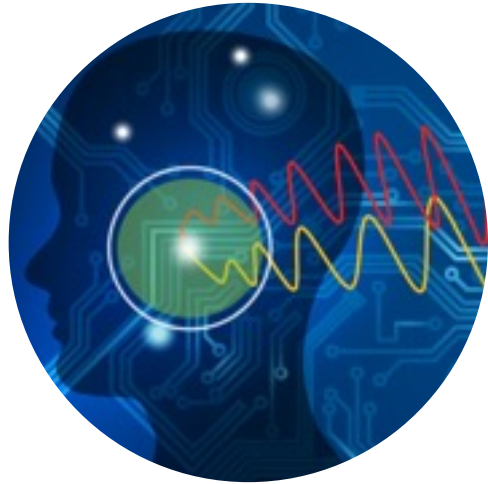


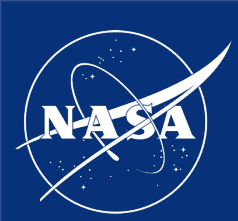
# NASA Earth Science Technology Office (ESTO) Intelligent Systems Technology (IST)



## Technology for Earth System Digital Twins

*Jacqueline Le Moigne, Ben Smith, Michael Little,  
Robert Morris, Laura Rogers, Jon Ranson and Nikunj Oza*

October 2024



# Earth System Digital Twins (ESDTs) Definition



**Earth Systems Digital Twins (ESDTs) are information systems for understanding, forecasting, and conjecturing the complex interconnections among Earth systems, including anthropomorphic forcings and impacts to humanity.**

## What now?

### Digital Replica . . .

An integrated picture of the past and current states of Earth systems.

## What next?

### Forecasting . . .

An integrated picture of how Earth systems will evolve in the future from the current state.

## What if?

### Impact Assessment . . .

An integrated picture of how Earth systems could evolve under different hypothetical what-if scenarios.

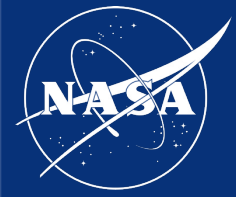


An Earth System Digital Twin or ESDT is a dynamic and interactive **information system** that first provides a **digital replica of the past and current states** of the Earth or Earth system, as accurately and timely as possible, second allows for **computing forecasts of future states** under nominal assumptions and based on the current replica, and third offers the **capability to investigate many hypothetical scenarios** under varying impact assumptions.

## => What Now? What Next? What If?

An ESDT includes:

- Continuous observations of interacting Earth & human systems
- From many disparate sources
- Driving inter-connected models
- At many physical and temporal scales
- With fast, powerful and integrated prediction, analysis & visualization capabilities
- Using Machine Learning, causality and uncertainty quantification
- Running at scale in order to improve our science understanding of those systems, their interactions and their applications



# What is different about Digital Twins?



1. **Continuous integration** of timely data (real- or near-real-time for some applications, “timely for others)
2. **Interactivity** with users => “playing with the models and the data” for policy/decision making and conjecturing/planning
3. Integration of anthropomorphic forcing and **impact models**
4. Heavy use of **Machine Learning**
  - Data Fusion and Data Assimilation
  - Super-Resolution/Downscaling
  - Speeding up models => higher spatial and temporal resolution possible
  - Causal Reasoning




# ESDT Background



ESDT Workshop Report available  
on AIST Website:

[https://esto.nasa.gov/files/ESDT\\_Workshop\\_Report.pdf](https://esto.nasa.gov/files/ESDT_Workshop_Report.pdf)




**Advanced Information Systems Technology (AIST)  
Earth Systems Digital Twin (ESDT)  
Workshop Report**

Jacqueline Le Moigne – NASA Earth Science Technology Office  
Benjamin Smith – NASA Earth Science Technology Office

*Workshop Co-Organized with Earth Science Information Partners (ESIP)  
Report Edited by ESDT Workshop Participants*

October 26-28, 2022  
Washington, D.C.



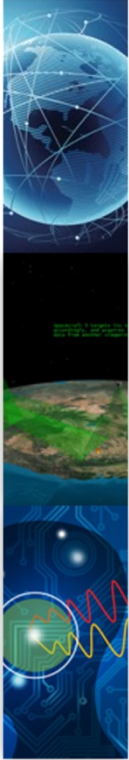
ESDT Use Case
Wildfires
Ocean Carbon
Water Cycle
Central Africa Carbon Corridors
Atmospheric Boundary Layer
Coastal Zone Digital Twin

**Standards for Interoperable Digital Twins  
Workshop**  
September 18, 2023

- Presentations:  
<https://esto.nasa.gov/files/AIST/ESDT%20Standards%202023.pdf>
- Video:  
<https://www.youtube.com/watch?v=qdpLOUi-jqc>

Document available  
on AIST Website:

[https://esto.nasa.gov/files/AIST/ESDT\\_ArchitectureFramework.pdf](https://esto.nasa.gov/files/AIST/ESDT_ArchitectureFramework.pdf)




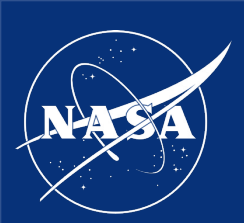
**Advanced Information  
Systems Technology (AIST)**

**Earth System Digital Twin (ESDT)  
Architecture Framework**

Jacqueline Le Moigne, Michael M. Little,  
Robert A. Morris, Nikunj C. Oza,  
K. Jon Ranson, Haris Riris,  
Laura J. Rogers, Benjamin D. Smith

October 2023





# Software and Information Systems Technology for ESDT



**ESDT = Earth System Digital Twins**

**Interrogate, Simulate, Trade and Visualize**  
Robust tools for interrogating, assessing uncertainties & causality, and for visualization, leveraging diverse data, models and products

**Intervene and Assess**  
Running “what-if” scenarios to assess the impact of natural and human activities on the planet.

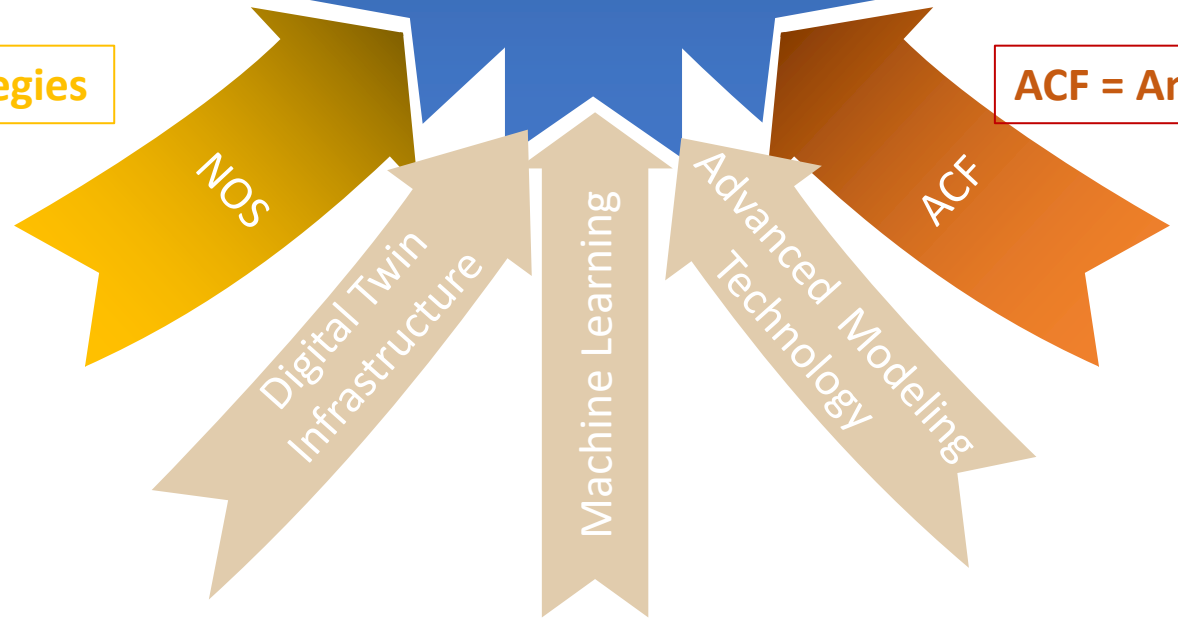
**Earth System Digital Twins (ESDT)**

**NOS = Novel Observing Strategies**

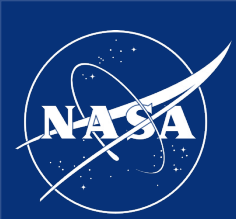
**Observe, Target and Coordinate**  
Edge and on-the-ground intelligent planning, evaluating, coordinating and operating collections of diverse and distributed observing assets

**ACF = Analytic Collaborative Frameworks**

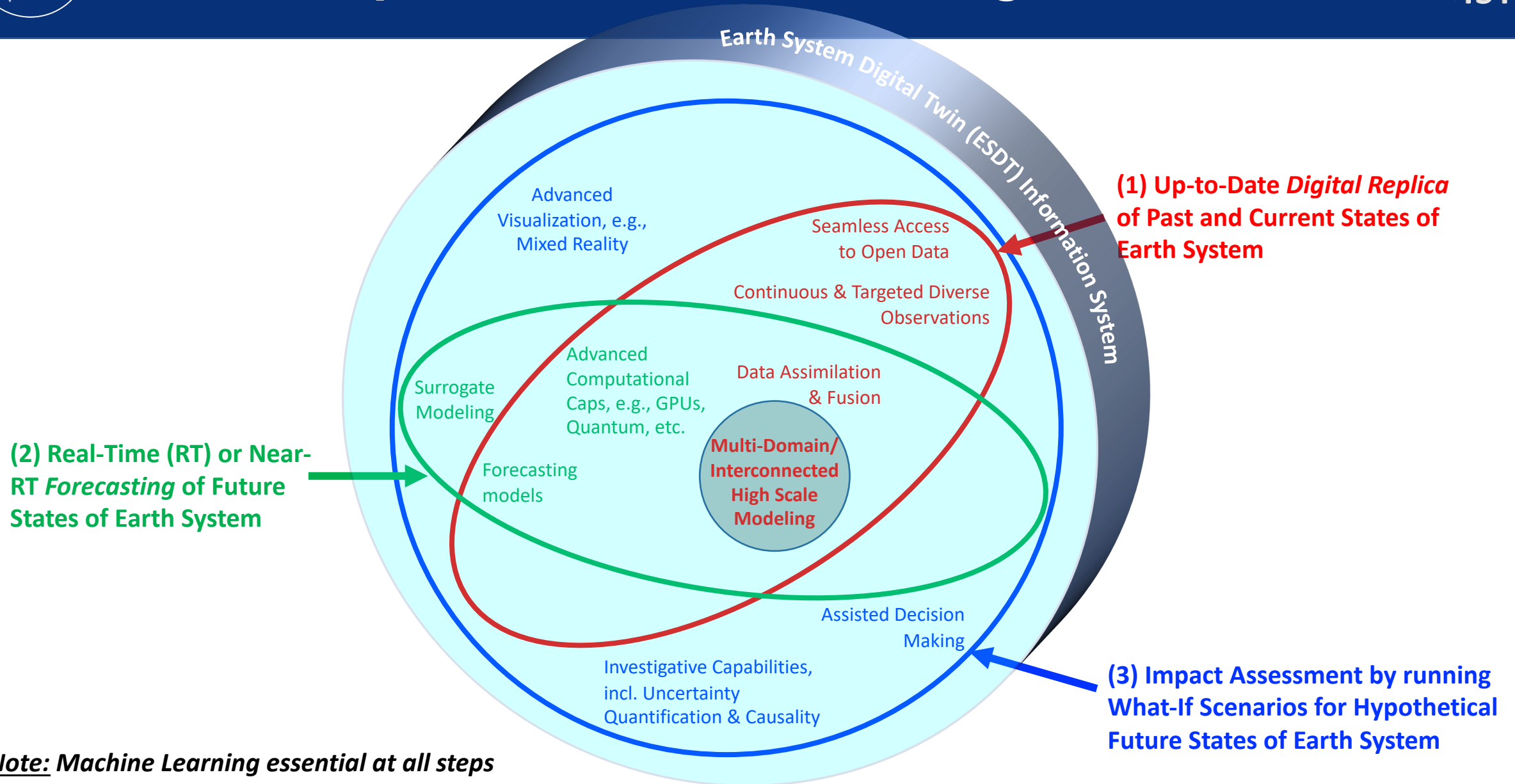
**Fuse, Analyze, Share and Collaborate**  
Simplify access to diverse and large amounts of data, analytics & modeling tools and advanced computational resources for collaborative science







# ESDT Capabilities and Technologies



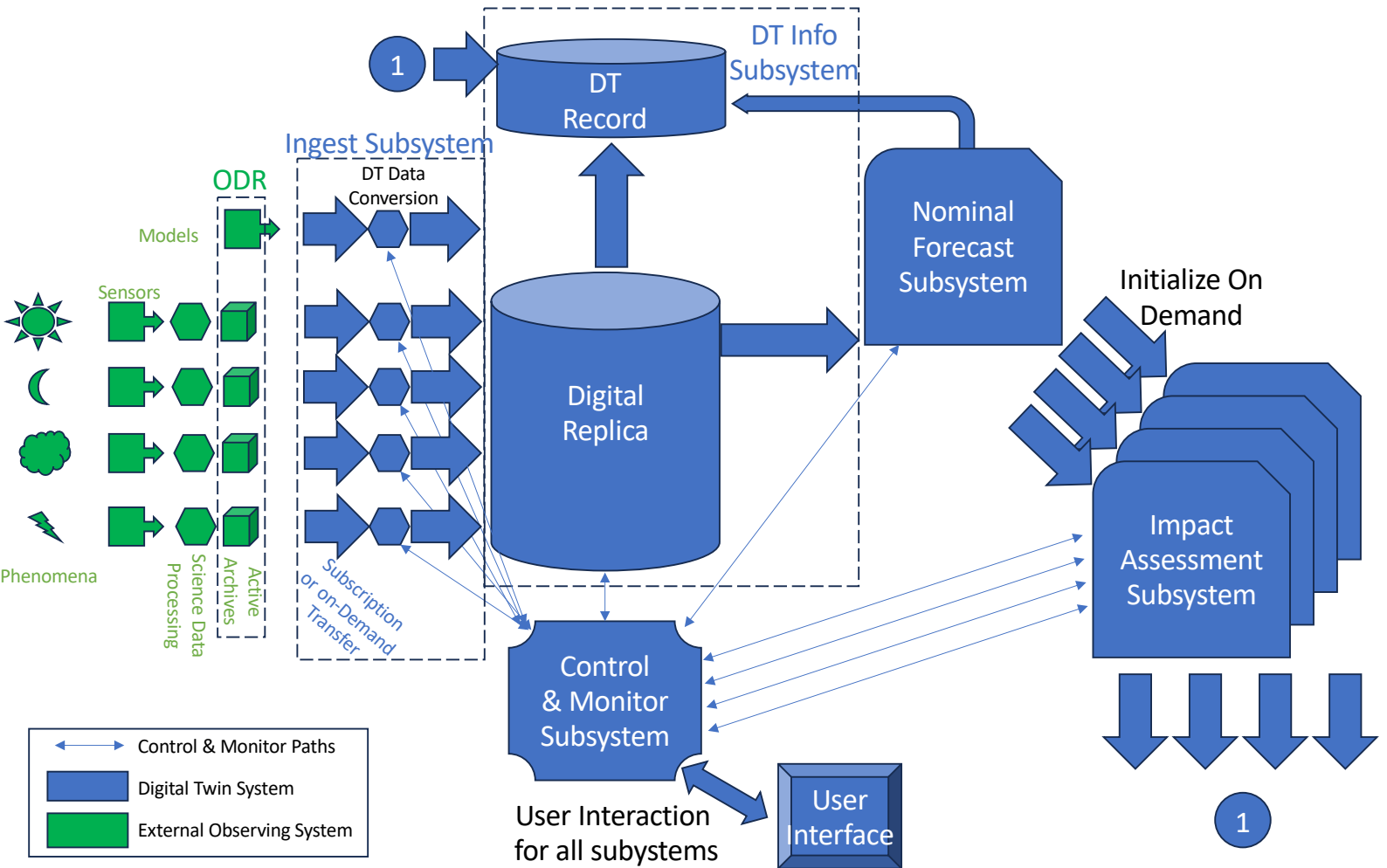
**Note:** Machine Learning essential at all steps



# ESDT Conceptual System Diagram



An ESDT architecture must consider the full range of components and their relationships



### Functional components:

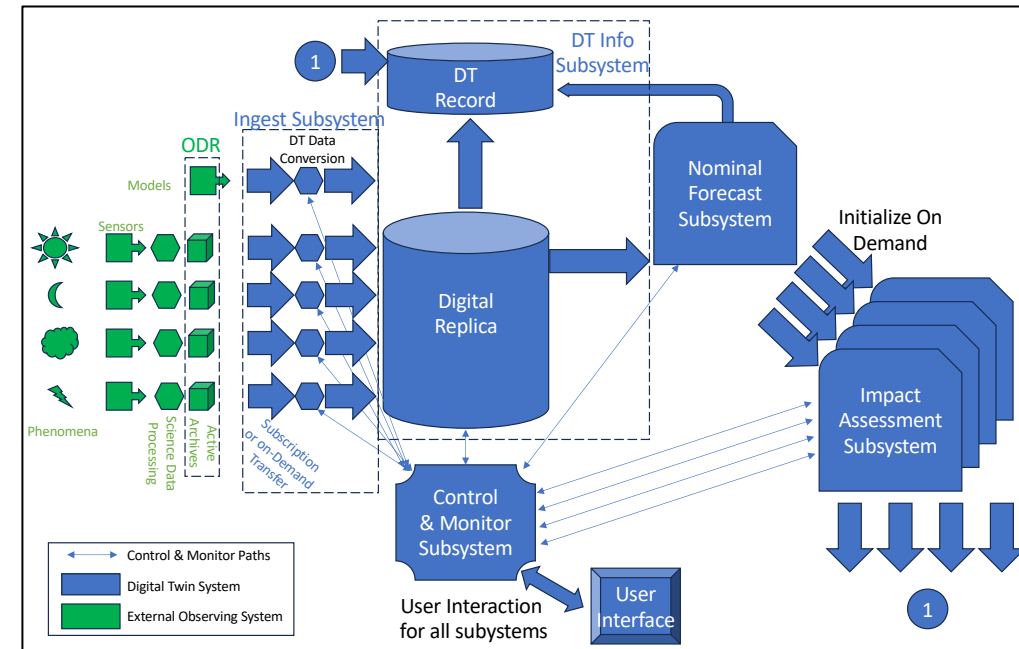
- Observational Data Repository (ODR)
- Ingest Subsystem (ISS)
- DT Information Subsystem (DISS)
- Nominal Forecast Subsystem (NFSS)
- Impact Assessment Subsystem (IASS)
- Control and Monitor Subsystem (CMSS)
- User Interface Subsystem (UISS)

Architecture design may combine components or group them differently

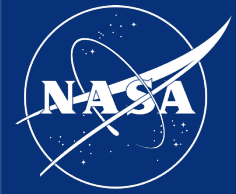


# ESDT Architecture Framework Considerations

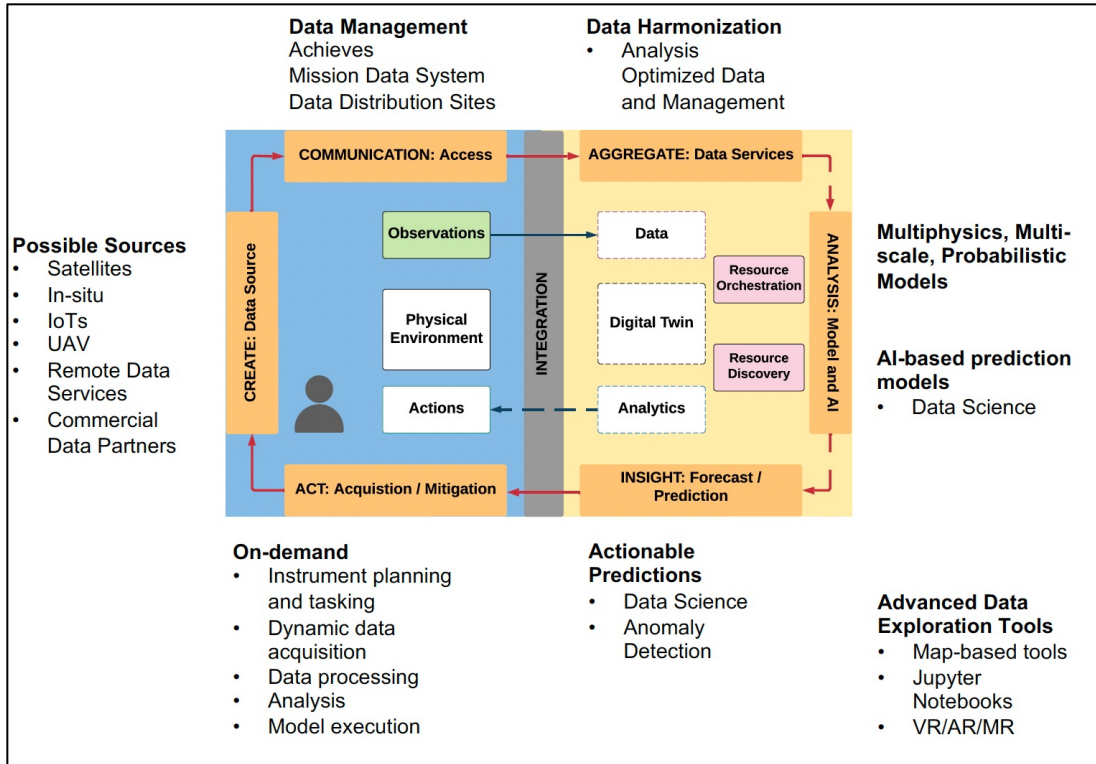
- **Consider architecture principles**
  - Modularity
  - Process automation and error checking
  - Comply with Open-Source Science principles from SPD-41A
  - Permit evolution of concepts and uses and reasonable addition of new components
  - Provide the Glue to stitch together all ESD capabilities
  - Open-standard interfaces enabling opportunities for broader use
  - Interfaces for federation with other ESDTs
  - User interfaces for a range of skill levels and interests (i.e., "from farmer to scientist")
- **Enable component technology developers to consider their place in the overall architecture**
  - Re-use beyond a single architecture
  - Identify technology gaps and what is required to fill them





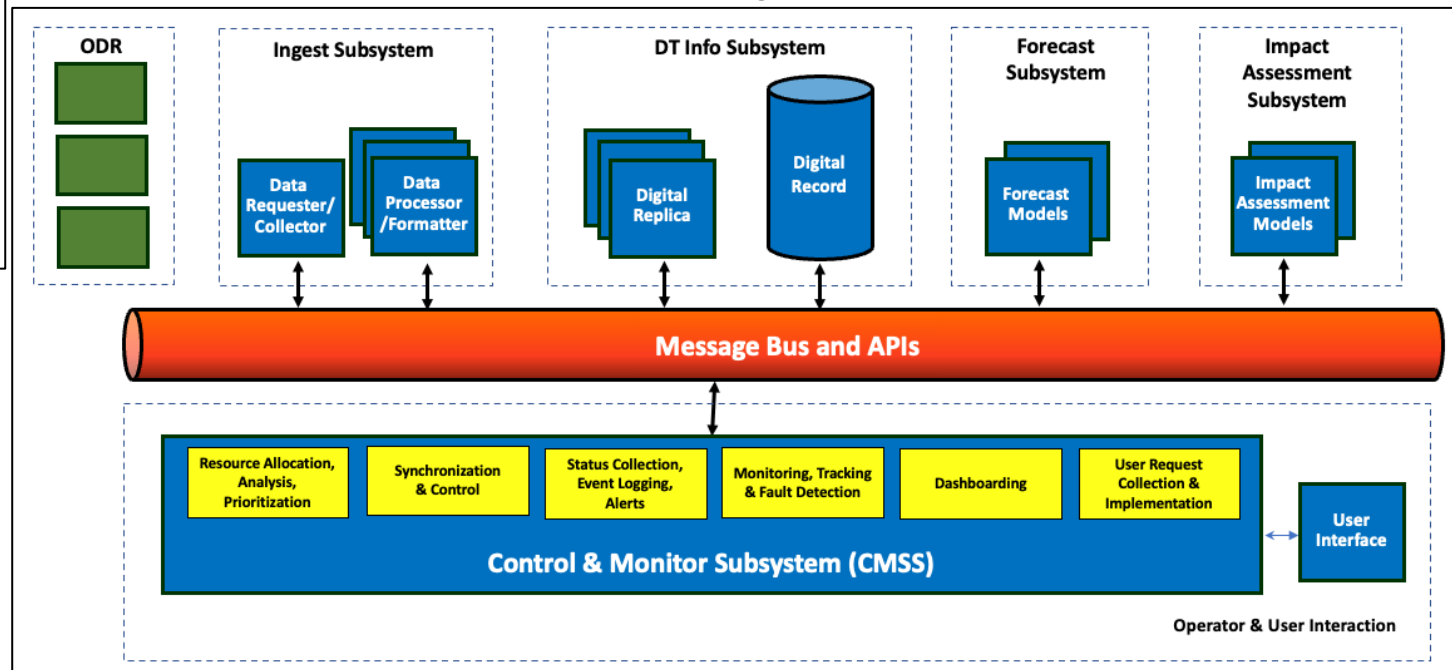


# ESDT Architecture Examples



**Integrated Digital Earth Analysis System (IDEAS) Framework**  
*On-demand Data Access*

## ESDT Message Bus – Based Framework *Continuous Digital Replica*



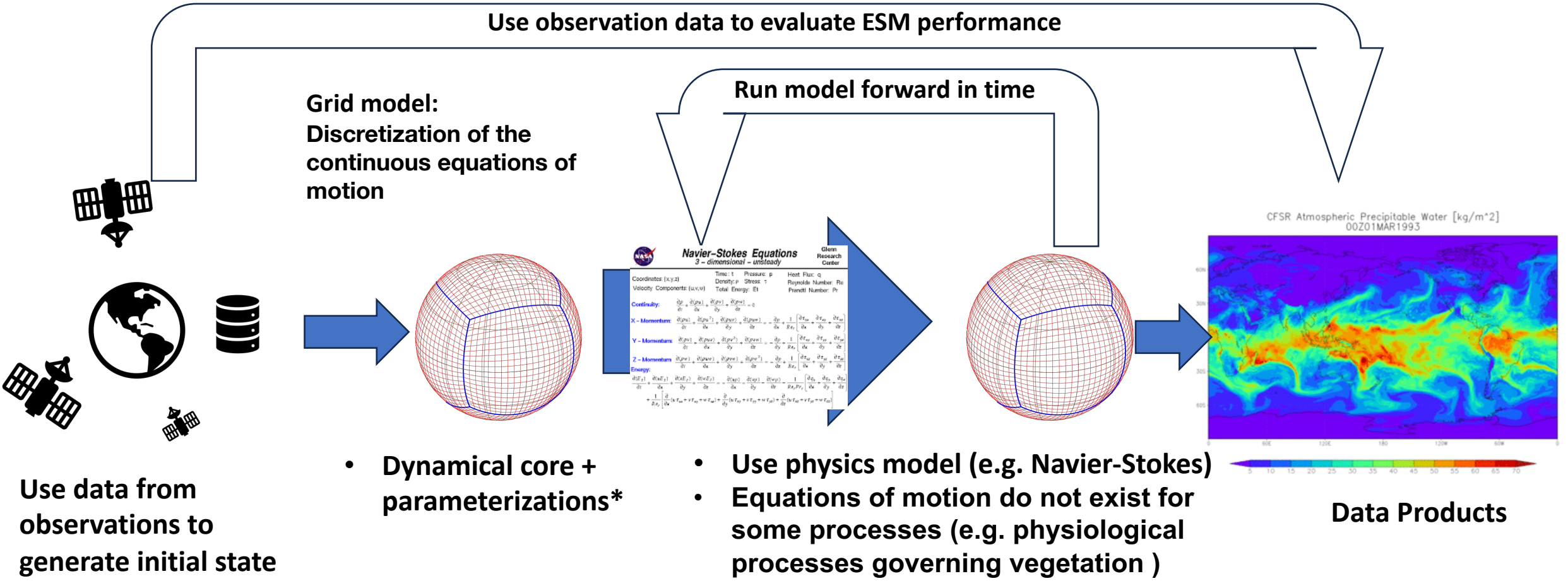


# Earth Science Modeling (ESM)

## Simplified Pipeline

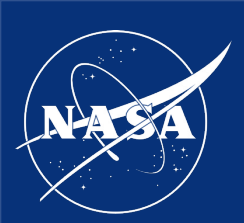


Earth system models (ESMs) combine process-based models of different sub-systems of the Earth system into an integrated numerical model that yields for a given state of a system at time  $t$  a prediction of the system state for time  $t + 1$ .



- Dynamical core + parameterizations\*
- Use physics model (e.g. Navier-Stokes)
- Equations of motion do not exist for some processes (e.g. physiological processes governing vegetation)

\*Simplified representations of natural phenomena used in ESMs. For example, to estimate sub-grid scale processes.

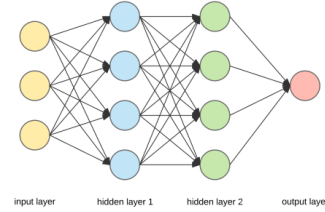


# Machine Learning for Earth Science Modeling



## 6. On-board autonomy

1. Specialized ML agents to uncover and categorize patterns in data



2. Physics-informed ML models (training with the physics)

**Navier-Stokes Equations**  
3 - dimensional - unsteady

Coordinates (x,y,z)    Time: t    Pressure: p    Heat Flux: q  
Density: ρ    Stress: τ    Reynolds Number: Re  
Velocity Components: (u,v,w)    Total Energy: Et    Prandtl Number: Pr

**Continuity:**  

$$\frac{\partial \rho}{\partial t} + \frac{\partial(\rho u)}{\partial x} + \frac{\partial(\rho v)}{\partial y} + \frac{\partial(\rho w)}{\partial z} = 0$$

**X - Momentum:**  

$$\rho \left( \frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} + v \frac{\partial u}{\partial y} + w \frac{\partial u}{\partial z} \right) = -\frac{\partial p}{\partial x} + \frac{\partial \tau_{xx}}{\partial x} + \frac{\partial \tau_{xy}}{\partial y} + \frac{\partial \tau_{xz}}{\partial z}$$

**Y - Momentum:**  

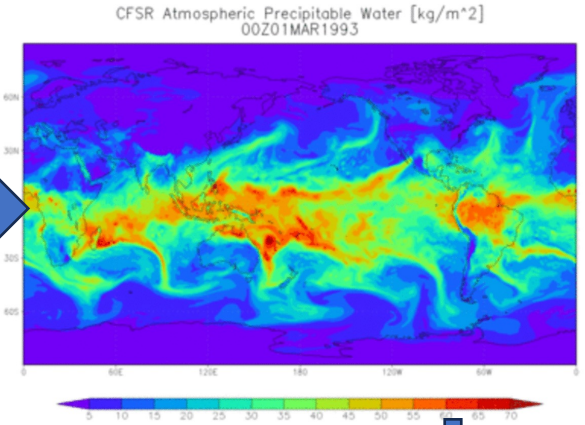
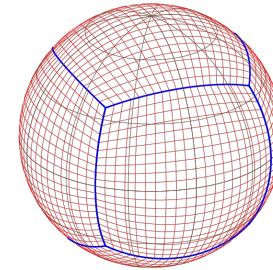
$$\rho \left( \frac{\partial v}{\partial t} + u \frac{\partial v}{\partial x} + v \frac{\partial v}{\partial y} + w \frac{\partial v}{\partial z} \right) = -\frac{\partial p}{\partial y} + \frac{\partial \tau_{xy}}{\partial x} + \frac{\partial \tau_{yy}}{\partial y} + \frac{\partial \tau_{yz}}{\partial z}$$

**Z - Momentum:**  

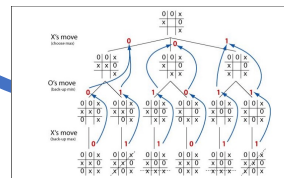
$$\rho \left( \frac{\partial w}{\partial t} + u \frac{\partial w}{\partial x} + v \frac{\partial w}{\partial y} + w \frac{\partial w}{\partial z} \right) = -\frac{\partial p}{\partial z} + \frac{\partial \tau_{xz}}{\partial x} + \frac{\partial \tau_{yz}}{\partial y} + \frac{\partial \tau_{zz}}{\partial z}$$

**Energy:**  

$$\rho \left( \frac{\partial E}{\partial t} + u \frac{\partial E}{\partial x} + v \frac{\partial E}{\partial y} + w \frac{\partial E}{\partial z} \right) = -\frac{\partial p}{\partial x} u - \frac{\partial p}{\partial y} v - \frac{\partial p}{\partial z} w + \frac{\partial q_x}{\partial x} + \frac{\partial q_y}{\partial y} + \frac{\partial q_z}{\partial z} + \frac{\partial \tau_{xx}}{\partial x} u + \frac{\partial \tau_{yy}}{\partial y} v + \frac{\partial \tau_{zz}}{\partial z} w + \frac{\partial \tau_{xy}}{\partial x} v + \frac{\partial \tau_{xy}}{\partial y} u + \frac{\partial \tau_{xz}}{\partial x} w + \frac{\partial \tau_{xz}}{\partial z} u + \frac{\partial \tau_{yz}}{\partial y} w + \frac{\partial \tau_{yz}}{\partial z} v$$

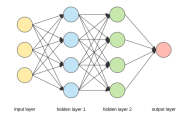


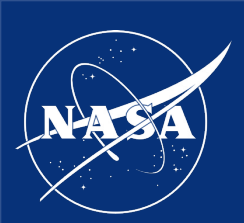
3. ML-based surrogate models for Improving efficiency of simulations



4. ML methods trained with process-based model data to emulate and accelerate simulations.

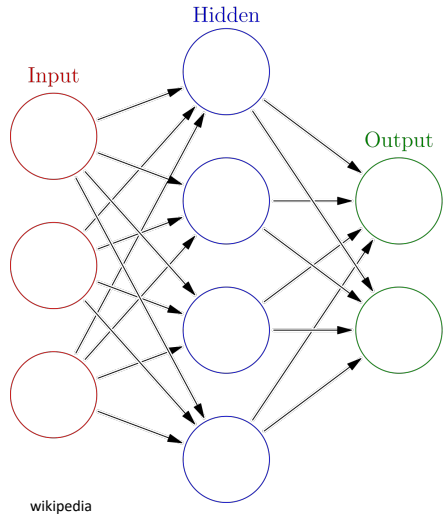
5. Science-driven observation planning





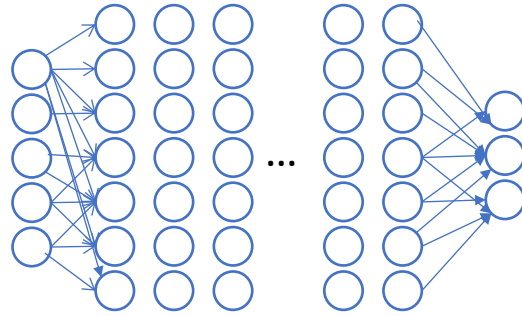
# Foundation Models

## Really Big Neural Networks



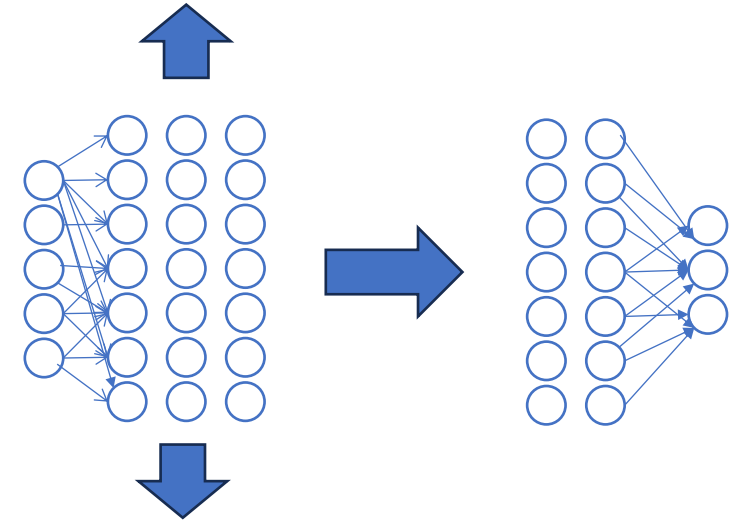
Early Neural Networks

Small networks.  
Performed ok but often eclipsed by other methods.



Deep Neural Networks

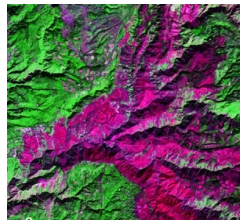
10k ~ M parameters  
*Lots* of (labeled) training data  
Great performance



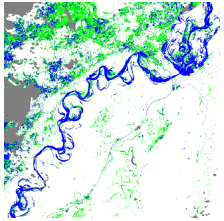
Foundation Models

Millions to Trillions of parameters  
Too much training data to hand-label  
Expensive to train (but only once)  
Newsworthy performance

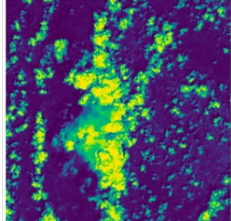




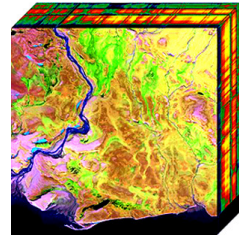
LU/LC



Surface Water  
Extent



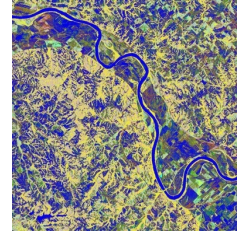
Cloud  
Masks



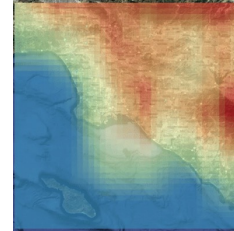
Spectral  
Unmixing

## Recognition and Classification

On the ground and onboard

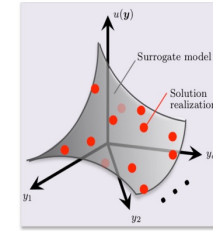


Hydrology



AQ

## Forecasting and Nowcasting



Fast  
Inversions

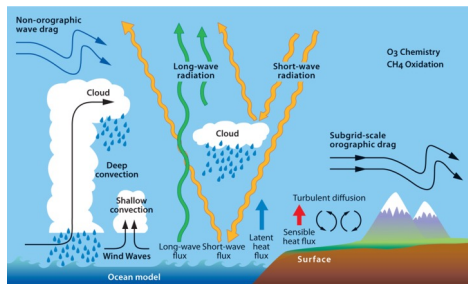


Four  
Cast Net

Fast  
Models

## Surrogate Models

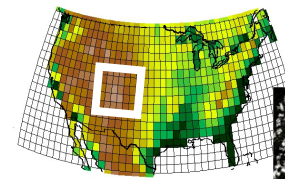
Boundary  
Conditions



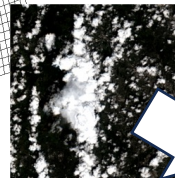
Parameterizations

Governing  
Equations

## Model Understanding and Physics-Inspired ML



Downscaling

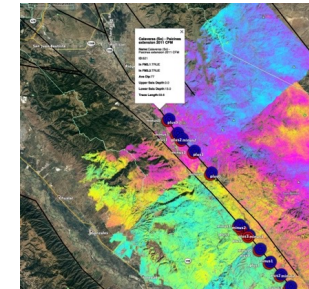


Generative  
Interpolation



Cloud removal  
Gap filling

## Interpolation and Reconstruction



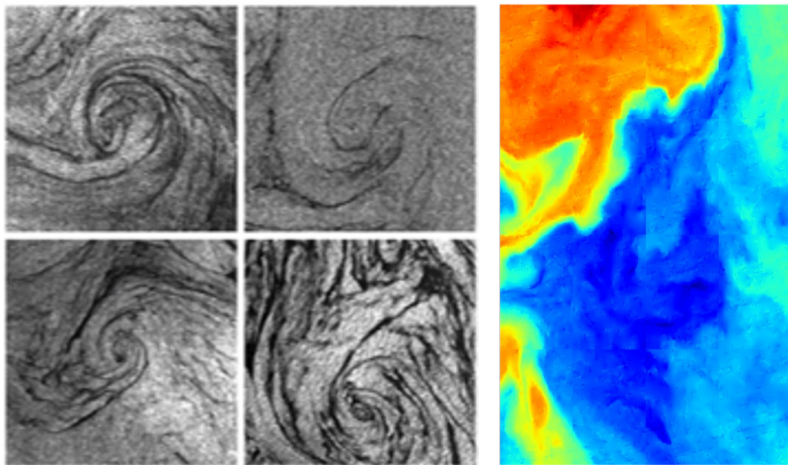
Data Fusion

Show me the relationship  
between SST and algae  
blooms over the last  
decade.

## Bespoke NL interfaces

## SLICE: Semi-supervised Learning from Images of a Changing Earth

Wilson, JPL; AIST-21-0025



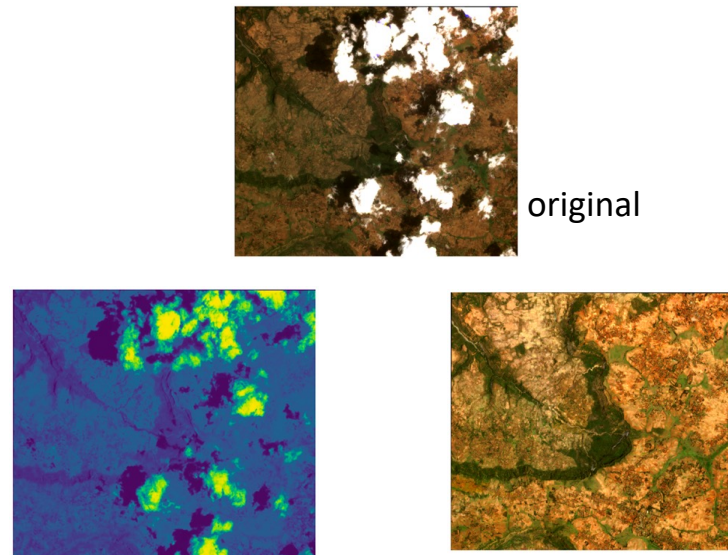
Eddy Detection from SAR imagery

SST reconstruction under clouds

Applications of **Vision Transformers** and **semi-supervised ML** to enable hard remote sensing problems and increase performance despite scarce labeled data.

## Coupled Statistics-Physics Guided Learning

Xie, UMD; AIST-21-0068



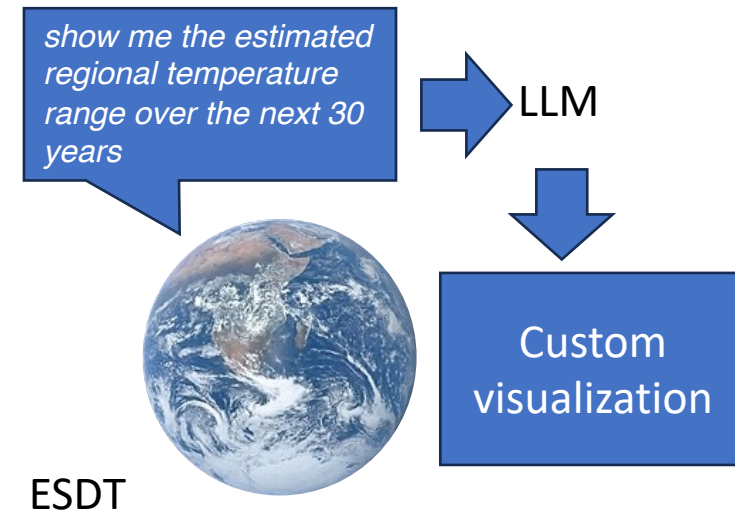
Cloud masks

reconstruction

**Semi-supervised learning**; physics-guided; and heterogeneity-aware learning.

## Digital twin technologies for climate projections

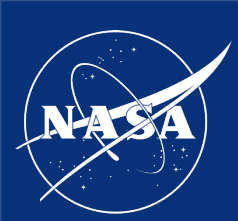
Schmidt, GISS; AIST-QRS-23-0005



ESDT

**Large Language Models (LLM)** to generate bespoke data visualizations for user queries





# Computational Challenges for ESDT

## CZ-DT Example



Function	SubSystem	A100 GPU-node-hours - annual	CPU-node hours-annual
Pre-train Forecast Models-Hydrology	FMSS	25 runs* 64 Nodes x48h from 800 TB data	
Pre-training updates (Hydrology)	FMSS	1 runs/mo* 64 Nodes x48h from 800 TB data	
Periodic forecast update	NFSS	2 Nodes*5min *6 runs/day*365d	
Monitor	CMSS		24h*7d*52w*3nodes
Ingest and feed DR	Ingest		24h*7d*52w*4 nodes*1time/hour
DR file service	Info SS		24h*7d*52w*2 nodes
Impact Assessment (Planner)	IASS	1 Node*2 min * 12/h * 10h (working cycle) * 5d/wk*52 wk/year	1 Node*30 min * 12 requests/h * 10h (working cycle) * 5d/wk*52 wk/year. (peak)
Visualization Support	UISS	1 Node * 15min* 6 requests/h *12h/d* 5d/w*52w/y	1 node *45min/req 6 requests/h *12h/d *5d/w*52w/y
DT Record file service	Info SS		24h*7d*52w*2 nodes
Initial Data conditioning	Ingest		16 nodes*16h/d*10d
Re-delivery Data conditioning	Ingest		4nodes*24h/d*365d/y
SysAdmin	CMSS		1 nodes*4h/d*365d/y
Archive	CMSS		4 nodes*24h/d*365d/y

Function	Assumptions
Pre-training (Initial)	24 runs for experiments + 1 final run w/ 800TB data (INTERACTIVE) AI models are constructed using a lot of experiments to try the model settings to get the best results.
Pre-training Updates	Repeat 1 pre-training run and no experiments once per month (INTERACTIVE)
Periodic forecast update	Inference run on model updated with prompts every 4 hours (BATCH)
Monitor	Monitor System Status, run message bus, direct traffic for an IASS request and monitor for faults, failed deliveries, etc. (BATCH)
Archive	Moving data from DR to DTRecord on schedule (BATCH)
Ingest and feed DR	Ongoing acquisition and conditioning observational data and putting into the Digital Replica (BATCH)
DT Record file service	continuous availability
DR file service	continuous availability for ongoing archiving and requests for historical data
Initial Data conditioning	Workflow to produce initial load of data for constructing AI model (assume 800 TB) (BATCH)
Re-delivery data conditioning	Out of cycle fixes to missed deliveries (BATCH)
Impact Assessment (Planner)	Peak is 12 requests/hour. Day work cycle is 12 hours for peak. (INTERACTIVE)
Visualization Support	6 requests/hour peak at 12 hour days (INTERACTIVE)
SysAdmin	24x7 availability to inspect system (INTERACTIVE)

**1st YEAR TOTAL NODE HOURS: 81,857 GPU or 270,180 CPU or about 10 GPU nodes for a year**

Note: Duty cycle not regular; some evolutions require a large number of GPU nodes for a few days, but only happen a few times a year. Others require a single node for a few seconds but occur frequently and on demand in a more interactive way. Load distribution among GPUs not always even, especially for training.

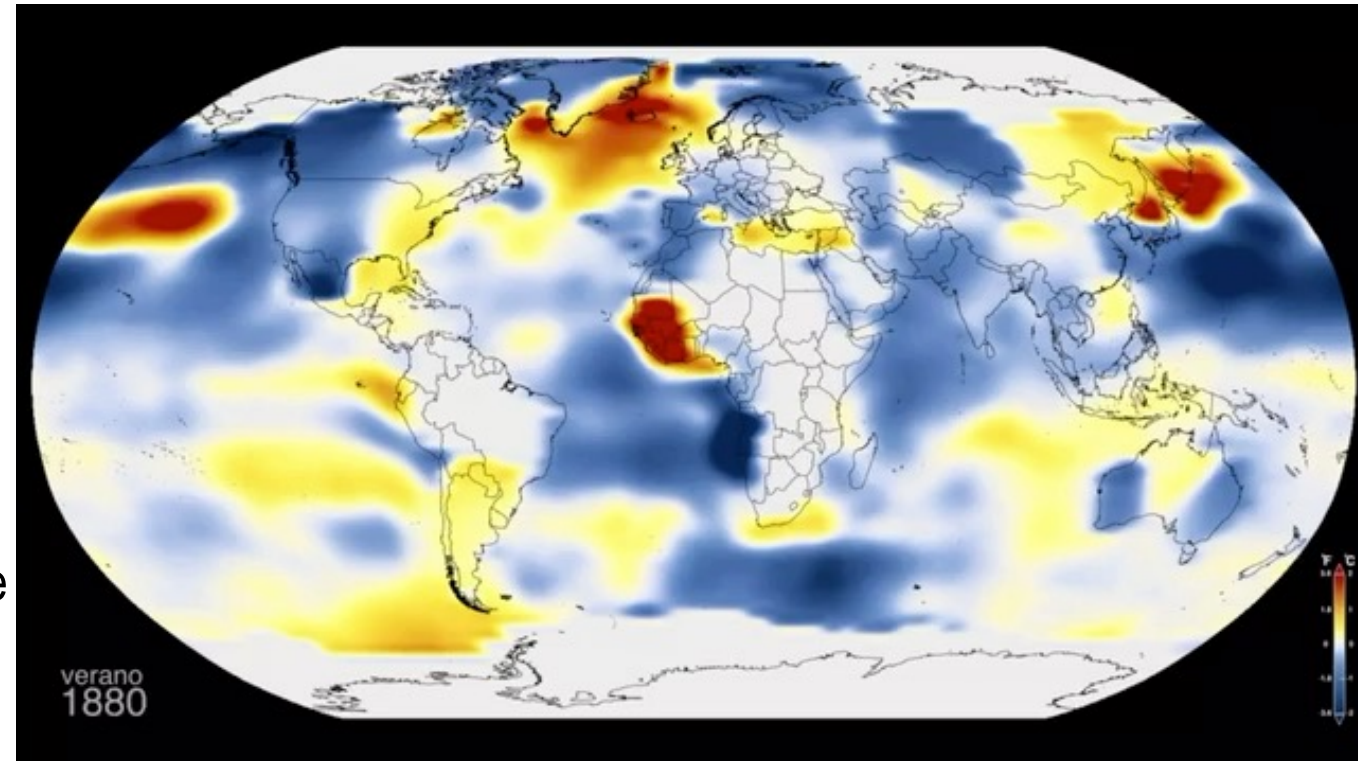
- **User interfaces and visualizations for a range of skill levels and interests (i.e., "from farmer to scientist")**
- **Various outputs and interactions:**
  - Raw data to complex data products, forecasts and impacts (e.g., risk maps, comparisons, etc.)
  - Real-Time, Near-Real-Time or
  - Regularly produced or on-demand
  - Pre-computed videos and visualizations at selected locations, regions of interest, timeframes, etc.
  - Snapshot Digital Replica at TBD-hours refresh rate
  - Interactive maps, graphs and results with a choice of variables, rendering, etc.
  - Virtual or Extended interactive reality to explore the data and data products

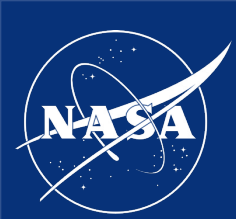
*Summer 2023 Record High Global Temperature*

NASA's Scientific Visualization Studio

(M. Subbarao, G. Schmidt, E. Hawkins, L. Schuler, I. Jones, E. Kaplan, P. Jacobs)

<https://svs.gsfc.nasa.gov/5161/>





# Earth System Digital Twins (ESDT) Roadmap

