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

Advantages & Challenges

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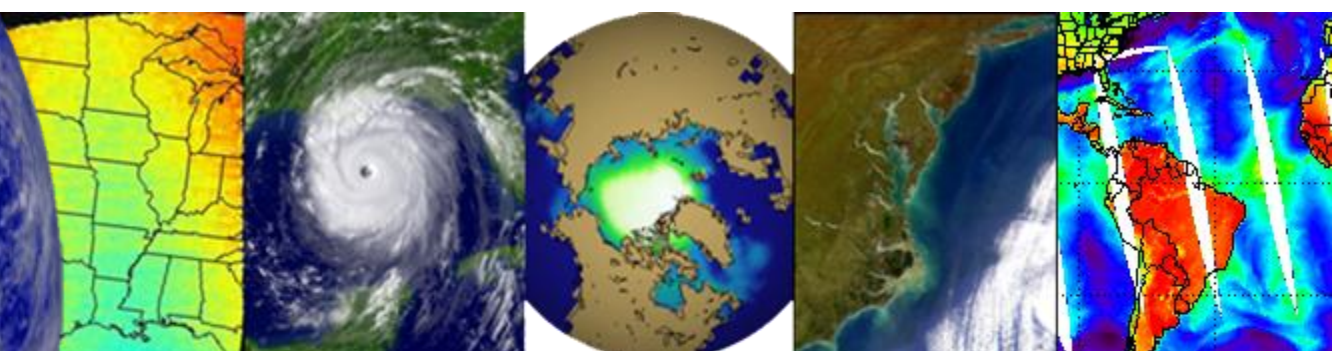


Agenda

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

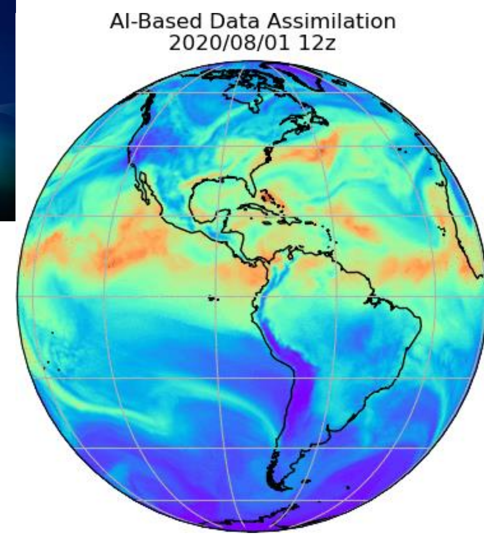
Users or Model #N

__Driving incentive :__ **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

Main Question(s) we want to Answer

- **Can we leverage new AI techniques <u>(not just ML)</u> 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 Physical Constraints are embedded in the Analysis while increasing the DA rate and ?**
- **Can We Feed the AI-Based Analysis to Traditional Forecast and Assess Impact? (a different presentation focuses on this)**

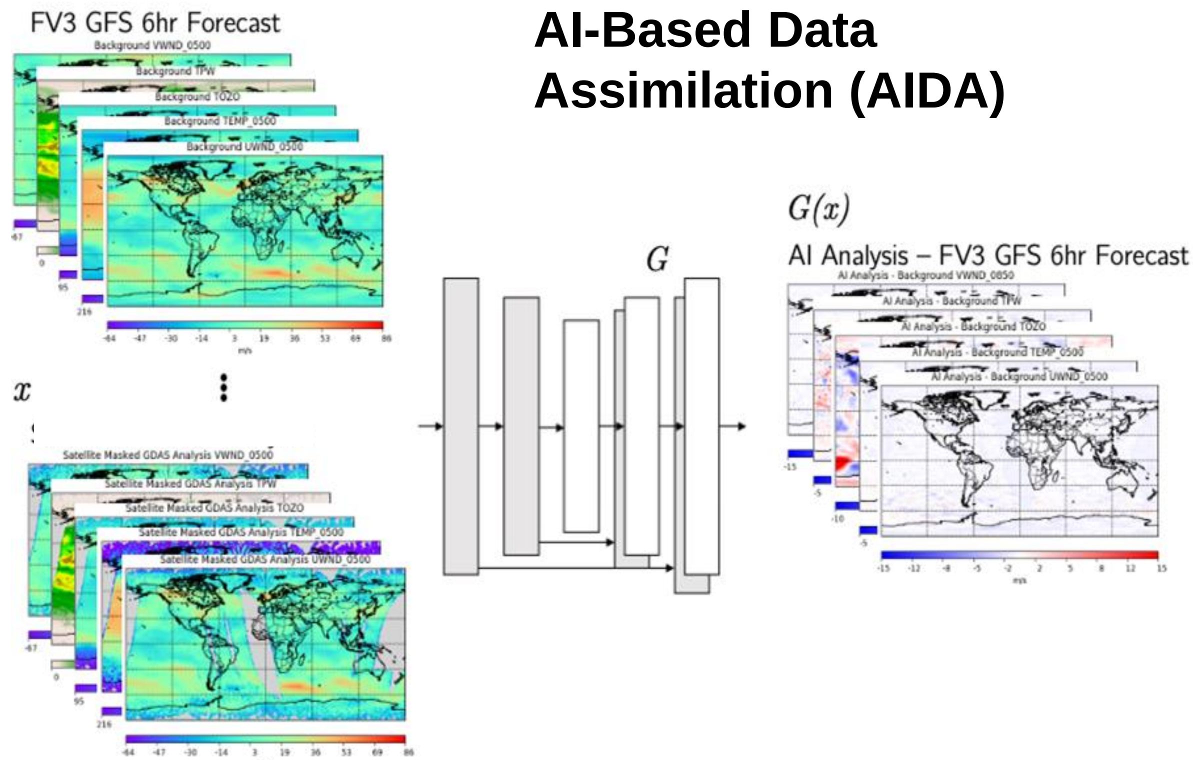
Note: Assumption of a clean slate: no constraints based on continuing legacy codes. which we know could be a serious impediment to fully taking advantage of AI techniques and tools (using Python, tensorflow, Keras, etc).

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
  - Satellite observation time resampled onto DA grid
- Network outputs
  - 2D gridded increment between GDAS and FV3GFS 6hour forecast
- Network trained using all GDAS/GFS cycles between 2019/01/01 – 2020/08/01

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: *AI mapping of observations and background to analysis state* and *training loss function with constraints*

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

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

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

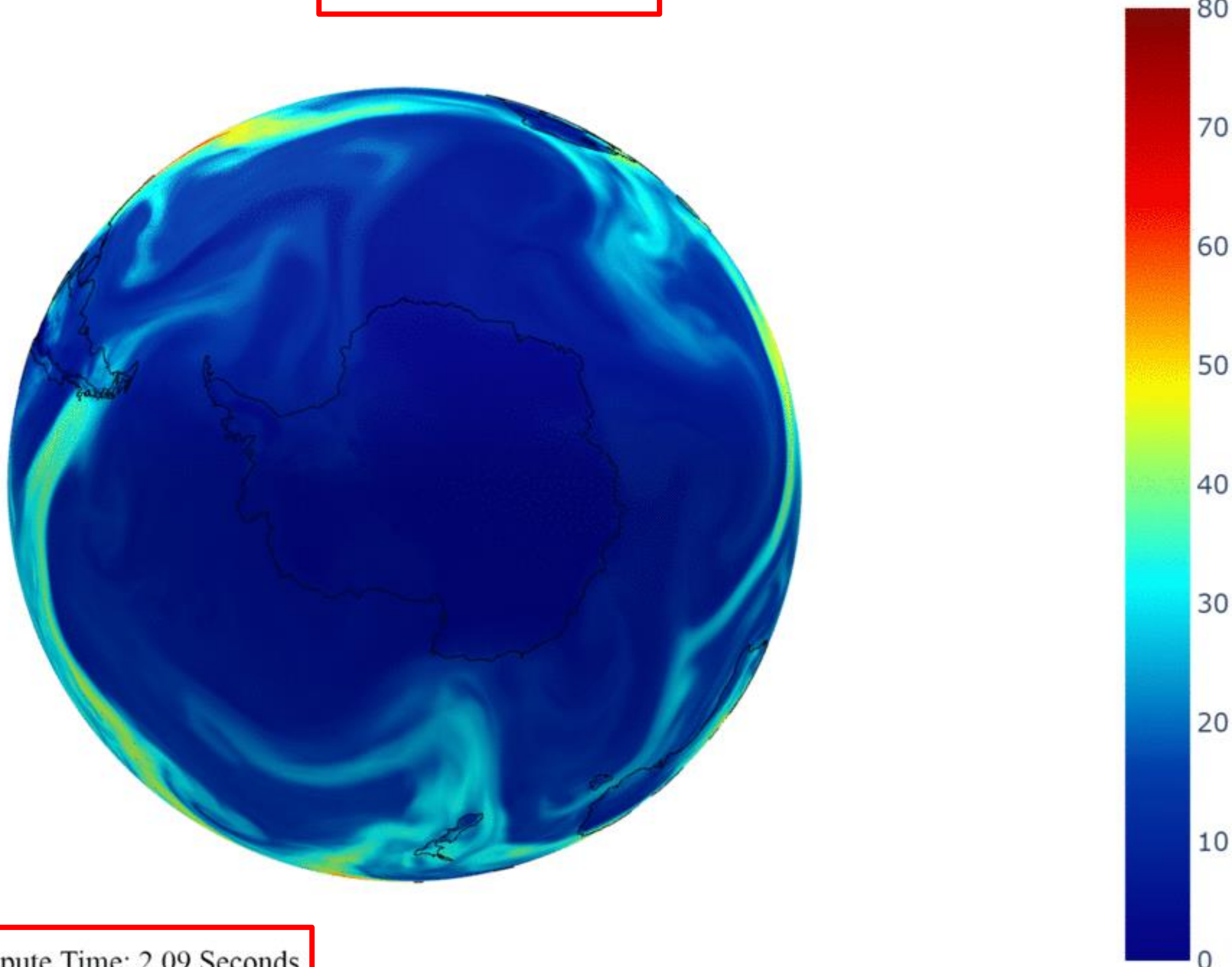
Proof of Concept demonstration:

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**

AI Based Analysis: Total Precipitable Water

2018-12-03 0z

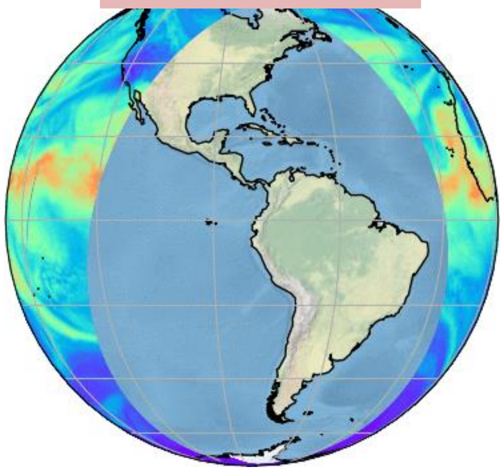


Running AI DA Compute Time: 2.09 Seconds

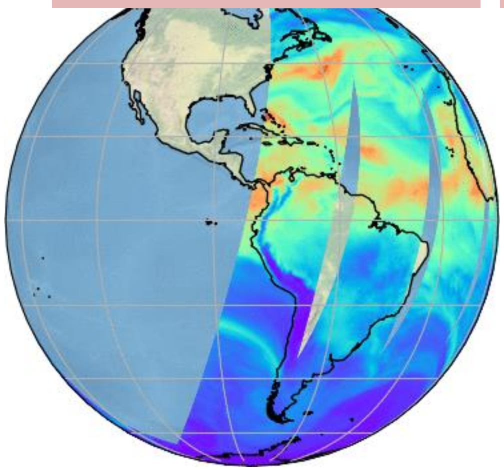
AI-Based Data Assimilation (AIDA):

Quality Assessment: Increments

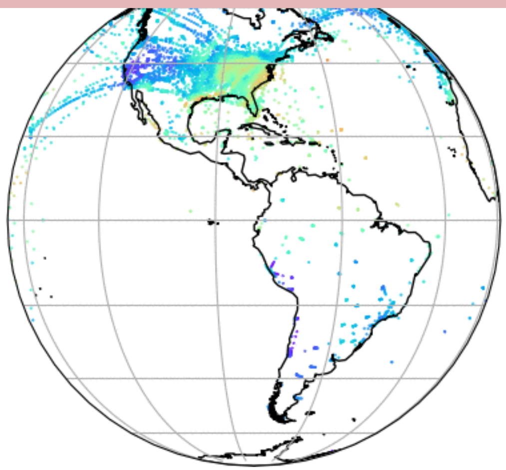
NOAA-20 ATMS



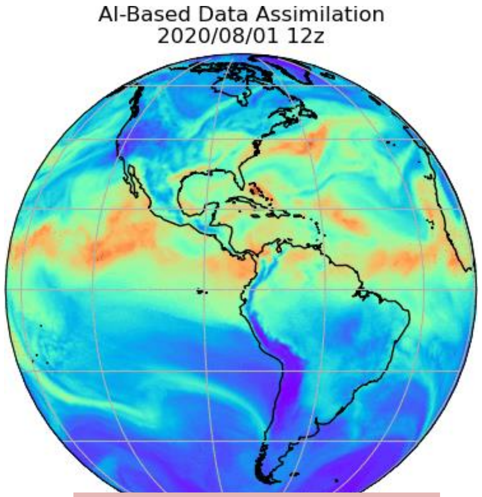
METOP-C AMSU/MHS



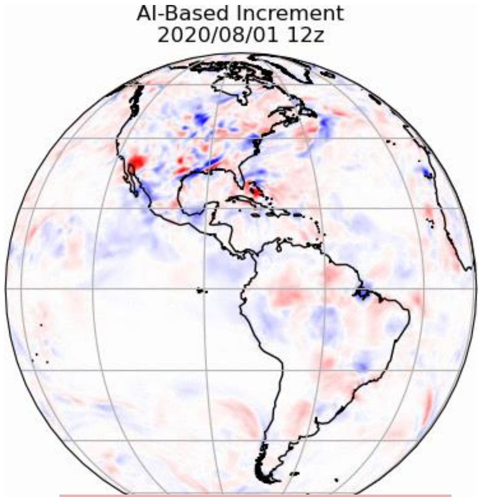
Conventional Sondes/Aircraft



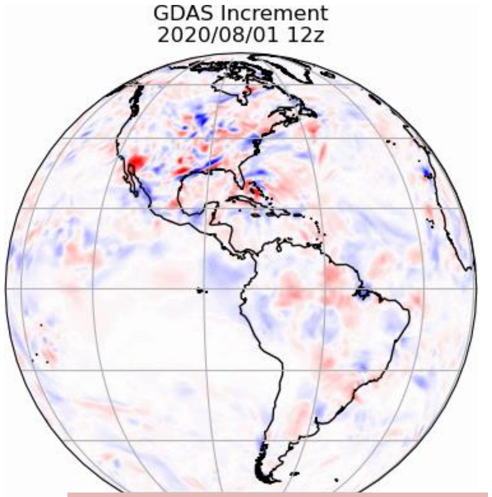
Inputs



AI-Based Analysis



AI-Based Increment

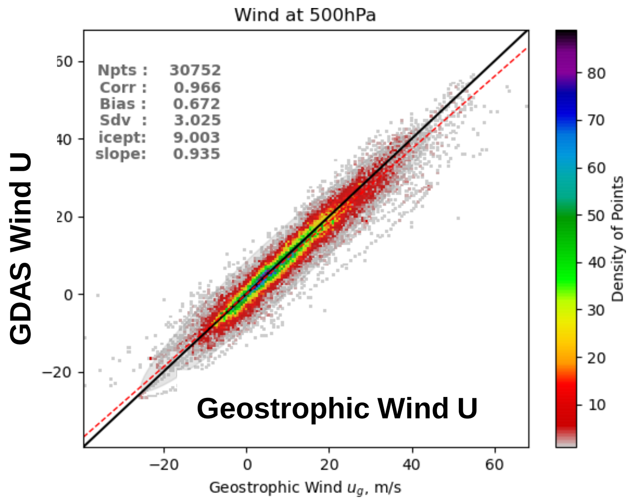


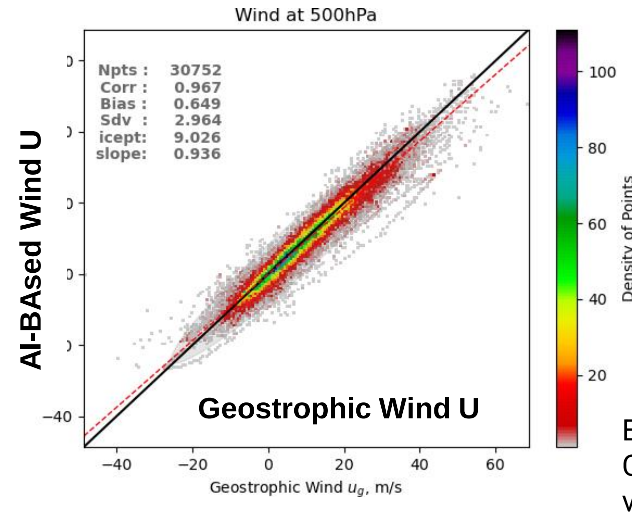
Traditional Increment

Outputs (Analyses & Increments)

Physical Constraints: Geostrophic Balance:

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



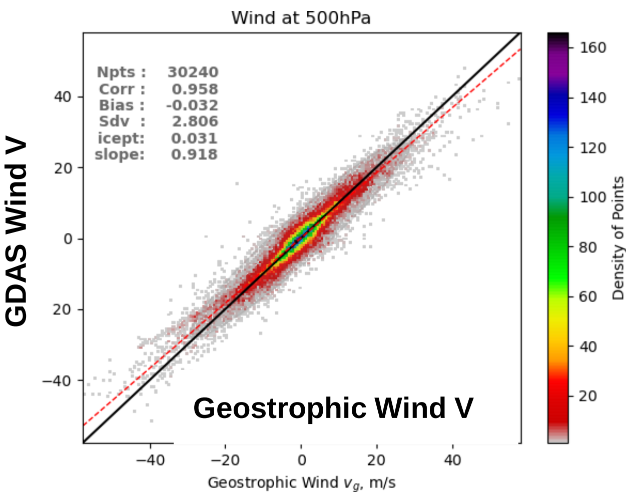


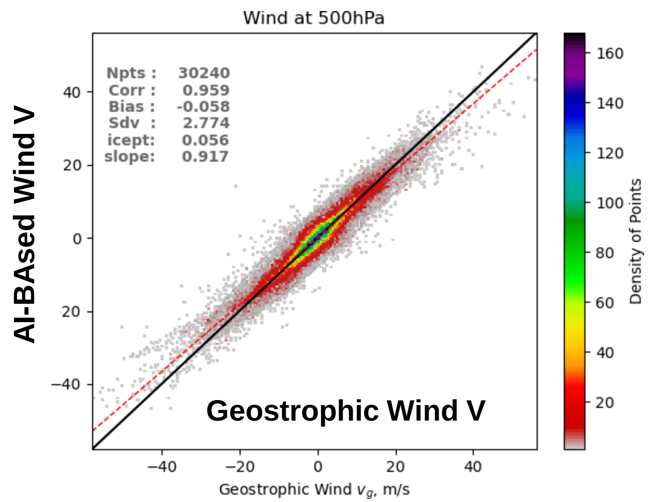
Geostrophic u, v winds computed from AI-DA and GDAS agree statistically and density scatterplots are nearly indistinguishable.

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

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

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

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

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

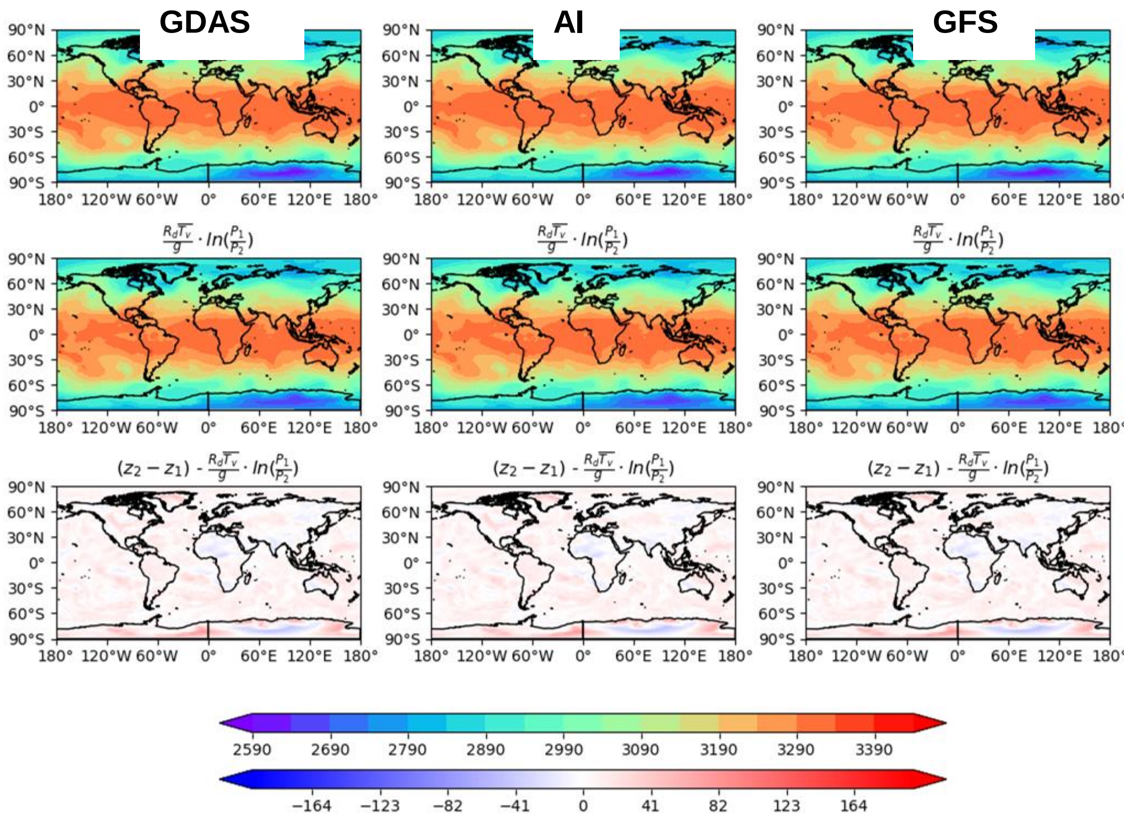
Physical Constraints: Hydrostatic Balance:

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

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

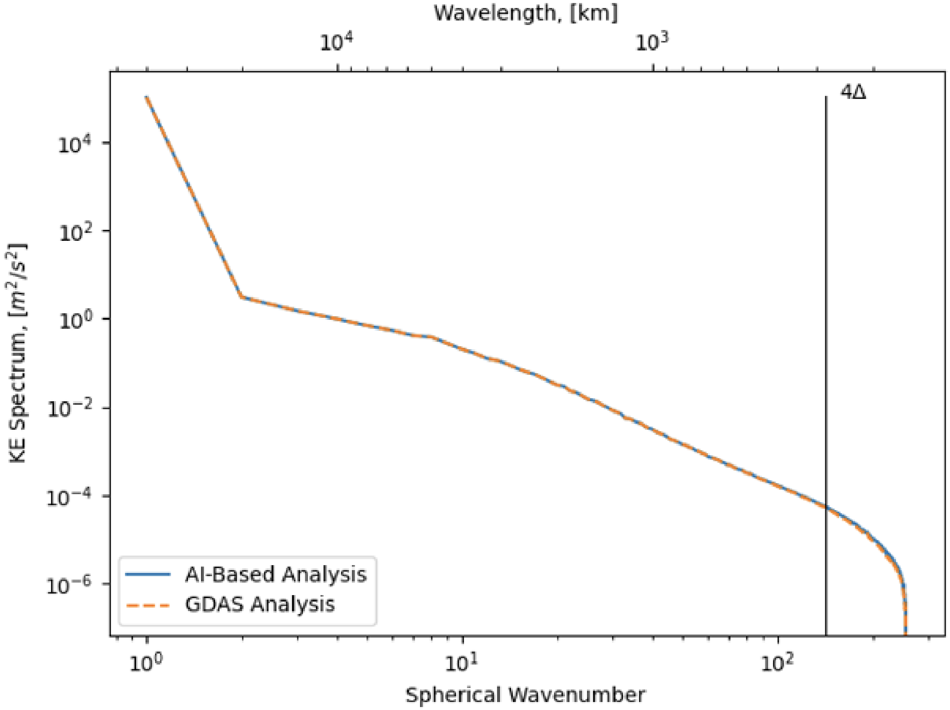
Physical Constraints: Kinetic Energy Conservation

- 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

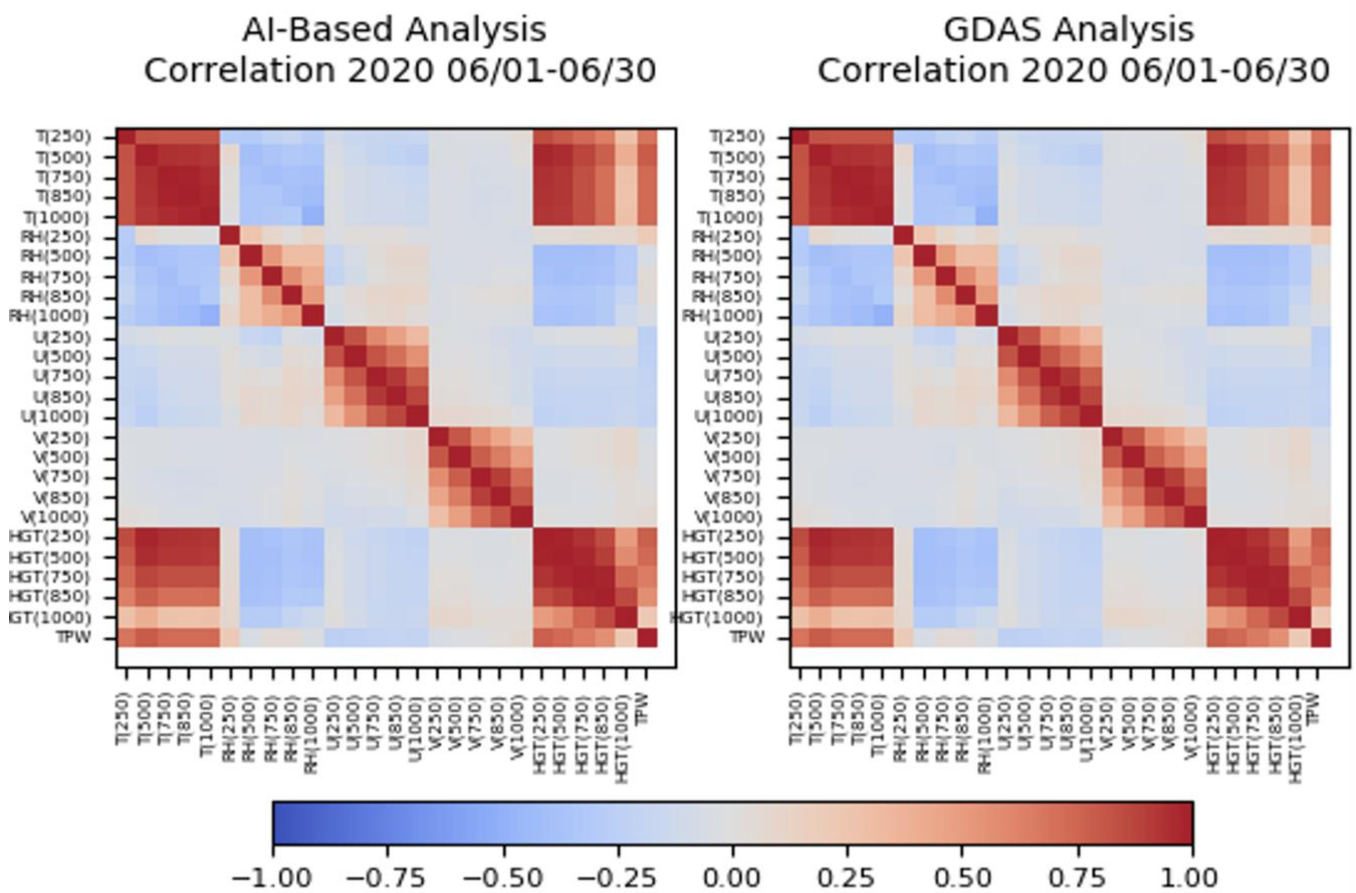
- A spherical harmonic transform of the resultant wind fields was computed and the spectral coefficient magnitude (square of coefficients) was calculated.

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

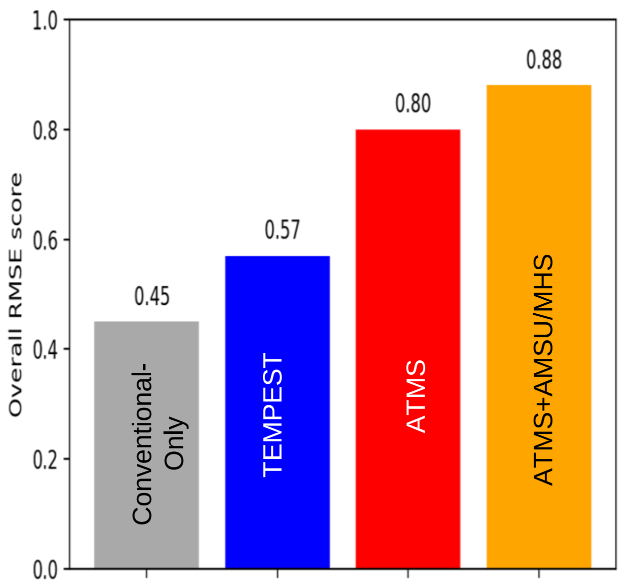


Inter-parameter Correlation of AI-DA (left) and GDAS analysis (right) for 1 month of both. AI-based results are producing expected behavior in terms of the interactions of the variables produced in our analysis. AI-based DA models have the capacity to learn and exploit patterns between different variables

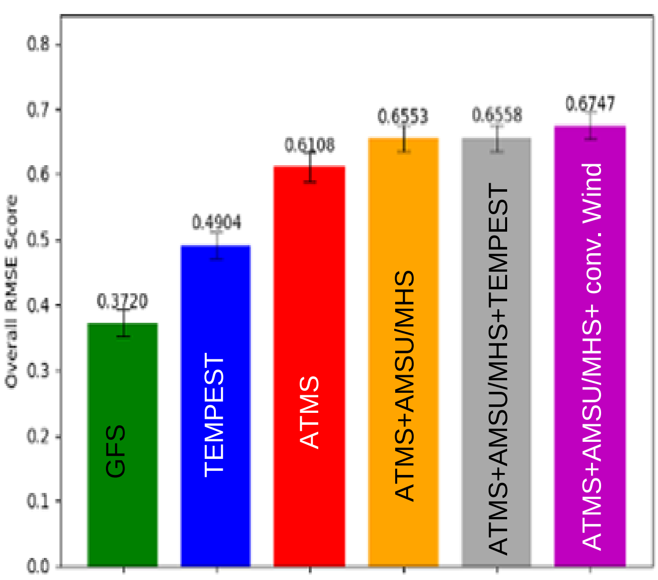
OSE Experiments based on AIDA:
Overall Analysis Score

- Overall Forecast and Analysis Score over all variables (*T,Q,U,V,Z,TPW*), levels (*250hPa, 500hPa, 750hPa, 850hPa*), domains (*Tropical, SH, NH*)

- These OSE results are produced in a fraction of the time needed for traditional OSEs



Traditional OSE Experiment:`



AI-Based OSE Experiment:

AI-DA improves scores relative to the operational FV3GFS forecast after assimilating Observations.

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

- **<u>Novel Approach:</u>**

  - 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 <u>assimilation step itself</u>. Uses forecast, satellite (geoph) & Conv data as inputs
  - It is a multi-variable fusion/assimilation with a representative but limited set of variables.

- **<u>Efficiency:</u>**

  - 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.

- **<u>Quality and Physical Constraints: Results</u>**

  - AI-based analysis consistent with traditional DA: fields, increments, OSE results.
  - AI-based analysis balanced (hydrostatic/geostrophic) with spatial/vertical thermodynamic consistency

- **<u>Challenges:</u>**

  - Results are highly encouraging but only a first initial step for an entirely AI-based DA.
  - Challenges: scalability, physical constraints at individual level, robustness, explicitly accounting for obs err.

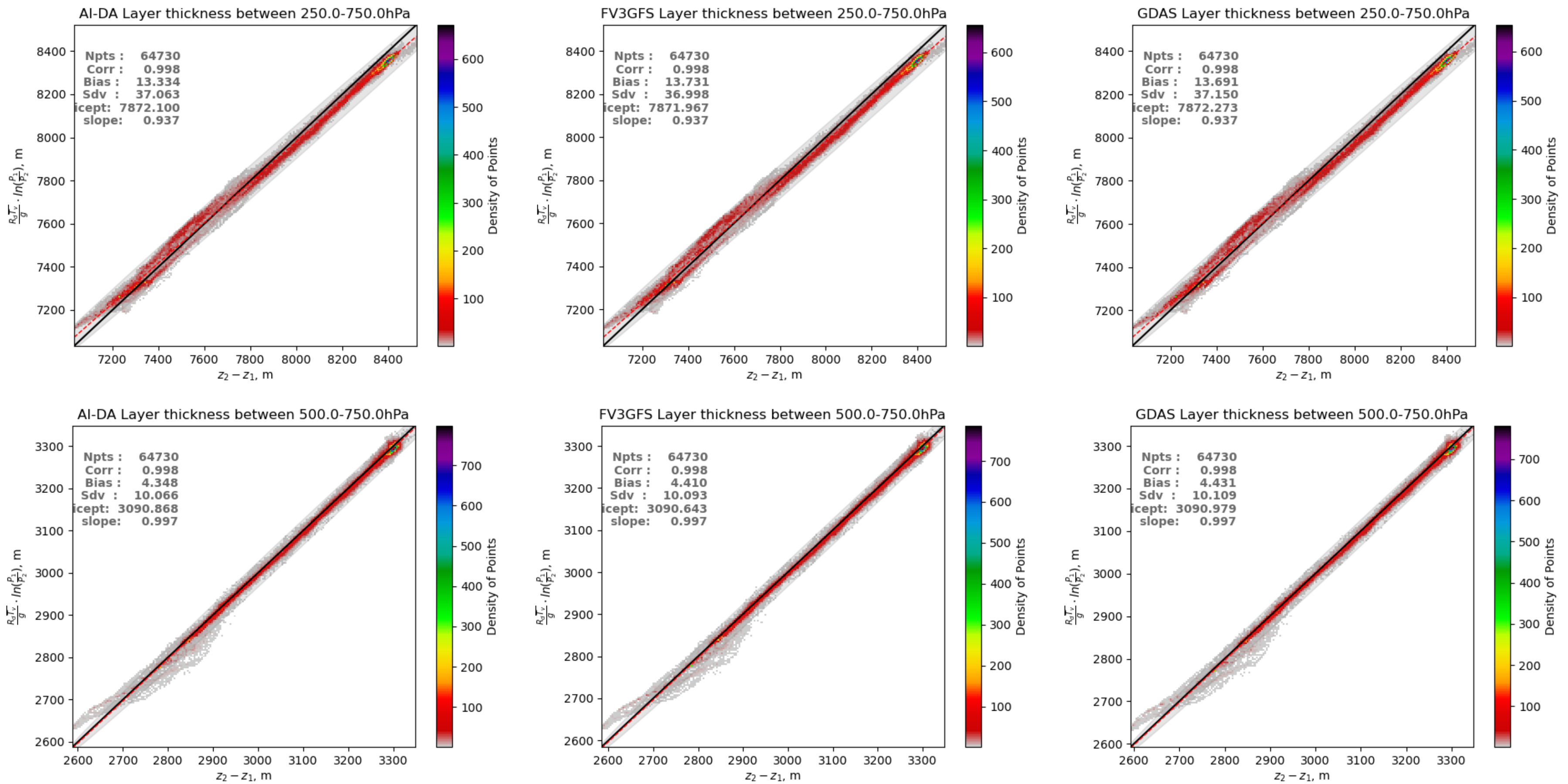
- **<u>Going forward:</u>**

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

BACKUP

Physical Constraints: Hydrostatic Balance:

Hypsometric approximation 250hPa - 750hPa and 500hPa - 750hPa layers



Layer thickness computed using hypsometric equation from AI-DA, FV3GFS and GDAS agree statistically and density scatterplots are nearly indistinguishable.