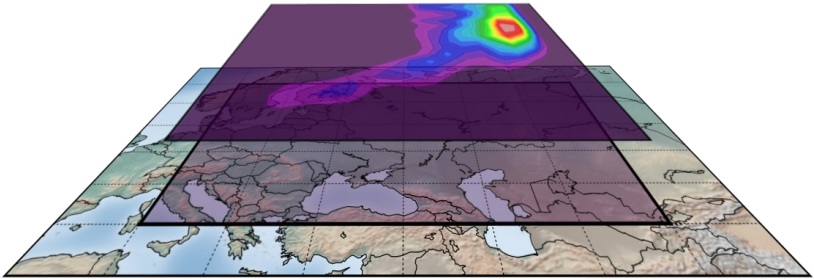
2011
Fukushima
Daiichi nuclear
power plant
accident,
Japan



2014
Waste Isolation
Pilot Plant release



2017 Ruthenium-106 Detections

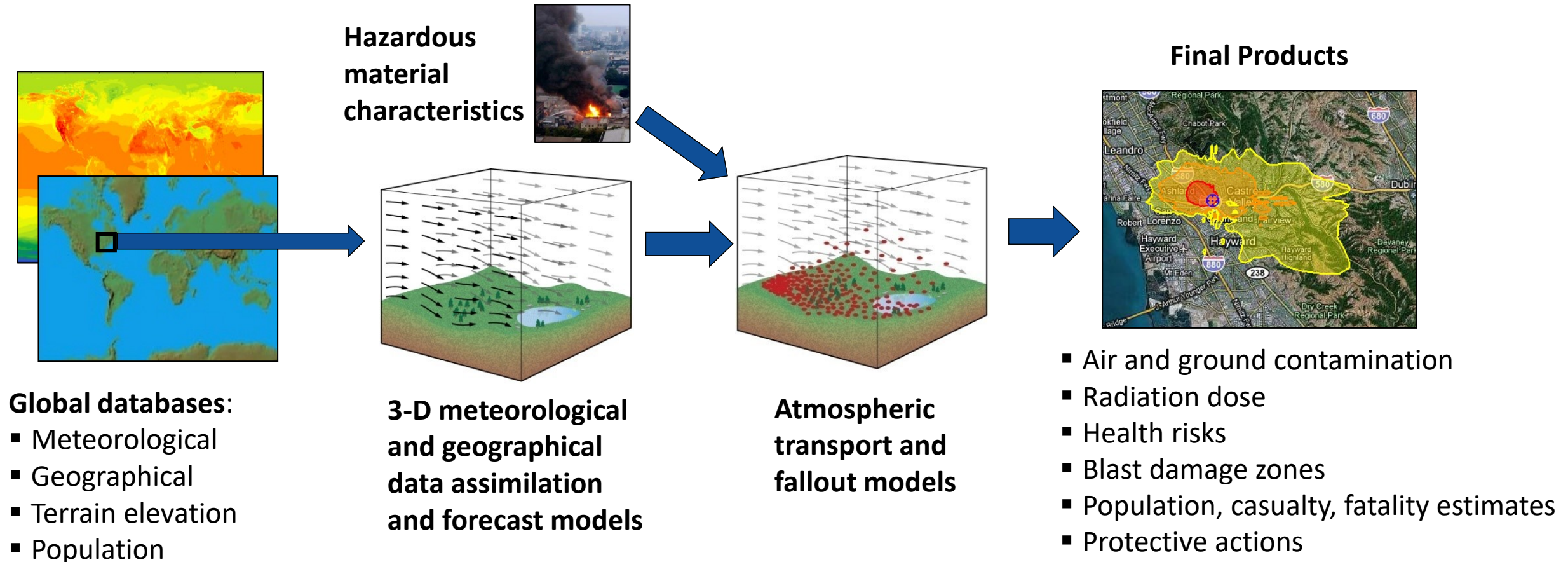


Monitoring
plan (zero
detect)

2019 Seattle
Harborview
release



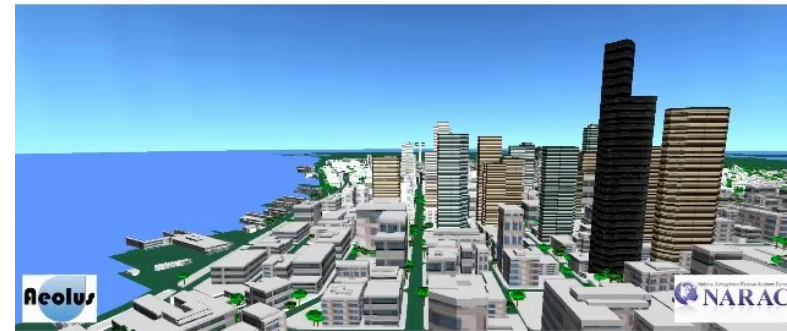
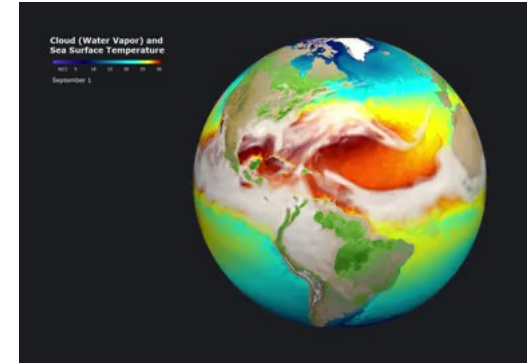
NARAC's computer modeling system provides worldwide real-time 3-D airborne plume model predictions



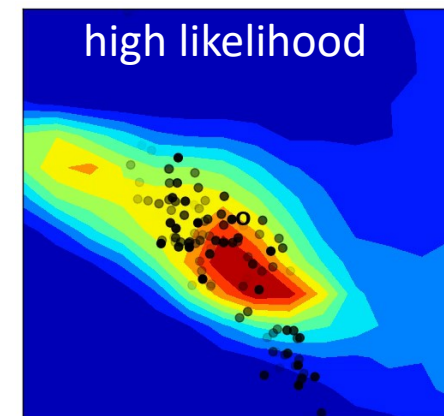
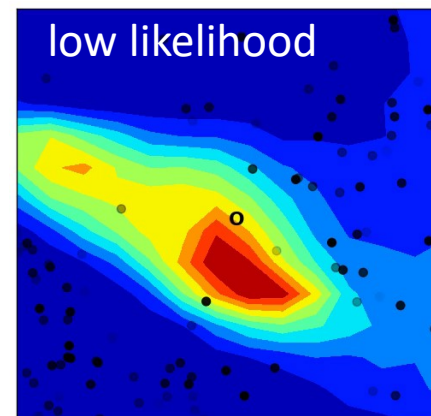
Software automation allows initial model predictions to be produced in 15 minutes

Atmospheric research for operations

- Research in physics and applied mathematics is breaking new ground
 - Characterize and parameterize atmospheric processes
 - Characterize sources of hazardous material
- Research benefits from
 - Subject matter expertise in all areas
 - High performance computing (HPC)
 - Long analysis timelines
- Operational missions require predictive methods with confidence and speed.



Advanced physics codes



Machine learning improves our analyses and speeds up our models

Machine Learning Accelerates Scientific Simulations and Analysis

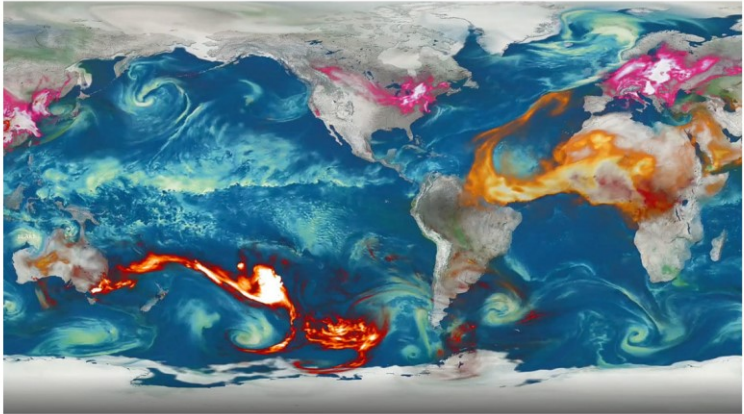
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958

42



Emulators speed up simulations, such as this NASA aerosol model that shows soot from fires in Australia. NASA

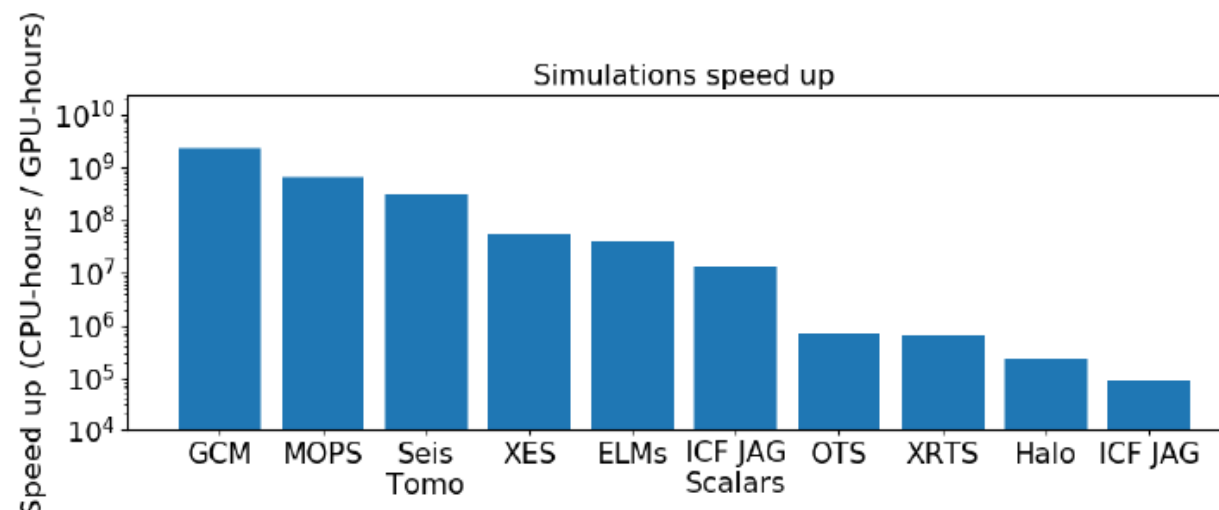
From models of galaxies to atoms, simple AI shortcuts speed up simulations by billions of times

By [Matthew Hutson](#) | Feb. 12, 2020, 2:35 PM

Modeling immensely complex natural phenomena such as how subatomic particles interact or how atmospheric haze affects climate can take many hours on even the fastest supercomputers. Emulators, algorithms that quickly approximate these detailed simulations, offer a shortcut. Now, work posted online shows how artificial intelligence (AI) can easily produce accurate emulators that can accelerate simulations across all of science by billions of times.

"This is a big deal," says Donald Lucas, who runs climate simulations at Lawrence Livermore National Laboratory and was not involved in the work. He says the new system automatically

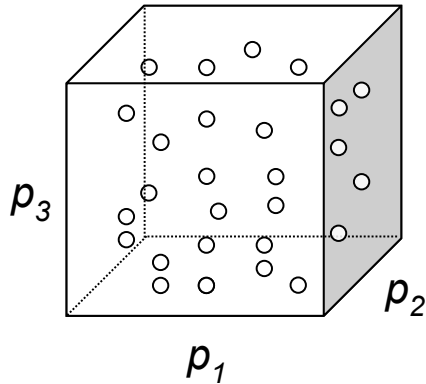
My interview with *Science Magazine* about the potential of adaptive deep learning techniques



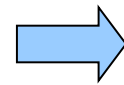
<https://sciencemag.org/news/2020/02/models-galaxies-atoms-simple-ai-shortcuts-speed-simulations-billions-times>

Simulations are Used to Create Training and Testing Data

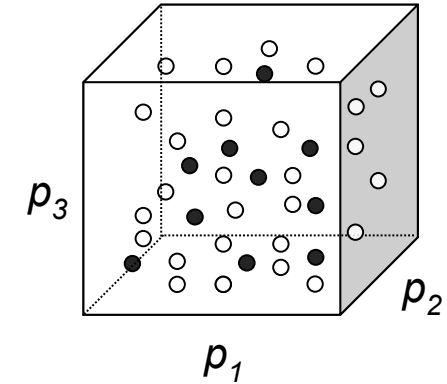
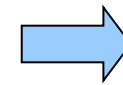
Supervised Machine Learning



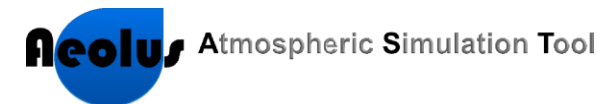
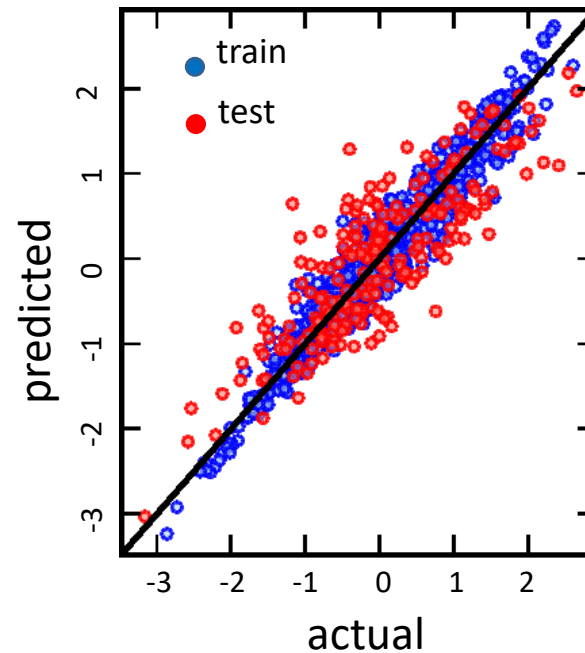
○ = Simulations at different model configurations and/or parameter values



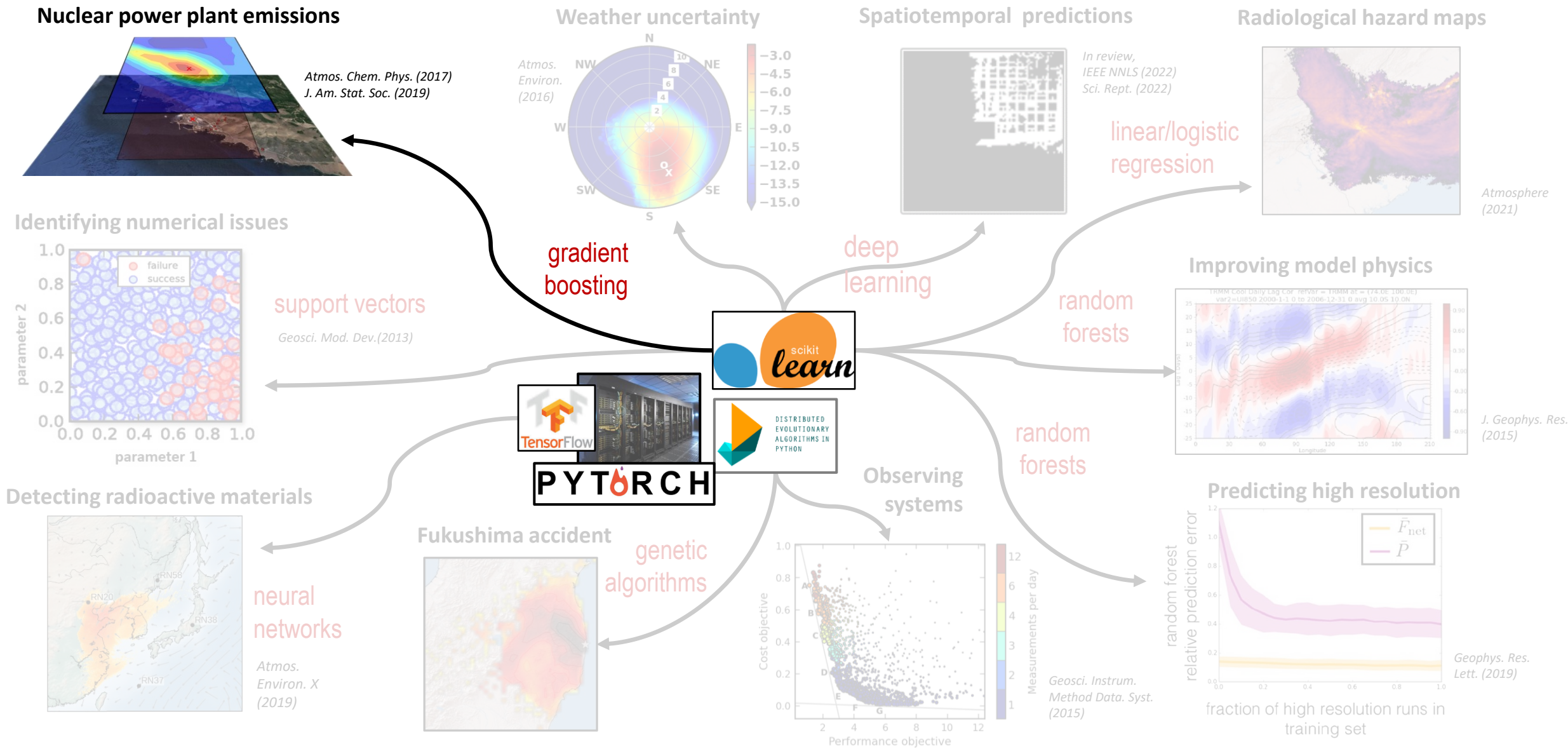
$$R = f(p_1, p_2, p_3, \dots)$$



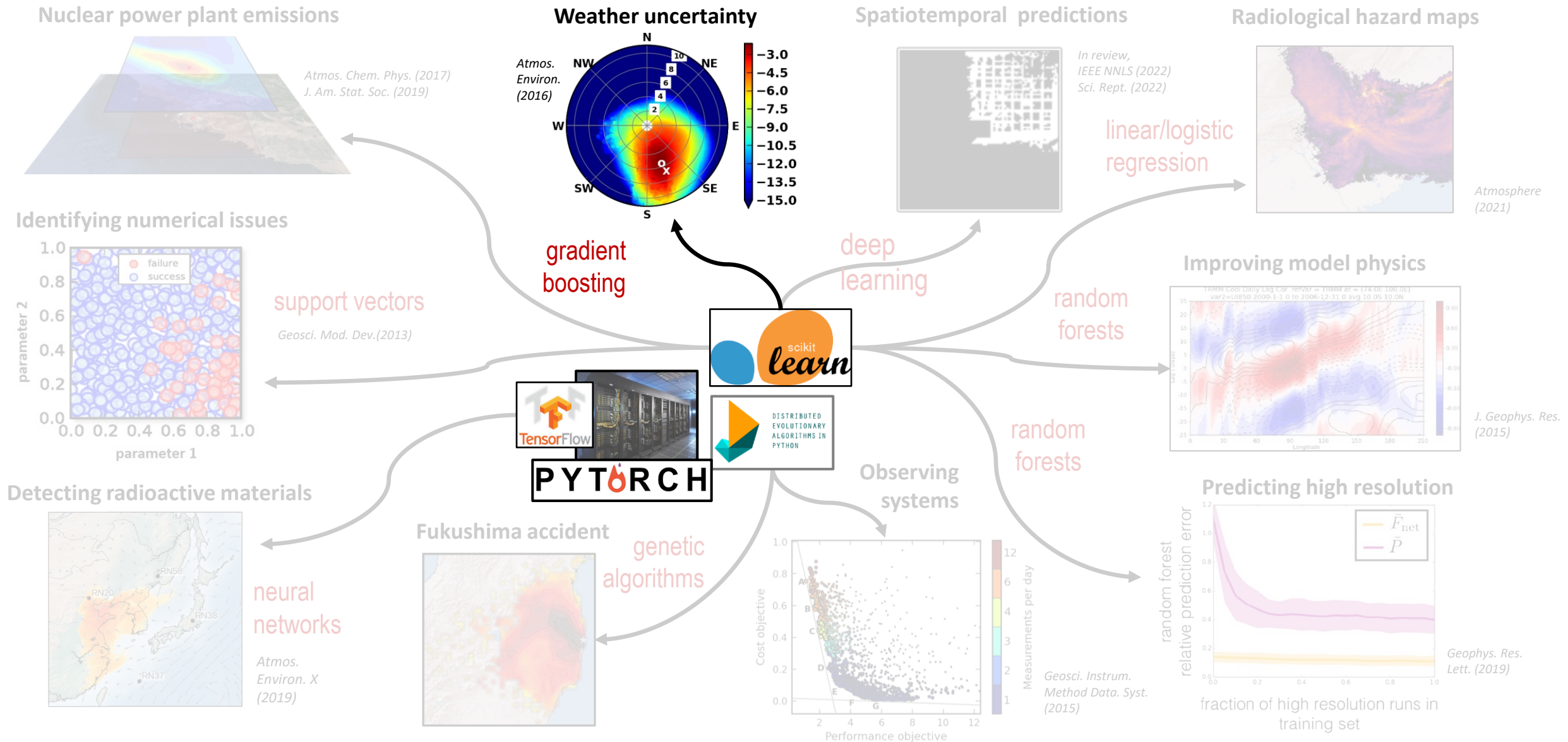
● = Predictions at new configurations and/or values



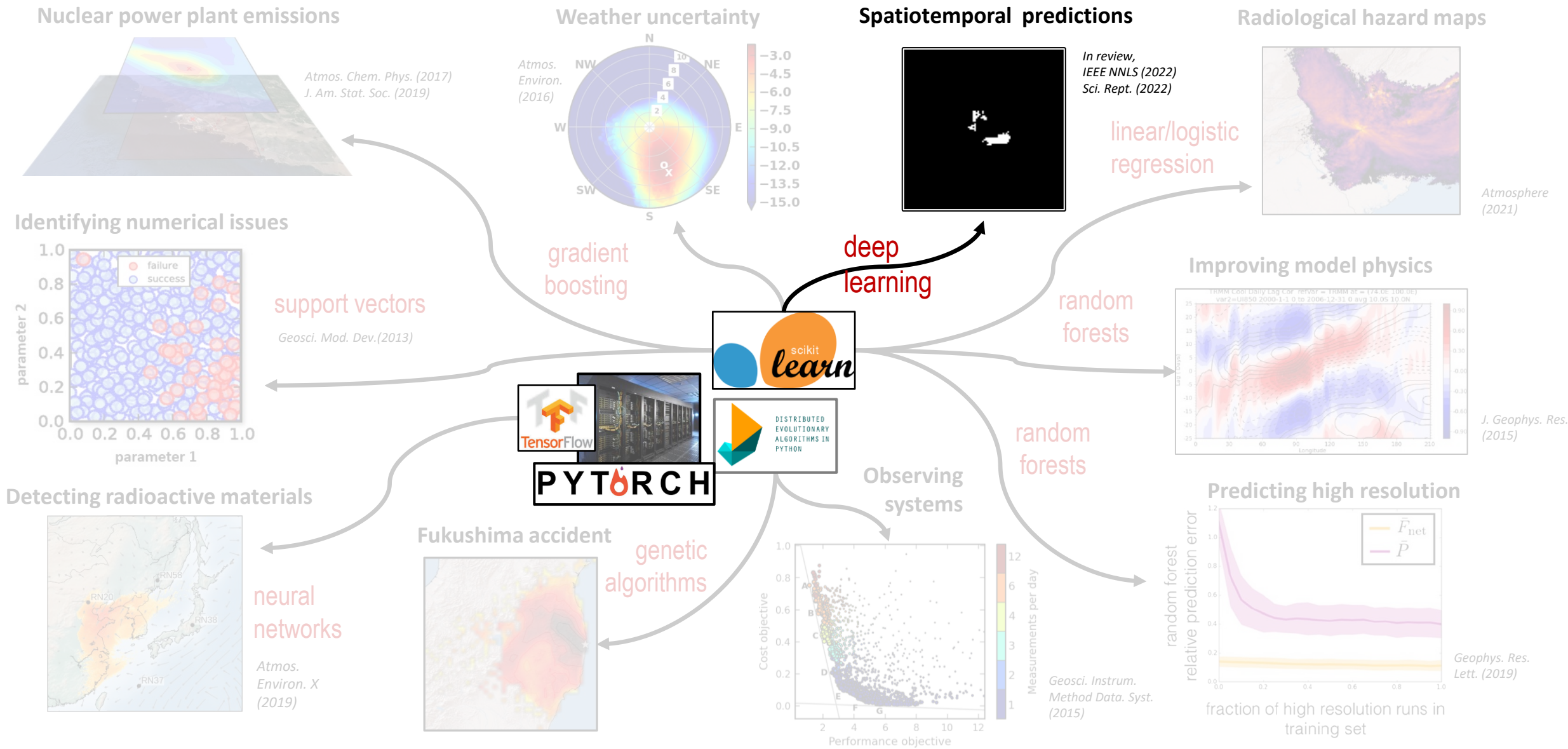
Over 10 Years of ML/AI Applications



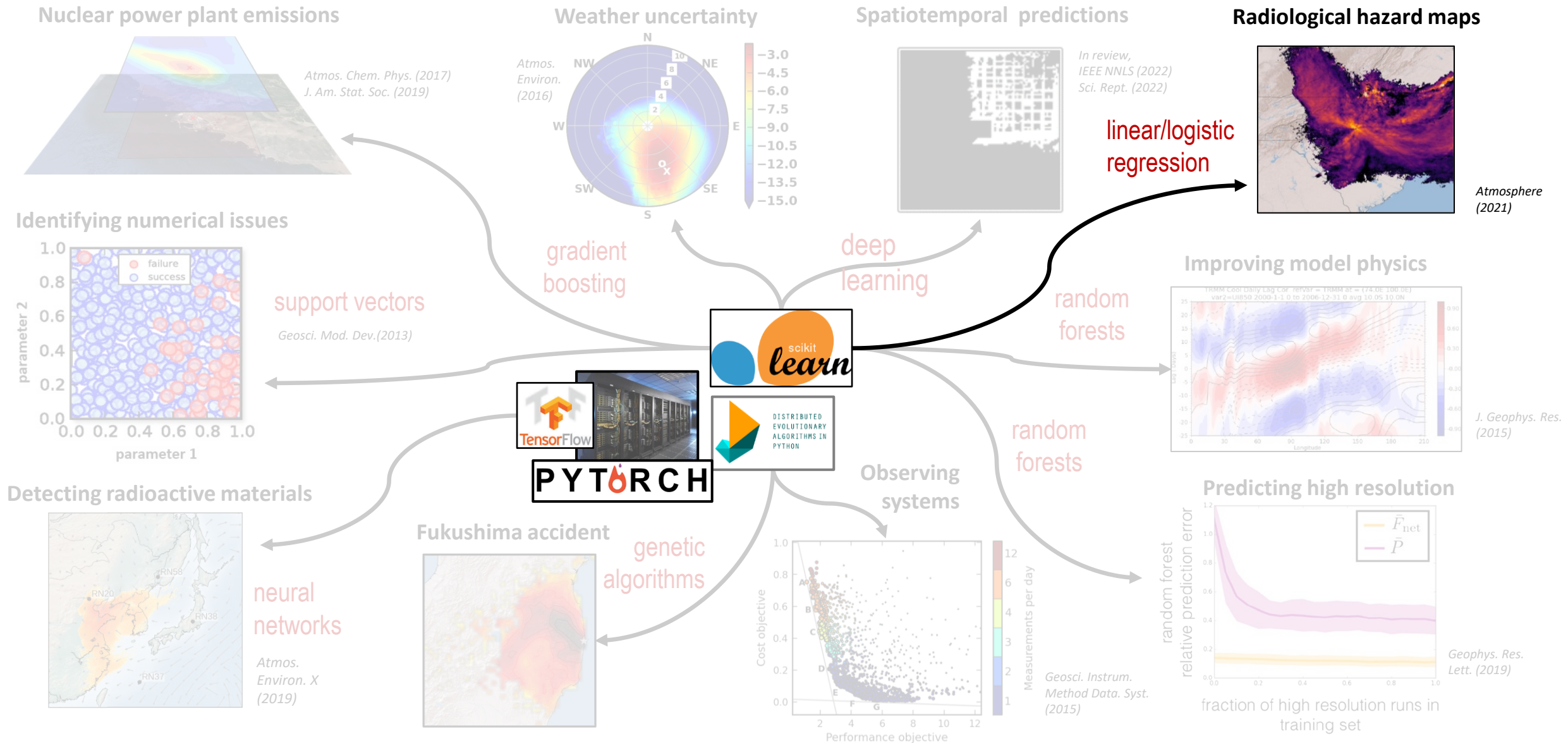
Over 10 Years of ML/AI Applications



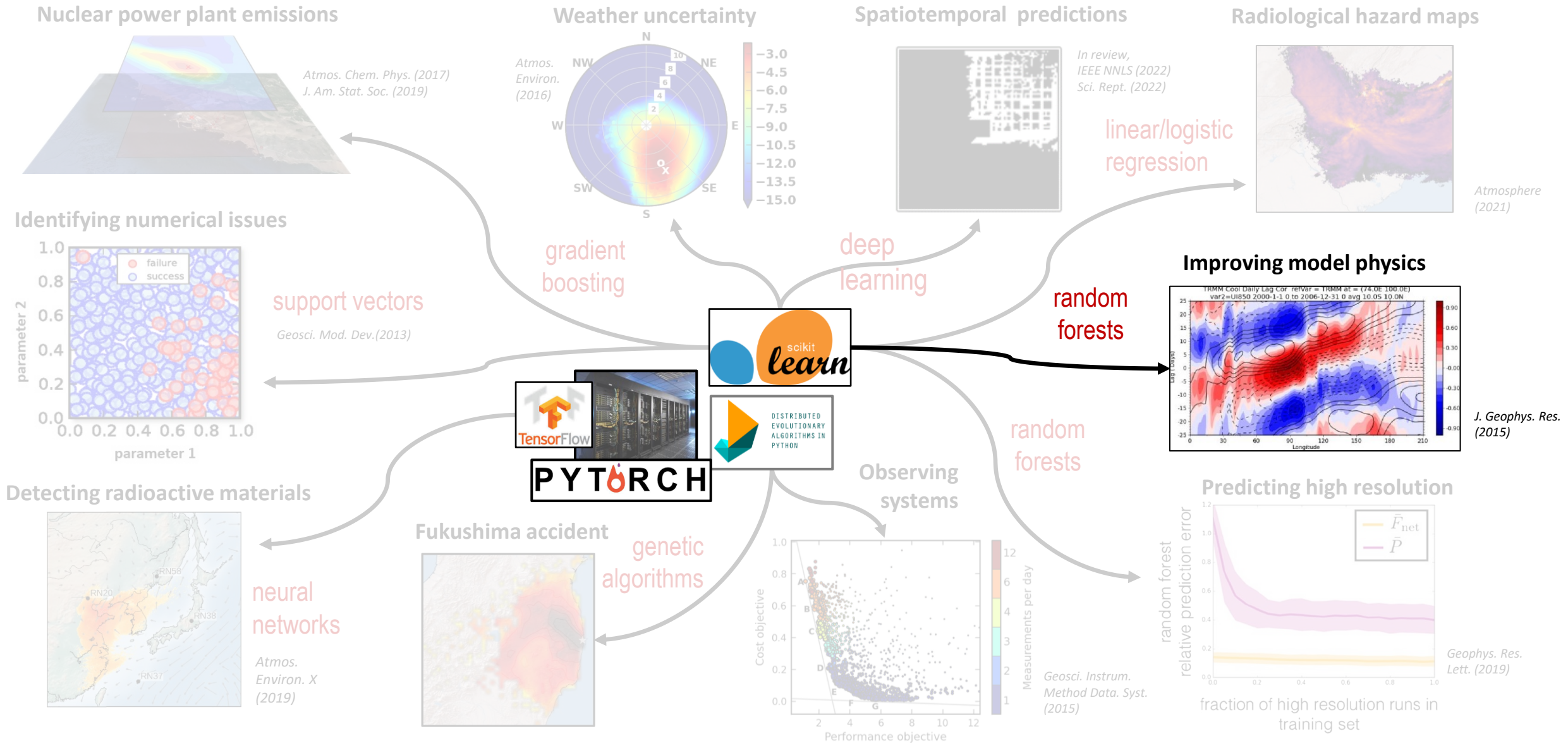
Over 10 Years of ML/AI Applications



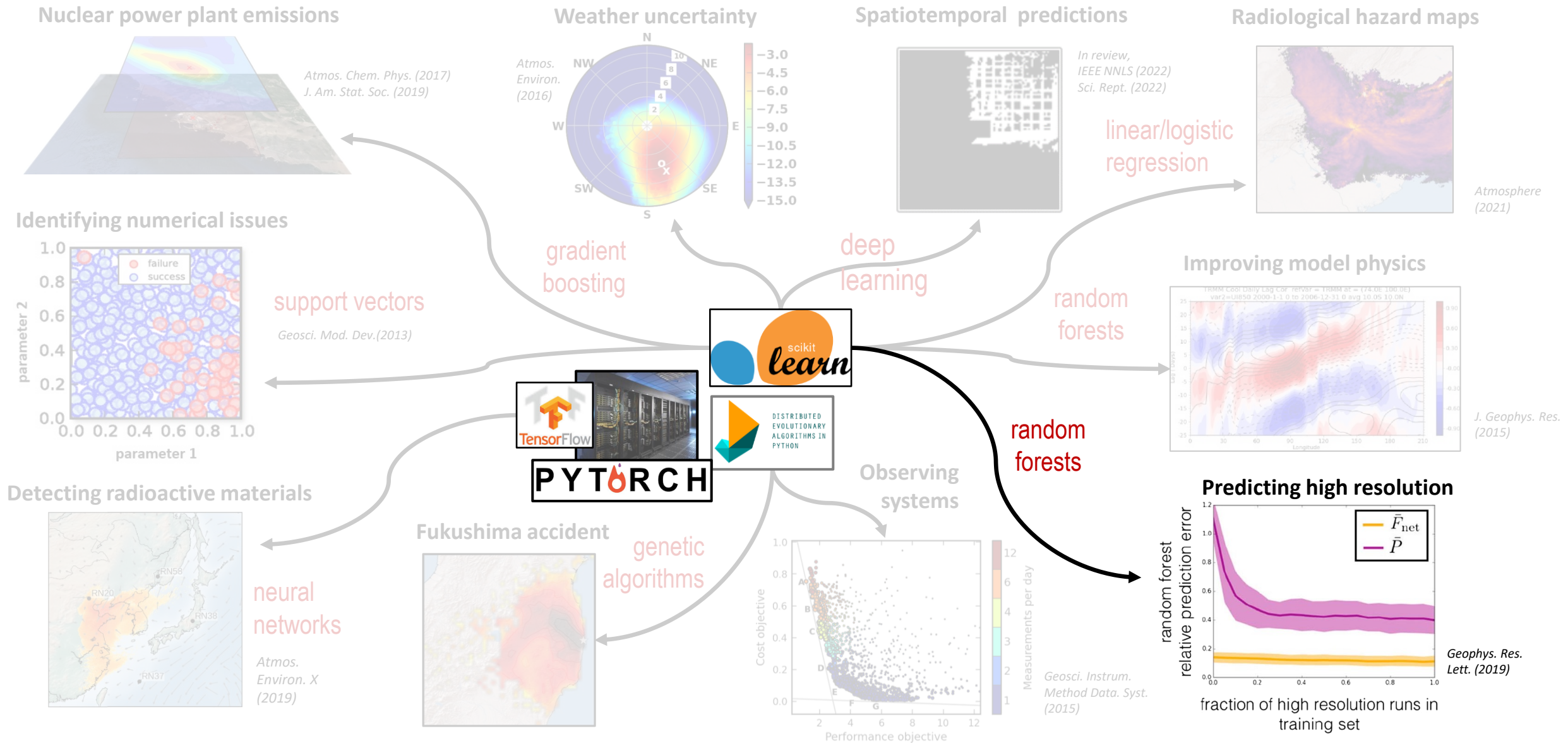
Over 10 Years of ML/AI Applications



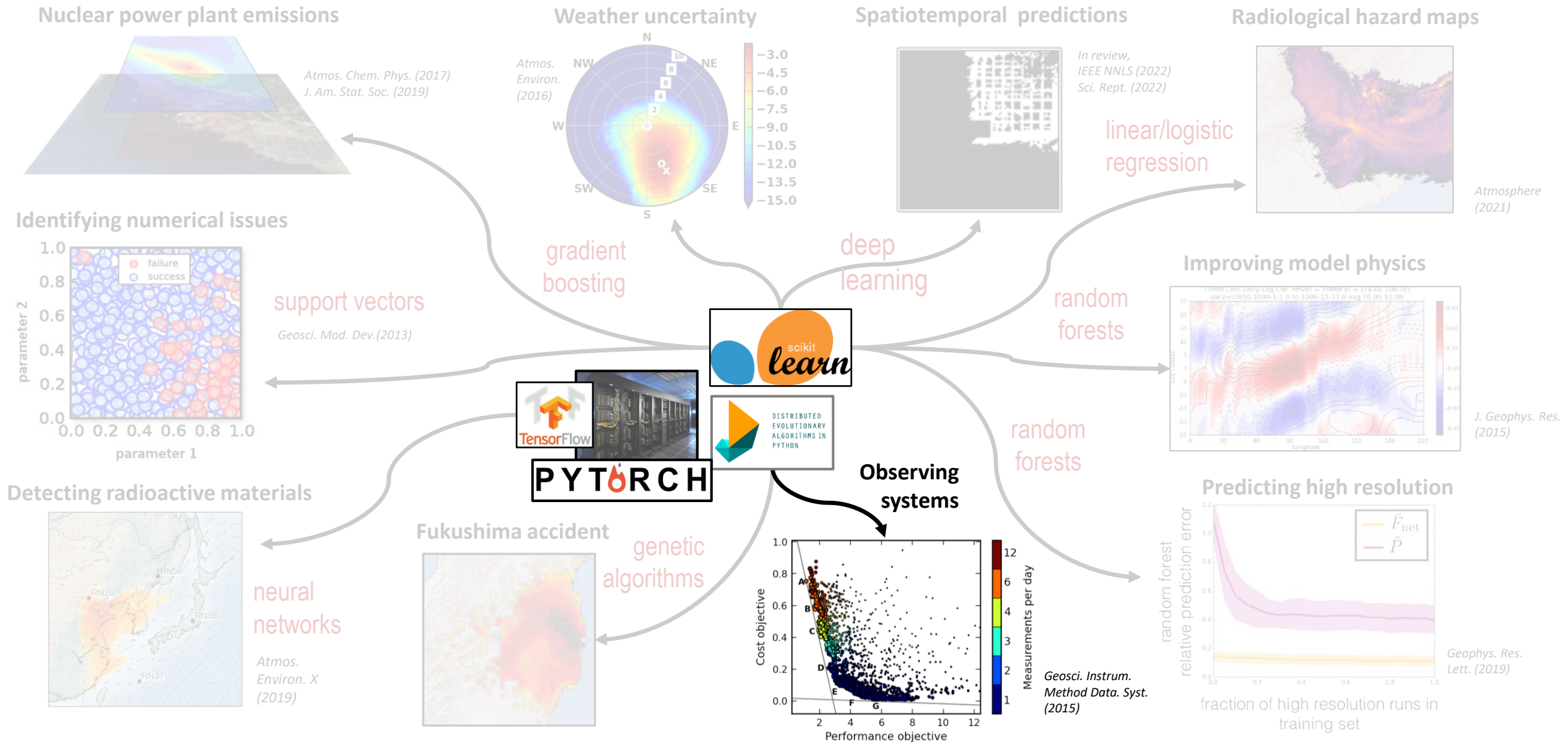
Over 10 Years of ML/AI Applications



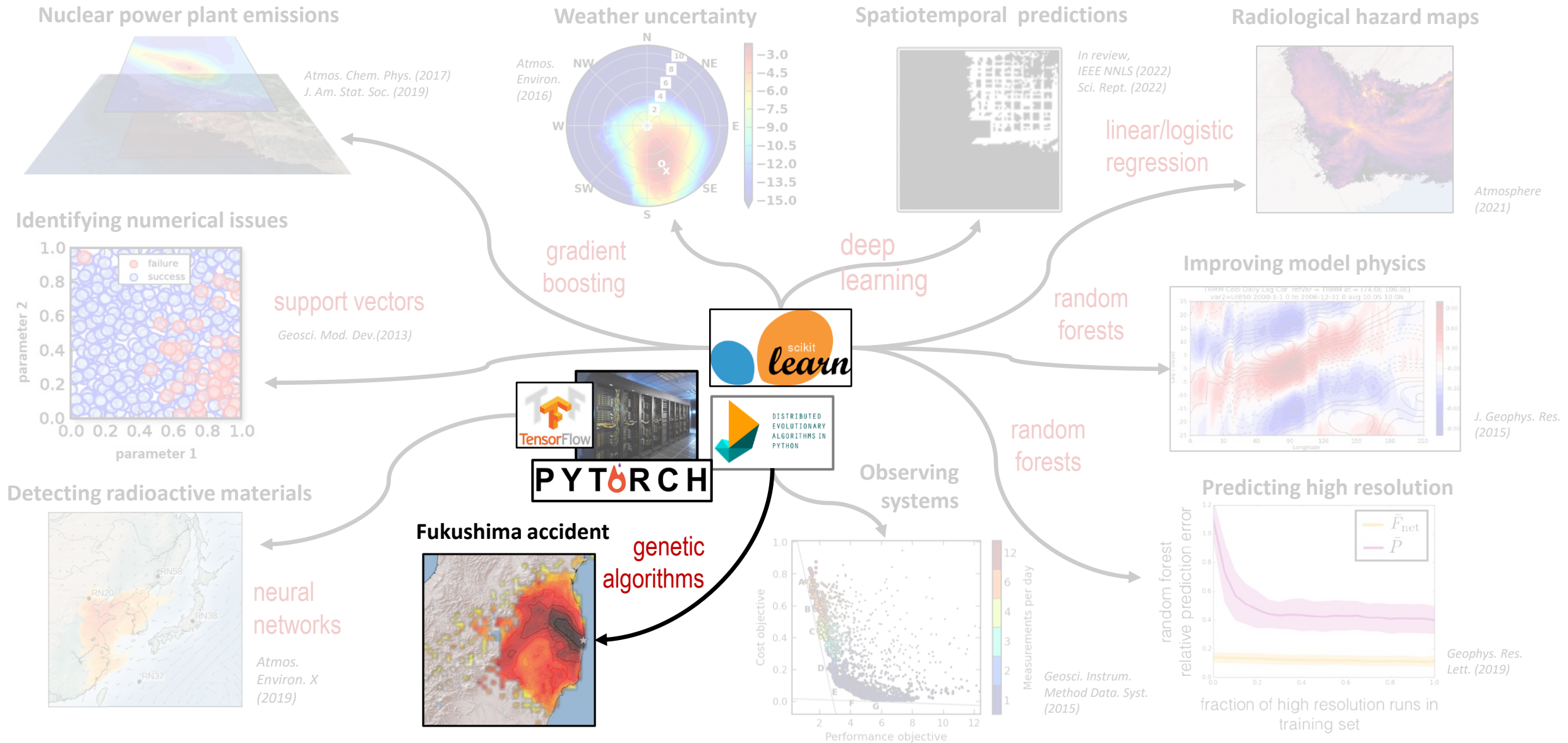
Over 10 Years of ML/AI Applications



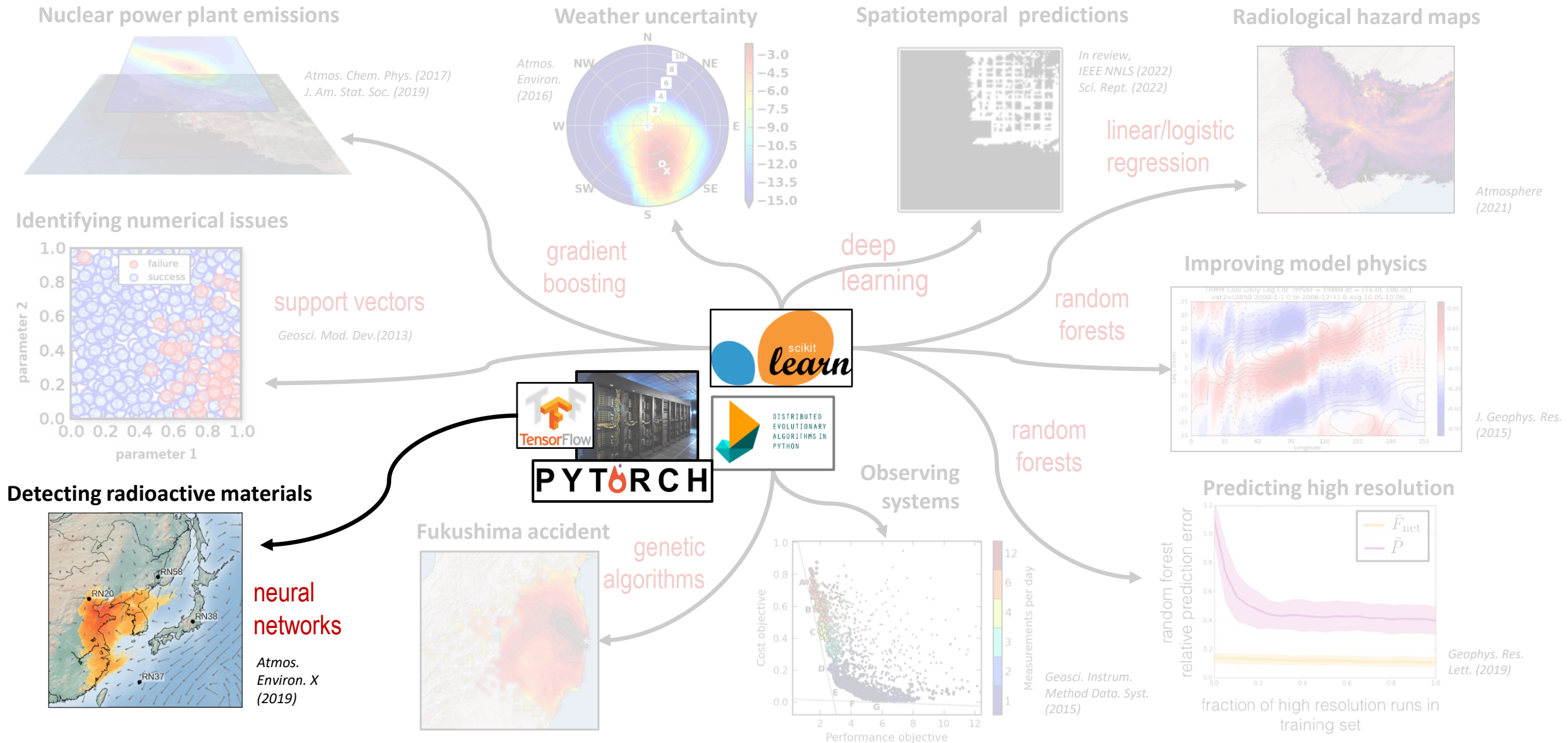
Over 10 Years of ML/AI Applications



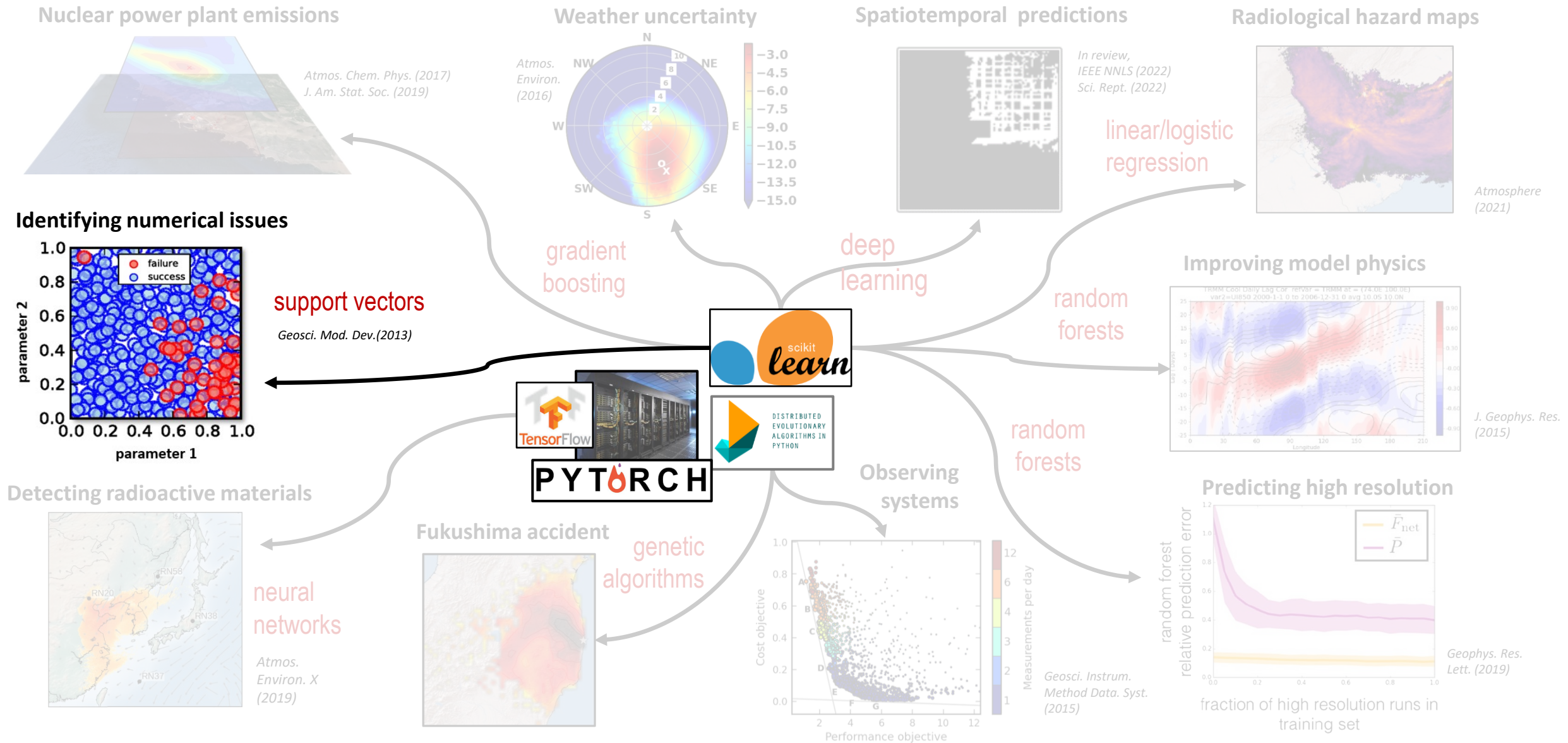
Over 10 Years of ML/AI Applications



Over 10 Years of ML/AI Applications

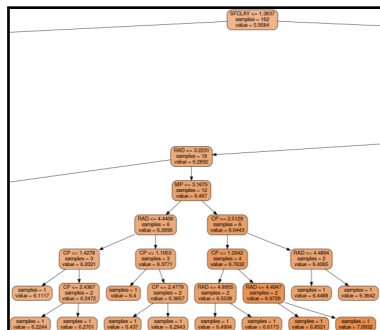


Over 10 Years of ML/AI Applications

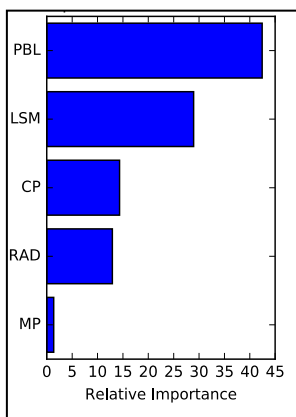


Predicting Radiological Hazard Maps with Machine Learning

Large weather ensembles are computationally expensive.



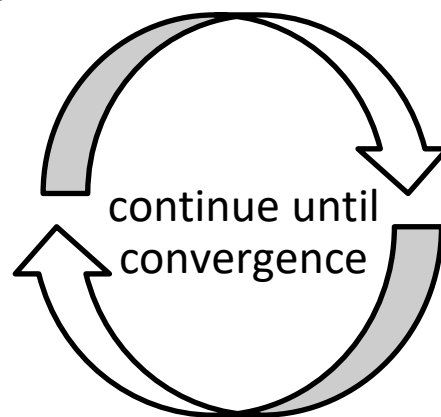
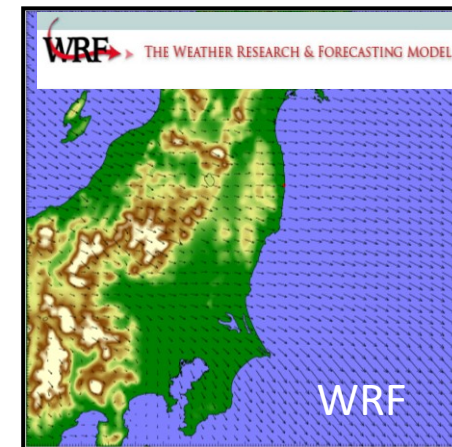
4. Apply machine learning to predict new physics configurations



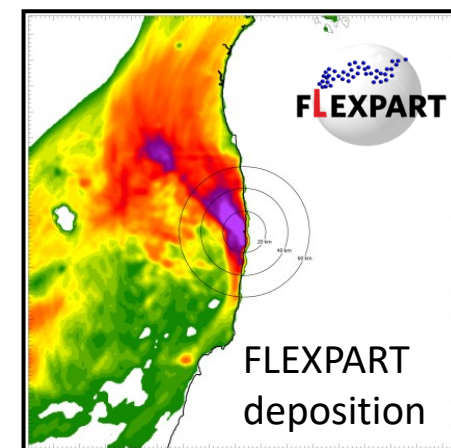
3. Use machine learning to quantify effects of model physics uncertainty

scikit-learn
Machine Learning in Python

1. Run simulation from weather ensemble for training/testing



2. Use weather data for transport simulations



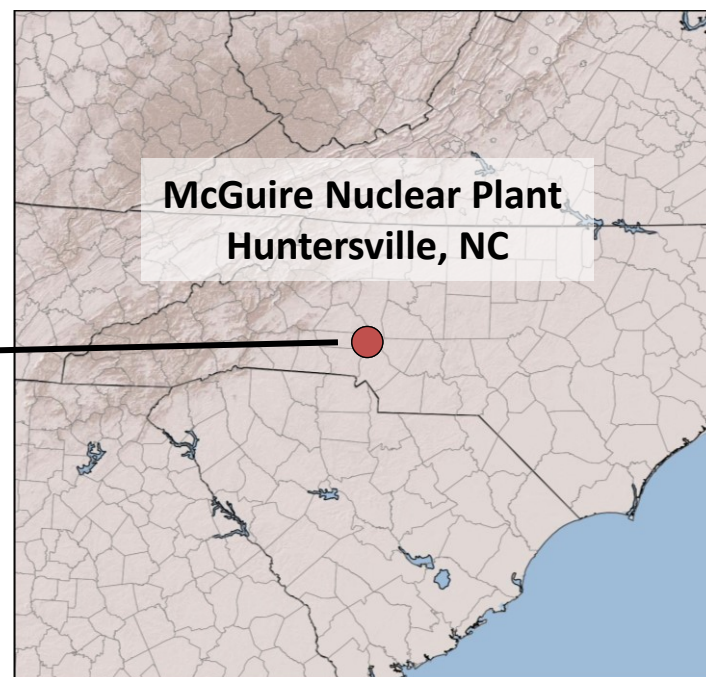
Predicting Radiological Hazard Maps with Machine Learning

- **Two-day forecast of hypothetical** release of cesium-137 near Charlotte, North Carolina, April 2018.
- **Weather** forecast uncertainty from different weather model configurations.
- **Transport** of Cs-137 using a community transport and dispersion model.

Hypothetical release
1 kg Cs-137 over 2 days



(4 kg and 25 kg of Cs-137 were released during Fukushima and Chernobyl, respectively.)



1200 weather forecasts!

Five Categories of Weather Model Physics Uncertainty

- 5 x Planetary boundary layer (PBL)
- 4 x Land surface models (LSM)
- 5 x Cumulus convection (CP)
- 4 x Microphysics (MP)
- 3 x Short and Longwave Radiation (RAD)

Predicting Radiological Hazard Maps with Machine Learning

Open Access

Article

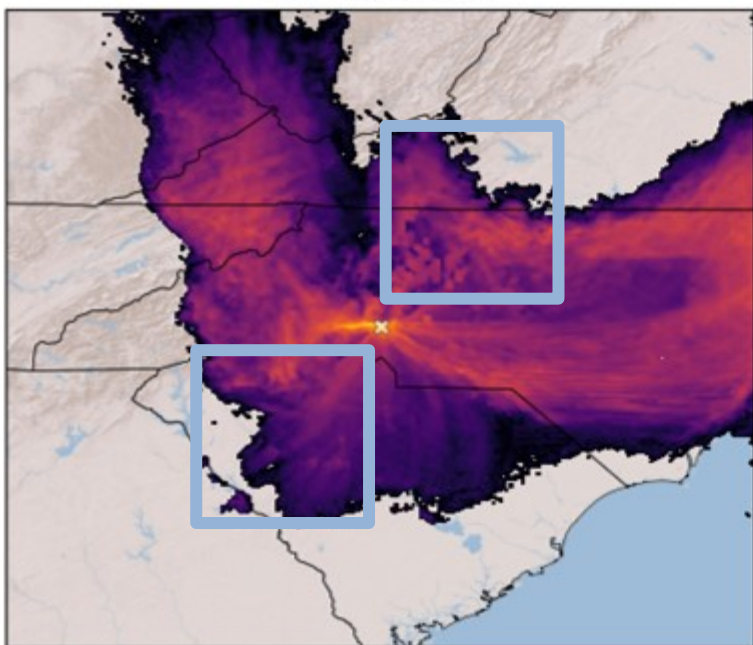


Machine Learning Emulation of Spatial Deposition from a Multi-Physics Ensemble of Weather and Atmospheric Transport Models

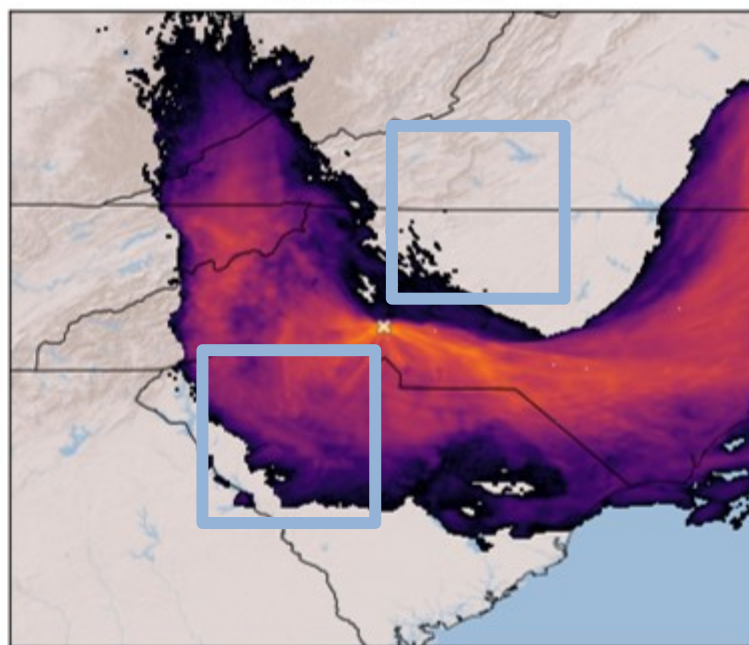
by Nipun Gunawardena ^{1,*} , Giuliana Pallotta ¹ , Matthew Simpson ² and Donald D. Lucas ^{1,*}

Ensemble members predict radiological contamination in different places

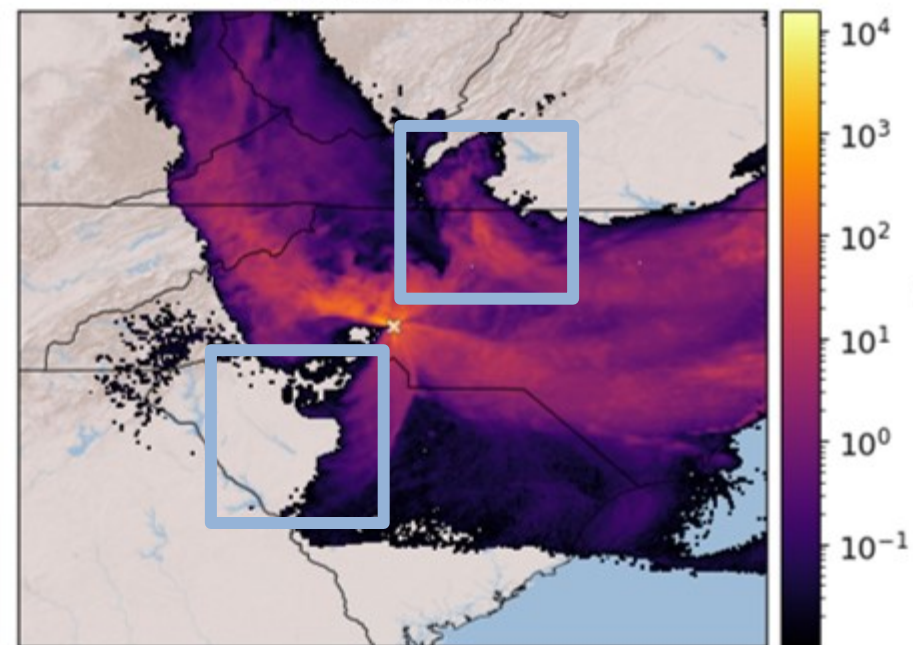
Member 245



Member 413

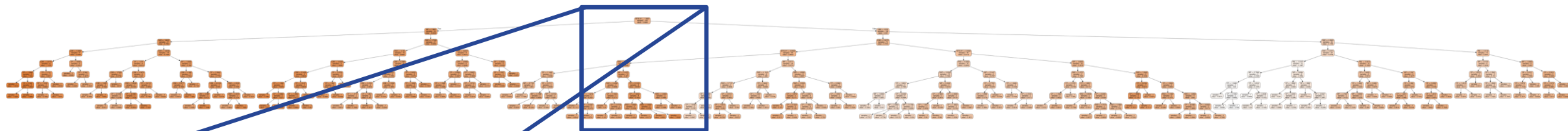


Member 1157

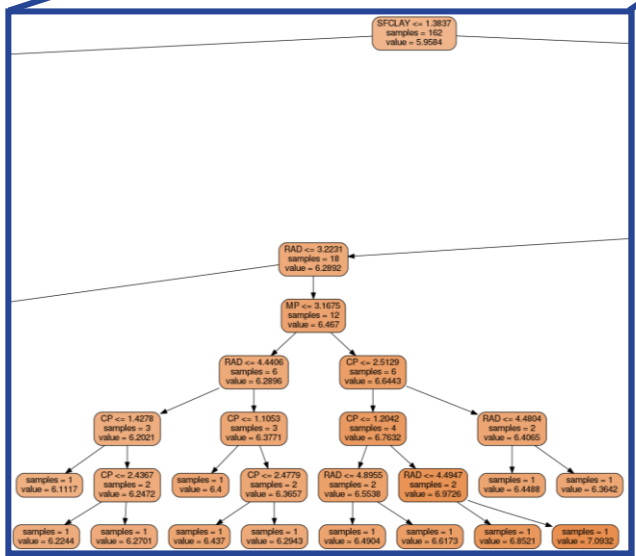


maps show cumulative radiological deposition over two days

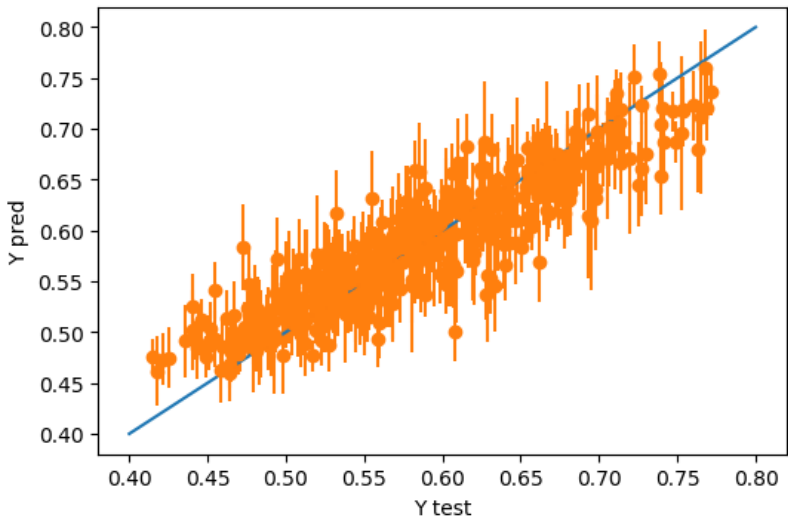
Predicting Radiological Hazard Maps with Machine Learning



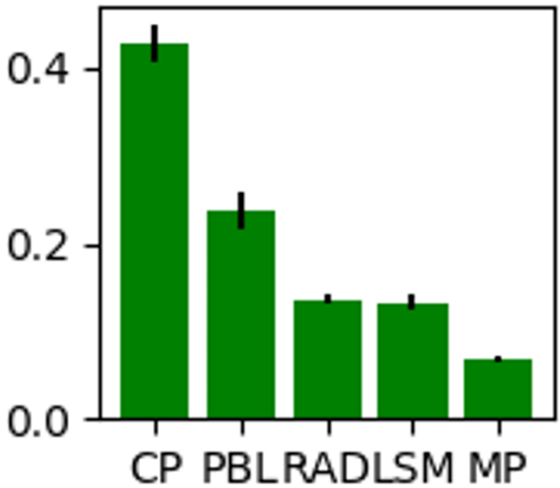
Example of a decision tree in a random forest trained on weather ensemble



Random forests and other machine learning algorithms are used to predict untested ensemble members.



Hold out data and cross validation are used to assess the machine learning algorithms.



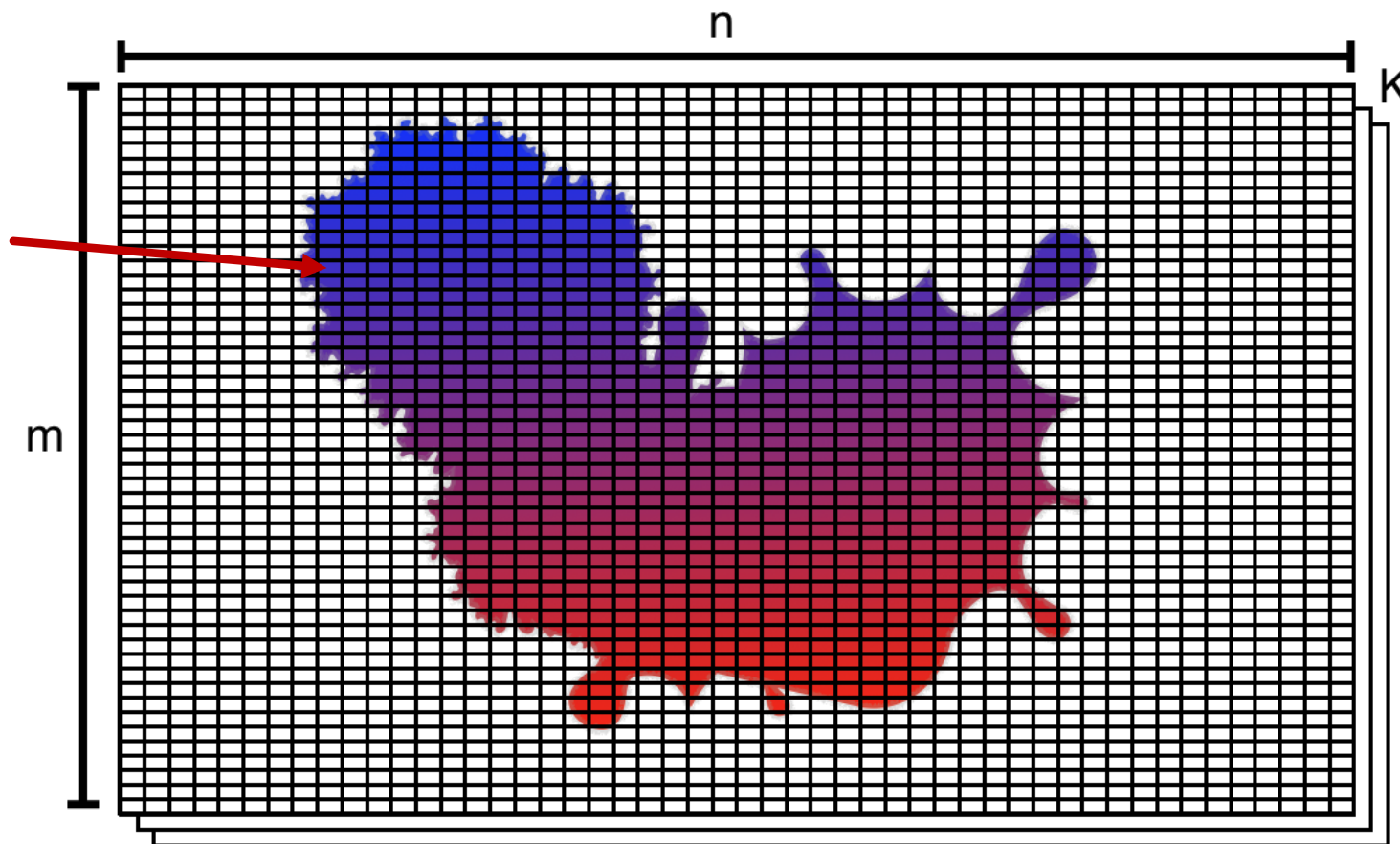
Training provides information about ensemble variability “features.”

Predicting Radiological Hazard Maps with Machine Learning

Each model output is an $m \times n$ grid

Each grid cell modeled by a combined logistic and linear regression system

For a 400x400 grid, we make predictions for 160,000 grid cells



K=1200
deposition maps
are used as
training data

Logistic regressions
predict the
presence of Cs-137

Linear regressions
predict the value

Predicting Radiological Hazard Maps with Machine Learning

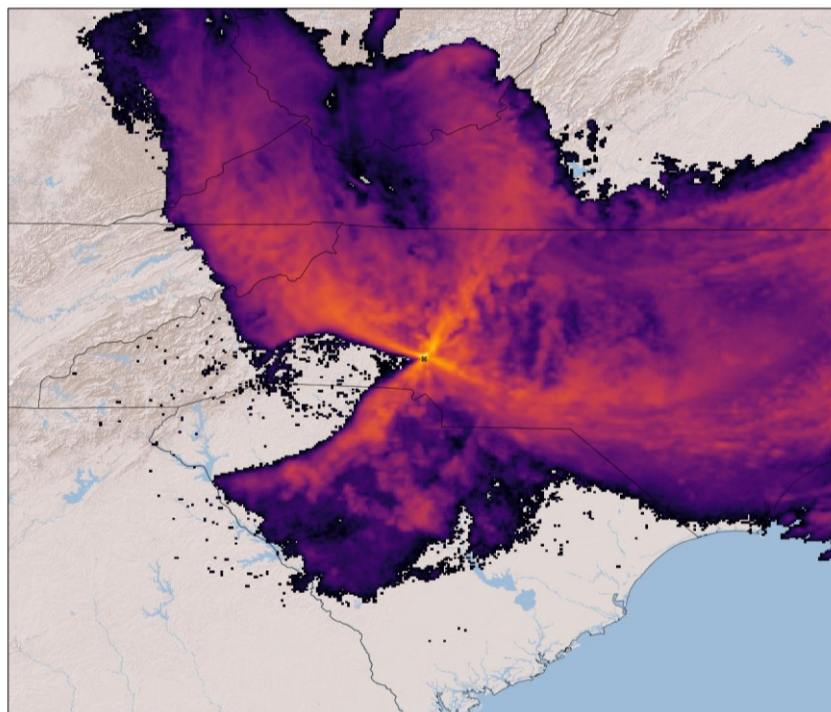
Q1: Which map is from the weather model and machine learning?

Q2: How many training examples were used for machine learning?

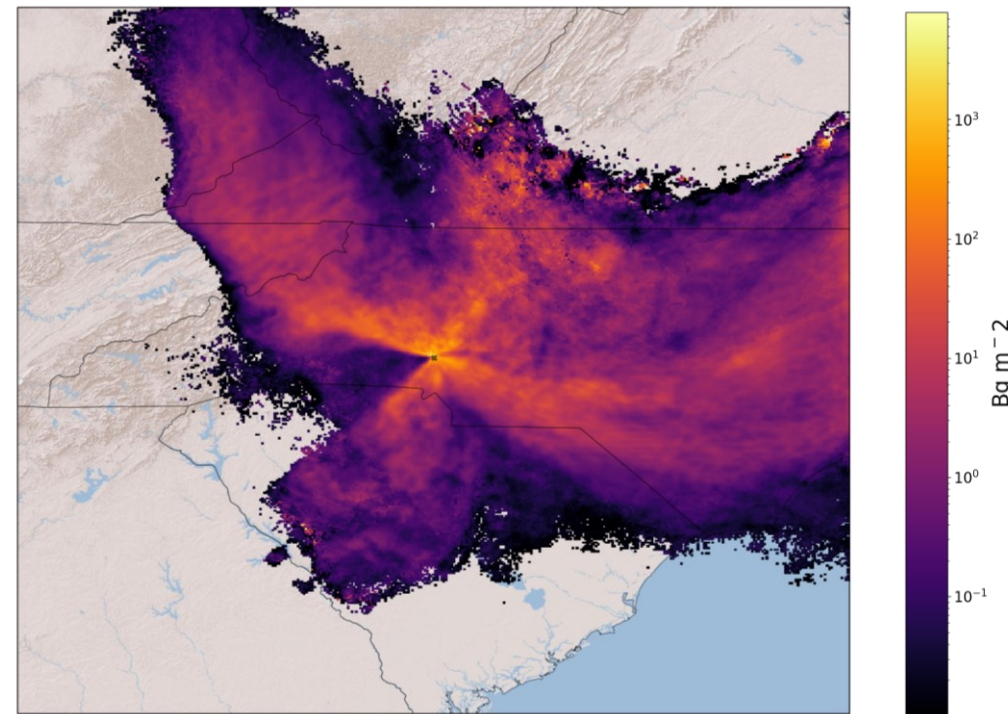
Weather model takes 3 hours to run on a super-computer.

Machine learning prediction takes milliseconds on a laptop.

Map A



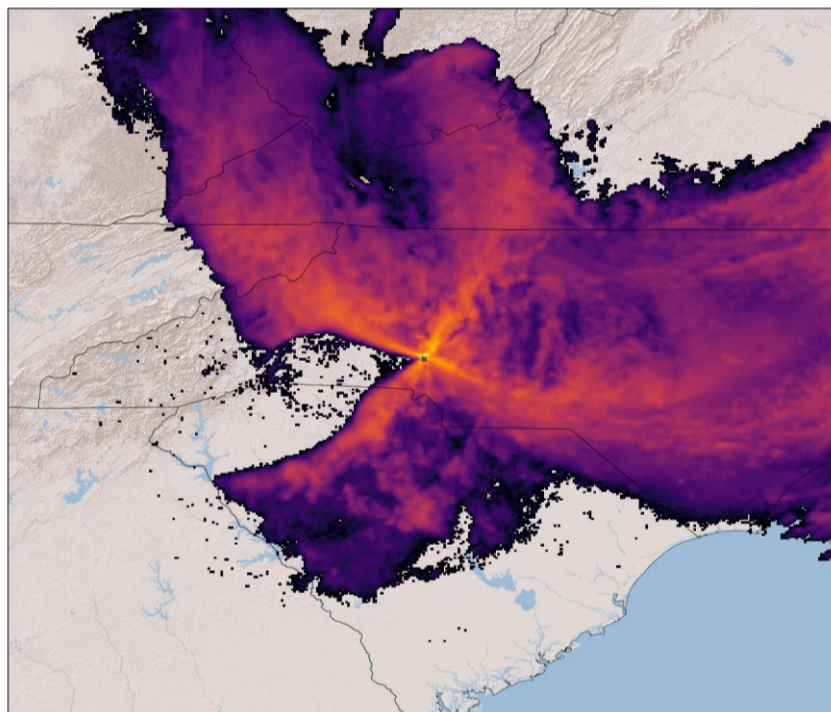
Map B



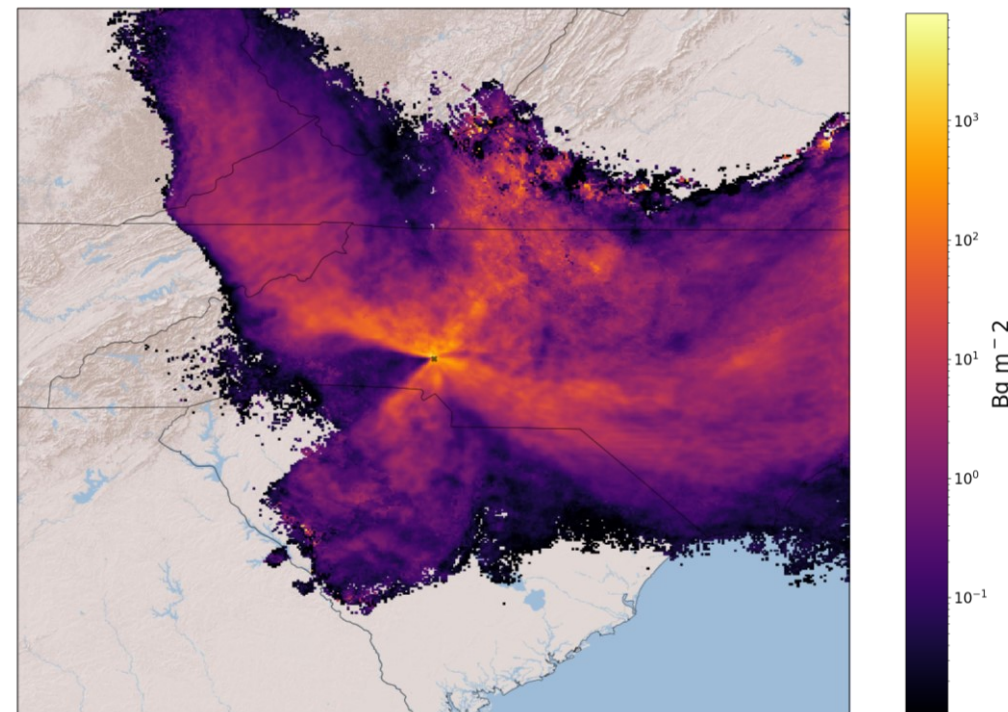
Predicting Radiological Hazard Maps with Machine Learning

Only 50 training samples used!

Map A: **Weather Model**



Map B: **Machine Learning**



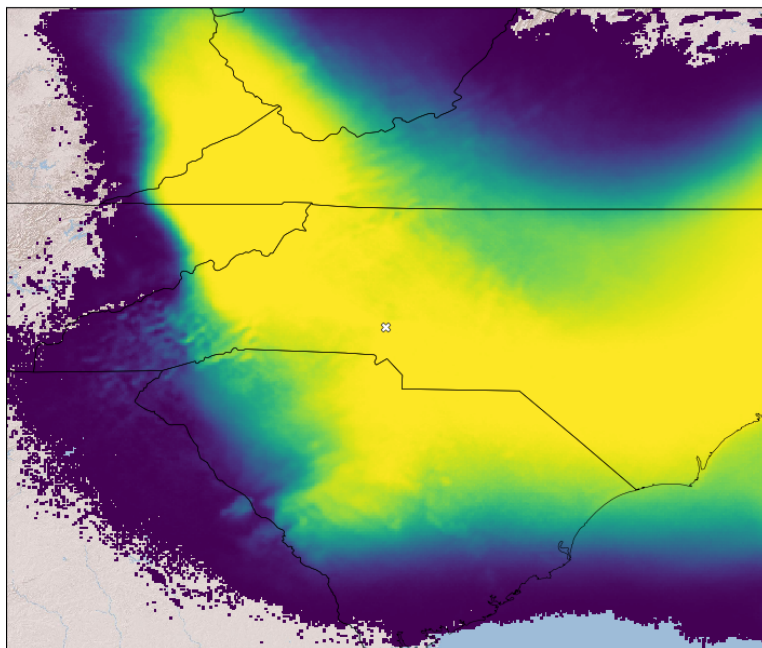
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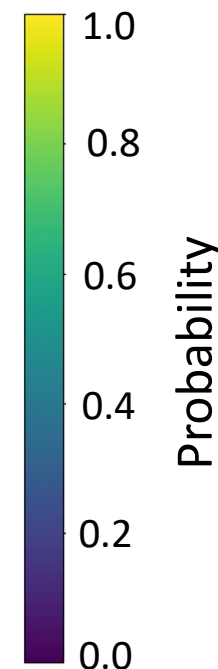
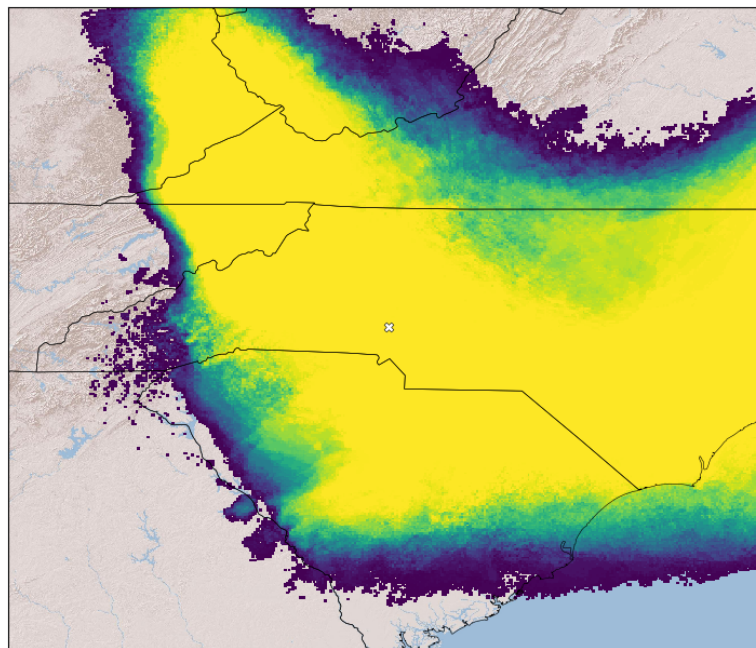
Predicting Radiological Hazard Maps with Machine Learning

Rapidly Estimate the Probability of Contamination

Weather Ensemble



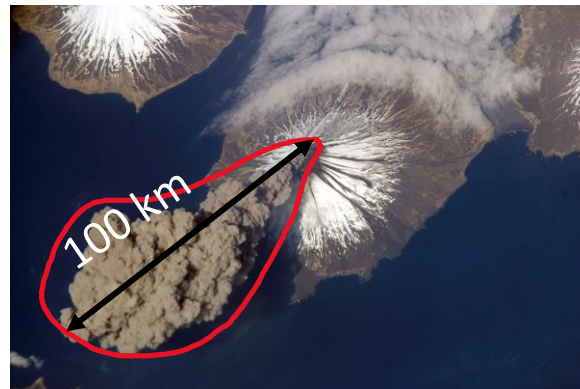
ML Prediction



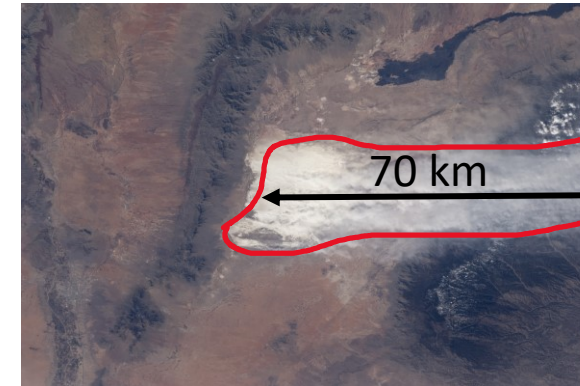
Probability of exceedance maps show the percentage of ensemble members that have a value above a threshold at a given location. Left shows the 1,200-member weather ensemble, right is predicted using 50 training examples.

Predicting Images of Wind-Driven Spatial Maps with Deep Learning

The Alaskan
Cleveland
Volcano eruption
on May 23, 2006



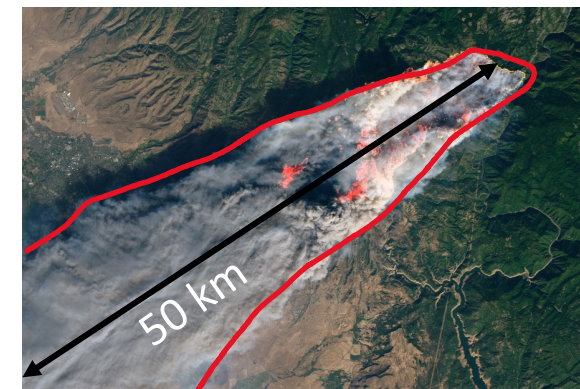
Storm in the White
Sands dune field in
New Mexico on
February 28, 2012



Accident at
Fukushima Daiichi
Nuclear Power Plant
on March 11, 2011



On November 8,
2018, a campfire
erupted in north
California

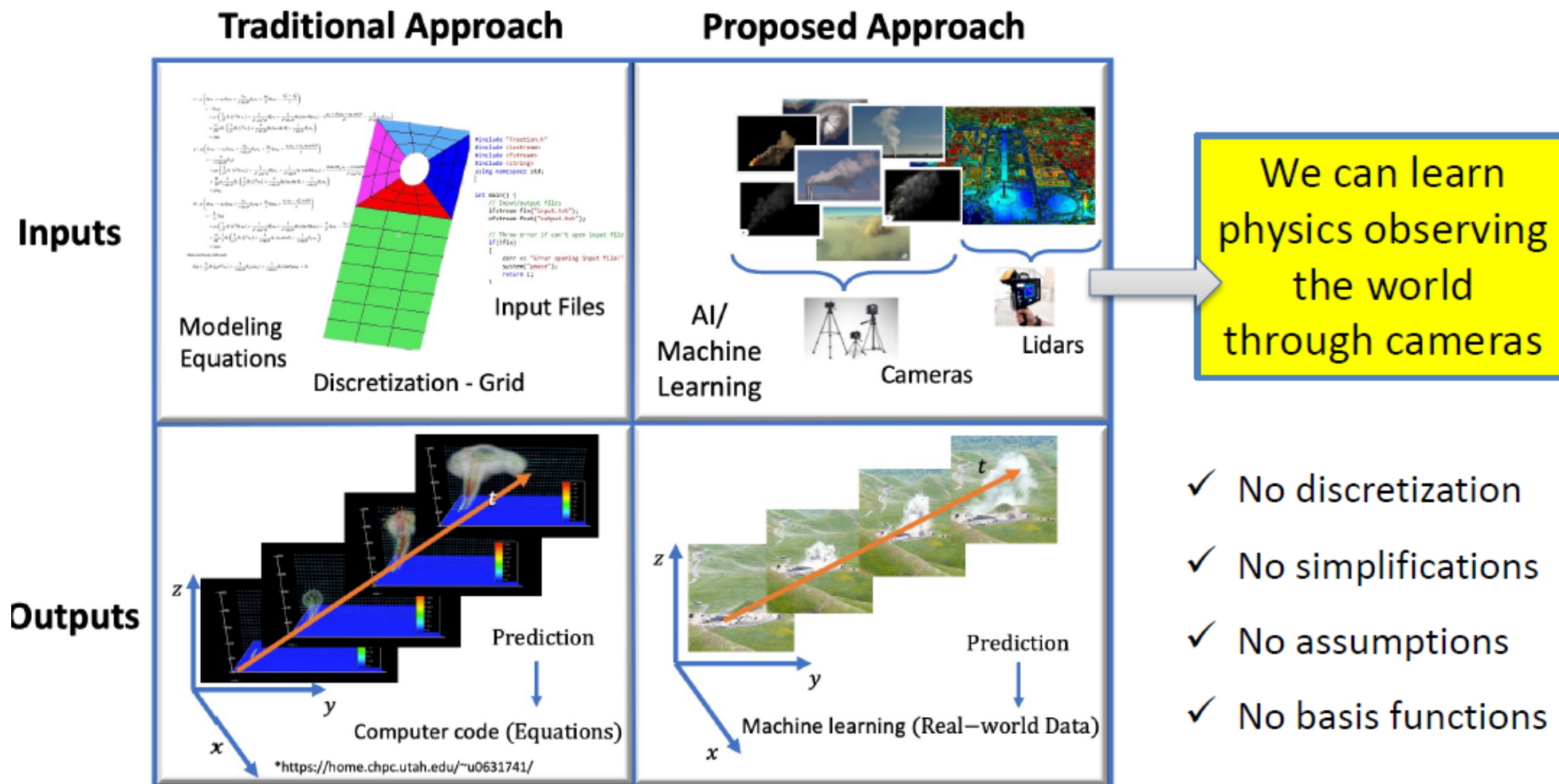


Predicting Images of Wind-Driven Spatial Maps with Deep Learning

Learning Physics through Images: An Application to Wind-Driven Spatial Patterns

Under
Review

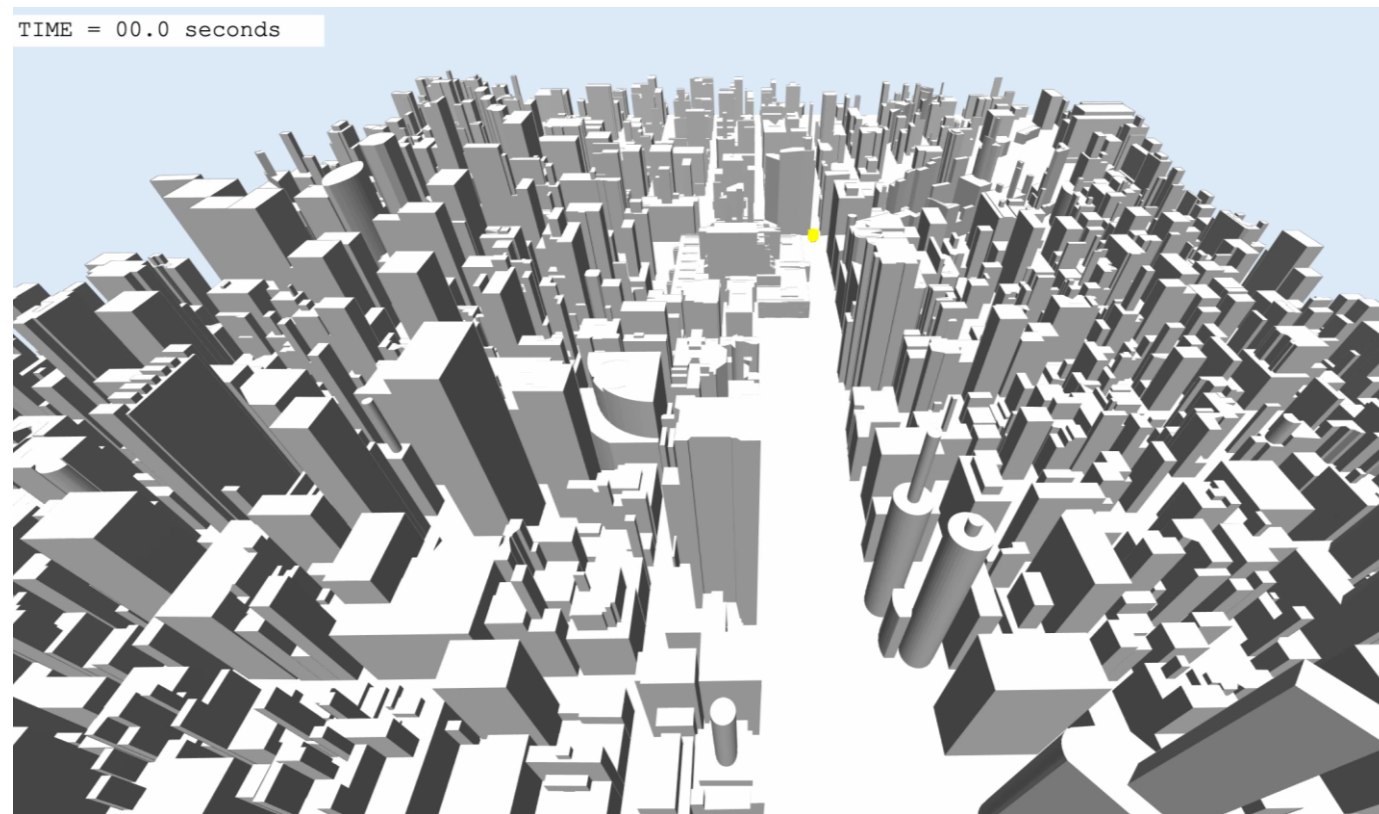
M. Giselle Fernández-Godino^{1,*}, Donald D. Lucas^{1,†}, and Qingkai Kong¹



Spatiotemporal Plume Predictions with Deep Learning

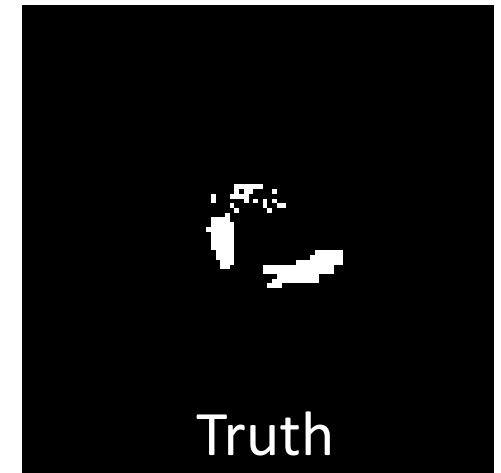
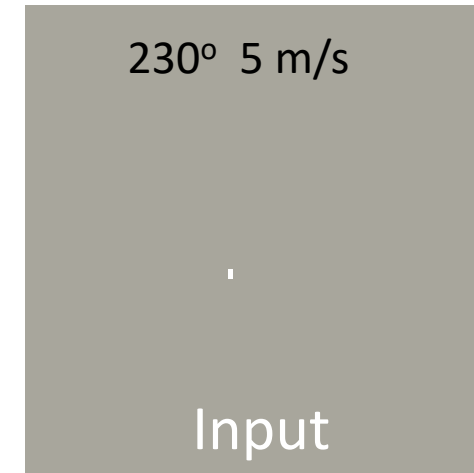
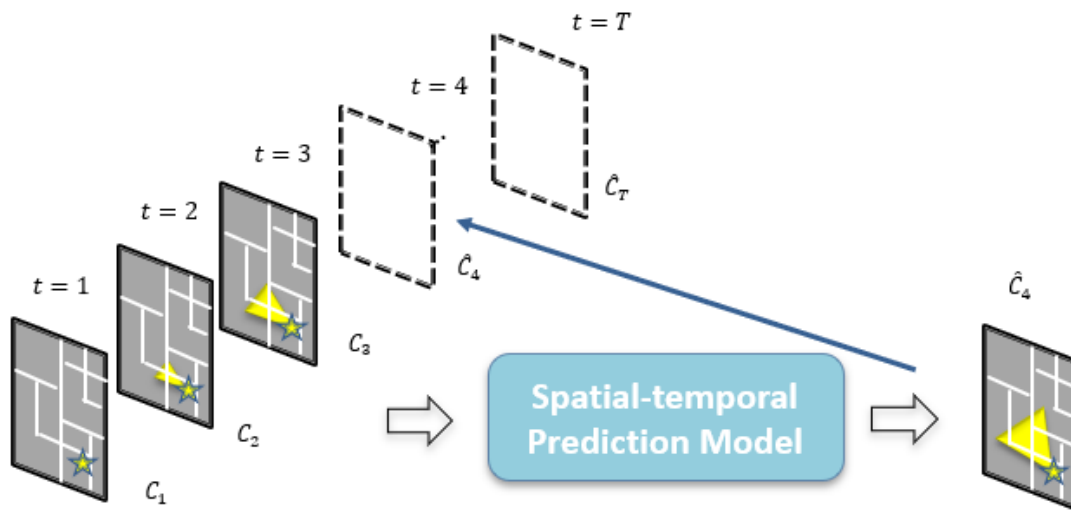
Can we use deep learning to predict the evolution of a hazardous dispersing cloud in complex areas?

The movie shows a high-resolution model simulation of a neutrally-buoyant gas plume moving through a city.



Spatiotemporal Plume Predictions with Deep Learning

- Can we use deep learning to predict the evolution of a hazardous dispersing cloud in complex areas?
- Computer models are expensive and uncertain.
- Data-driven methods may be faster and better.



We can predict the binary *presence* or *absence* of the cloud at ground level.



Summary

Machine Learning and AI are powerful tools that can be used for many different emergency response and atmospheric science applications.

Our team at LLNL has used ML and AI to acceleration atmospheric models for hazard predictions by factors of 10,000 or more.

We are currently researching ways to use new deep learning methods from the field of computer vision to create predictive, data-driven atmospheric transport and dispersion models.

Questions?

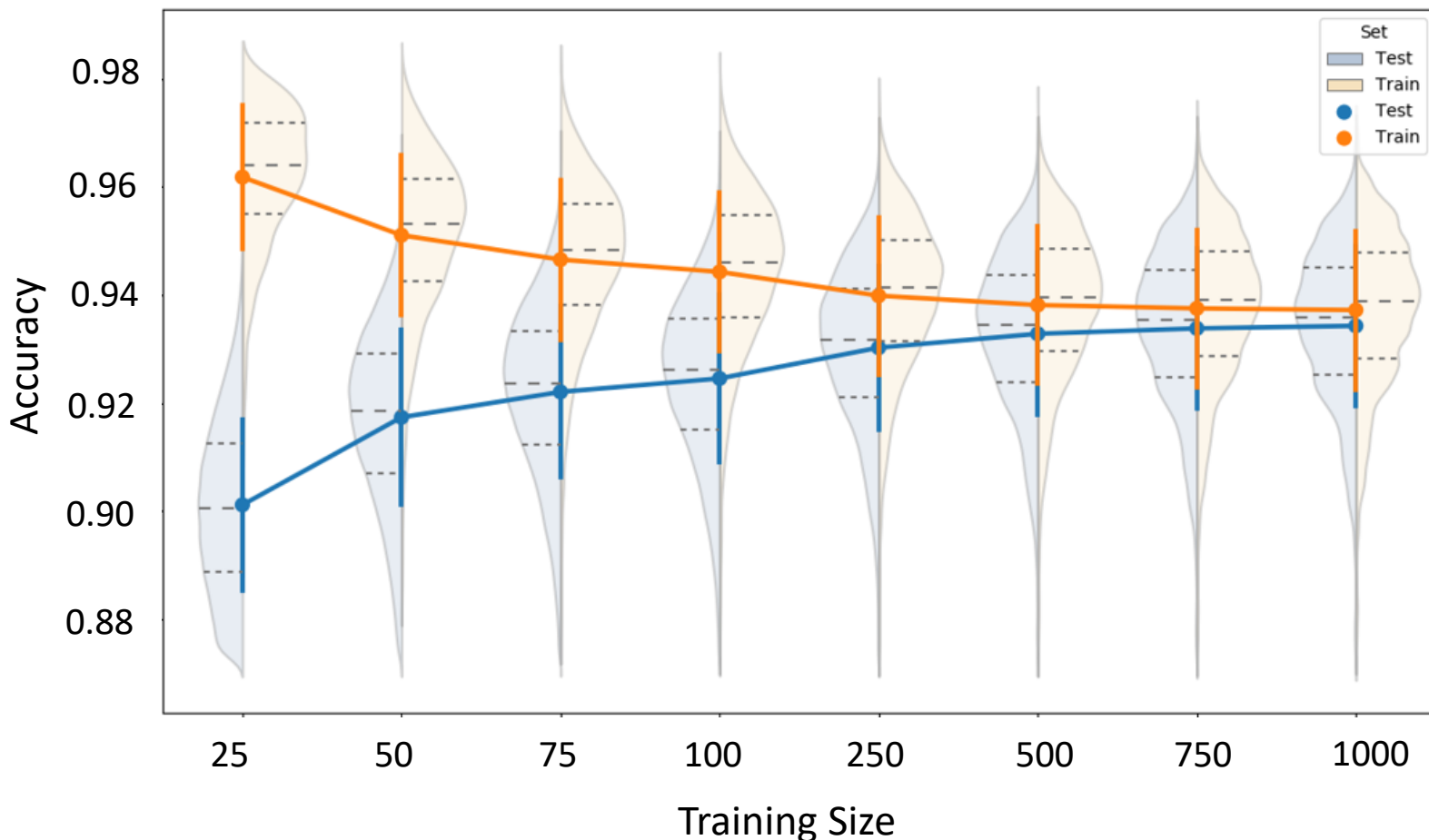


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Predicting Radiological Hazard Maps with Machine Learning

Spatial regression performance improves quickly with increasing training size



Curves show predictability as a function of training size.

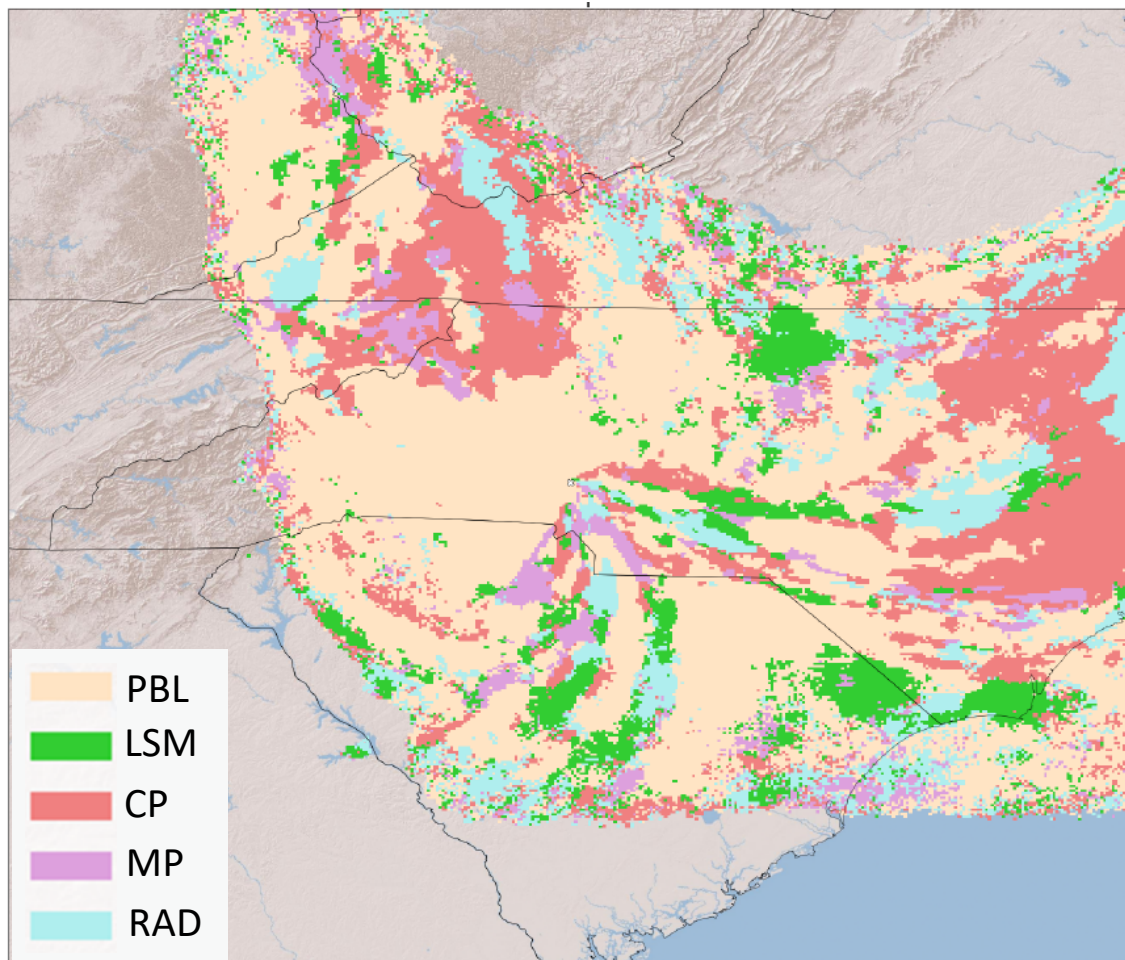
Reasonable predictability with <5% of the ensemble.

Performance monitored for multiple metrics:

- Accuracy
- Jaccard similarity index
- Fraction within a factor of 5 (FAC5)
- Pearson's correlation
- Rank score

Predicting Radiological Hazard Maps with Machine Learning

Regression coefficients facilitate spatial interpretability



Method enables easy interpretation of the spatial dependence of the dominate physics packages.

- Planetary boundary layer physics is the most important scheme over a wide area.
- Cumulus convection physics is important over steep terrain and coastal areas.
- Regions where microphysics is important are adjacent to regions with dominate convection.

Predicting Images of Wind-Driven Spatial Maps with Deep Learning

Learning Physics through Images: An Application to Wind-Driven Spatial Patterns

Under
Review

M. Giselle Fernández-Godino^{1,*}, Donald D. Lucas^{1,†}, and Qingkai Kong¹

OUTPUT

$d(x, y)$ = deposition as a function of the horizontal location x and the vertical location y

$$d(x, y) = f(x_r, y_r, u, v)$$

INPUTS

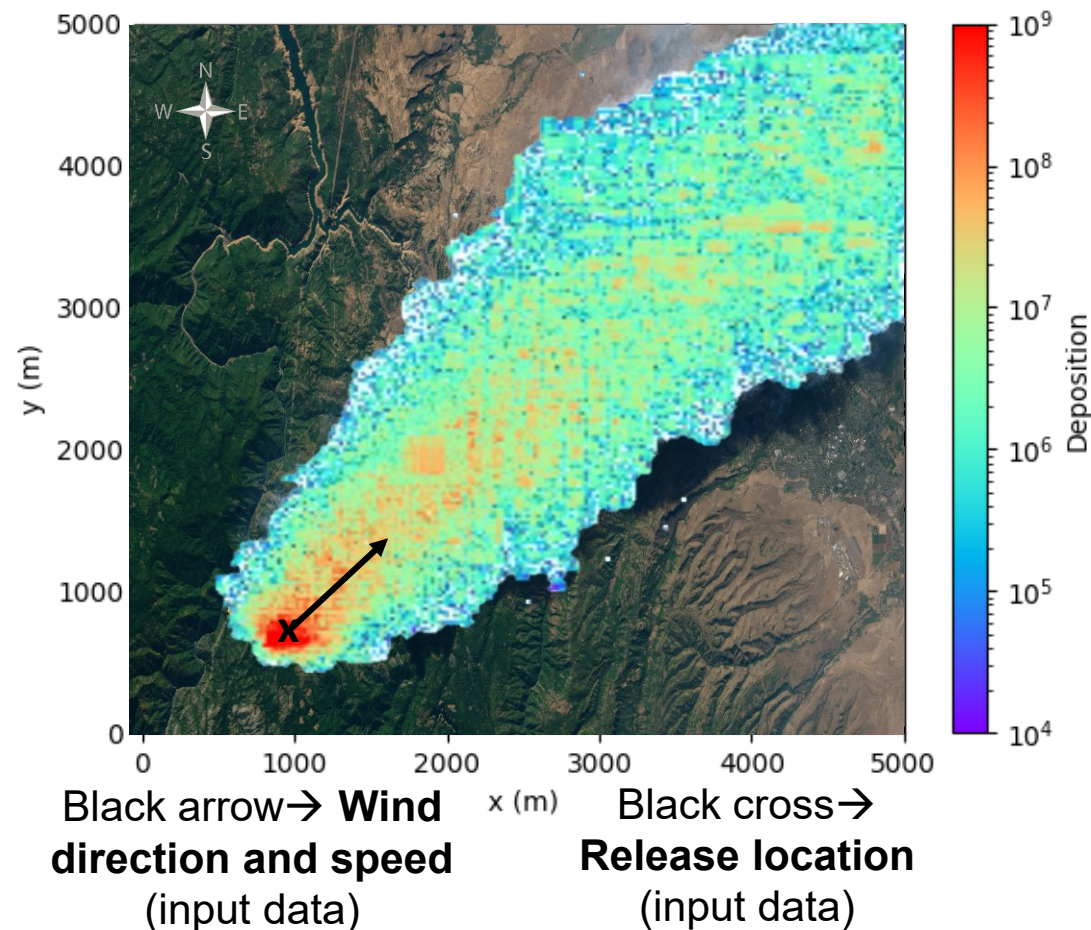
x_r = x-coordinate of release location

y_r = y-coordinate of release location

u = wind speed in the x direction

v = wind speed in the y direction

Deposition simulated using the Aeolus physics model



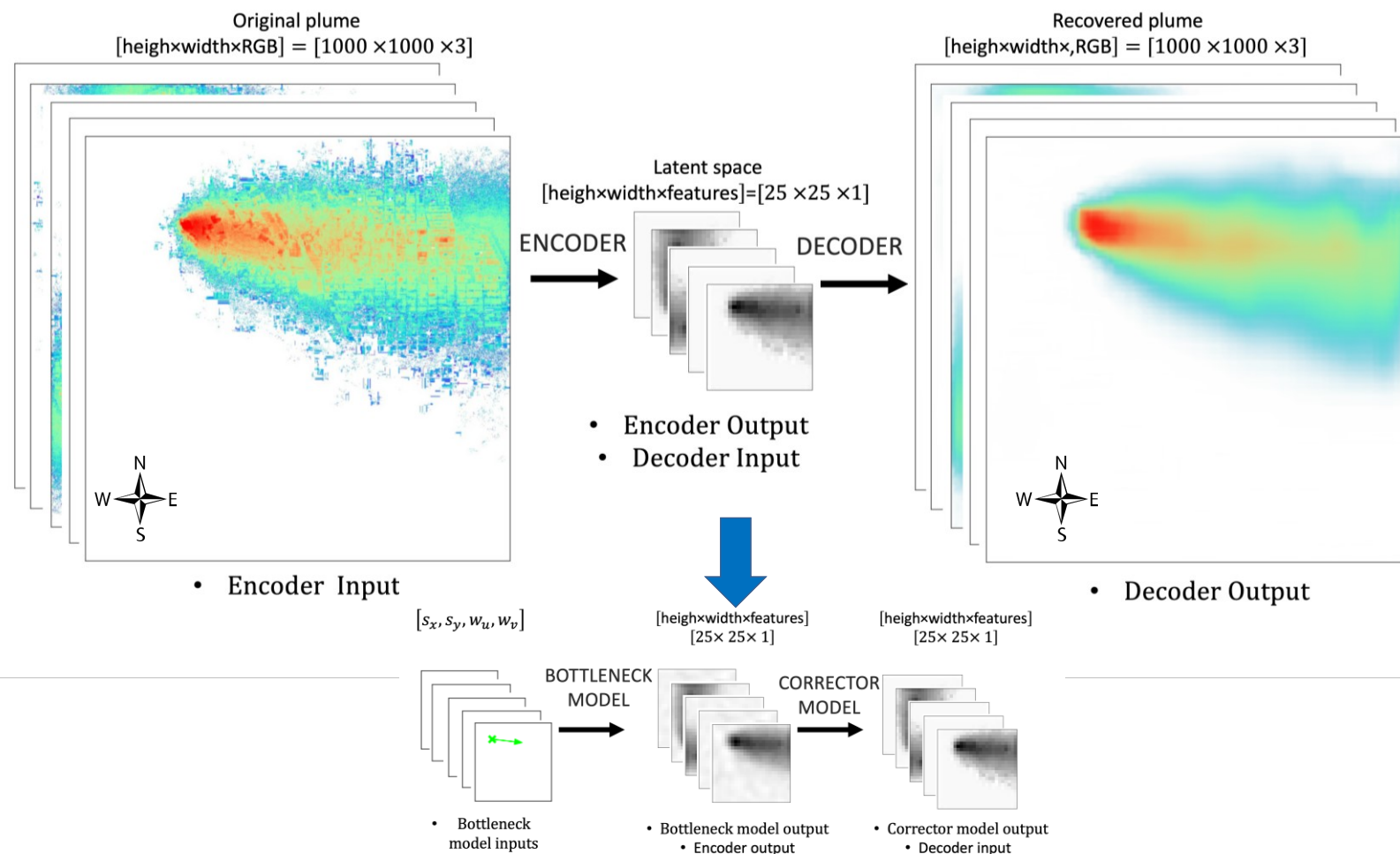
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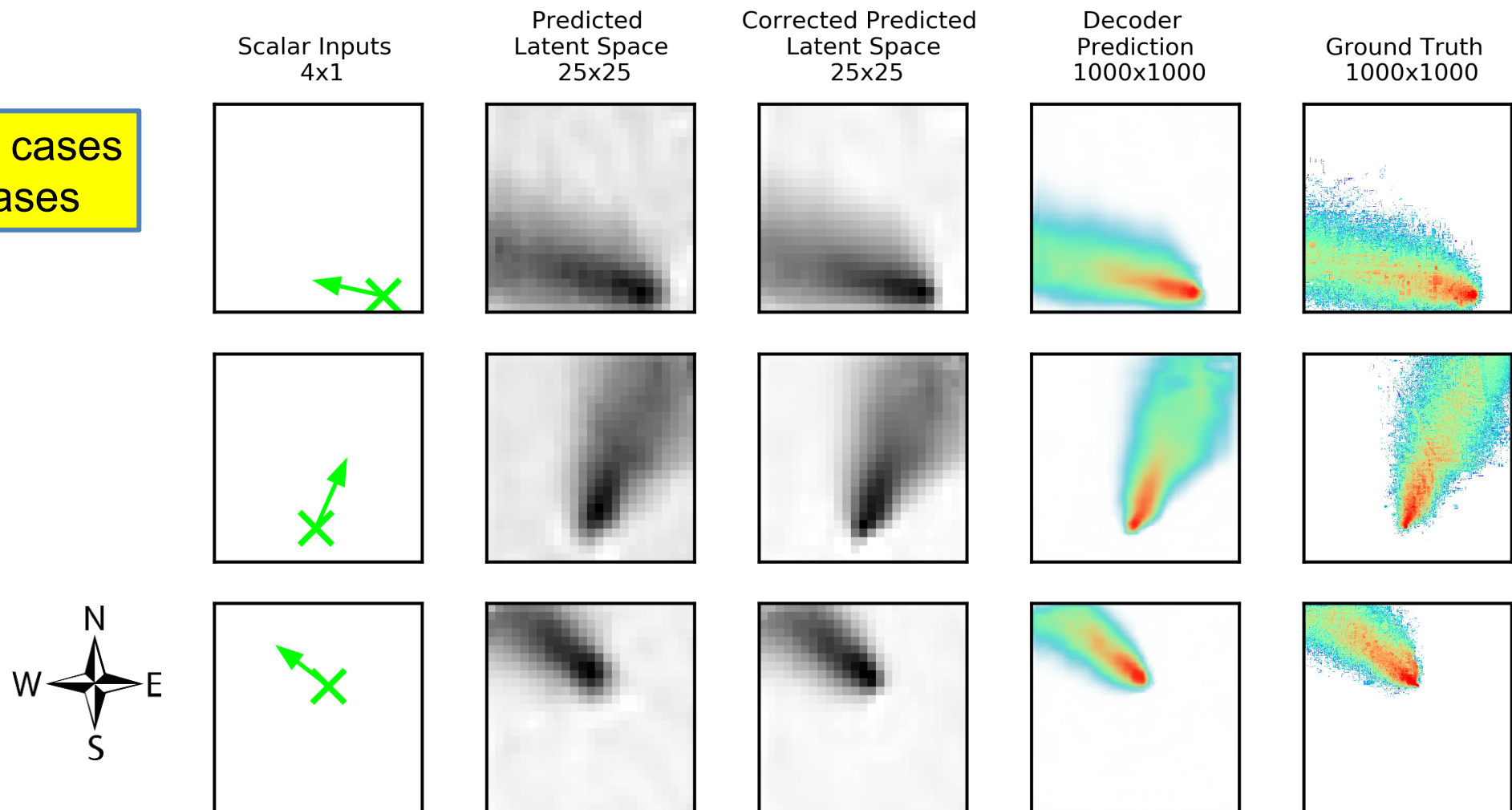
M. Giselle Fernández-Godino^{1,*}, Donald D. Lucas^{1,†}, and Qingkai Kong¹

- Autoencoders are convolutional neural networks that reduce the dimensionality of spatial maps.
- Encoder reduces the dimension of the image.
- Decoder recovers the original image.
- Fully connected neural networks can be used on the low dimensional representation.



Predicting Images of Wind-Driven Spatial Maps with Deep Learning

Train data= 11,700 cases
Test data=300 cases



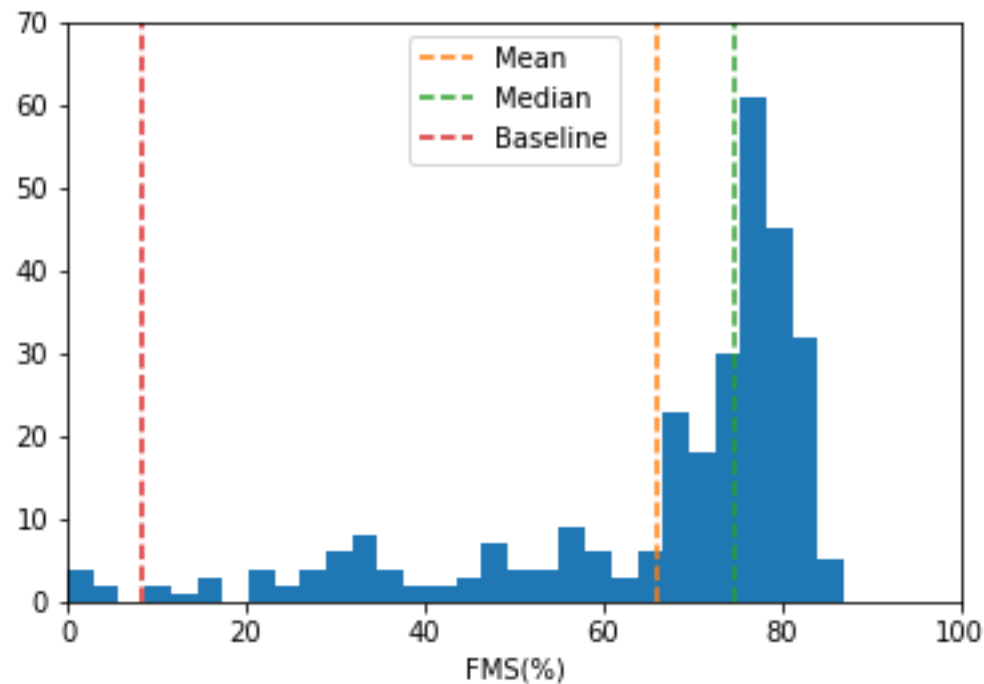
Predicting Images of Wind-Driven Spatial Maps with Deep Learning

Under
Review

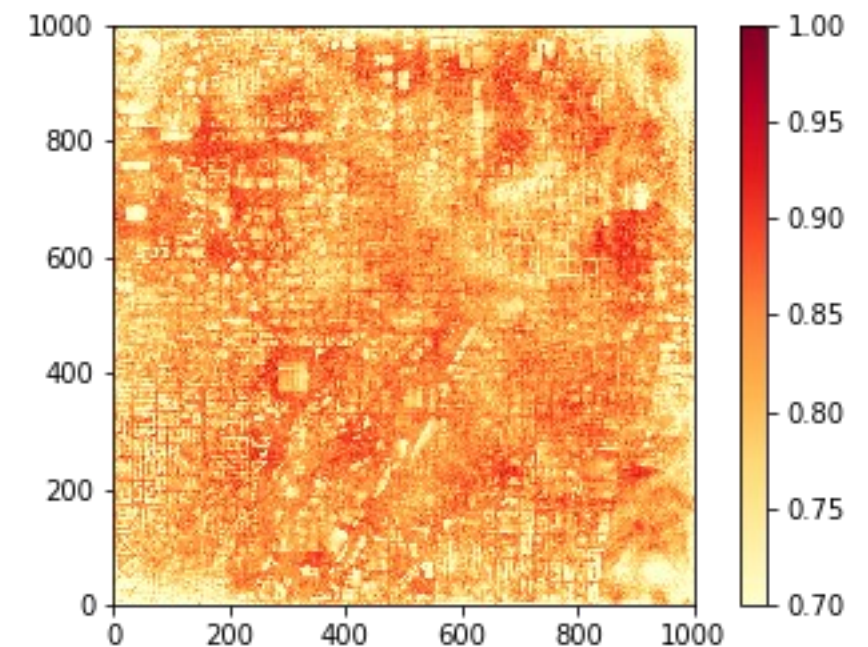
Learning Physics through Images: An Application to
Wind-Driven Spatial Patterns

M. Giselle Fernández-Godino^{1,*}, Donald D. Lucas^{1,†}, and Qingkai Kong¹

Figure of Merit in the Space ~ 78%

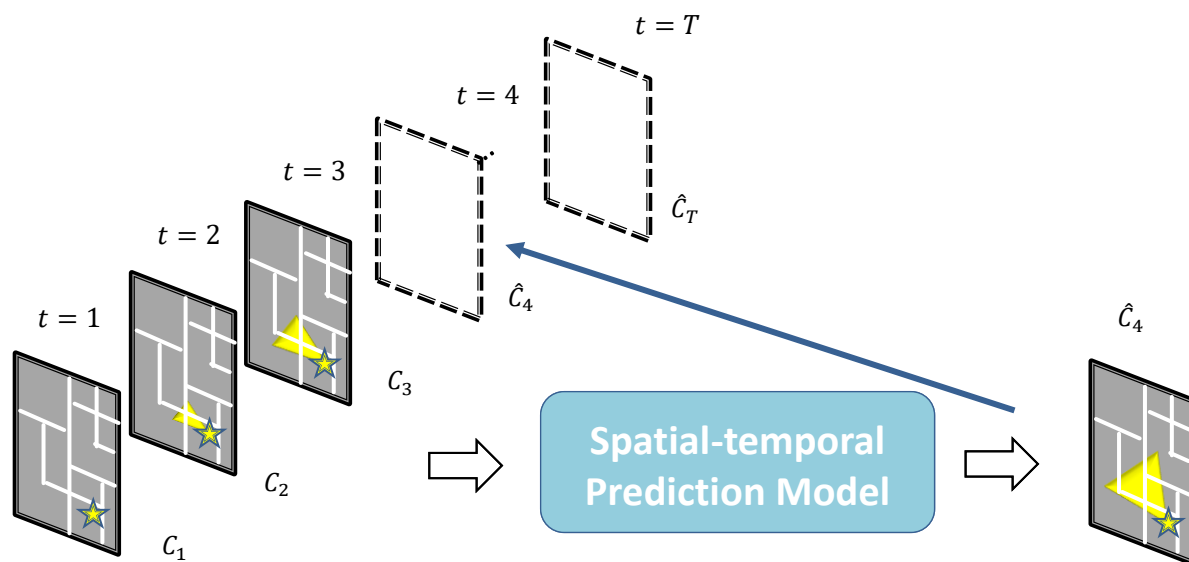


Mean correlation values between the truth and predicted images corresponding to each pixel for the available 300 test cases.



Spatiotemporal Plume Predictions with Deep Learning

- Can we use deep learning to predict the evolution of a dispersing cloud in complex areas?
- Computer models are expensive and uncertain
- Data-driven methods may be faster and better



Training Data

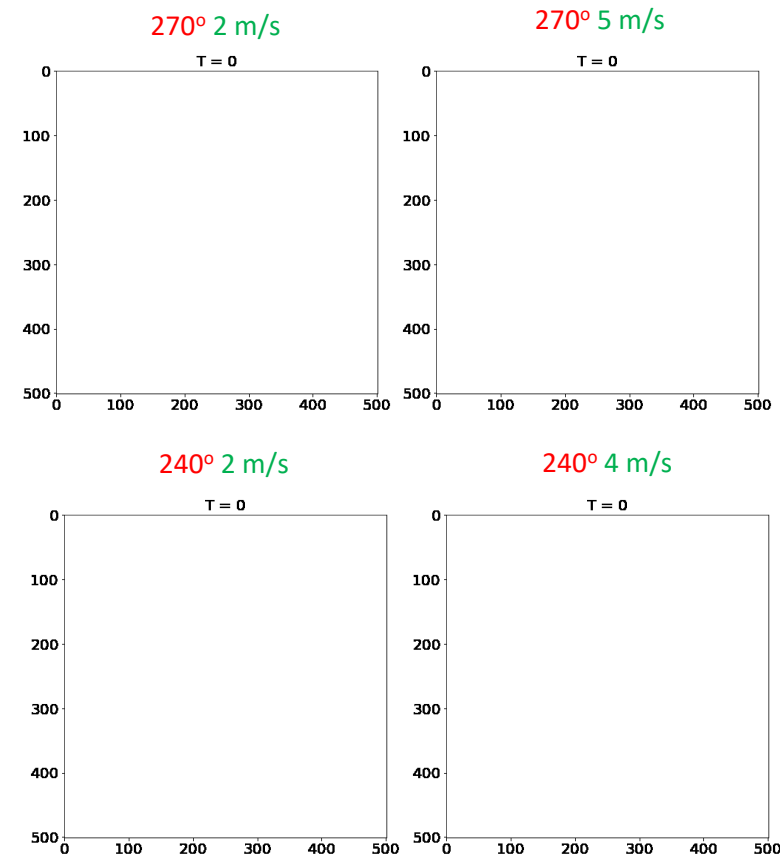
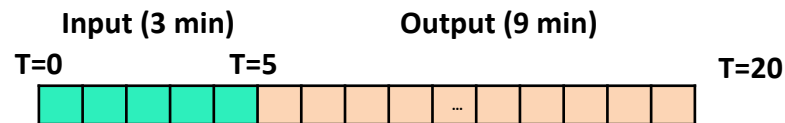


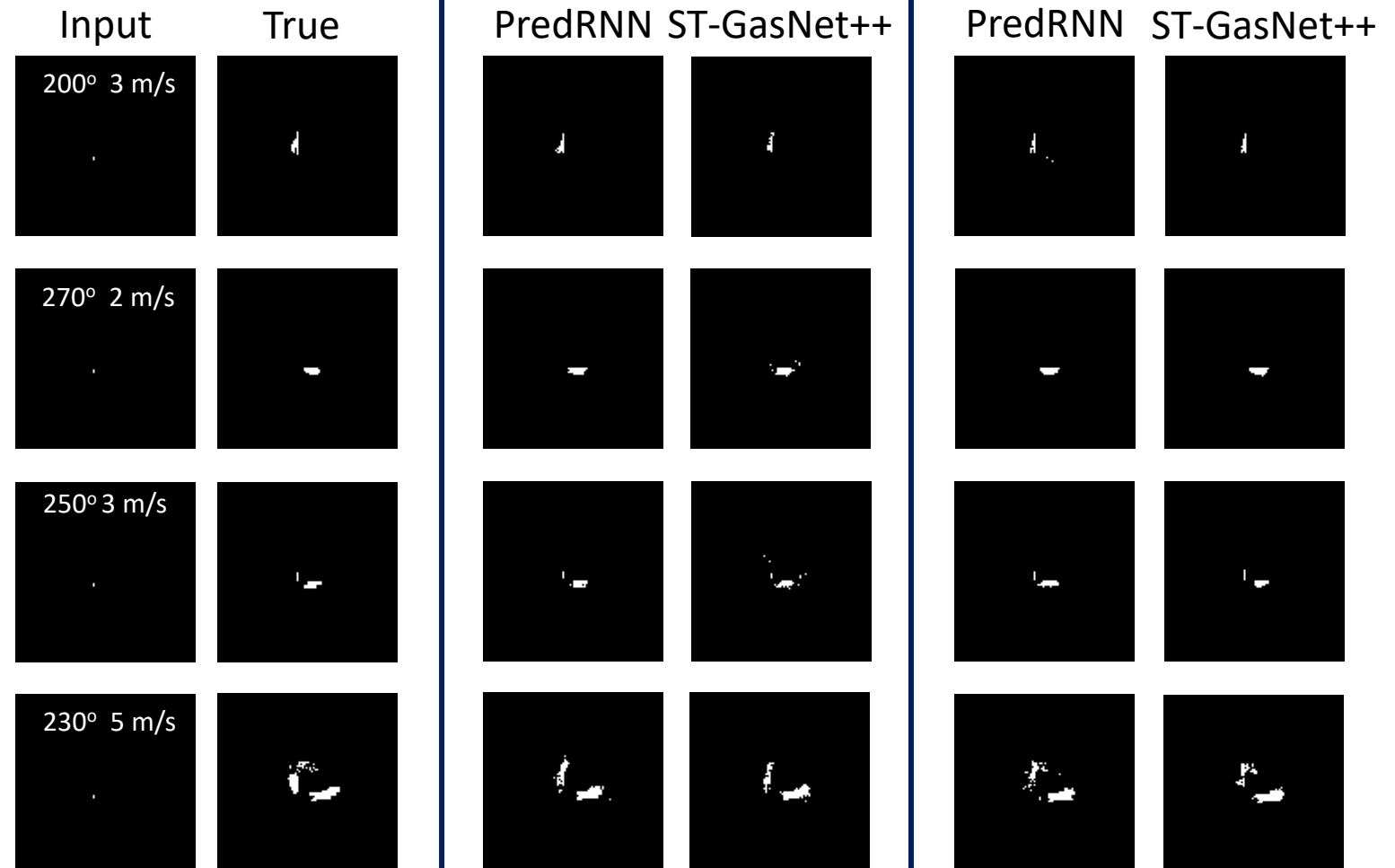
Figure 1. Plume evolution for different wind directions and wind speeds.

Spatiotemporal Plume Predictions with Deep Learning



Trained and assessed four different deep learning models

- *PredRNN* considers the previous time instance
- *ST-GasNet++* considers the two previous time instances
- Either learn the winds from the plume evolution or include wind as predictors



Spatiotemporal Plume Predictions with Deep Learning

Spatial-temporal Prediction Models

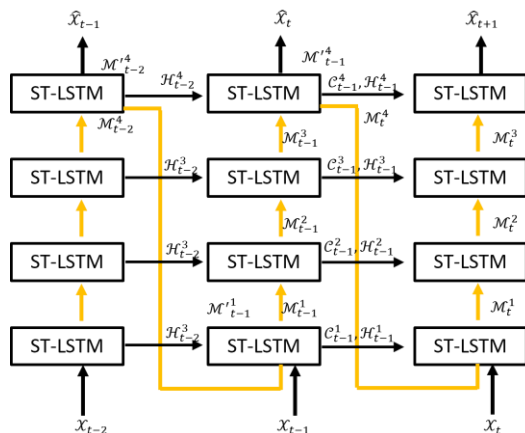


Figure 2. Model structure of **PredRNN**

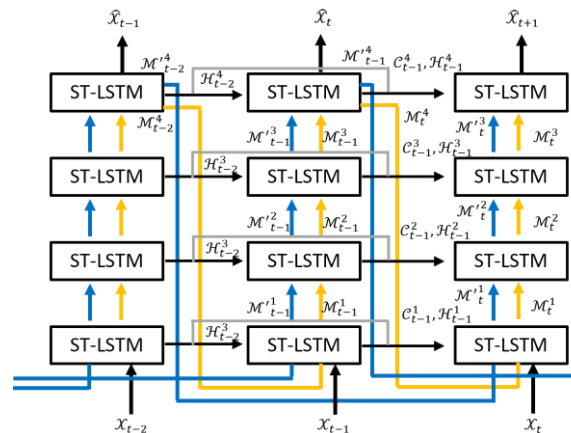
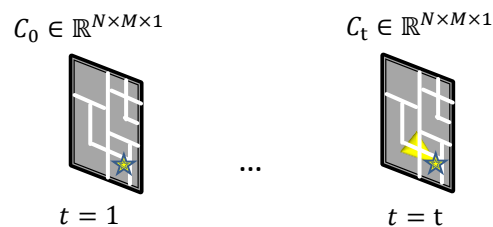
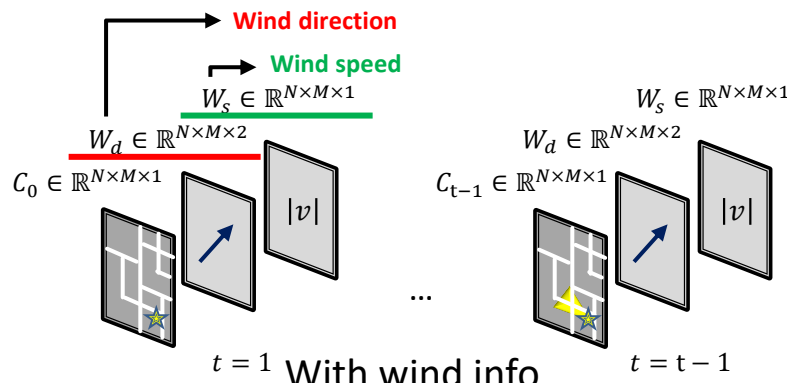


Figure 3. Model structure of **ST-GasNet++**

Formulations of Input



Without wind info



With wind info

$$\begin{aligned} & \hat{x}_{t+1} \otimes x_{t+1} \\ & \downarrow \\ & |\hat{x}_{t+1} - x_{t+1}|_2^2 \\ & + \\ & \beta_1 |\cos(\Delta C_t^l, \Delta M_t^l)| \\ & + \\ & \beta_2 |\cos(\Delta C_t^l, \Delta M_t^{l'})| \end{aligned}$$

Spatiotemporal Plume Predictions with Deep Learning

Under Review

ST-GasNet: Spatiotemporal Prediction of Plumes Evolution using Deep Learning

Yinan Wang, M. Giselle Fernández-Godino, Nipun Gunawardena, Donald D. Lucas, and Xiaowei Yue Senior Member, IEEE

