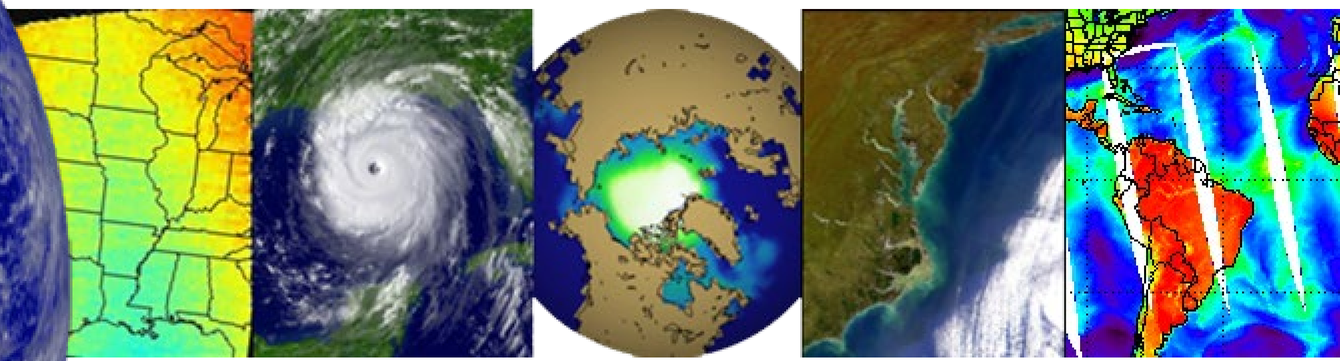
Can we Design a New NWP Data Assimilation System Based Entirely on AI Techniques?

Advantages & Challenges

Presented by Flavio Iturbide-Sanchez[1]
Co-authors: S.-A. Boukabara[2] and E. Maddy[3]

[1]NOAA/NESDIS/Center for Satellite Applications and Research
[2]NOAA/NESDIS/Office of System Architecture and Advanced Planning
[3]Riverside Technology Inc. (RTI)



Oultine

1. **Challenge, Objective, Motivation & Questions We want to Answer**
2. **Description of the Approach:** *Architecture, Mathematical basis, etc*
3. **Assessing Performance:**
   - *Execution Efficiency*
   - *Analysis Quality: Increments' spatial and Temporal Distributions*
   - *Physical Constraints: Geostrophic Balance*
   - *Physical Constraints: Hydrostatic Balance*
   - *Physical Constraints: Kinetic Energy Conservation*
   - *Physical Constraints: Inter-Parameters Geophysical Correlation*
   - *Qualitative Assessment Using AI-Based Data Denials OSEs*
4. **Summary and Conclusions**

Challenge: Complexity of the Observations Exploitation

Satellites:
National, Internat., LEO, GEO, MW, IR, RO, Act/Passiv, etc.

Conventional:
Airborne, sondes, ground based, etc

Commercial:
RO, MW, SpcWx, etc

NOAA's Commercial Data Buy Program (CDBP)

Unmanned:
Air, Ocean-based, , etc

Internet-Of-things:
Communication towers, vehicles, etc

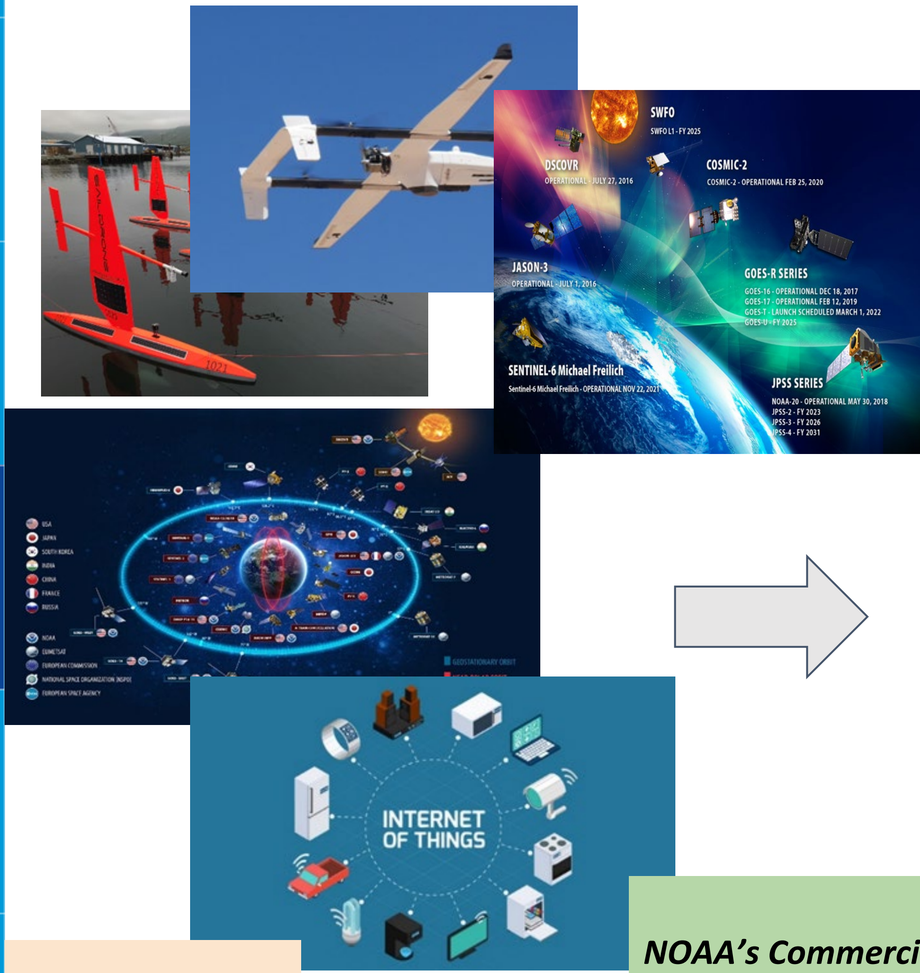
Next-Gen Satellites:
Smallsats, Hyperspectral GEO, etc

Users or Model #1

Users or Model #N

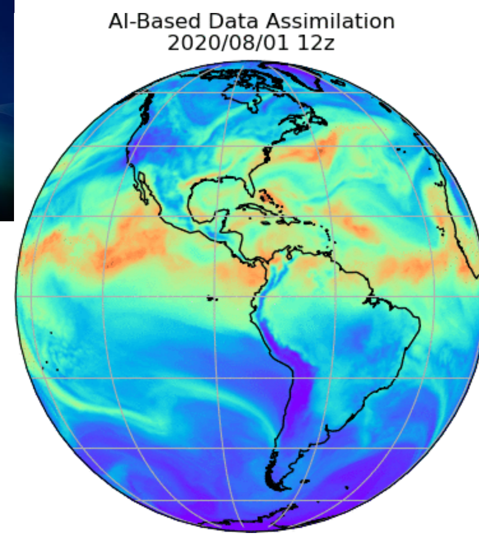
<u>Driving incentive :</u> Efficiently and fully Exploiting all observations (current, future, emerging) across all users and applications will be challenging if our approach is not enhanced.

Objective: Exploiting the large Diversity and Volume of Evolving Observations Through an AI-based Data Fusion/Assimilation System



National and International Partnerships (missions of opportunity)

NOAA's Commercial Data Buy Program (CDBP)



Users & Models including NWP

Pulling incentive : Generate a Data Assimilation that satisfies the physical constraints but also does without the unnecessary assumptions of current systems (local linearity, gaussian distributions of errors, etc).

Main Question(s) we want to Answer

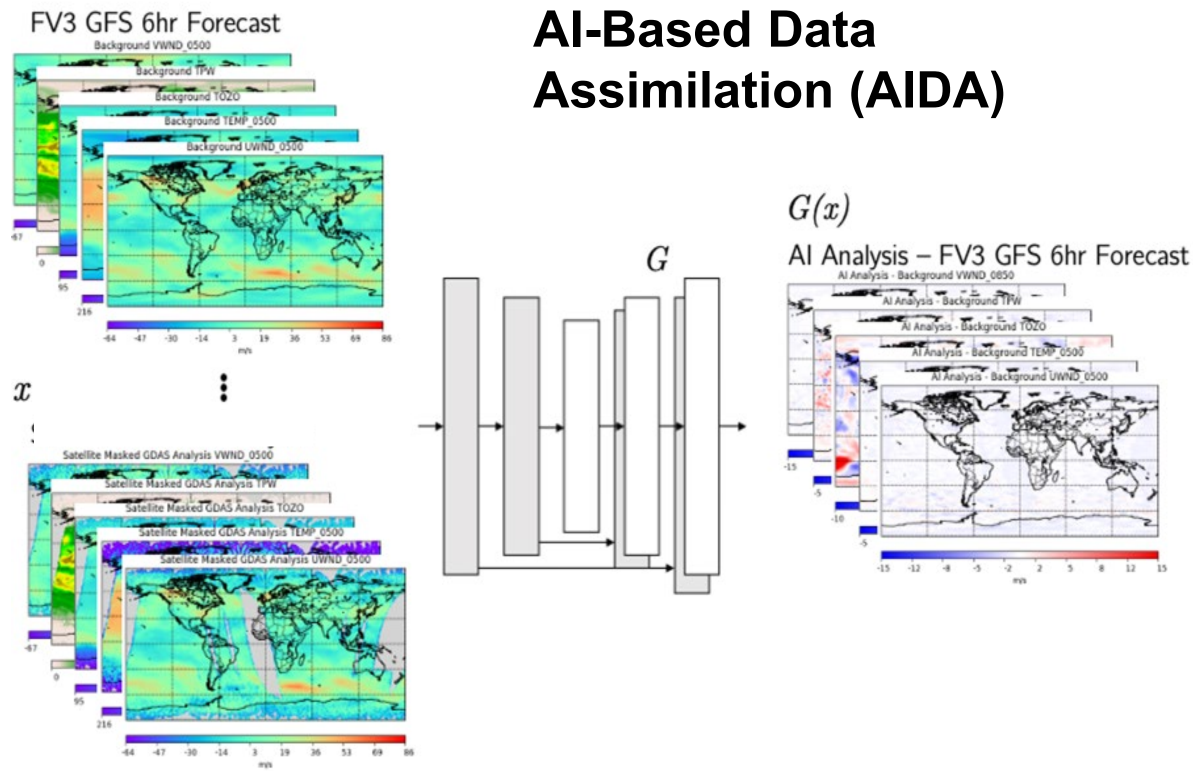
- Can we leverage new AI techniques (not just ML) to develop an efficient DA system for NWP and Earth System Modeling?
- Can we Develop a Prototype Version to demonstrate efficiency?
- Can we Achieve/Exceed the Quality of a Traditional Analysis ?
- Can we Ensure that Physical Constraints are embedded in the Analysis while increasing the DA rate?

Proposed AI-Based Data Assimilation & Fusion:

Methodology and Proposed Architecture

- Network inputs
  - FV3 GFS 6 hour forecast fields
  - Satellite radiometric observations projected into geophysical space **using AI-based MIIDAPS-AI and resampled onto DA grid**
  - Conventional Data at global location and time
  - Satellite observation time resampled onto DA grid
- Network outputs
  - 2D gridded increment between AI Analysis and FV3GFS 6hour forecast
- Network trained using all GDAS/GFS cycles between 2019/01/01 – 2020/08/01 (19 months)

AI-Based Data Assimilation (AIDA)



- Framed as an image-to-image translation problem "computer vision"
- U-Net generator
  - 8 layers downsampling, 8 layers upsampling
  - *55 million trainable parameters*

Mathematical Similarity Between Traditional DA and AI-Based DA

Traditional 3DVar cost function: observation term, background term weighted by uncertainties

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{y} - H[\mathbf{x}])^T \mathbf{R}^{-1}(\mathbf{y} - H[\mathbf{x}]) + \frac{1}{2}(\mathbf{x} - \mathbf{x}_b)^T \mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b)$$

AI-Based DA Training: *Has the objective of performing the AI mapping of observations and background to analysis state* and *training loss function with constraints*

$$f_\theta(\mathbf{y}, \mathbf{x}_b) : (\mathbf{y}, \mathbf{x}_b) \mapsto \mathbf{x}$$

Cost function for computing the optimal weights

$$\tilde{J}(\theta) = (\mathbf{x} - f_\theta(\mathbf{y}, \mathbf{x}_b))^T (\mathbf{x} - f_\theta(\mathbf{y}, \mathbf{x}_b)) + \lambda\theta^T\theta + \text{physical constraints}$$

During training, the network, f_θ, learns an optimal set of weights, $\boldsymbol{\theta}$, such that the mapping of observations, **y**, and background, $\mathbf{x}_b$, agree with analysis, **x**.

In that sense, the weights contain statistical information relating to the forward operator, *H*(x), the observation covariance, R, and the background error covariance, B, used in the real DA.

Efficiency: Leverage Modern AI Techniques For a:

Hyper Efficient Data Assimilation

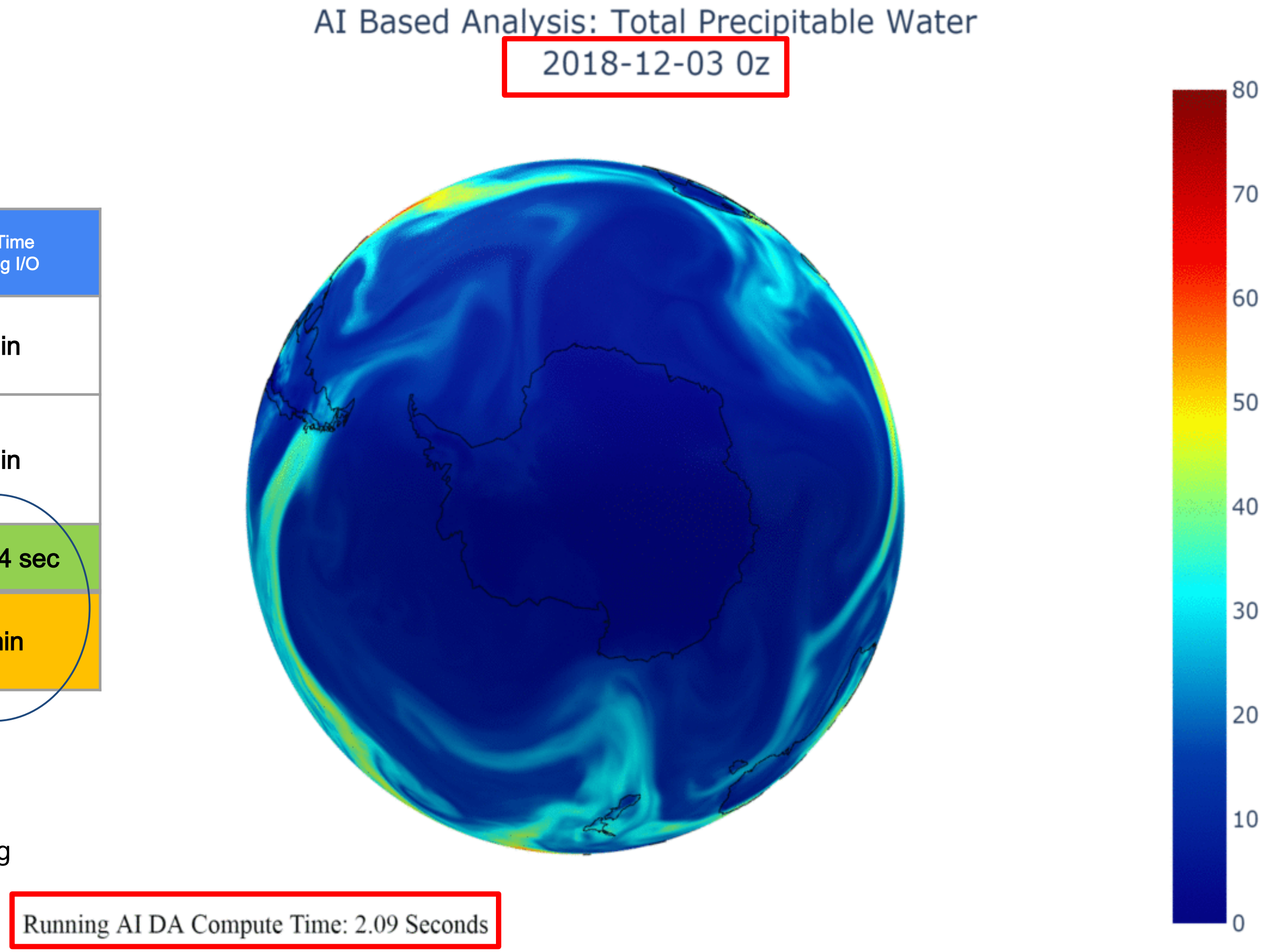
Proof of Concept demonstration:

Efficiency assessment

Step	CPU Time Including I/O	Clock Time Including I/O
Forecast (GrIB) Preprocessing	4 min	4 min
MIIDAPS-AI (Satellite Remote Sensing)	1 min	5 min
AI-based DA	4 sec	5 min, 4 sec
Traditional DA (Analysis only)	30 min	30min

Timing for traditional DA using 1000s of processors and AI-DA usinga single CPU node (48 cores) as a mostly serial process. AI-DA algorithm execution time mostly spent in reading of input files (forecasts) which is not optimized and performed in serial.

MIIDAPS-AI and AI-DA use 100% of satellite observations from ATMS and AMSU-A/MHS. After resampling to the AI-DA grid, that's equivalent to ~20x the amount of satellite observations used by the operational analysis.

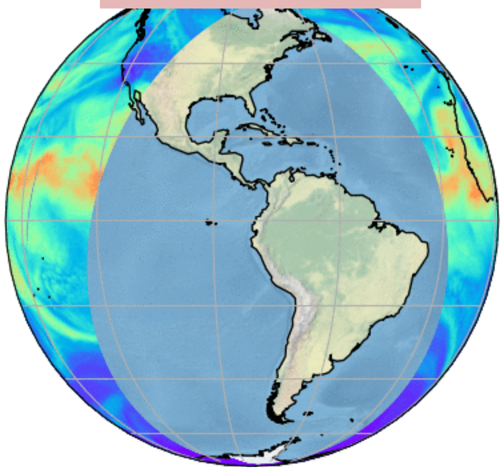


450 times improvement in processing efficiency

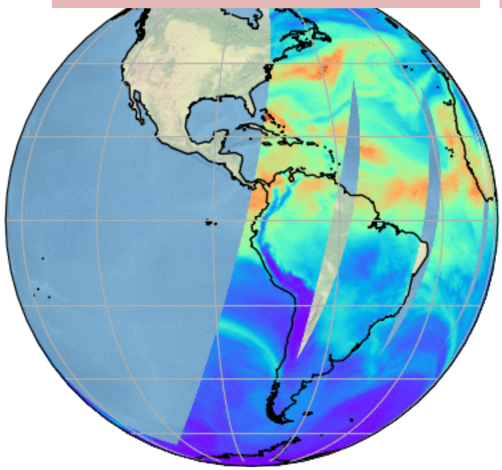
AI-Based Data Assimilation (AIDA):

Quality Assessment of Increments

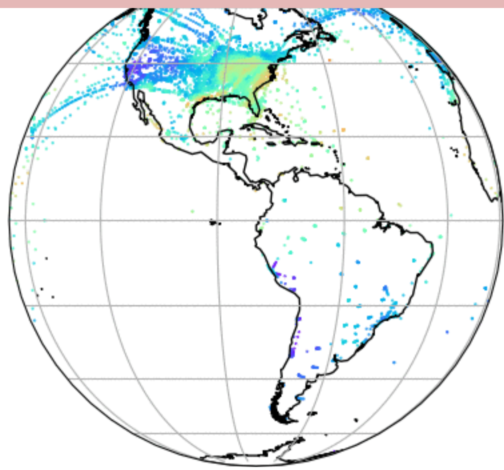
NOAA-20 ATMS



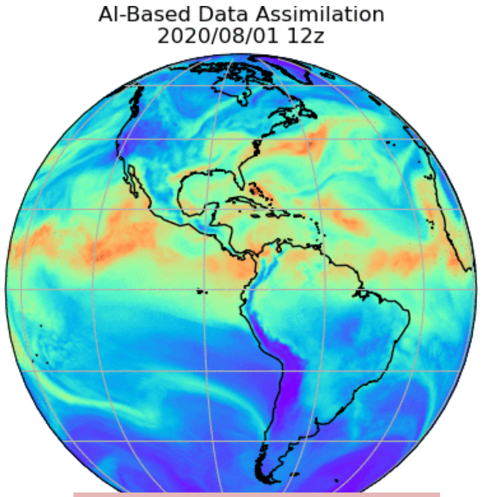
METOP-C AMSU/MHS



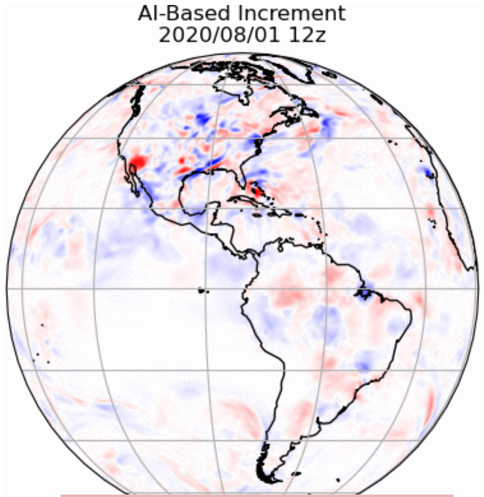
Conventional Sondes/Aircraft



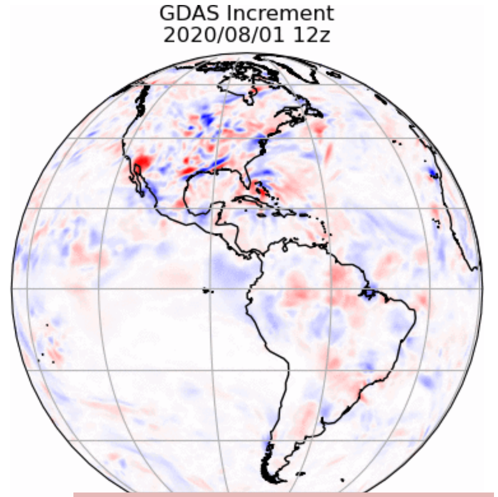
Inputs



AI-Based Analysis



AI-Based Increment

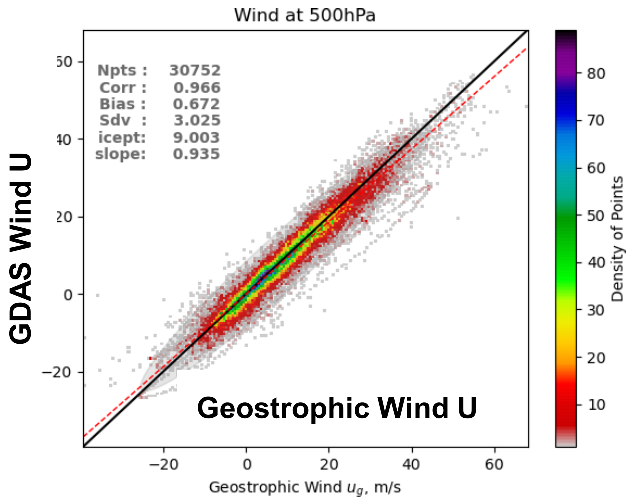


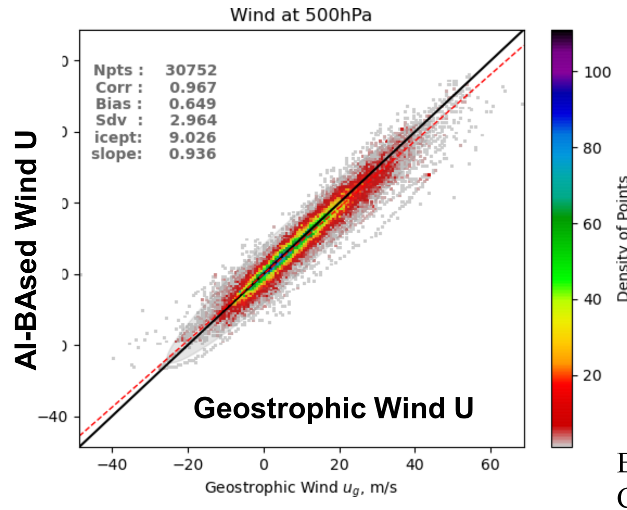
Traditional Increment

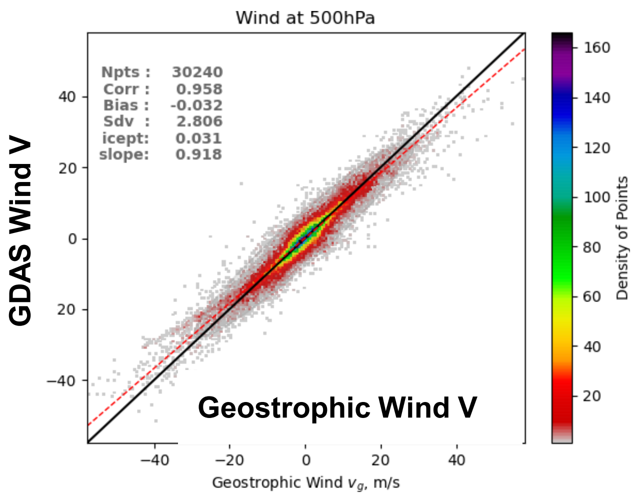
Outputs (Analyses & Increments)

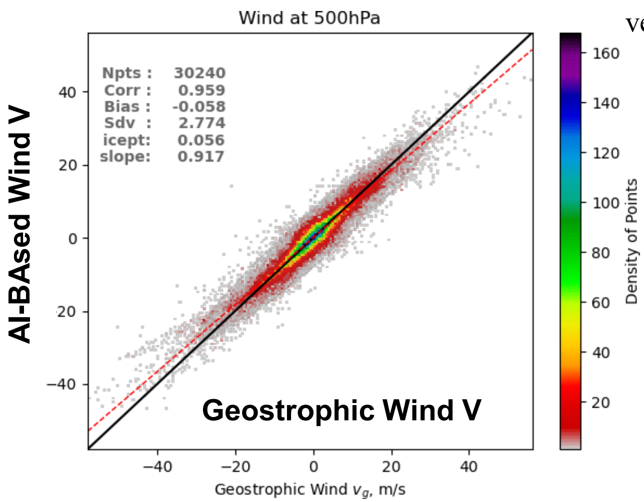
Physical Constraints: Geostrophic Balance:

U and V wind components and computed geostrophic winds at 500hPa









Geostrophic u, v winds computed from AI-DA and GDAS agree statistically and density scatterplots are nearly indistinguishable. ***Satisfy Geostrophic Balance***

Equations of motion of atmosphere in Cartesian coordinates neglecting friction and vertical motion

$$\frac{du}{dt} = fv - \frac{1}{\rho}\frac{\partial p}{\partial x}$$

$$\frac{dv}{dt} = -fu - \frac{1}{\rho}\frac{\partial p}{\partial y}$$

Geostrophic Approximation assumes steady state

$$v_g = \frac{g}{f}\frac{\partial Z}{\partial x}$$

$$u_g = \frac{-g}{f}\frac{\partial Z}{\partial y}$$

A key concept in physical oceanography and dynamical meteorology

$$f = 2\Omega \sin(\phi)$$

f Coriolis Parameter
Ω is the angular velocity of Earth
φ is latitude

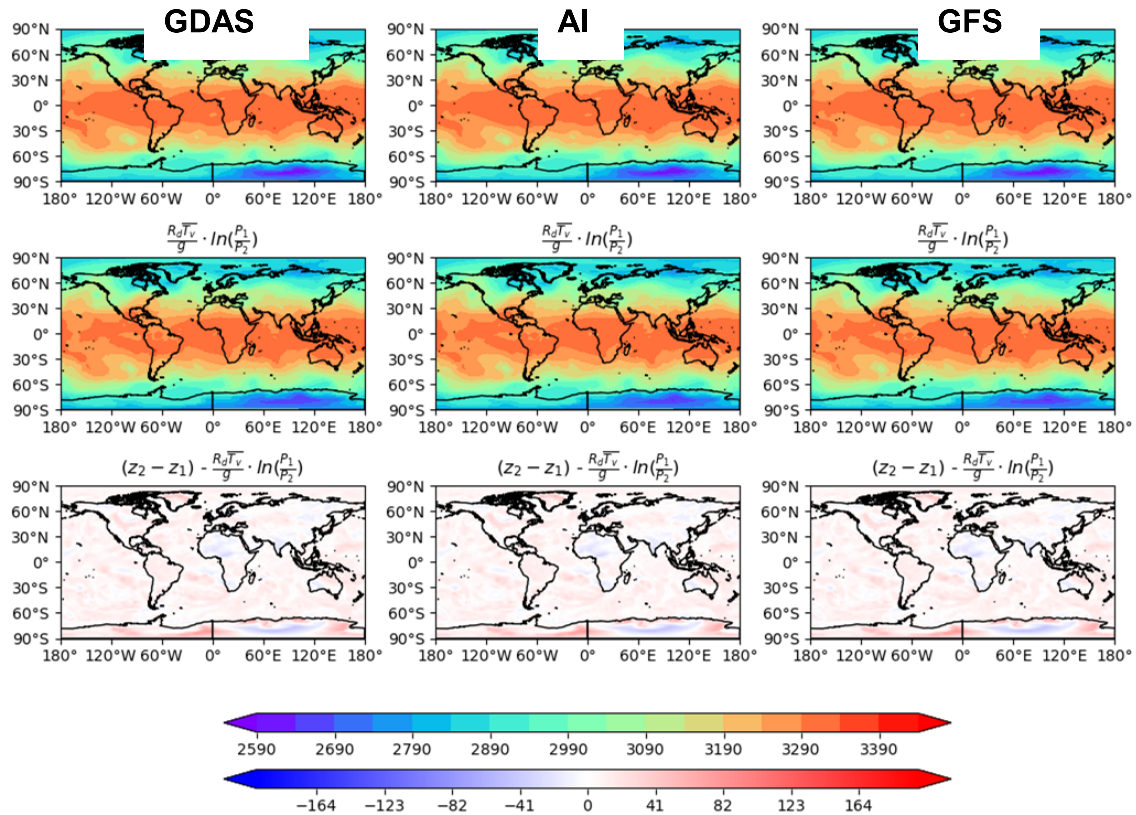
Physical Constraints: Hydrostatic Balance:

Hypsometric approximation 500hPa - 750hPa layer

Difference in geopotential height

Hypsometric Approximation

Difference between two



GDAS, AI-DA, and FV3GFS difference between actual thickness and the hypsometric approximation are nearly indistinguishable.

Hydrostatic Equation with Ideal Gas Law

$$\frac{\partial p}{\partial z} = -\rho g = -\frac{pg}{R_d T_v}$$

$$\frac{\partial \ln p}{\partial z} = -\frac{g}{R_d T_v}$$

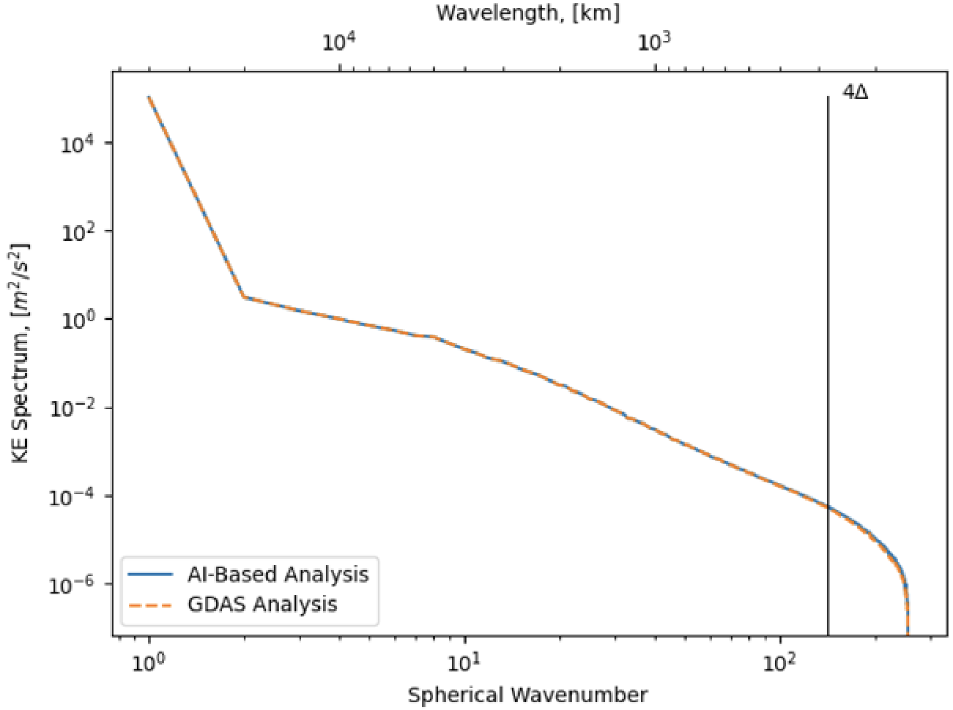
Integrate between two layers to obtain hypsometric equation

$$\Delta z = \frac{R_d\ \overline{T_v}}{g} \ln(\frac{p_1}{p_2})$$

Physical Constraints: Kinetic Energy Conservation

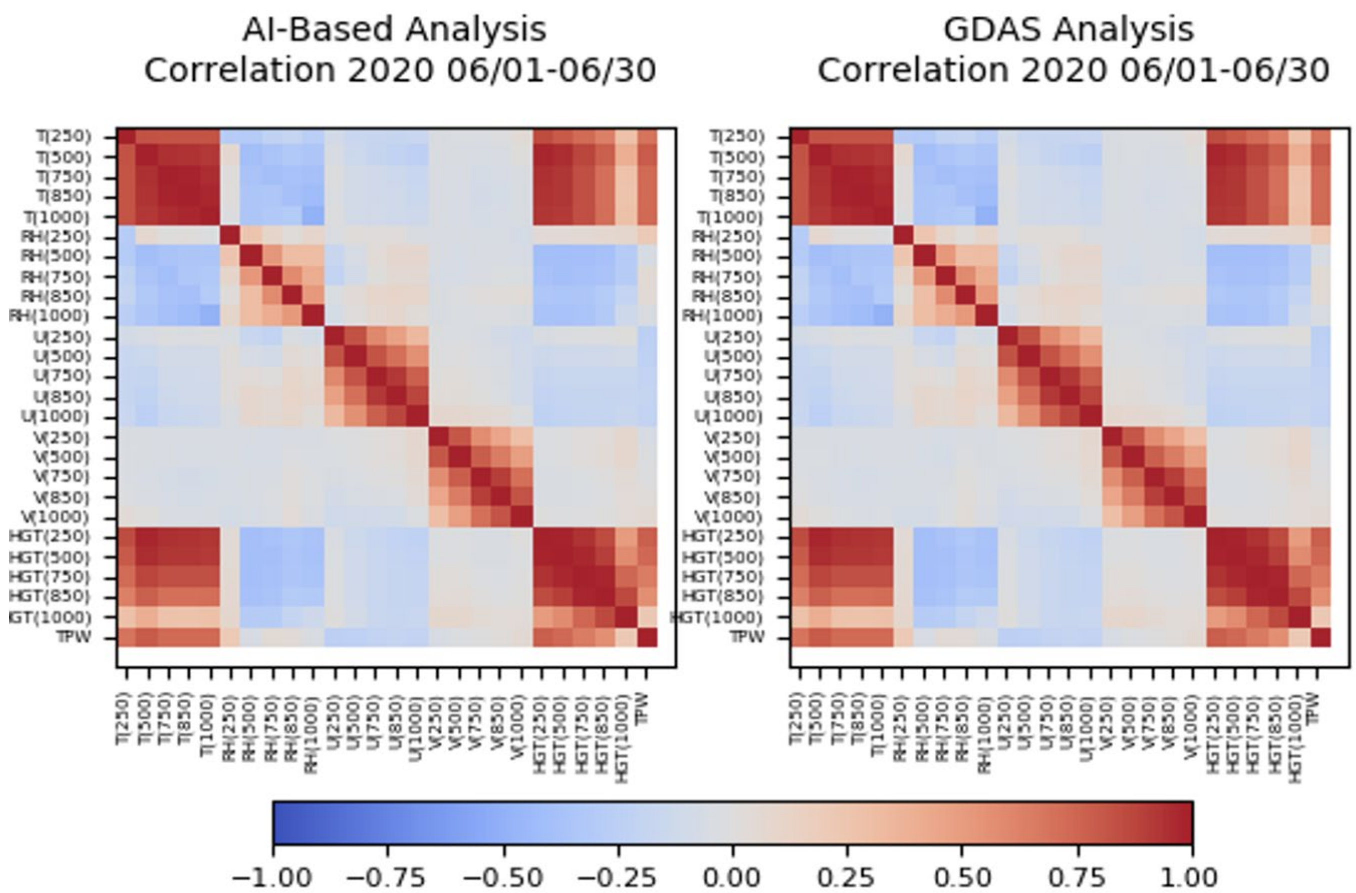
- Kinetic energy spectrum, computed from U/V winds for both the AI-based DA and GDAS fields at 256x512 spatial resolution and averaged vertically in a 250hPa – 700hPa layer.
- 1 Month of AI-DA and GDAS analyses used
- A spherical harmonic transform of the resultant wind fields was computed and the spectral coefficient magnitude (square of coefficients) was calculated.

Average Kinetic Energy Spectrum (250-700hPa layer) 2020 06/01 – 06/30



AI-based results are producing expected behavior in terms of spatial patterns of variability observed in real GDAS analyses.

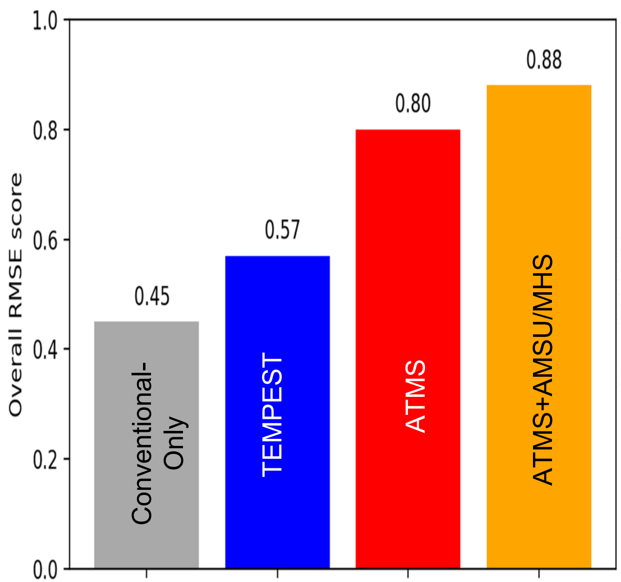
Physical Constraints:
Inter Parameters Geophysical Correlation



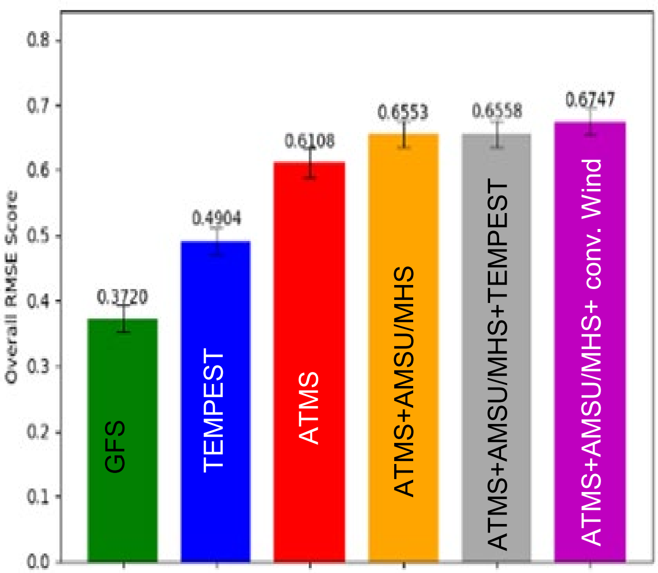
Inter-parameter Correlation of AI-DA (left) and GDAS analysis (right) for 1 month of both. AI-based results are producing expected behavior in terms of the interactions of the variables produced in our analysis. ***AI-based DA models have the capacity to learn and exploit patterns between different variables***

Observing System Experiments (OSE) based on AIDA: Overall Analysis Score

- Overall Forecast and Analysis Score over all variables (*T,Q,U,V,Z,TPW*), levels (*250hPa, 500hPa, 750hPa, 850hPa*), domains (*Tropical, SH, NH*)
- ECMWF used as a reference
- These OSE results are produced in a fraction of the time needed for traditional OSEs



Traditional OSE Experiment:`



AI-Based OSE Experiment:

Incremental addition of observing system components increases the overall RMSE and Correlation scores of the AI-DA. **Consistency between Traditional DA and AI-DA**

Summary & Conclusions

- **Novel Approach:**
  - **New approach for data fusion and assimilation, based entirely on AI** (mixture of ML and CV) is presented.
  - Mathematically, AI technique *training* has similarities with traditional Variational DA.
  - Approach emulates assimilation step itself. Uses forecast, satellite (geoph) & Conv data as inputs.
  - It is a multi-variable fusion/assimilation with a representative but limited set of variables.

- **Efficiency:**
  - An order of magnitude efficiency: large gains in amount of data that can be assimilated.
  - **Efficiency allows assimilating more data and new (non-tradition.) environmental data, not fully exploited.**

- **Quality and Physical Constraints: Results**
  - **AI-based analysis Physically consistent with traditional DA**: fields, increments, OSE results.
  - AI-based analysis balanced (hydrostatic/geostrophic) with spatial/vertical thermodynamic consistency.

- **Challenges:**
  - **Results are highly encouraging but only a first initial step for an entirely AI-based DA.**
  - **Challenges: scalability (to more variables, layers, sensors), physical constraints at individual level, robustness, explicitly accounting for observation errors.**

- **Going forward:**

Entirely AI-Based data Fusion/Assimilation for NWP purposes is a real possibility with further efforts. It offers a wide range of new perspectives: Efficiency, Higher Assimilation rate, assimilating new emerging sources of environmental data, Handling highly non-linear and non-continuous phenomena, etc.

Disclaimer: The scientific results and conclusions, as well as any views or opinions expressed herein, are those of the author(s) and do not necessarily reflect those of NOAA or the Department of Commerce.