AI FOR SCIENCE: DEEP LEARNING FOR IMPROVED SATELLITE OBSERVATIONS AND NUMERICAL MODELING

Craig Tierney and David Hall, NVIDIA

AI CAN DO IMPRESSIVE THINGS

DEFEAT WORLD CHAMPION STRATEGISTS

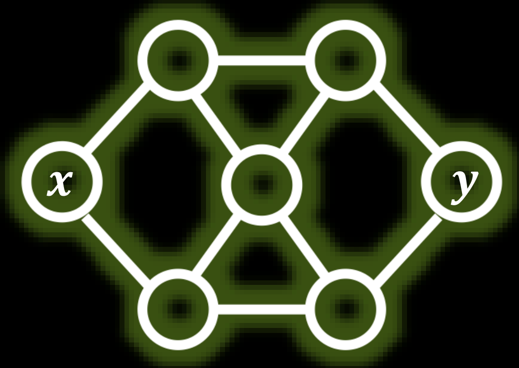
OPERATE VEHICLES AUTONOMOUSLY

COMMUNICATE IN NATURAL LANGUAGE

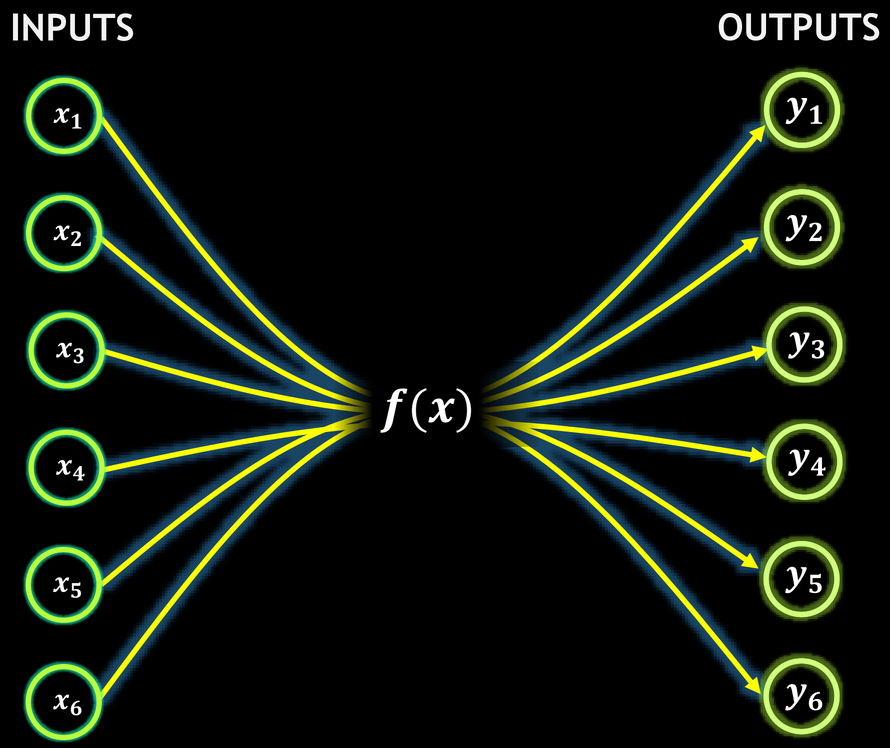
GENERATE ORIGINAL CONTENT

DEEP LEARNING BUILDS FUNCTIONS FROM DATA

Find f, given x and y



SUPERVISED
DEEP
LEARNING



A NEW TOOL FOR SOFTWARE DEVELOPMENT

TEMP, PRESSURE, MOISTURE

PROBABILITY OF RAIN

HAND-WRITTEN FUNCTION

```
Function1(T,P,Q)
update_mass()
update_momentum()
update_energy()
do_macrophysics()
do_microphysics()
y = get_precipitation()
return y
```

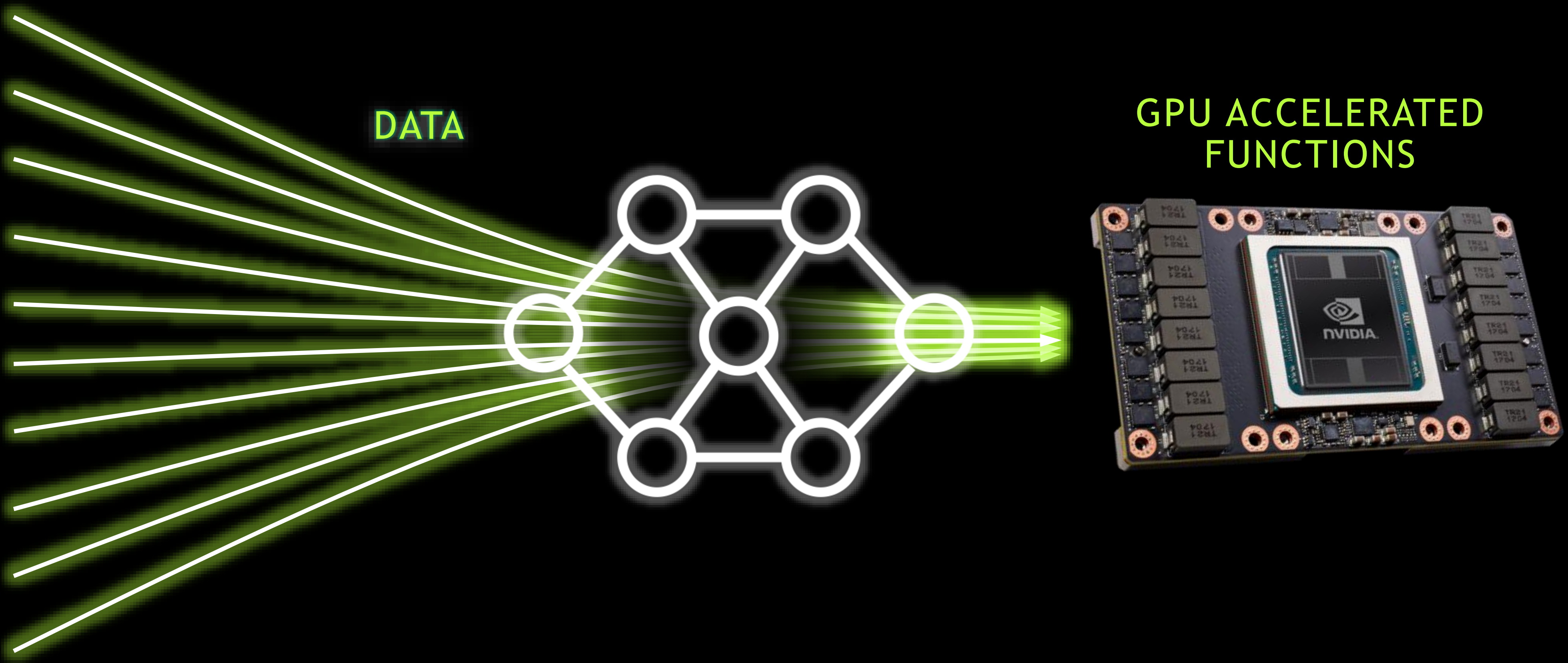
Convert expert
knowledge into a function

LEARNED FUNCTION

```
Function1(T,P,Q)
A = relu( w1 * [T,P,Q] + b1)
B = relu( w2 * A       + b2)
C = relu( w3 * B       + b3)
D = relu( w4 * C       + b4)
E = relu( w5 * D       + b5)
y = sigmoid(w6 * E     + b6)
return y
```

Reverse-engineer a function
from inputs / outputs

LEARNED FUNCTIONS ARE GPU ACCELERATED

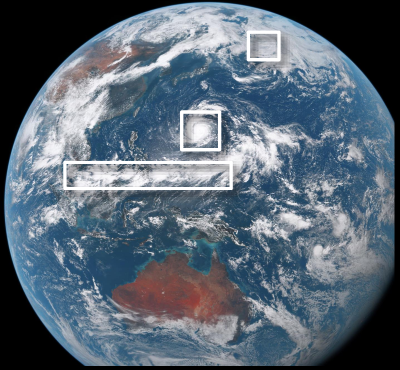


ENHANCE EXISTING APPLICATIONS

Improve all stages of numerical weather prediction

COLLECTION THINNING ASSIMILATION EMULATION PARAMETRIZATION COMMUNICATION

BUILD NEW CAPABILITIES



REAL-TIME
WEATHER DETECTION

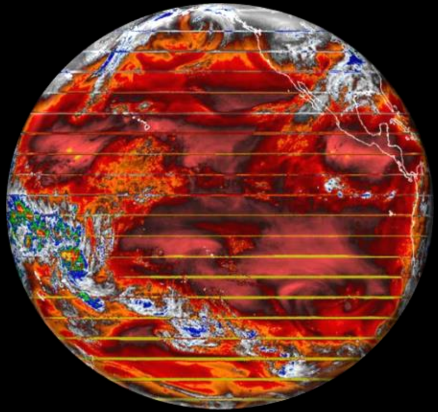
ENVIRONMENTAL
MONITORING

DISASTER PLANNING,
SEARCH AND RESCUE

NEAR-EARTH OBJECT
DETECTION

ACCELERATED
DATA ASSIMILATION

AUTONOMOUS SENSORS
AND ROVERS



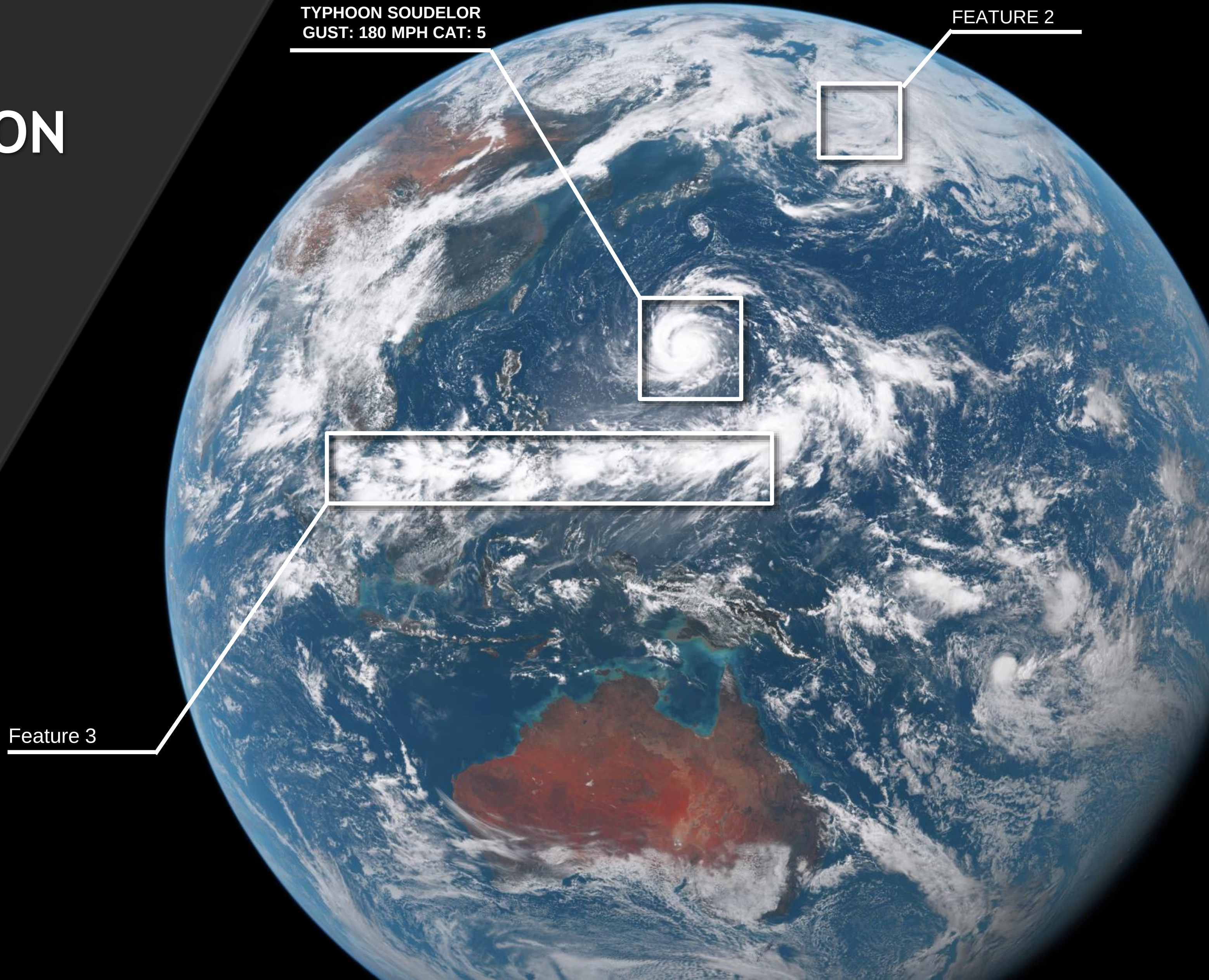
DATA ENHANCEMENT
AND REPAIR

FASTER / MORE ACCURATE
PARAMETERIZATIONS

REAL-TIME WEATHER DETECTION

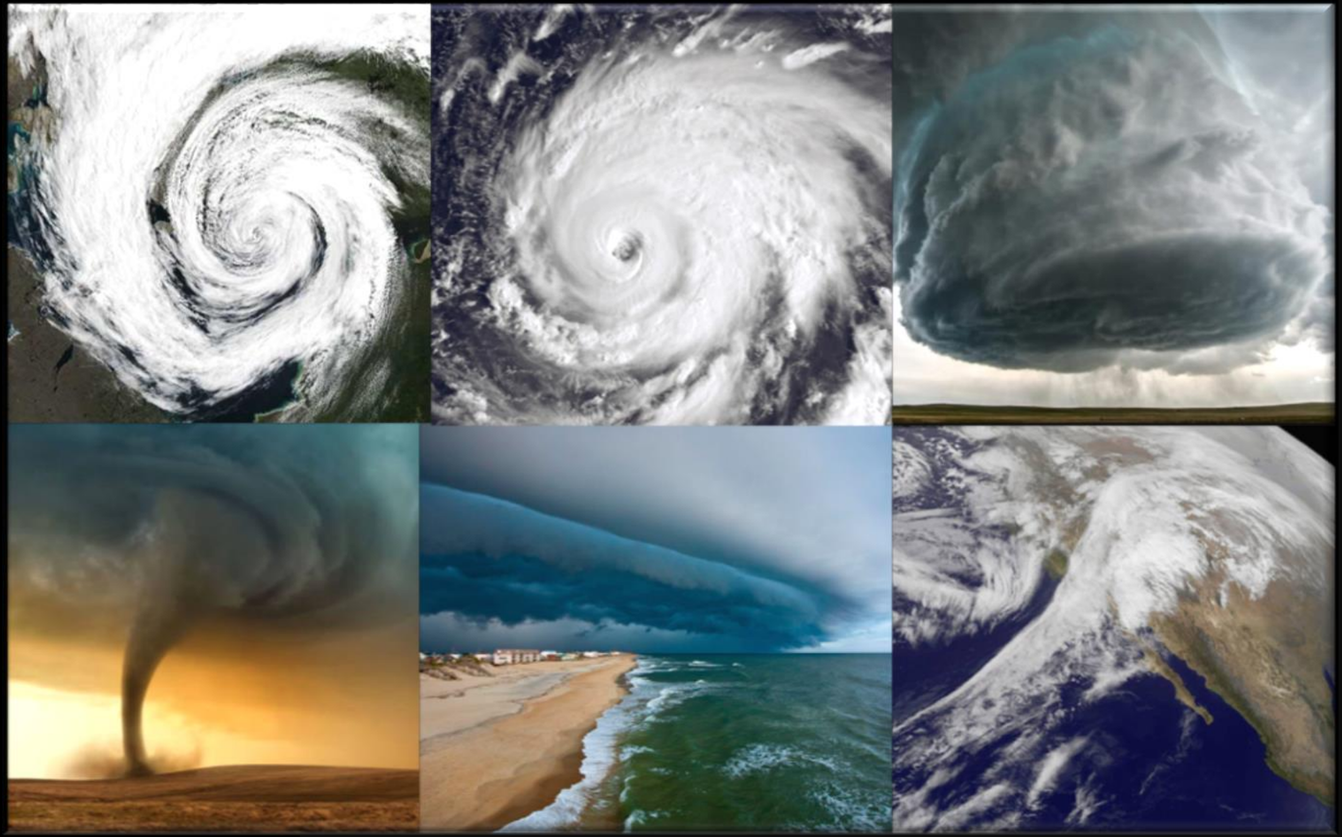
NOAA ESRL & NVIDIA

An interesting application of AI is the real time detection of features of interests, such as tropical storms, hurricanes, tornados, atmospheric rivers, volcanic eruptions, and more. Using AI we can rapidly process the data streaming in from multiple satellites around the globe, enabling us to examine every pixel in detail for important information.



FEATURES OF INTEREST

- Tropical Cyclones
- Extra-tropical Cyclones
- Atmospheric Rivers
- Storm Fronts
- Tornados
- Convection Initiation
- Cyclogenesis
- Wildfires
- Blocking Highs
- Volcanic Eruptions
- Tsunamis

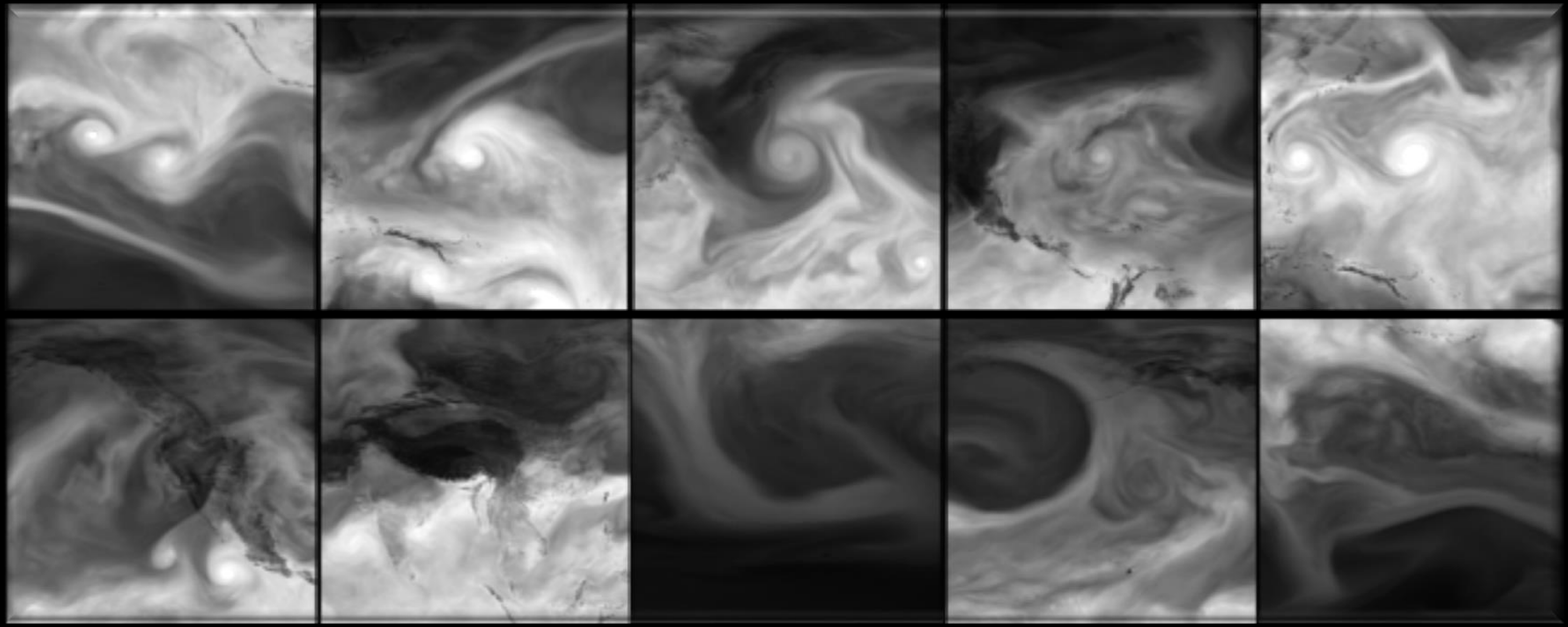


TROPICAL STORM DATASET FROM IBTRACS AND GFS

Extract positive and negative examples for supervised learning

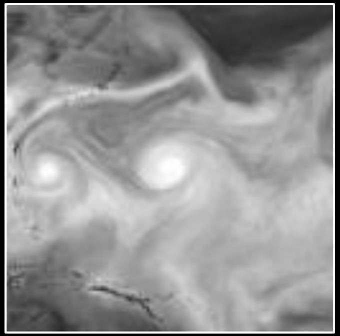
POSITIVE

NEGATIVE

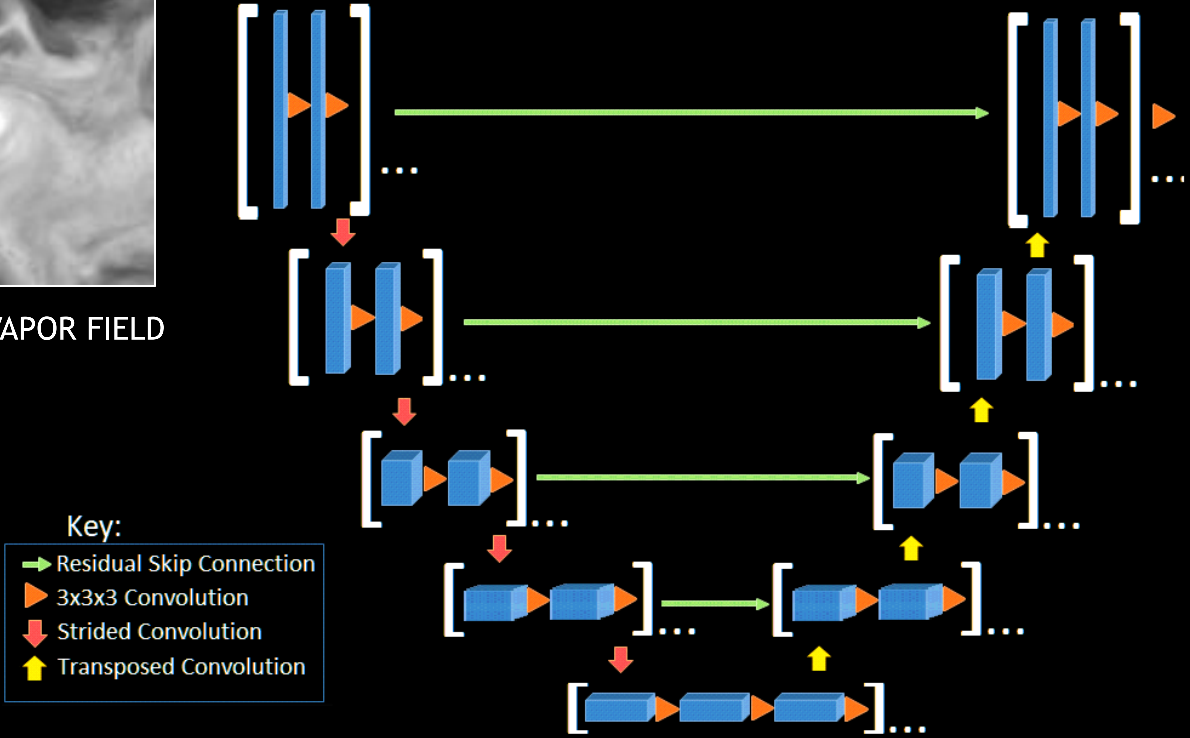


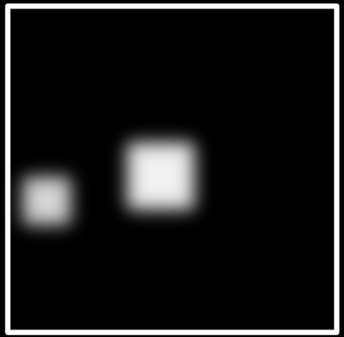
U-NET

Multi-scale Convolutional Neural Net for Image Segmentation



GFS WATER VAPOR FIELD





TARGET SEMENTATION

RESULTS: TROPICAL STORMS

NOAA ESRL
Mark Govett
Jebb Stewart
Christina Bonfonti

NVIDIA
David Hall

SOURCE
GFS Water Vapor

TARGET
IBTRACS Storm Locations

Ground Truth
Prediction

RESULTS:
TROPICAL STORMS

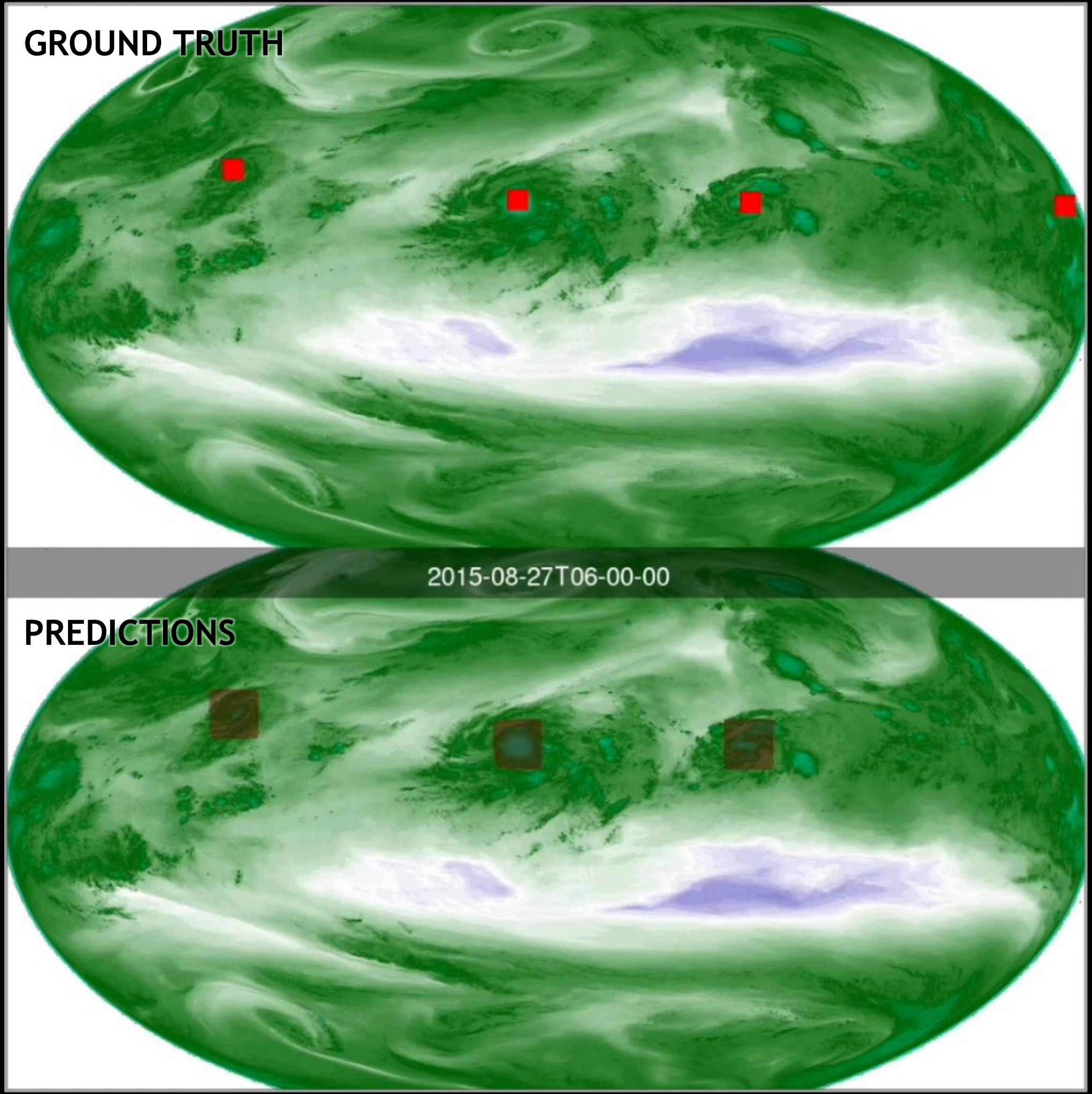
GOES SATELLITE OBSERVATIONS
UPPER-TROPOSPHERIC

NOAA ESRL
Mark Govett
Jebb Stewart
Christina Bonfonti

NVIDIA
David Hall

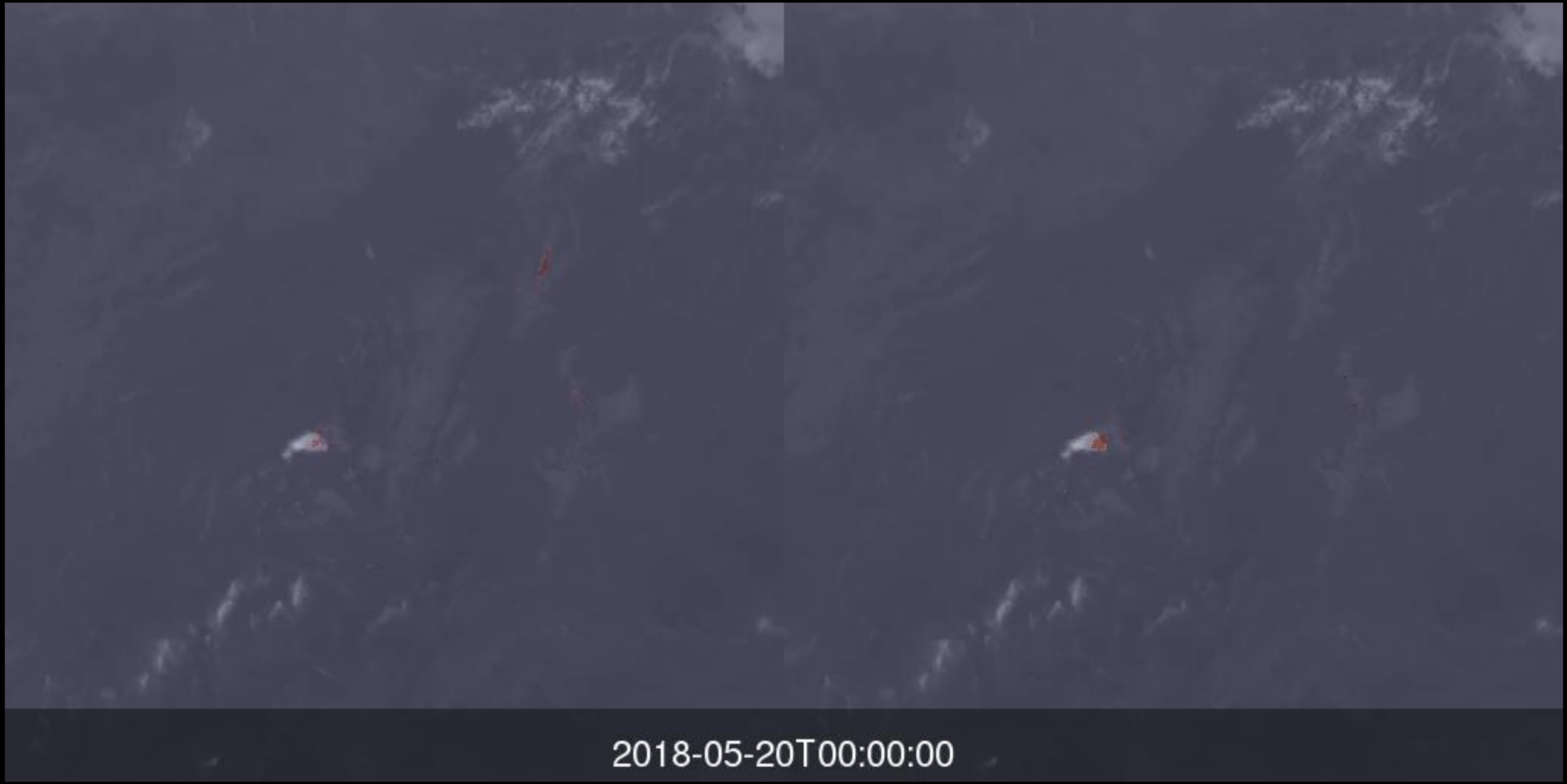
SOURCE
GOES 12-15 Upper Tropospheric
Water Vapor Band

TARGET
IBTRACS Storm Locations



RESULTS: CONVECTION INITIATION

GROUND TRUTH PREDICTION



NOAA ESRL
Mark Govett
Jebb Stewart
Christina Bonfonti

NVIDIA
David Hall

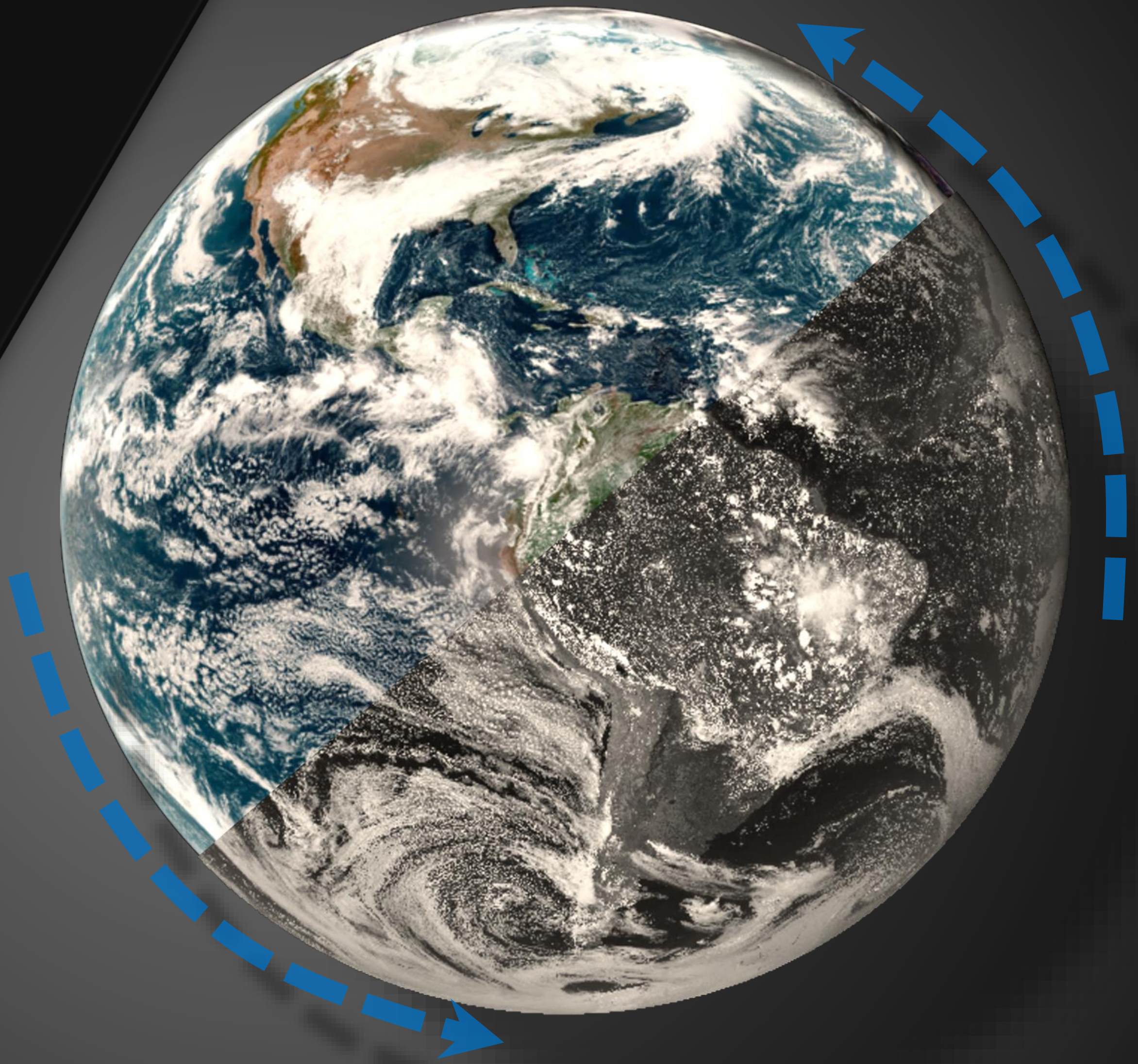
SOURCE
Himawari8 band 8,13

TARGET
Composite Radar
Reflectivity DBZ>35

CONDITIONAL GANS FOR DATA ASSIMILATION

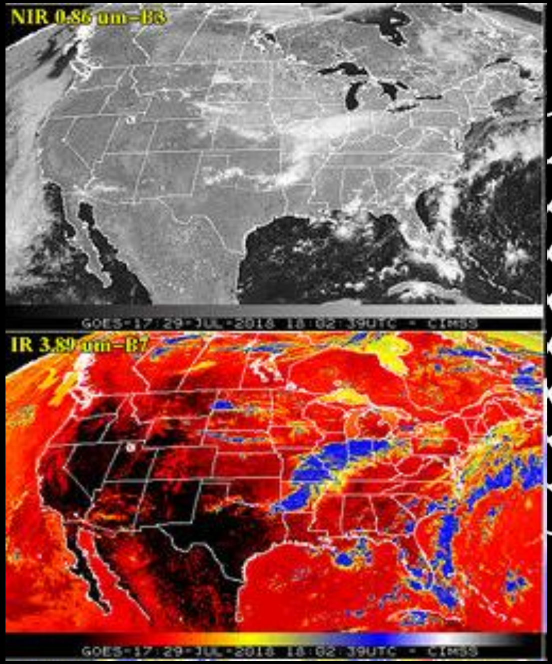
NVIDIA

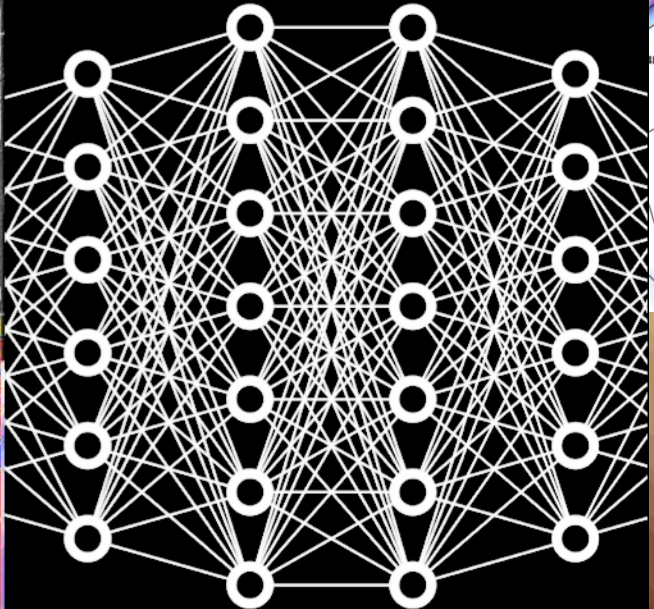
In cases where a 1-1 map is not possible, we can employ conditional generative adversarial networks in order to generate a single, physically plausible state from a distribution of possible states. This prevents the dilution or blurring caused by under-constrained output.



FORWARD AND INVERSE OPERATOR APPROXIMATION

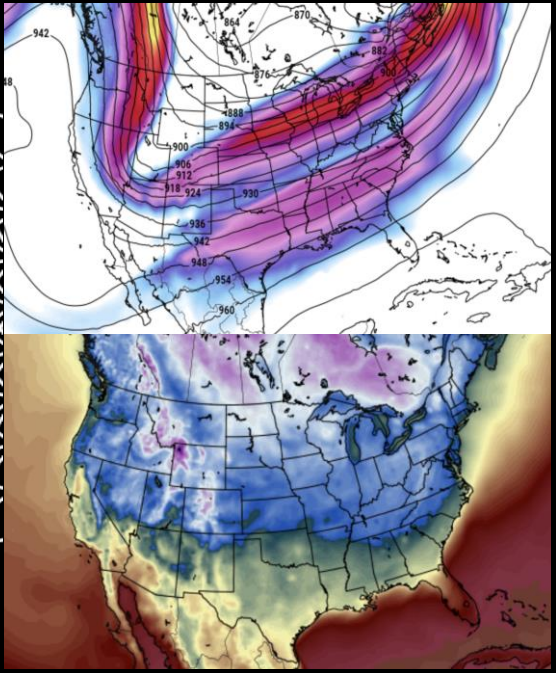
SATELLITE RADIANCES





NEURAL NETWORK

MODEL VARIABLES

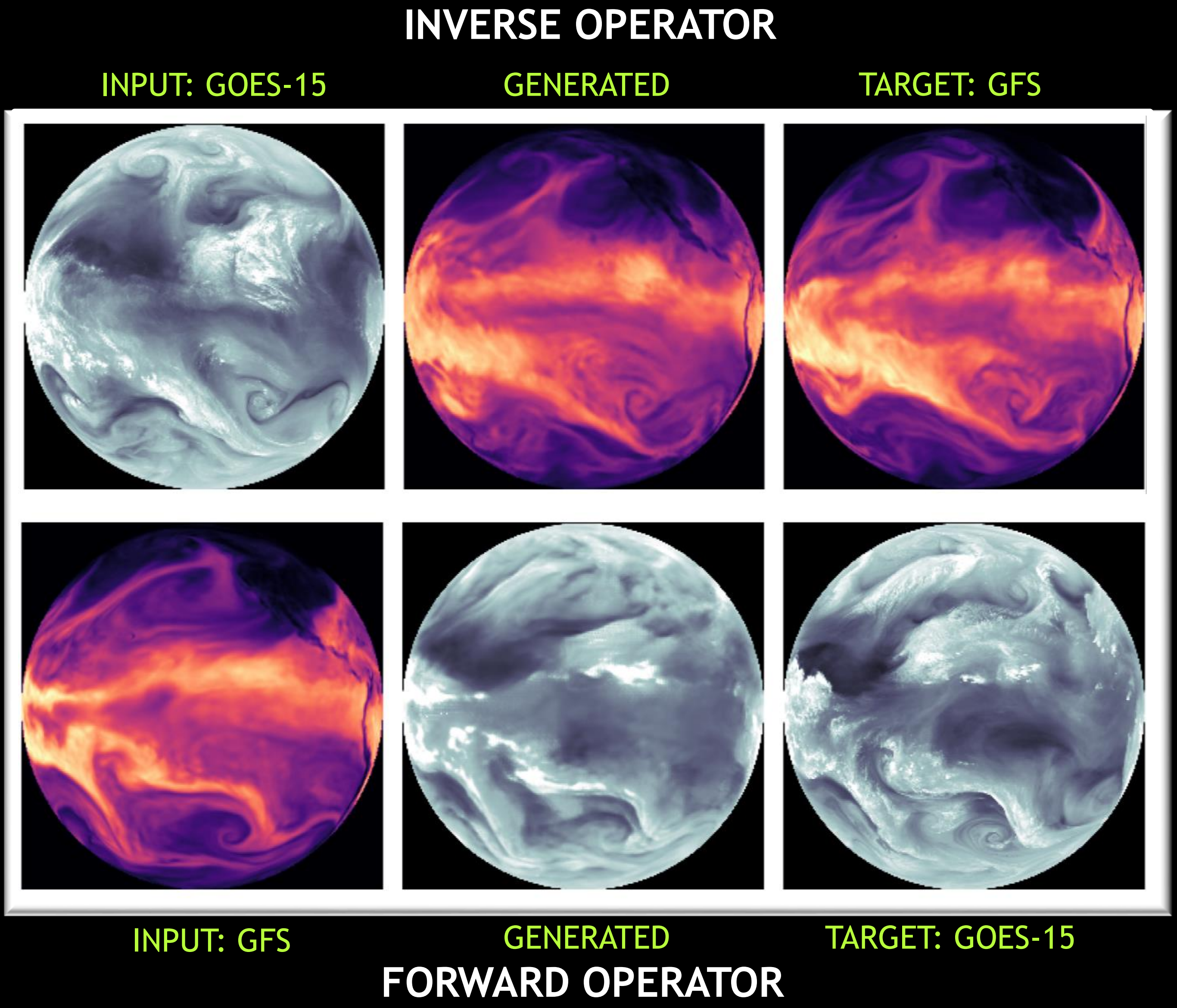


RESULTS: SATELLITE TO MODEL CONDITIONAL GAN

NVIDIA
David Hall

SOURCE
GOES-15 Band 3
GFS Water Vapor

TARGET
GFS Water Vapor
GOES-15 Band 3



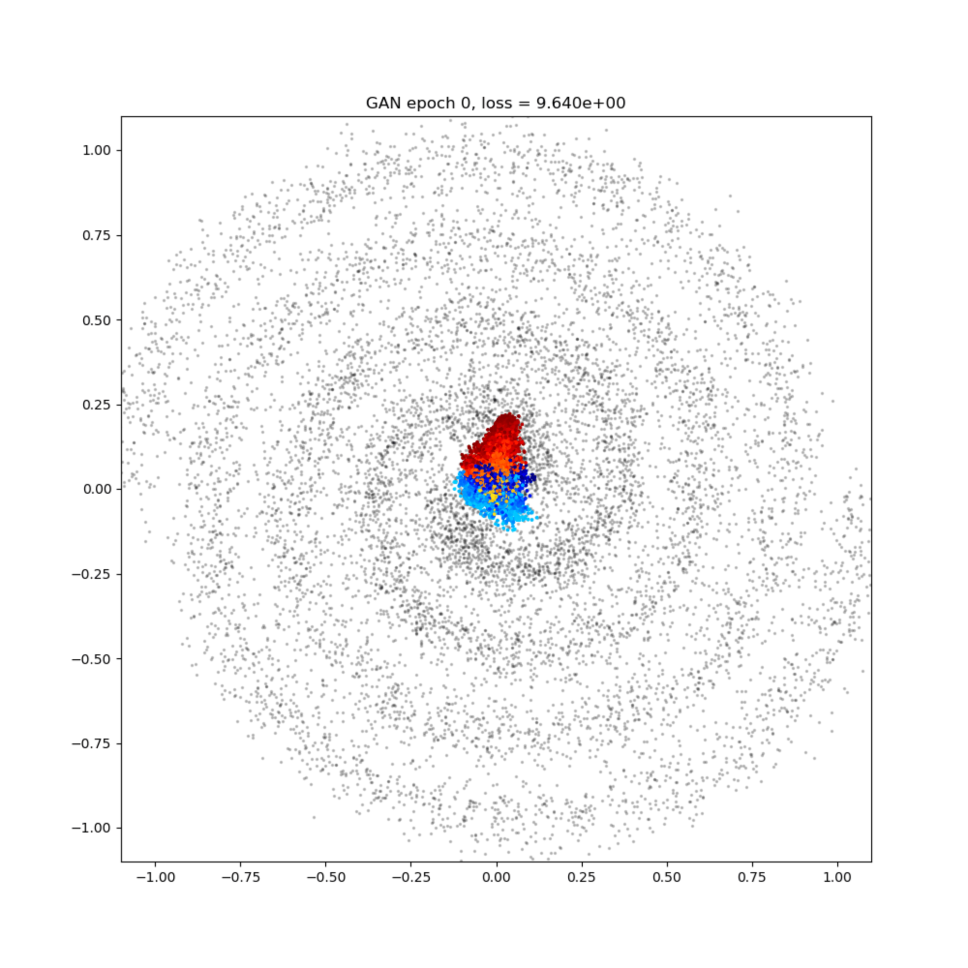
“REGRESS THEN GAN”

TOY PROBLEM: TRAINING A 2D CONDITIONAL GAN

NVIDIA
David Hall

SOURCE
1d parametric coordinate

TARGET
Synthetic point distribution distribution



RESULTS: CGAN CLOUD GENERATION

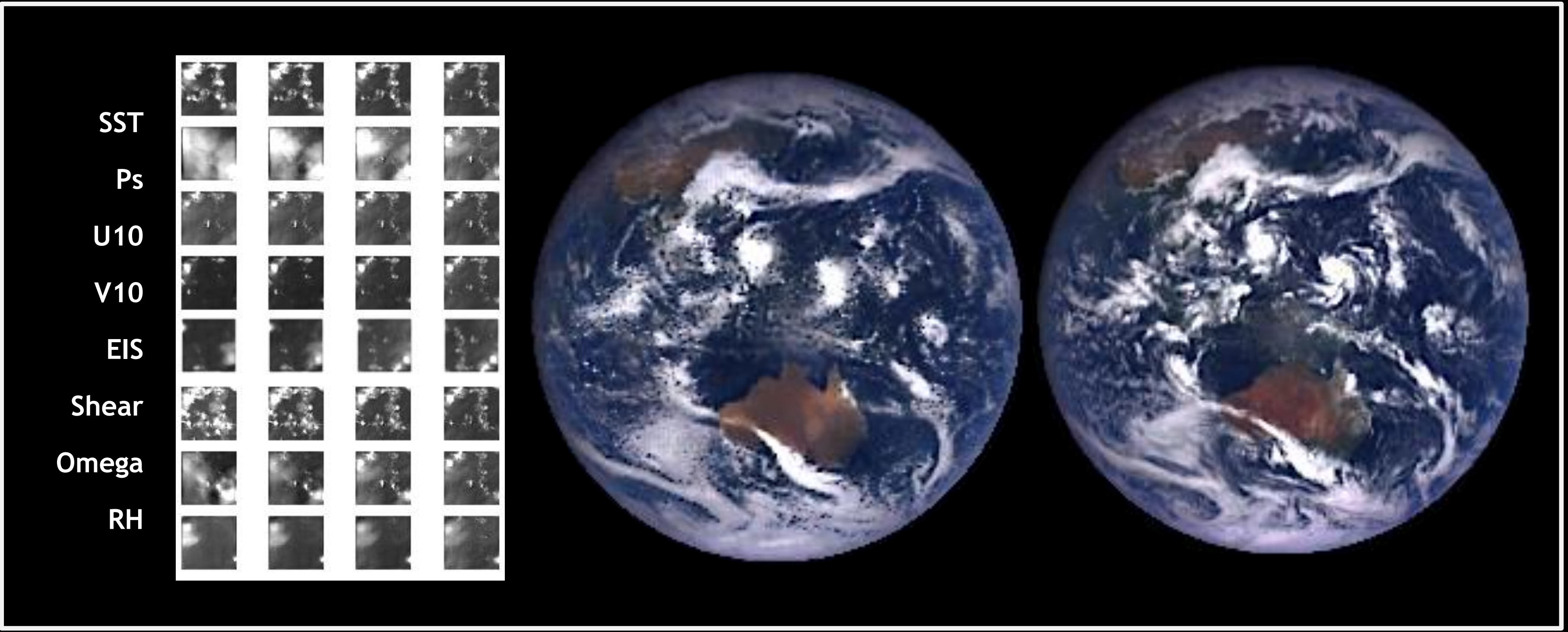
NASA Goddard
Tianle Yuan
Hua Song
Victor Schmidt
Kris Sankaran

MILA
Yoshua Bengio

NVIDIA
David Hall

SOURCE
Hadcrut4, cmip, 20cr

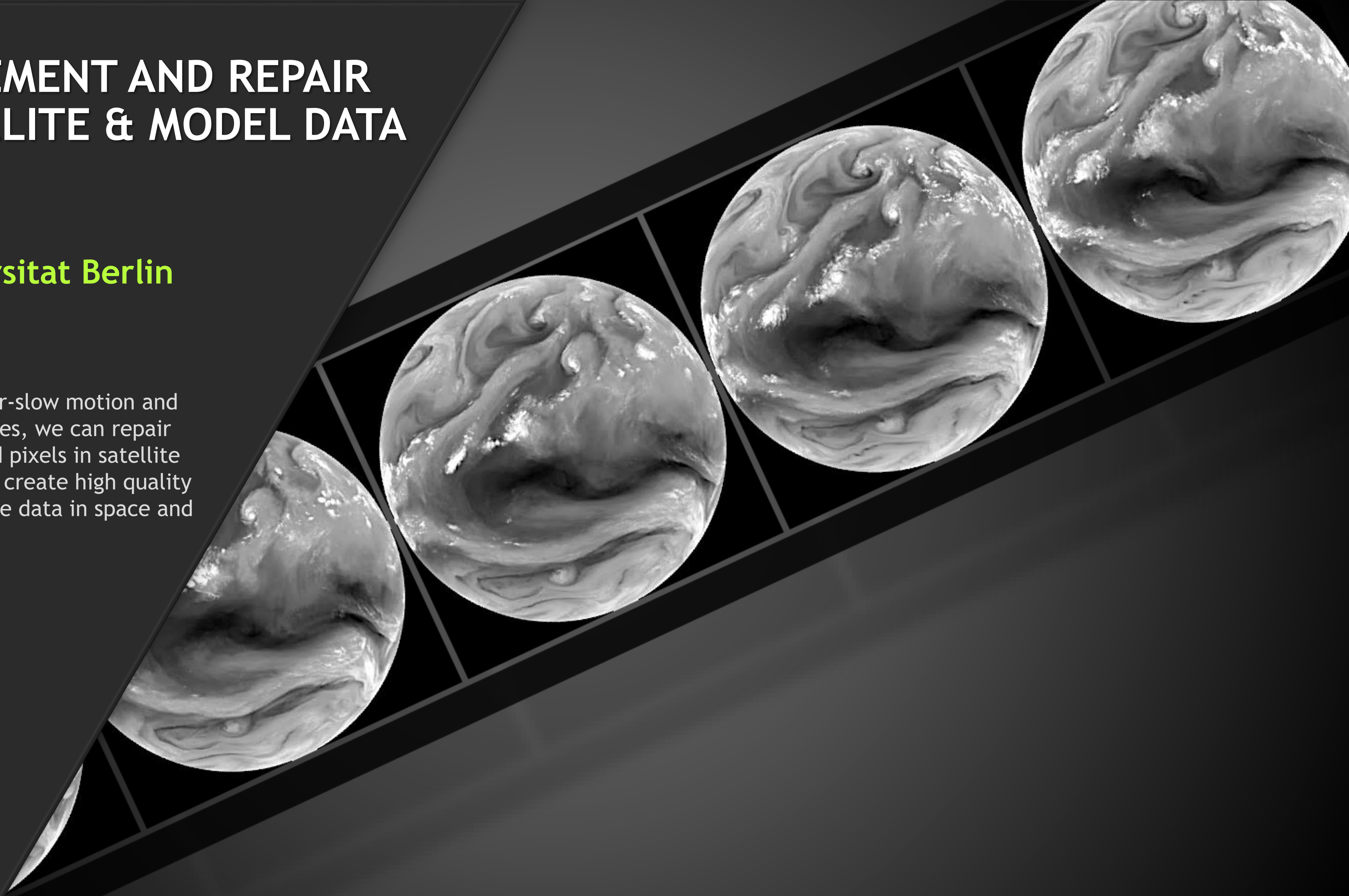
TARGET
Hadcrut4, cmip, 20cr



ENHANCEMENT AND REPAIR OF SATELLITE & MODEL DATA

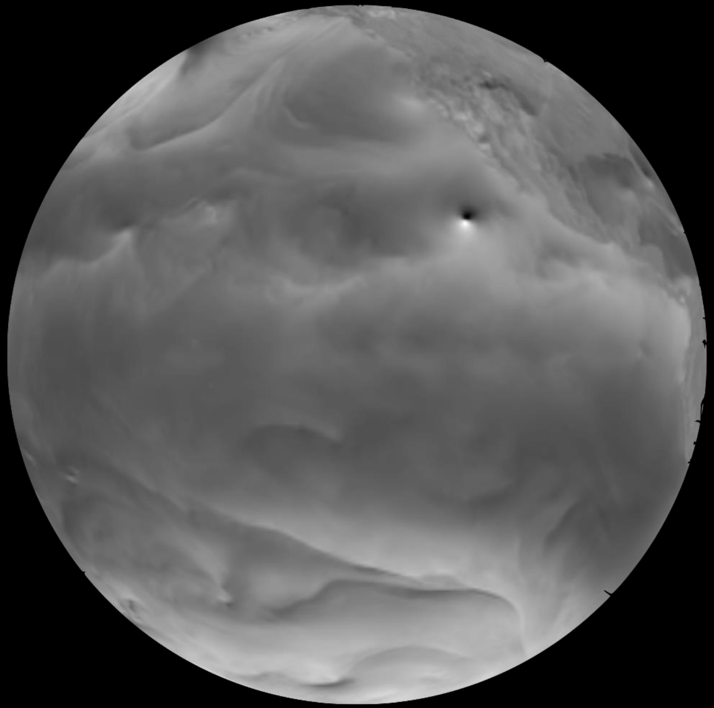
NOAA STAR
Freie Universitat Berlin
NVIDIA

Using NVIDIA’s super-slow motion and inpainting techniques, we can repair missing or damaged pixels in satellite and model data, or create high quality interpolations of the data in space and time.

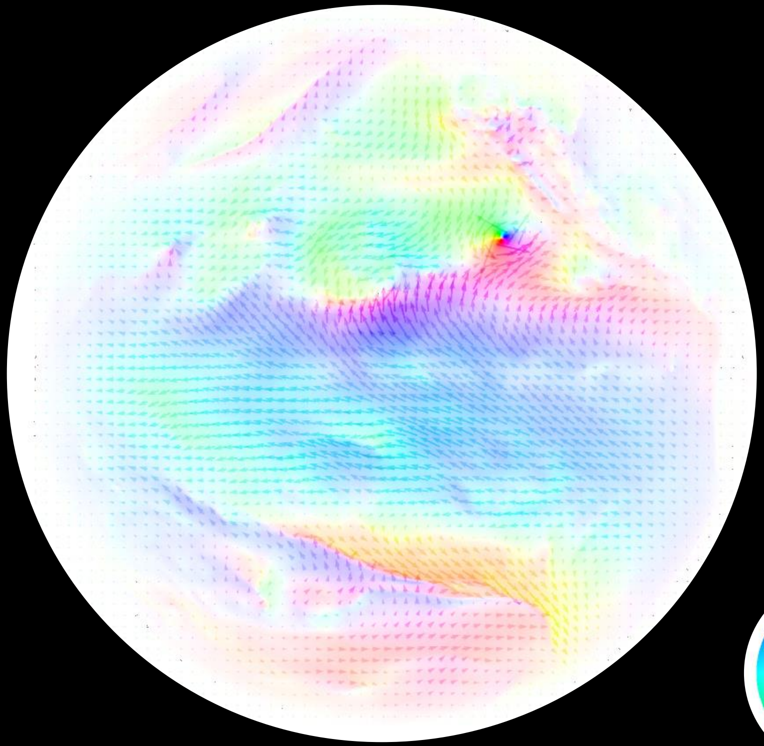


NVIDIA SUPER SLOW-MOTION

USE DEEP LEARNING TO PREDICT OPTICAL FLOW



U-COMPONENT OF WIND



2D OPTICAL FLOW

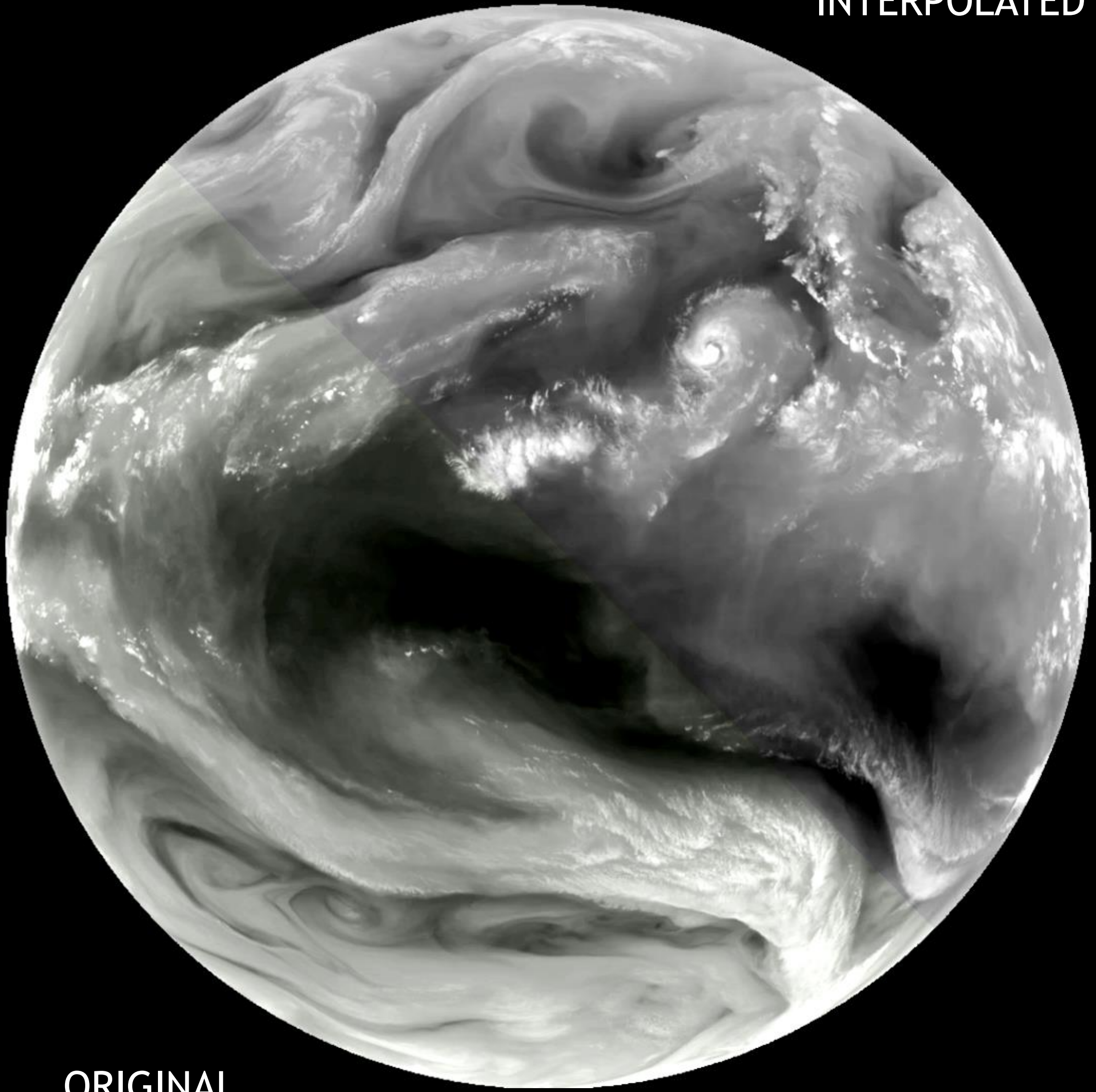
RESULTS: SLOW MOTION ADVECTION

NVIDIA
David Hall

SOURCE
GOES-15 Band 3

TARGET
GFS u,v wind fields

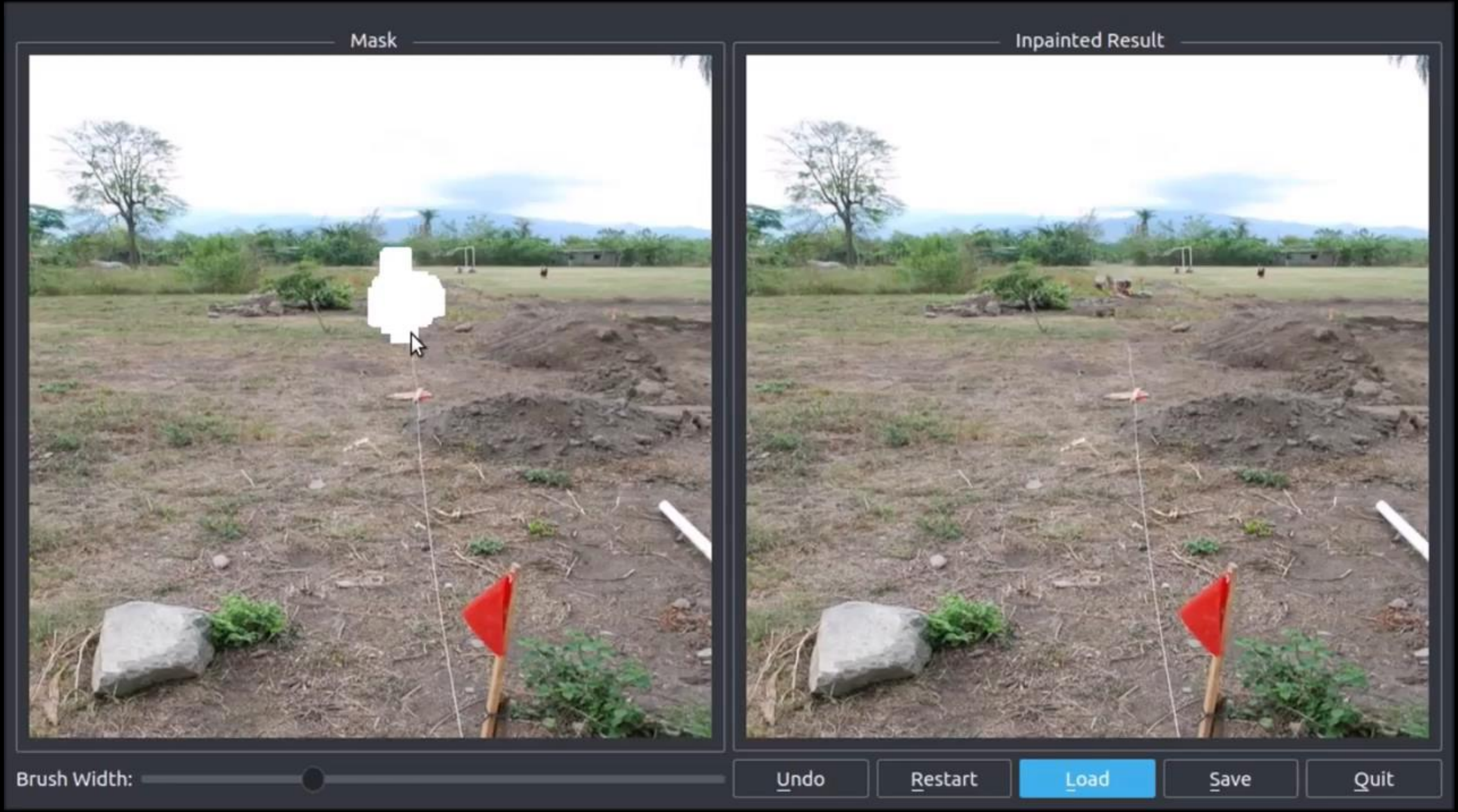
INTERPOLATED (10x)



ORIGINAL

IN-PAINTING

Use partial-convolutions to fill in missing data



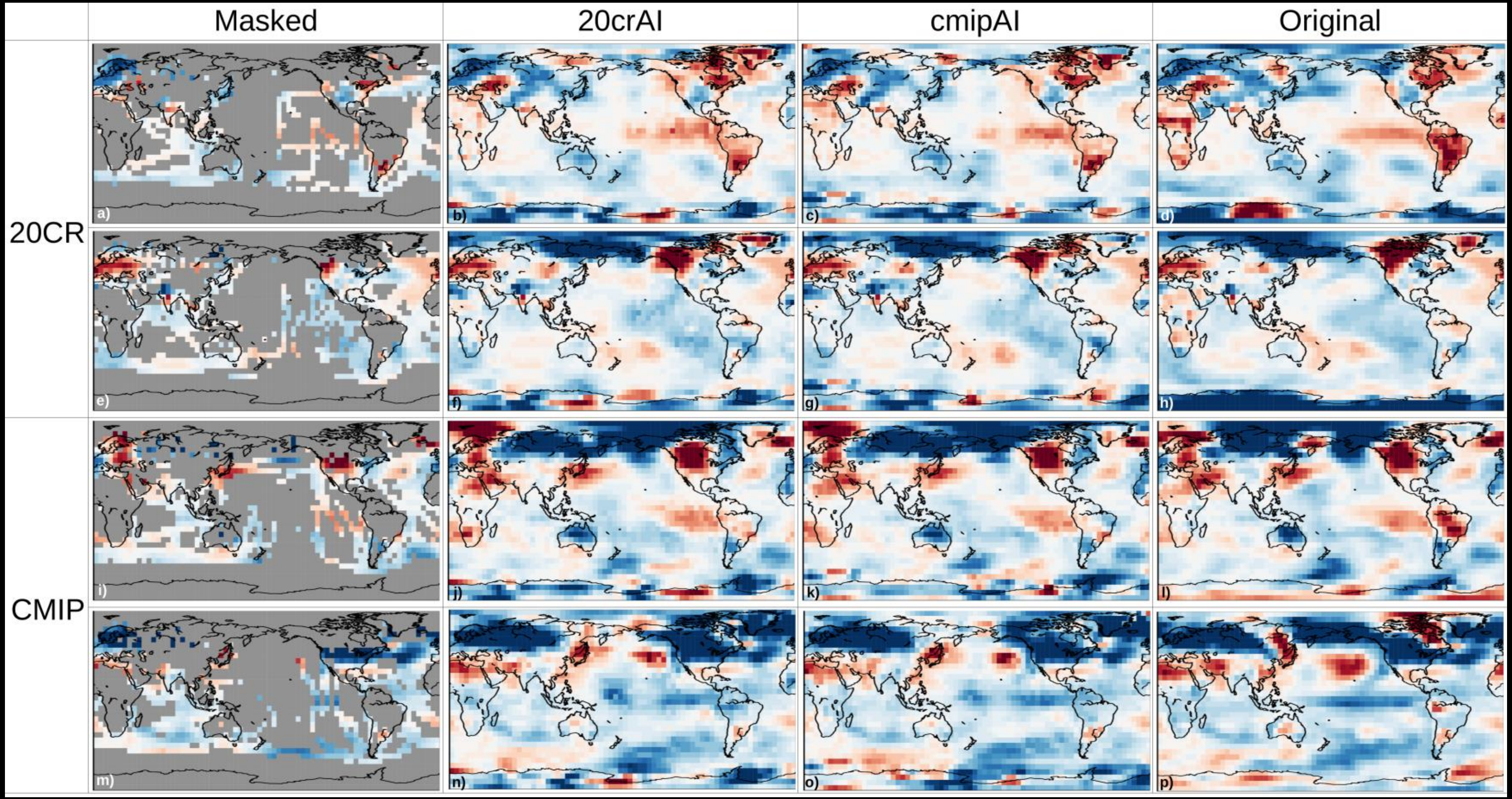
RESULTS: INPAINTING MISSING HADCRUT4 CLIMATE DATA

FREI UNIVERSITAT BERLIN
Christopher Kadow

NVIDIA
David Hall

SOURCE
Hadcrut4, cmip, 20cr

TARGET
Hadcrut4, cmip, 20cr

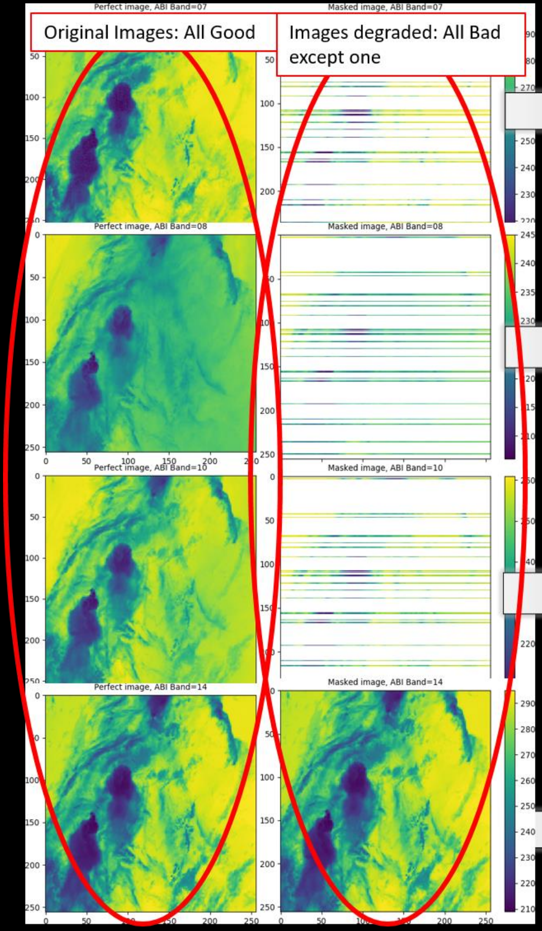


INPAINTING MISSING GOES-17 OBSERVATIONS

NOAA STAR
E. Maddy (RTI)
N. Shahroudi (RTI)
R. Hoffman (UMD)
T. Connor (AER)
S. Upton (AER)
J. Ten Hoeve (NWS)

SOURCE
GOES-17

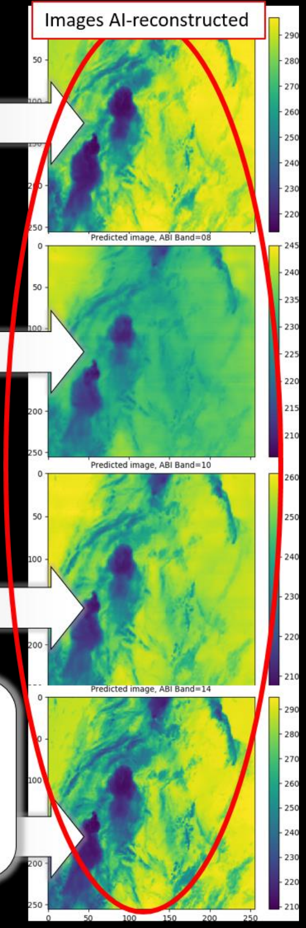
TARGET
GOES-17



AI-BASED IMAGE CORRECTION ALGORITHM

Correction based on NVIDIA's inpainting algorithm but applied for 256 x 256 pixel ABI thermal band images

AI-based correction produces realistic images in corrupted bands.
Corrections can be applied when all thermal bands are corrupted or when only a subset of bands are corrupted. In the latter case, image reconstruction improved due to spatial/spectral redundancy.



STREAMFLOW PREDICTION UNDER CLIMATE CHANGE

UC Davis, NVIDIA

Climate models are able to predict changes in precipitation, but how will this effect streamflow rates? To answer this question one can built a detailed physical model, or train a neural network to predict time series data. In this case, we find a simple network performs just as well.

GOES-16 CIRA GEO COLOR / GOES-15 RED BAND

STREAMFLOW FROM PRECIPITATION

Predicting streamflow probabilities under climate change

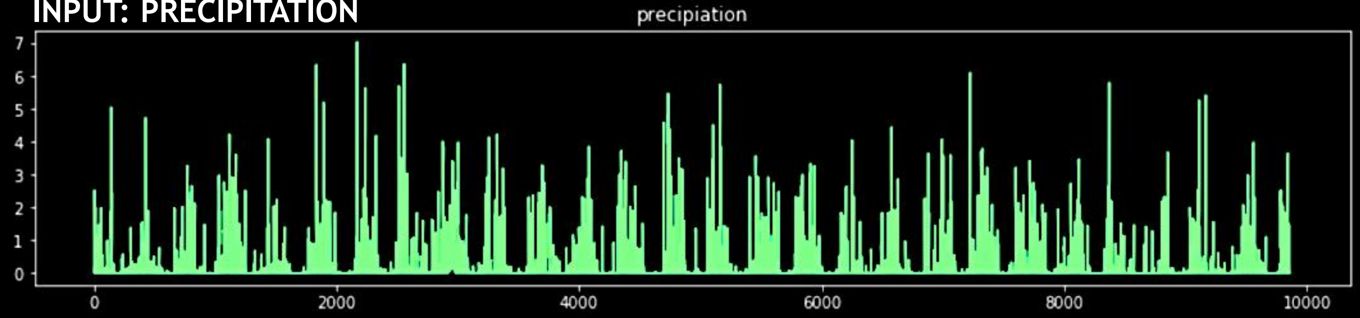
UC Davis
Paul Ullrich, Lele Shu, Shiheng Duan

NVIDIA
David Hall

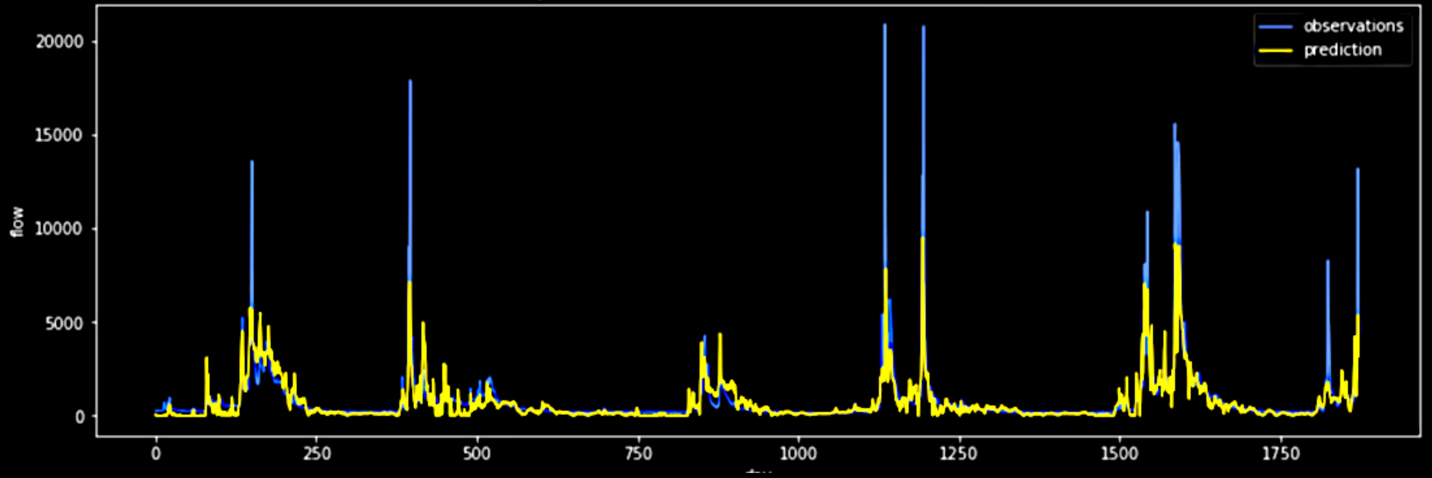
Source
PRISM

Target
Stream Gauge Data

INPUT: PRECIPITATION



OUTPUT: STREAMFLOW



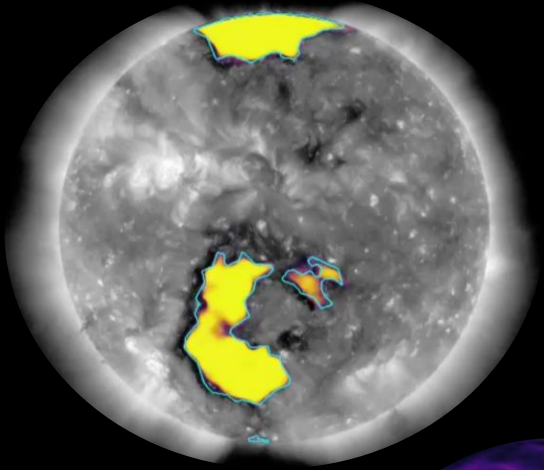
SUMMARY

- Deep Learning is another way to write software
- DL functions are created from data
- Can enforce conservation with Lagrange multipliers or hard constraints
- An alternative route to GPU optimization
- Can automate or improve many tasks
- Build functions too unintuitive / complex for humans
- Regression returns a single value (the mean)
- GANs randomly sample states from a distribution
- DL functions are limited by data + model expressiveness
- Hand-written functions can be limited by imagination + programming language

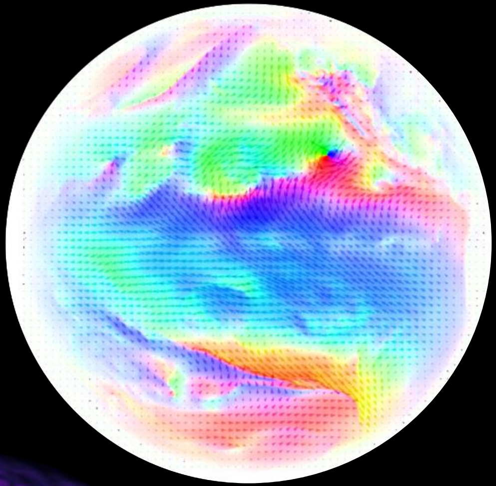
ctierney@nvidia.com

SUMMARY

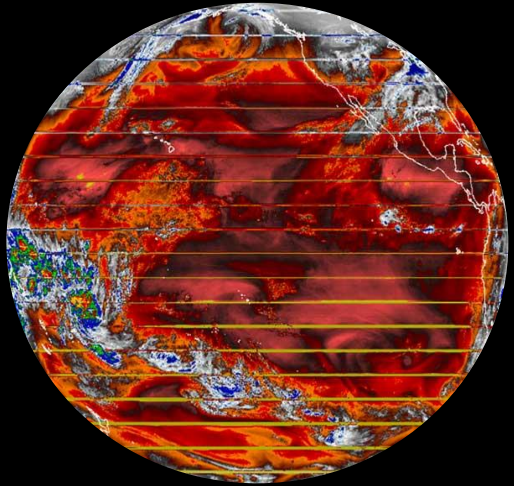
UNETS FOR WEATHER AND SPACE-WEATHER DETECTION



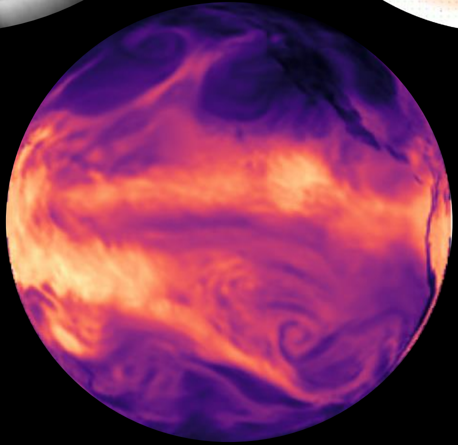
SLOW MOTION INTERPOLATION VIA OPTICAL FLOW PREDICTION



INPAINTING FOR IMPUTING MISSING HADCRUT4 AND GOES-17 DATA



CONDITIONAL GANS FOR DATA ASSIMILATION AND CLOUD GENERATION



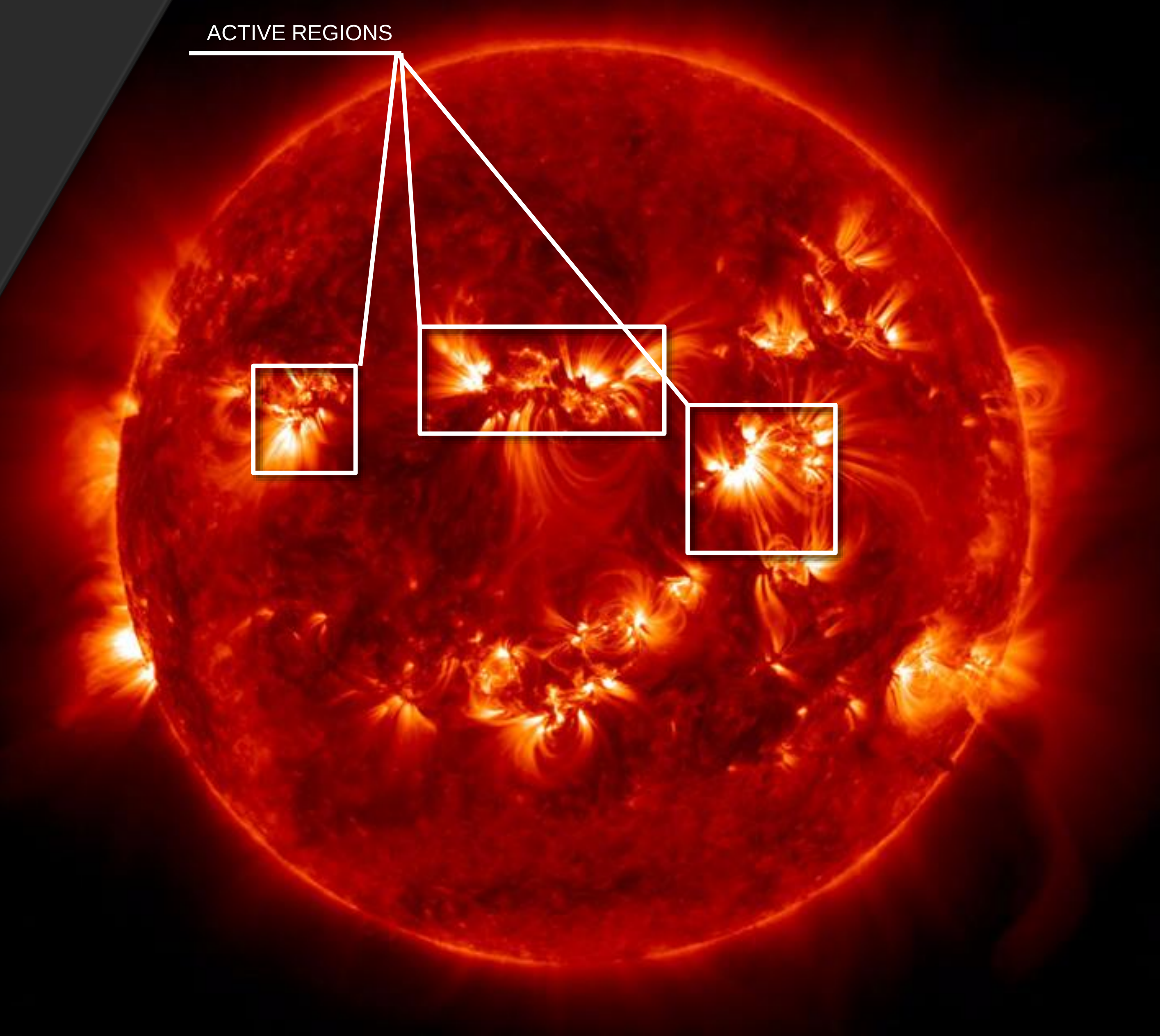
CONVOLUTIONS IN TIME FOR STREAMFLOW PREDICTION

ctierney@nvidia.com

SPACE-WEATHER DETECTION

NASA GODDARD
ALTAMIRA & NVIDIA

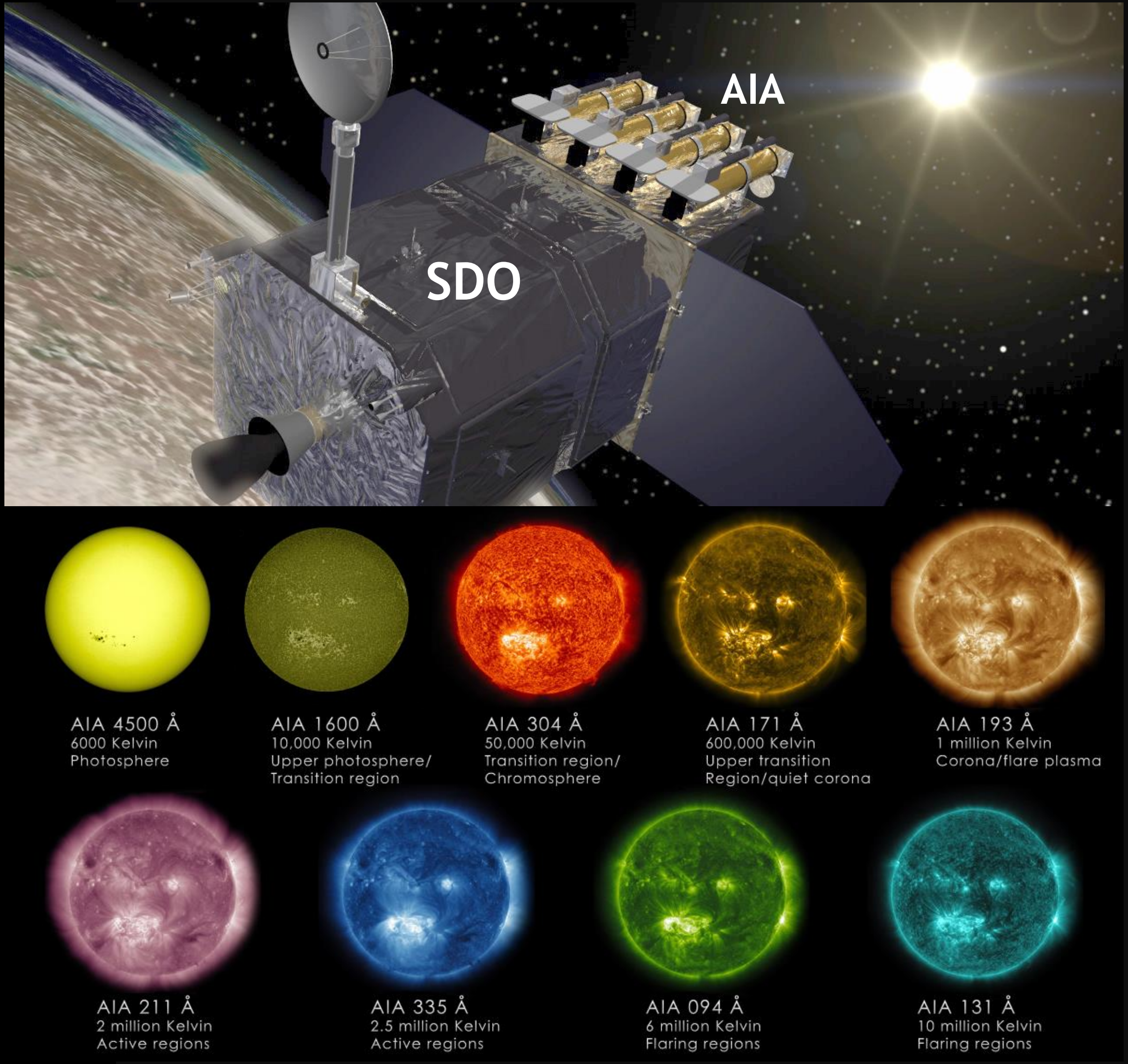
Feature detection can be applied to detect features on the Sun and other astrophysical bodies. In particular, we can apply AI to solar flares and coronal mass ejections in order to predict the influx of highly charged particles on Earth's atmosphere.



SOLAR DYNAMICS OBSERVATORY

- 1.5 TB Data / Day
- Operational Since 2010
- AIA: 10 Wavelength Channels
- 150M Images To Be Labelled
- 30k Images Labelled so far

- Coronal Holes
- Active Regions
- Sunspots
- Solar Flares
- Coronal Mass Ejections
- Filaments



RESULTS:
CORONAL HOLES

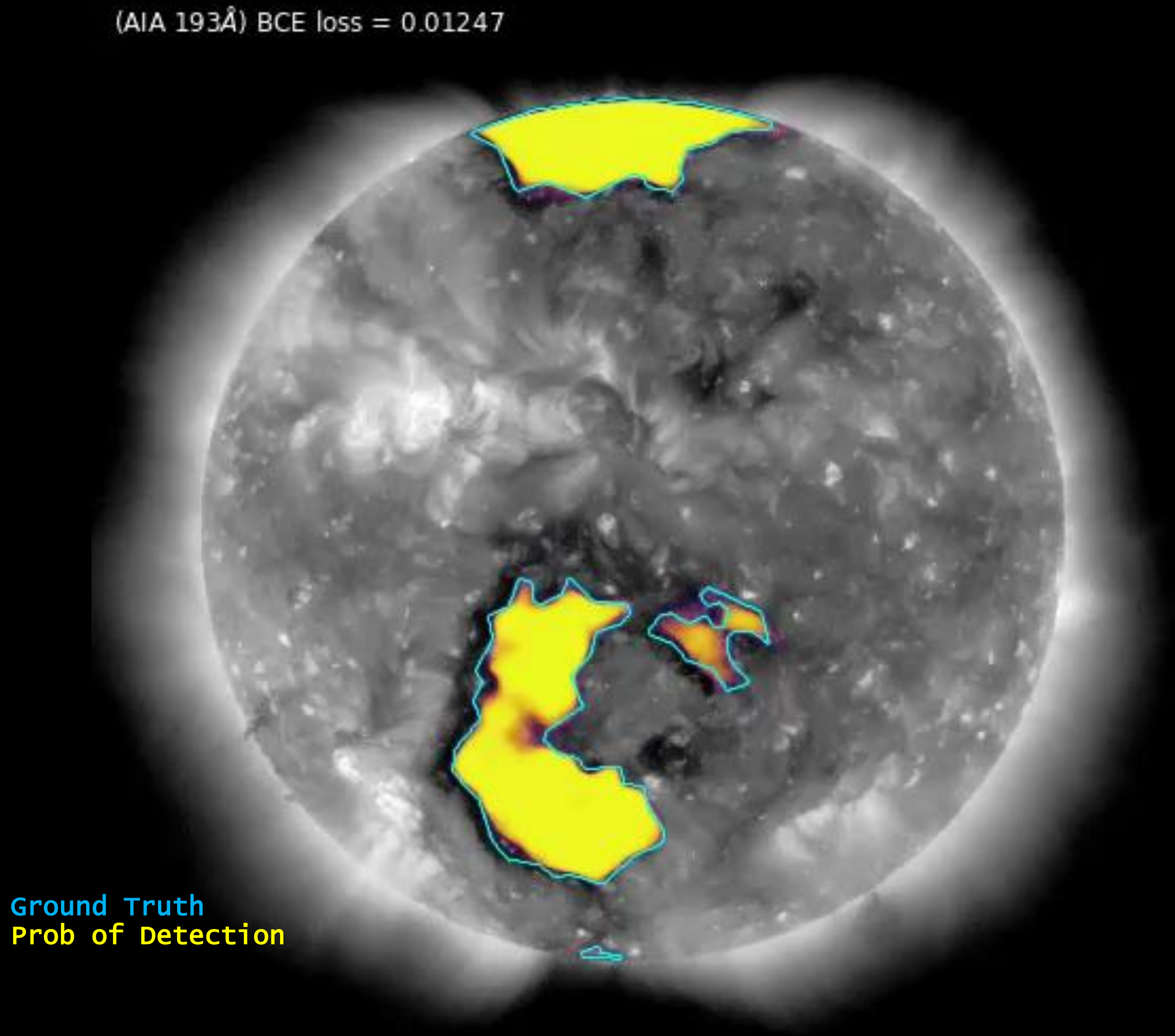
NASA Goddard
Michale Kirk, Barbara Thompson,
Jack Ireland, Raphael Attie

NVIDIA
David Hall

Altamira
Matt Penn, James Stockton,

SOURCE
Solar Dynamics Observatory
AIA Imager

TARGET
Hand-crafted detection algorithm



SUNSPOT PREDICTIONS

Highly imbalanced dataset. Needs special care.

Predicts all 0s unless special care is taken

- Super-sample minority class
- Under-sample majority class
- Use focal loss

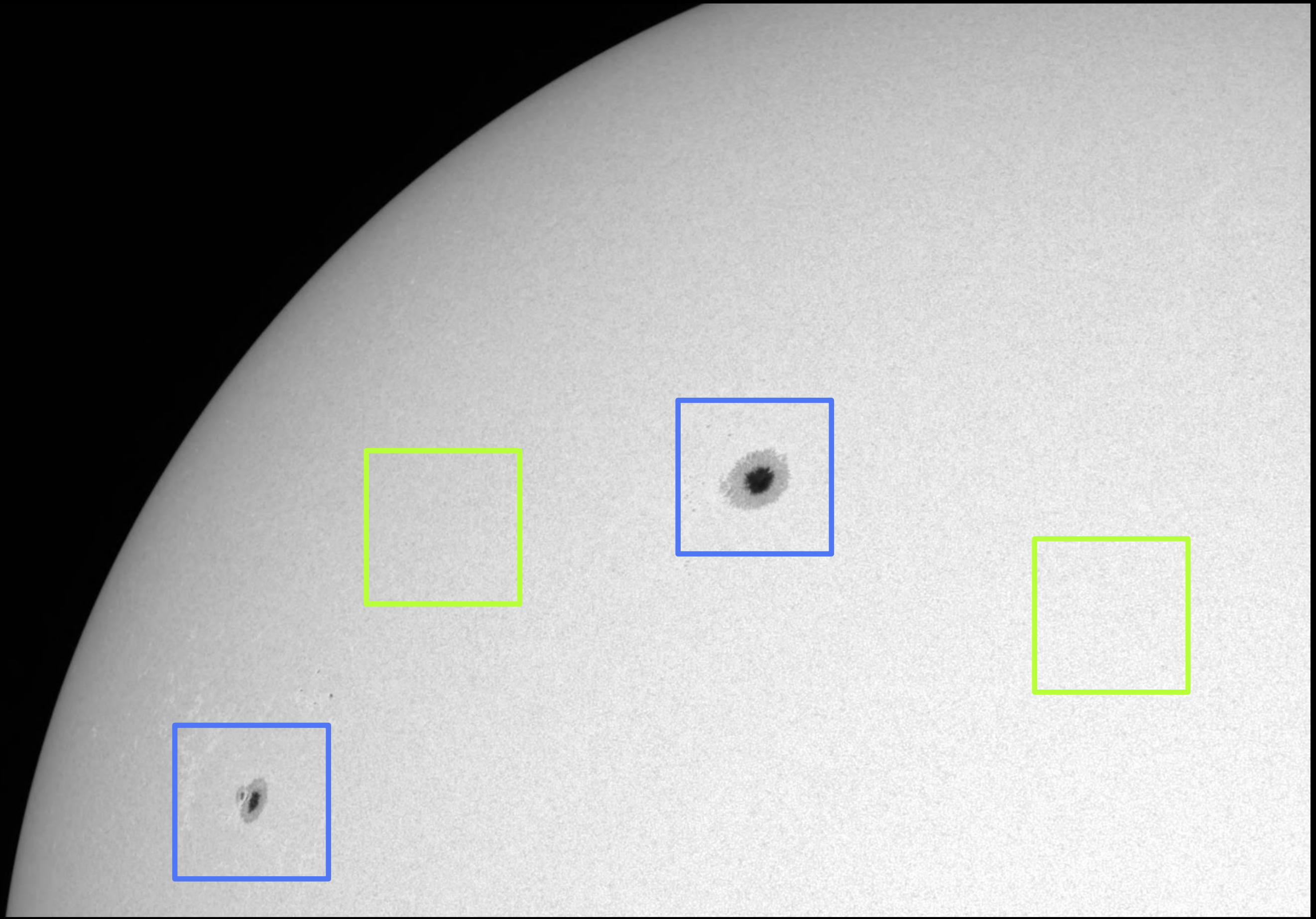
Select small crops from high-res imagery

Pos : crops w/large fraction sunspot pixels

Neg : randomly selected crops

Train conv net on small crops only

Predict on full-resolution images



RESULTS: SUNSPOTS

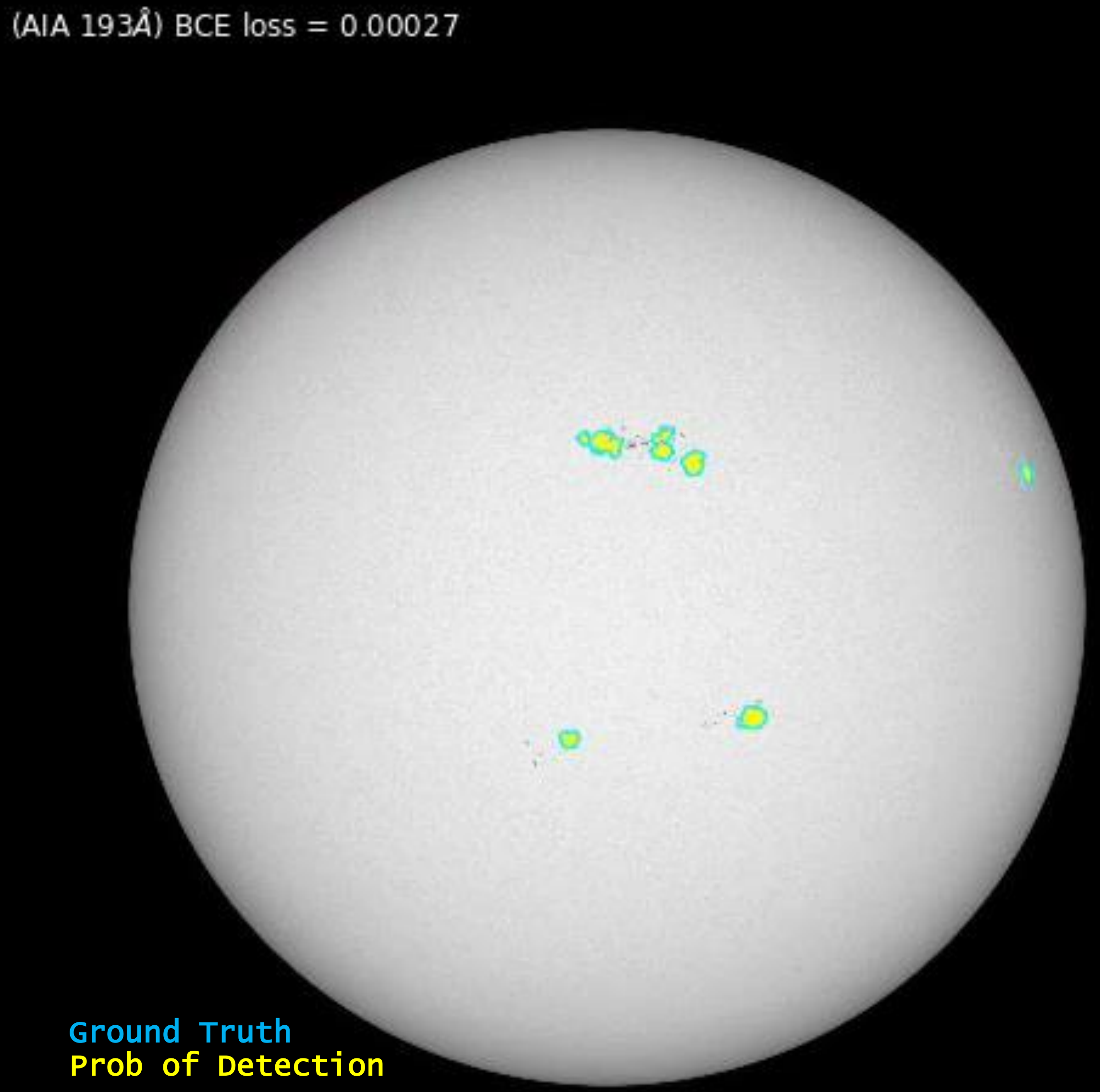
NASA Goddard
Michale Kirk, Barbara Thompson,
Jack Ireland, Raphael Attie

NVIDIA
David Hall

Altamira
Matt Penn, James Stockton,

SOURCE
Solar Dynamics Observatory
AIA Imager

TARGET
Hand-crafted detection algorithm



RESULTS:
ACTIVE REGIONS

NASA Goddard
Michale Kirk, Barbara Thompson,
Jack Ireland, Raphael Attie

NVIDIA
David Hall

Altamira
Matt Penn, James Stockton,

SOURCE
Solar Dynamics Observatory
AIA Imager

TARGET
Hand-crafted detection algorithm