DEEP LEARNING APPLIED TO SATELLITE DATA PROCESSING

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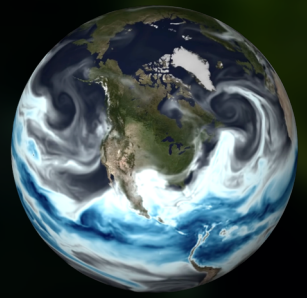
Nov 2018

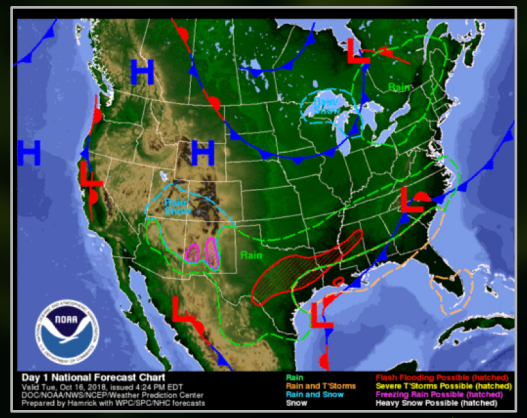
A NEW SET OF TOOLS

Deep Learning has the potential to improve all stages of NWP

3D/4D-VAR

CRTM



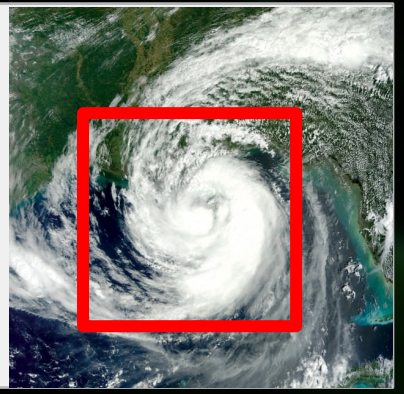


COLLECTION	THINNING	ASSIMILATION	DYNAMICS	PHYSICS	FORECASTING
Error correction Bias correction Enhancement	Utilization Optimization	Forward/Inverse Operator Automation	Acceleration via Emulation	Improved Physics	Anomaly detection, visualization, statistical analysis

DETECTION

- **Tropical storms**

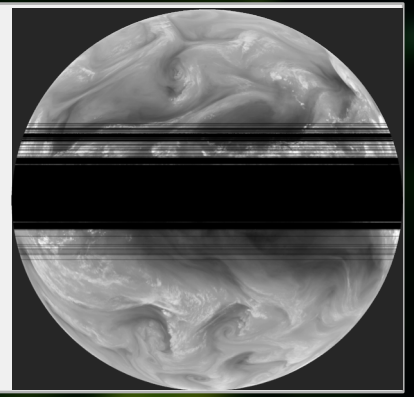
Extra-tropical cyclones
Atmospheric rivers
Cyclogenesis events
Convection initiation
Change detection



ENHANCEMENT

Frame repair
Sequence repair
- **Slow motion**

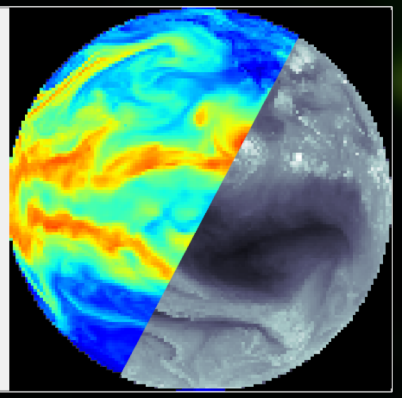
Anomaly detection
Super-resolution
Cloud removal



TRANSLATION

- **Data Assimilation**

Forecast verification
Model inter-comparison
Common data formatting
Colorization



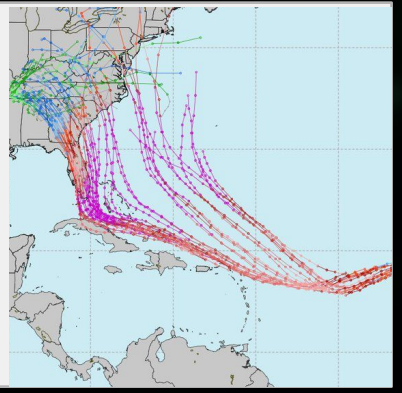
EMULATION

Physics Acceleration
Turbulence
- **Radiation**

Convection
Microphysics
Dynamics Acceleration

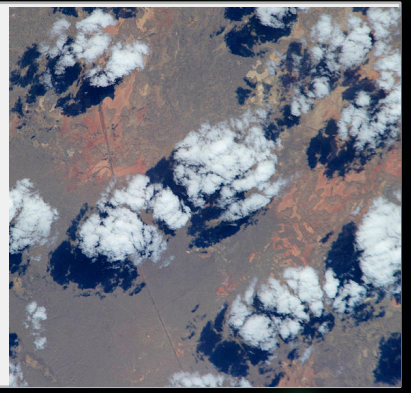
PREDICTION

Uncertainty prediction
Storm track
Storm intensity
Fluid motion
Now casting
Satellite frame prediction



PARAMETRIZATION

New parametrizations
From higher resolution model
- **From observational data**



GOAL: IMPROVED SATELLITE UTILIZATION

Apply AI to improve data thinning, enhancement, and assimilation

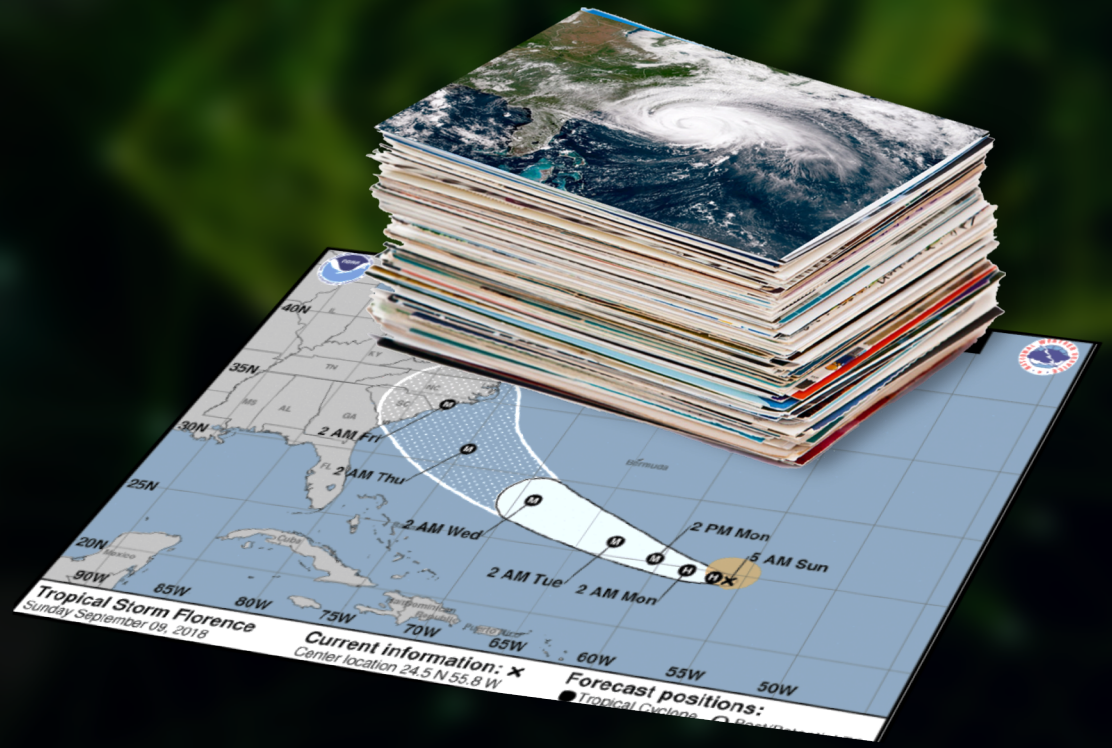
NOAA's Mission: Timely & accurate weather prediction

Satellite data valuable resource for data assimilation

Data volume far exceeds quantity which can be used

Less than 3% utilized

Goal: Improve quality and utilization through AI



DEEP LEARNING PROJECTS

NVIDIA collaborations with NOAA ESRL and JCSDA

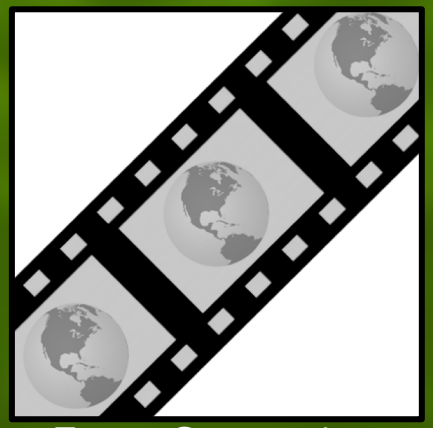
REGION OF INTEREST DETECTION

Data Thinning

DATA-TO-DATA TRANSLATION

Data Assimilation

SLOW MOTION INTERPOLATION



Error Correction

PROJECT 1: REGION OF INTEREST DETECTION FOR DATA THINNING

The amount of satellite data collected far exceeds the limits of what may be assimilated in 20 minutes, and most data remains unused. Can we improve upon this data thinning process by selecting observations that have a larger impact on the forecast?

NOAA ESRL

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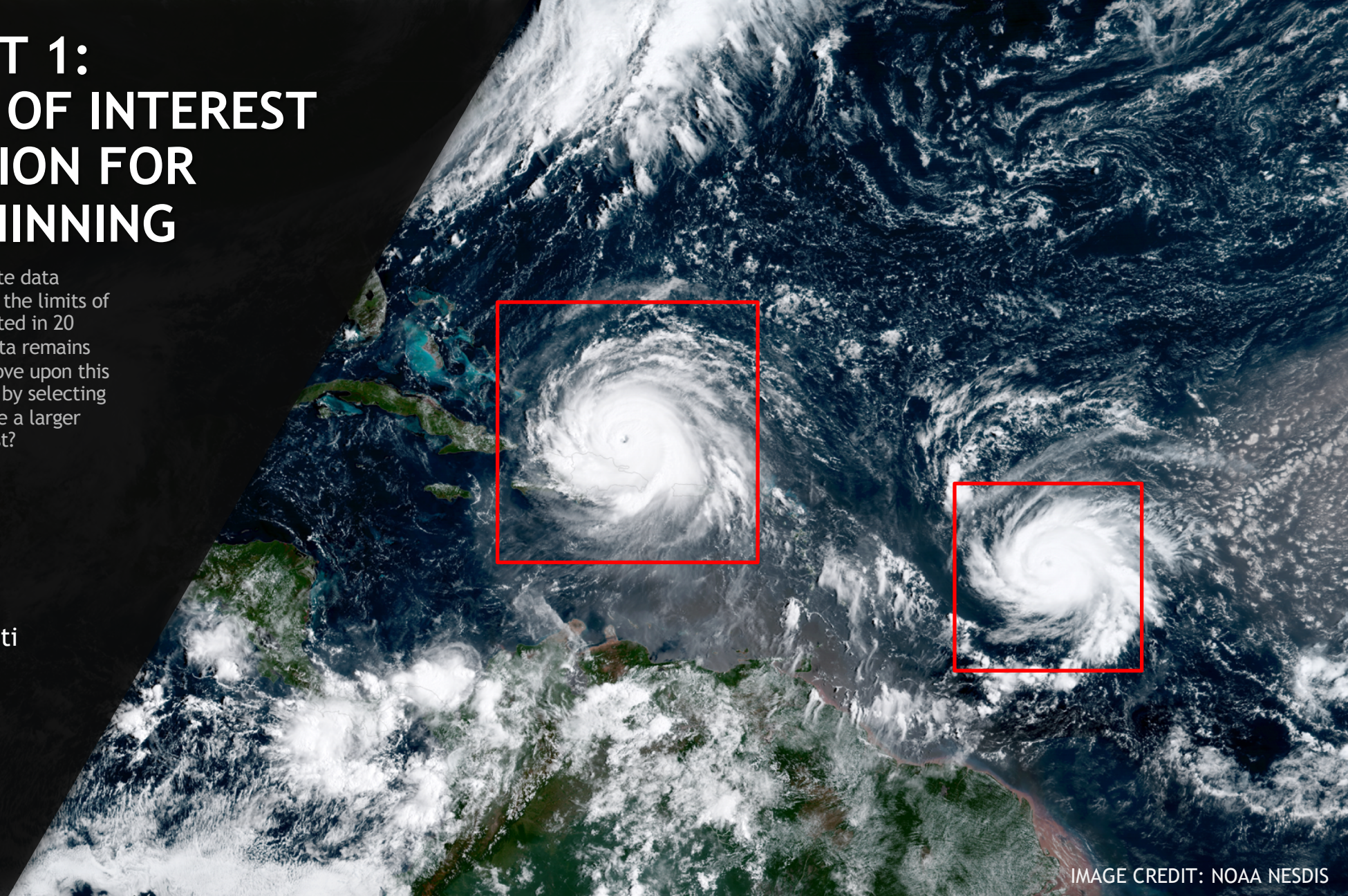


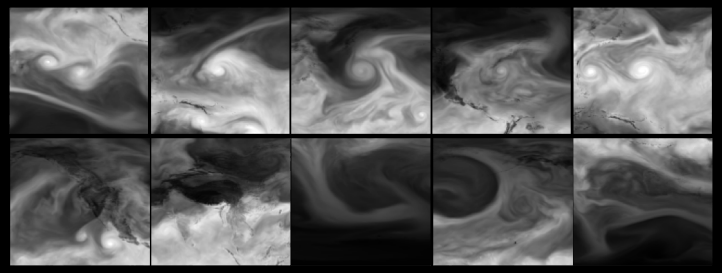
IMAGE CREDIT: NOAA NESDIS

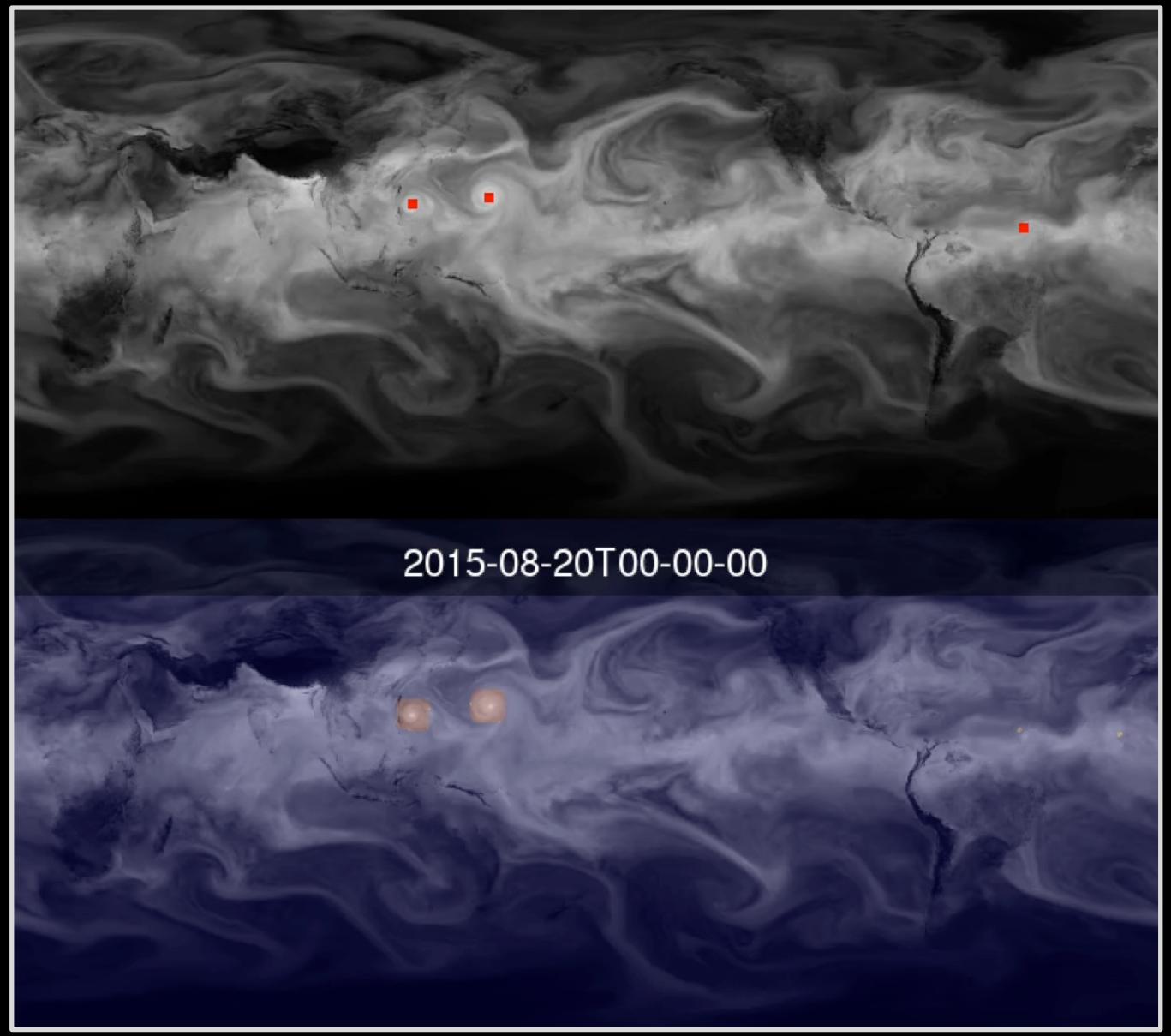
RESULTS: GFS MODEL DATA

Tropical Storms from GFS water vapor

INPUT	**GFS PWAT+ IBTRACS**
OUTPUT	Detection confidence
TRAINING SET	2010-2015
TEST SET	2016
NETWORK(s)	**U-NET**

TRAINING EXAMPLES





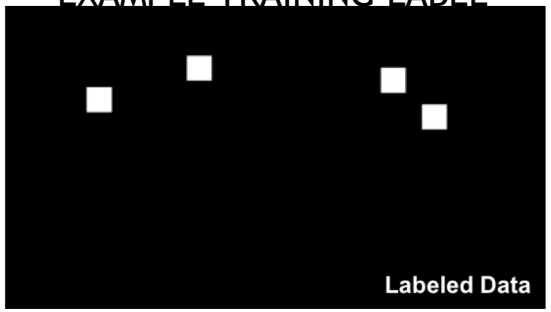
Next Steps: cyclogenesis, convection initiation

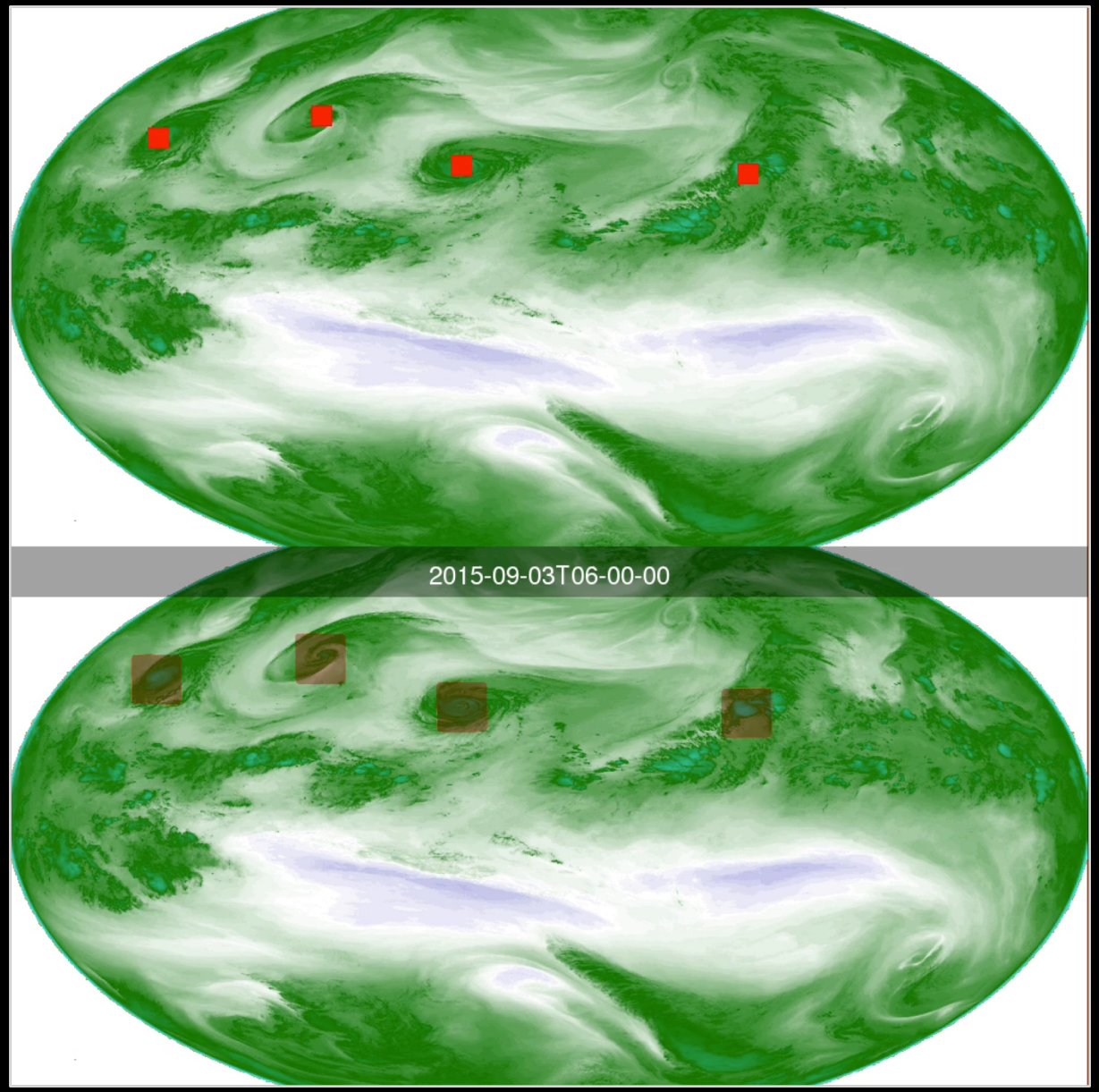
RESULTS: GOES OBSERVATIONS

Tropical Storms from GOES water vapor

INPUT	GOES upper tropo WV + IBTRACS
OUTPUT	Detection confidence
TRAINING SET	2010-2013
TEST SET	2015
NETWORK(s)	U-NET

EXAMPLE TRAINING LABEL





Next Steps: cyclogenesis, extra-tropical cyclones

PROJECT 2: IMAGE-TO-IMAGE TRANSLATION FOR DATA ASSIMILATION

Can we improve data assimilation and forecast verification by employing neural networks to automatically map observations onto model variables?

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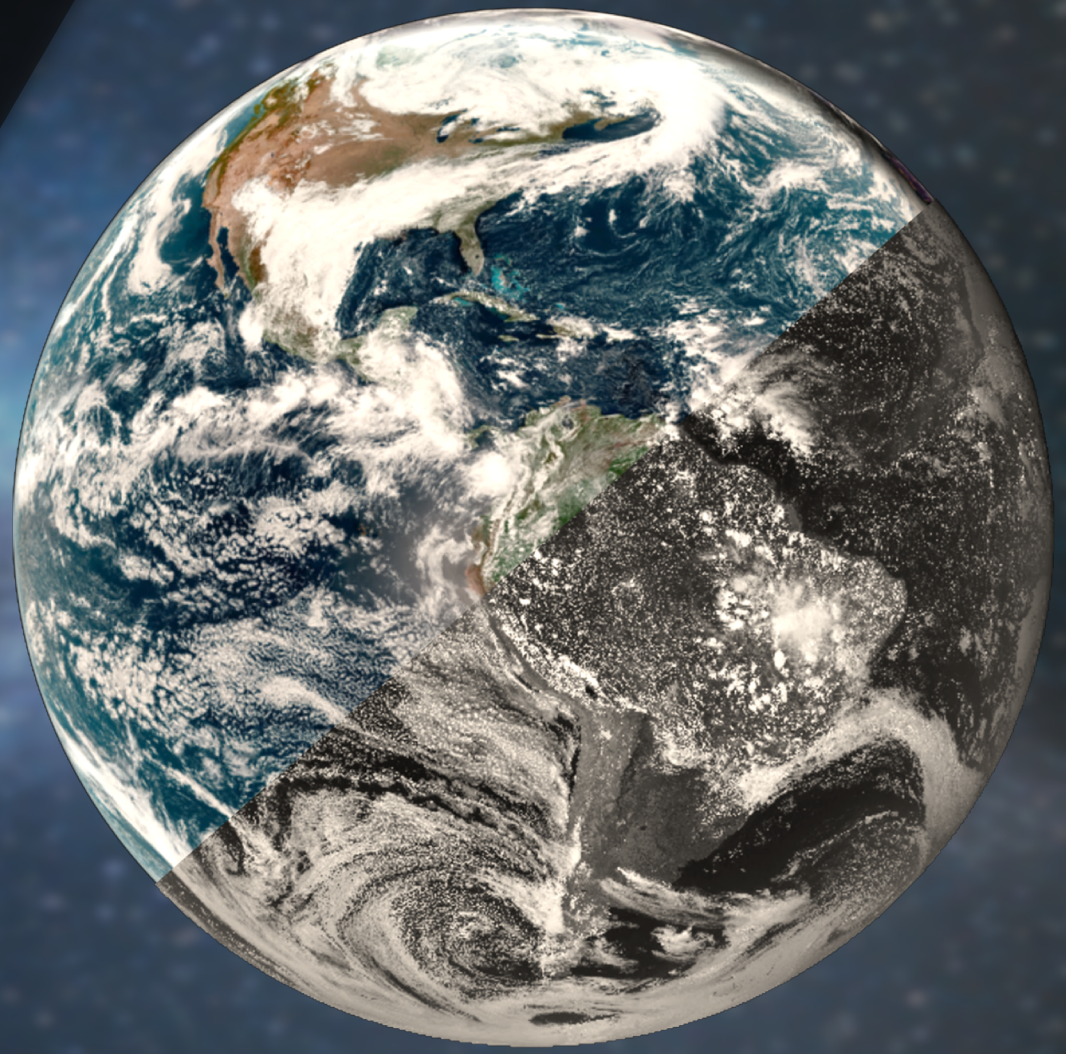


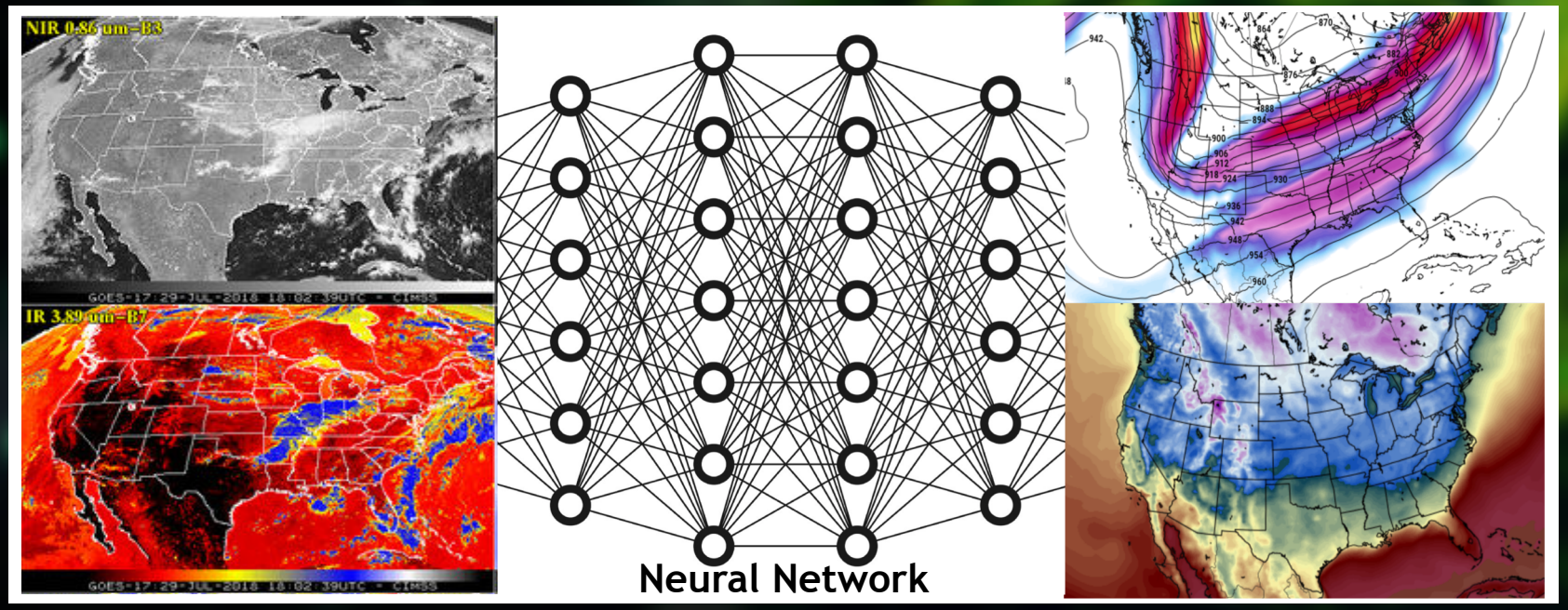
GOES-16 CIRA GEO COLOR / GOES-15 RED BAND

SATELLITE TO MODEL CONVERSION

Goal: Construct map from satellite to model

SATELLITE RADIANCES

GFS MODEL VARIABLES



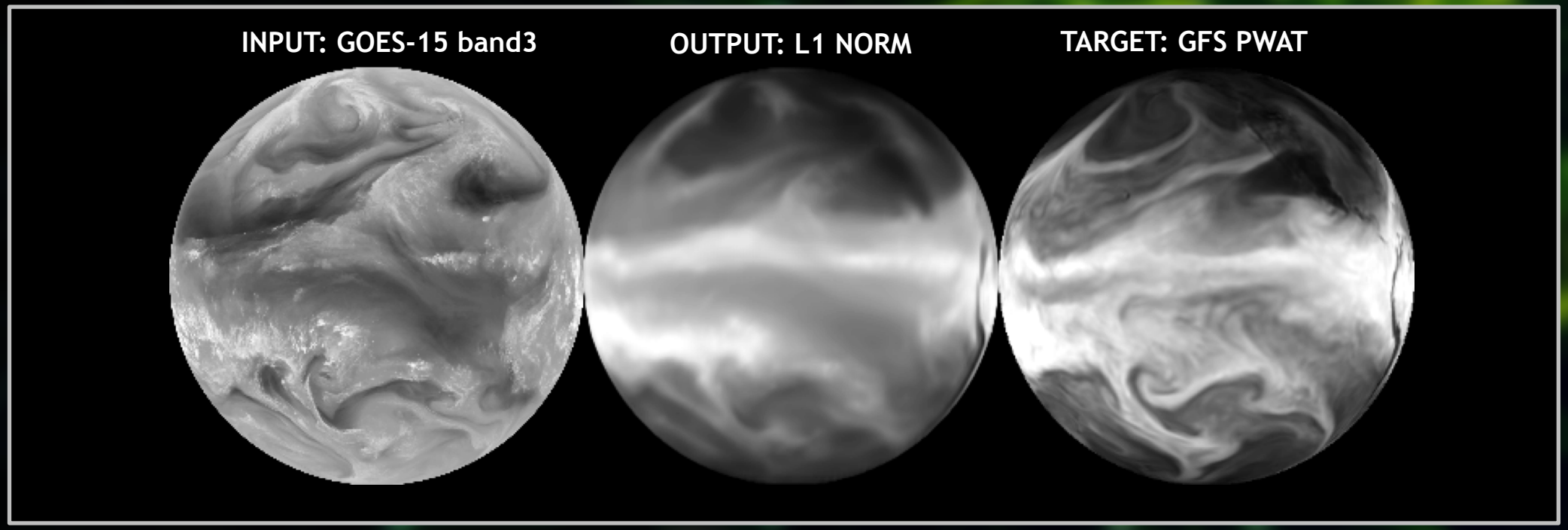
No analytic formula available (inverse operator)

Data assimilation: forward operator + adjoint-sensitivity analysis

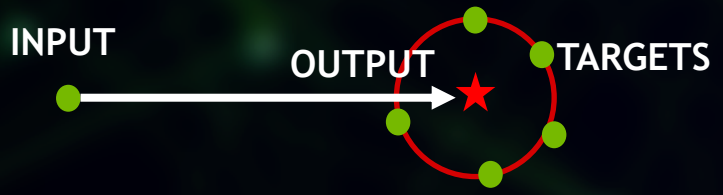
Deep learning can potentially obtain inverse operator numerically

RESULTS: REGRESSION

One-to-many map results in ‘regression to the mean’



- L1 output is *average* of multiple plausible states
- Not consistent with any single realizable state
- Adding bands can more fully constrain the output

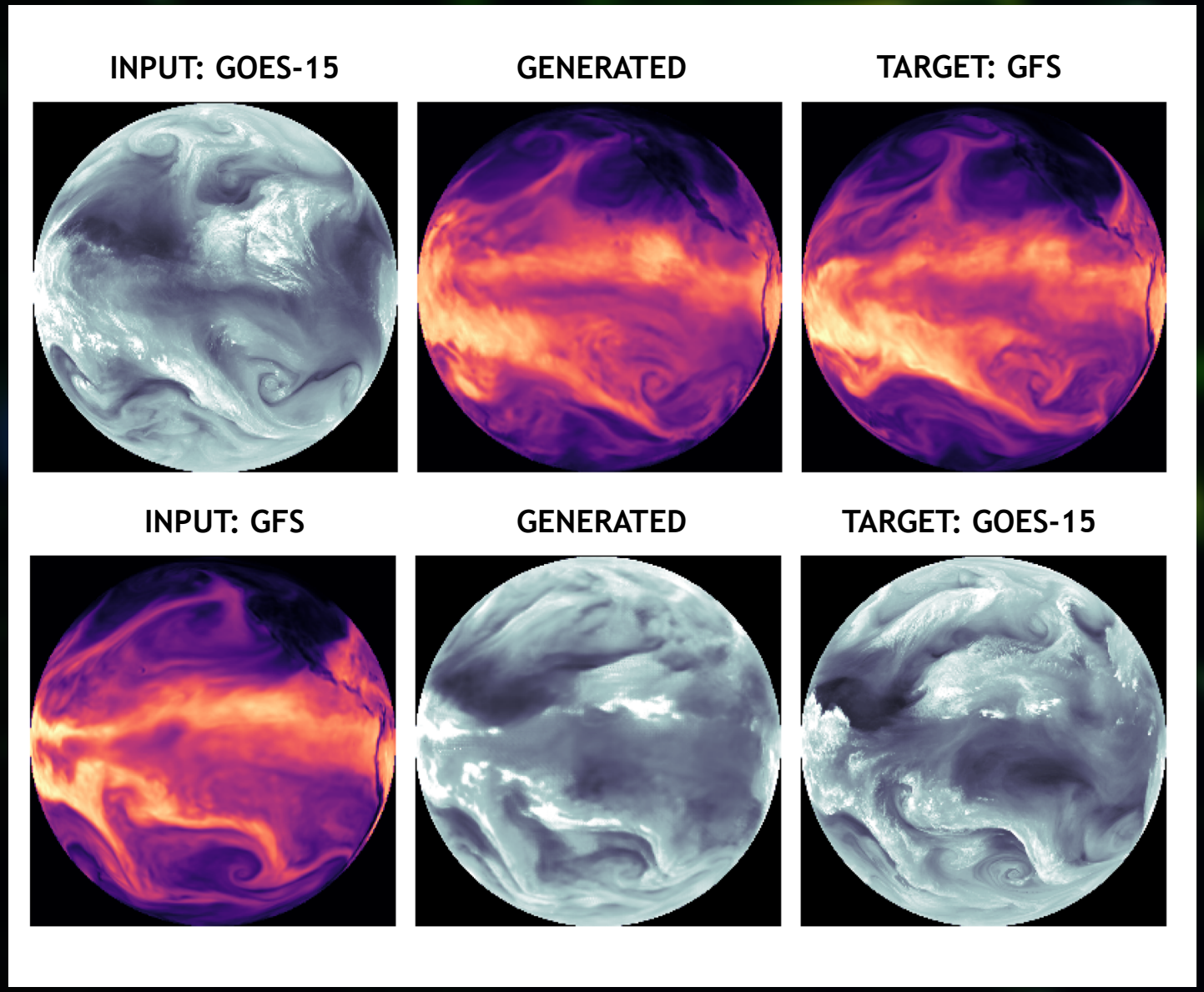


RESULTS: C-GAN

Physically plausible state from incomplete data

OBSERVATION	GOES-15 band 3
MODEL VAR	GFS Precipitable water
Training	2014-2016
Test	2013

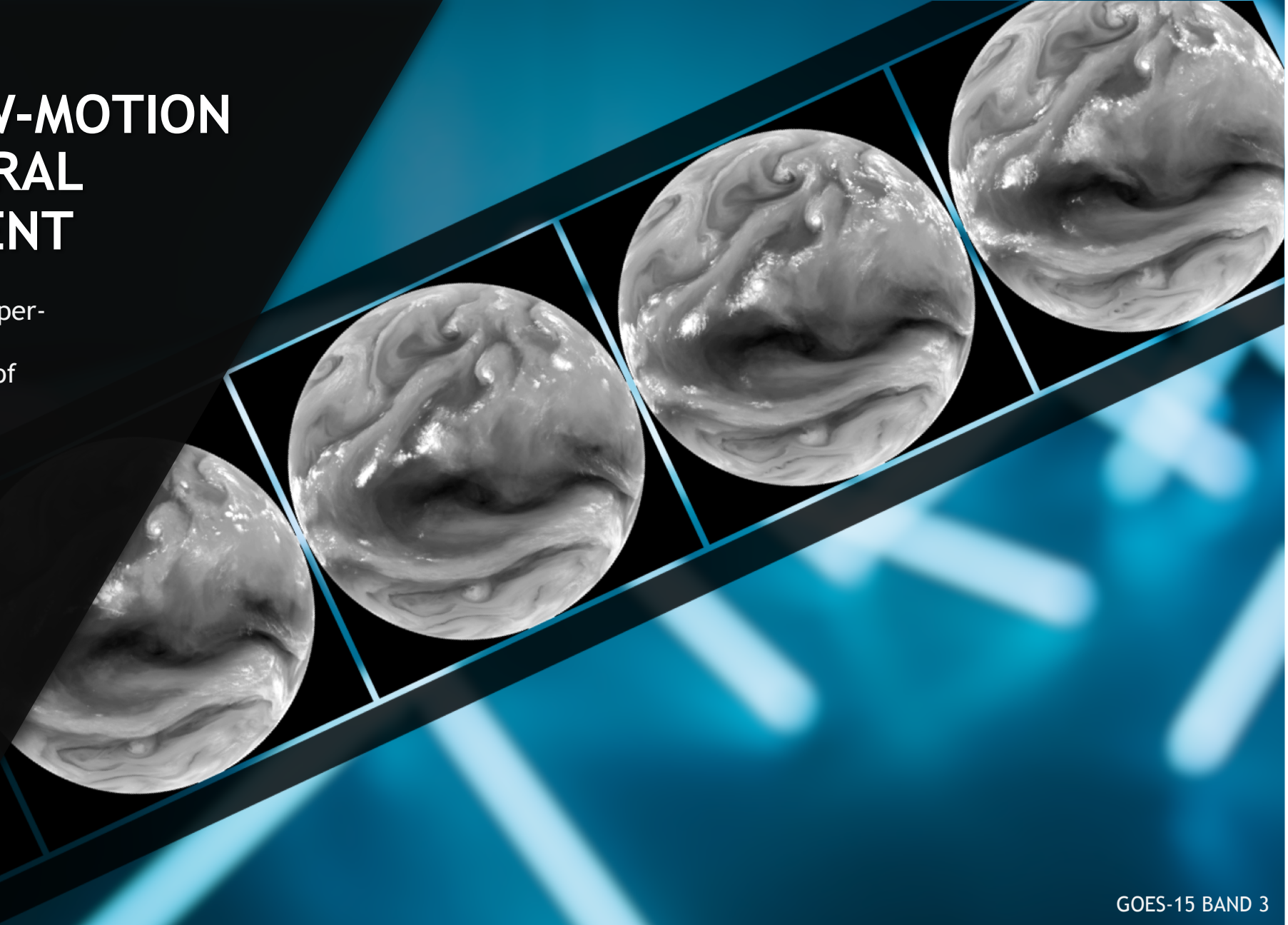
- Adversarial model outputs a physically plausible state
- Like an ensemble member from uncertain initial conditions
- Sat->model and model->sat
- For data assimilation and forecast verification
- Next: quantify error covariances



PROJECT 3: SUPER SLOW-MOTION FOR TEMPORAL ENHANCEMENT

Can we apply NVIDIA's super-slow motion algorithm to increase the frame rate of satellite observations?

NVIDIA
David Hall



GOES-15 BAND 3

NVIDIA SUPER SLOW-MOTION

Deep learning technique for slow-motion interpolation

SLOW MOTION FOR SATELLITE LOOPS

Goal: Adapt for geophysical fluid dynamics

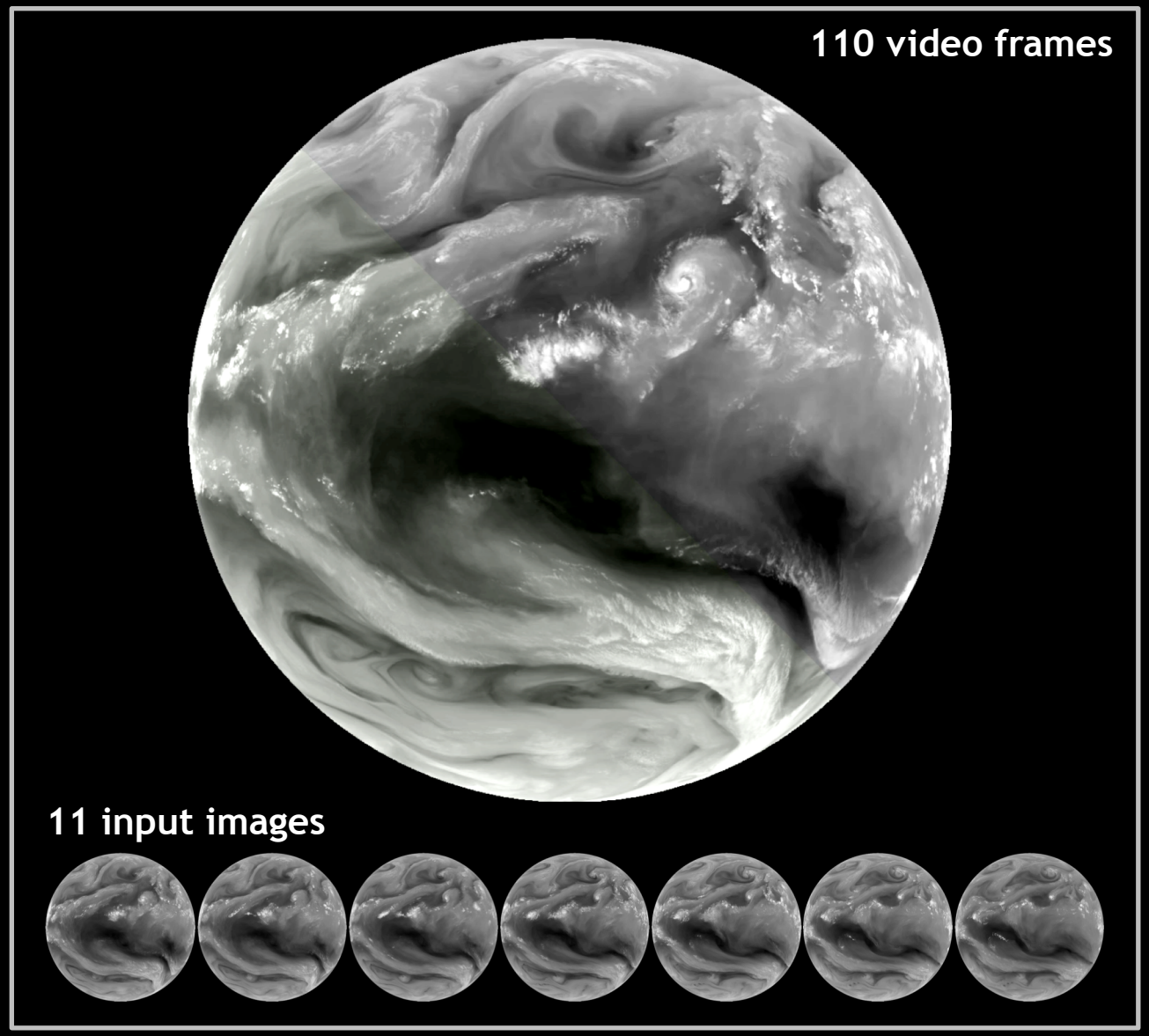
INPUT	GOES-15 band 3 GFS winds @ 350 hPa
OUTPUT	Interpolated GOES-15
INPUT FREQ	1 every 3 hours
OUTPUT FREQ	1 every 18 minutes

Applications:

- Visualization
- Data Augmentation
- Replace dropped frames
- Reduce storage requirements

Next Steps

- Predict winds directly from GOES imagery
- Back-propagate to fine-tune winds
- Fine tune ODE from data
- Augment detection and translation tasks



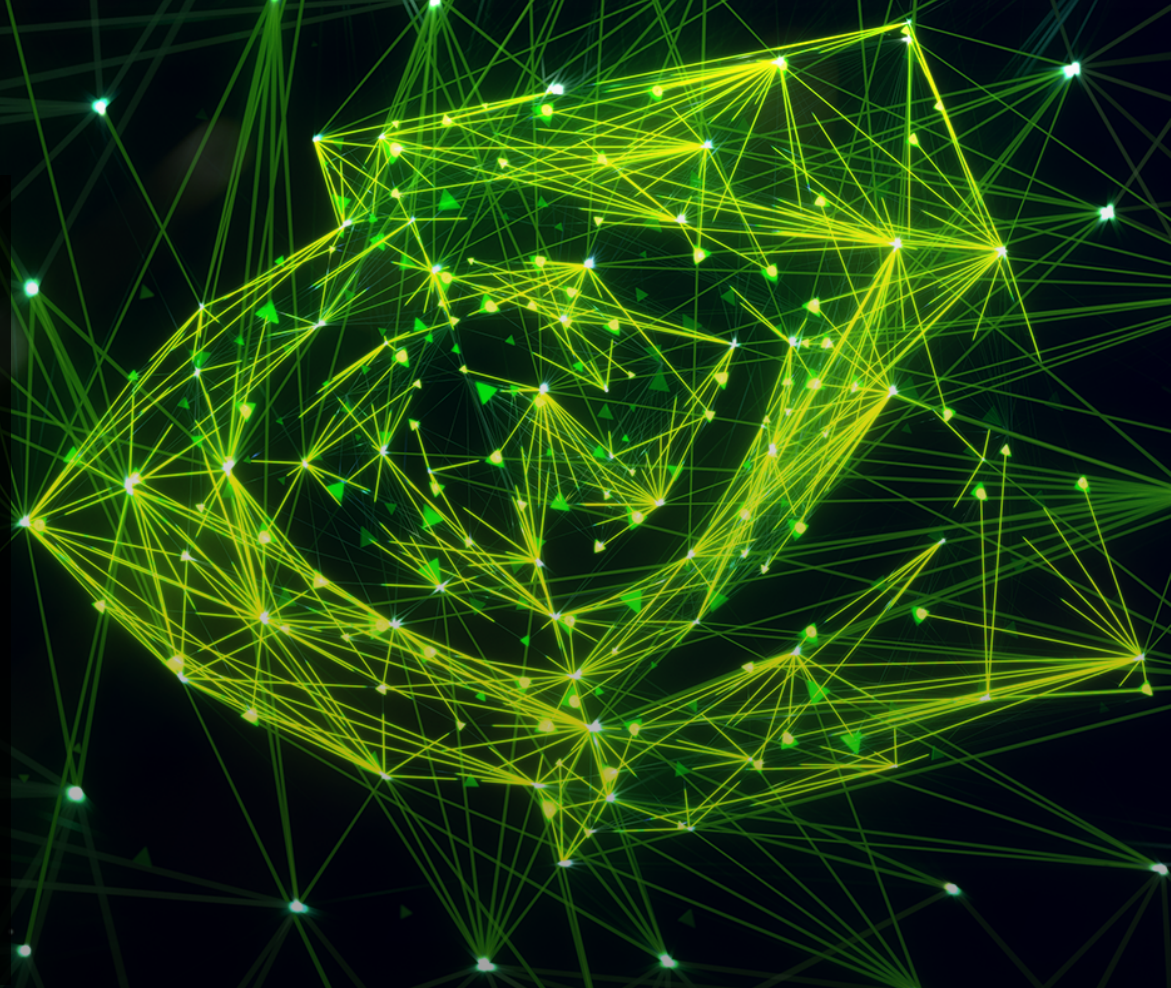
SUMMARY

Deep learning is useful for all stages of NWP

Satellite Projects:

1. Locate ROIs for data thinning

2. Satellite->model map for data assimilation

3. Satellite slow-motion for augmentation and error correction

Many more applications possible