Machine Learning-Informed Numerical Weather Prediction

Troy Arcomano Istvan Szunyogh

Texas A&M University
College Station, TX

Supercomputing Conference (SC20), November 17-19th, 2020

General Approach

The **modeling approach** is based on **combining** (Pathak et al. 2018b and Wikner et al. 2020)

- a **numerical weather prediction (NWP) model** and
- a computationally highly efficient **machine learning (ML) algorithm** to obtain
- a **hybrid weather prediction (HWP) model** that provides more accurate predictions than either component

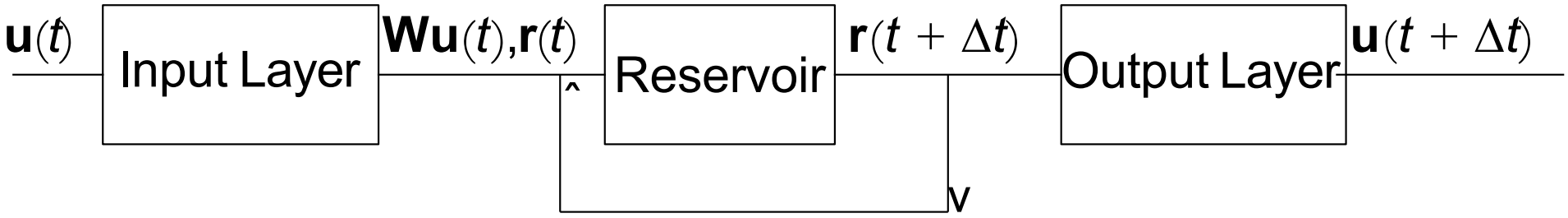
The **ML model component** uses

- a **parallel** (Pathak et al. 2018a) **reservoir computing** (Jaeger 2001, Maas et al. 2002, Lukoševicius and Jaeger 2009) approach

Our goal is to prove the concept by building a **low-resolution, global, HWP model**

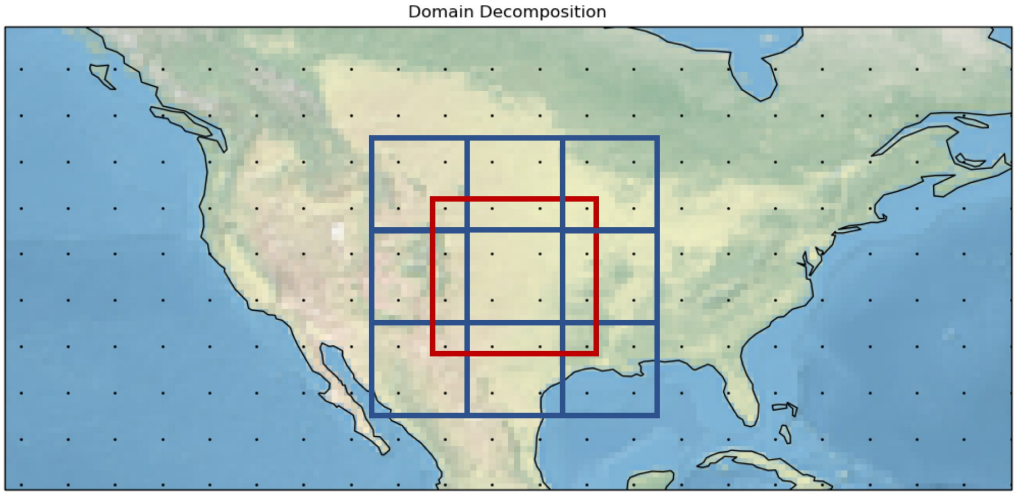
Reservoir Computing

A **'time step' of the ML model** is a **composite function** that predicts the physical state $\mathbf{u}(t + \Delta t)$ from the physical state $\mathbf{u}(t)$



- **Input Layer:** Maps the physical state $\mathbf{u}(t)$ into a much higher dimensional reservoir state $\mathbf{Wu}(t)$ (**W** is typically the matrix of a random projection)
- **Reservoir:** A **high-dimensional dynamical system**
- **Output Layer:** Reads out the physical state $\mathbf{u}(t + \Delta t)$ from the reservoir state $\mathbf{r}(t + \Delta t)$

Computationally Efficient, Parallel Algorithm

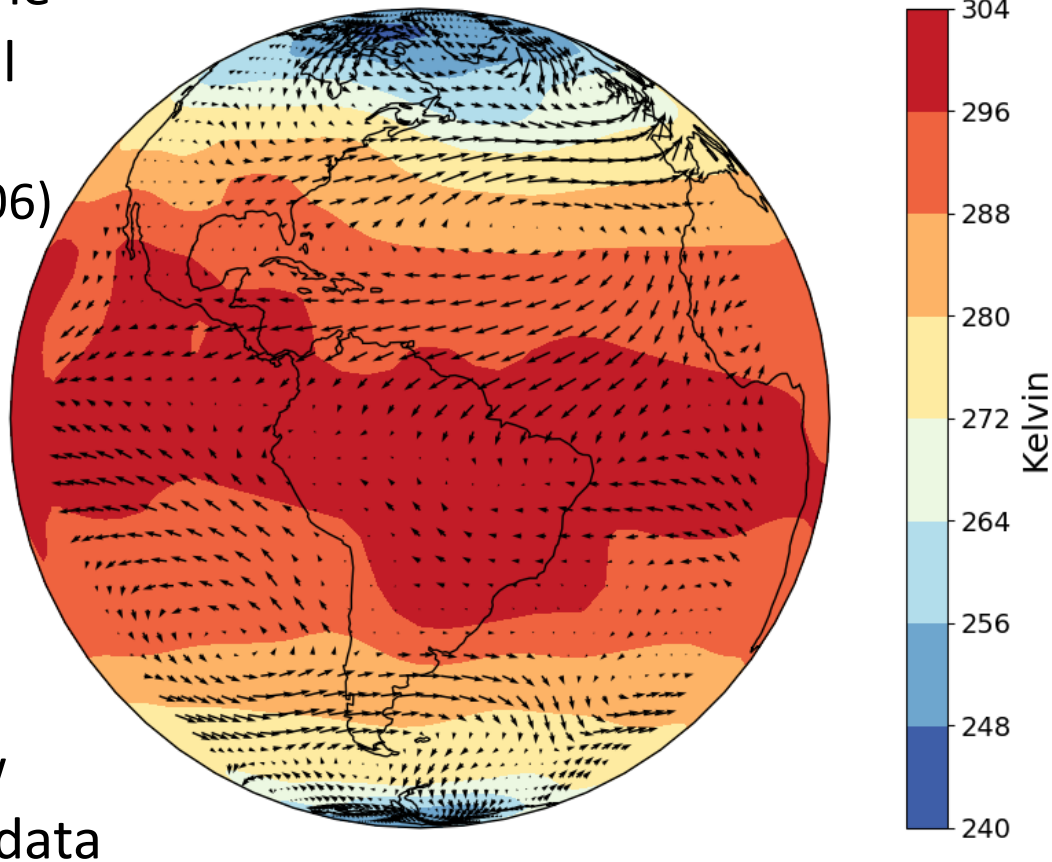


The global state vector $\mathbf{u}(t)$ is partitioned into L **local state vectors:**

- **Local State Vector:** Each local state vector is predicted independently (the linear regression problem is solved in parallel for the different local state vectors)
- **Extended Local State Vector:** Input layer operates on an extended local state vector, so information can propagate between the local regions

SPEEDY

- **S**implified **P**arameterizations, primitive **E**quation **DY**namics Version 42 of the International Centre for Theoretical Physics (ICTP)
  - (Molteni 2003, Kucharski et al 2006)
- **Equations**:
  - Primitive equations
  - Simplified but modern parameterization
- **Resolution:**
  - 8 vertical layers
  - T30 (~300km)
- Been used to test and develop new numerical weather prediction and data assimilation techniques



Training

- Observation-based data set of past states of the atmosphere, regridded to SPEEDY horizontal and vertical grid

- Used the 5 prognostic variables for SPEEDY
  - Temperature
  - 2 components of the wind
  - Specific Humidity
  - Surface Pressure

- 11 years of data from 1981- 1991
  - 9.5 years for training
  - 7 months for validation

Computational Details

- A distributed and parallel architecture

- Each local region is trained independently in parallel
  - Currently assigning 1 core per local region
  - **1152** regions used to represent the globe

- Dense and sparse linear algebra calculations are done using OpenMP threaded **LAPACK, BLAS,** and **Sparse BLAS** functions found in the Intel's **Math Kernel Library** (MKL)

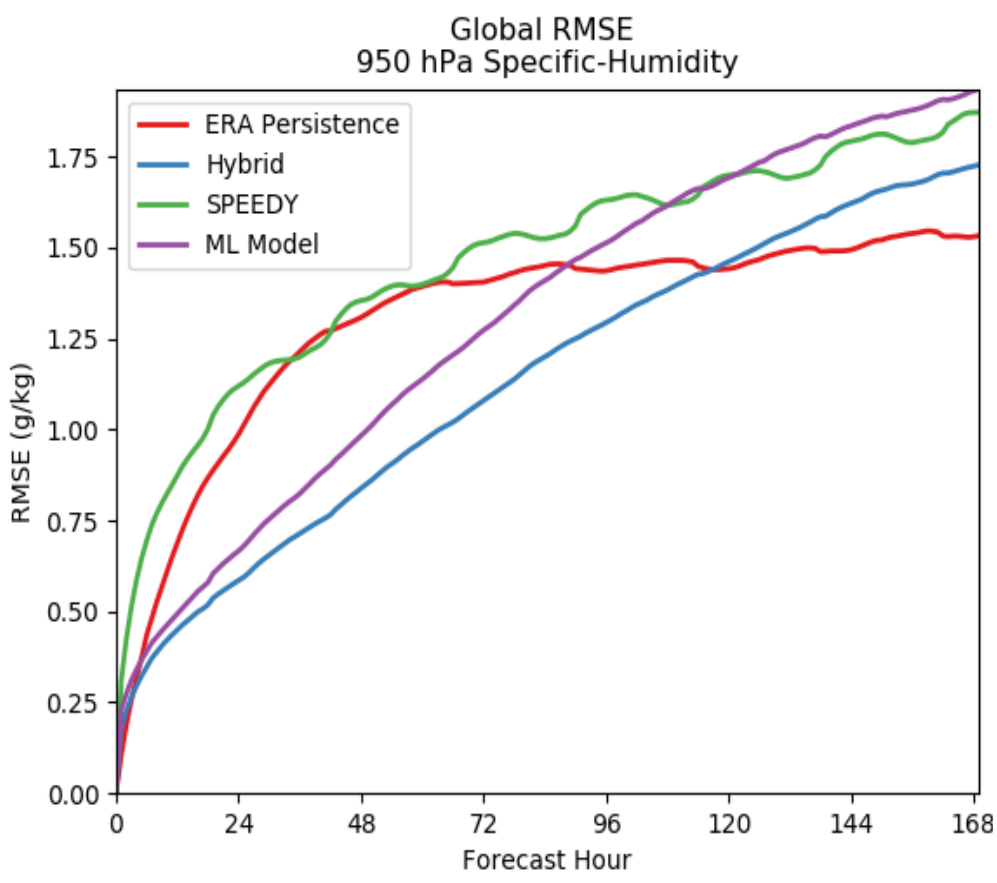
- Parallel IO
  - Non-collective, parallel HDF5 reading and writing of data
  - Reading in **750 GB** of data with 1152 processors takes 10 minutes

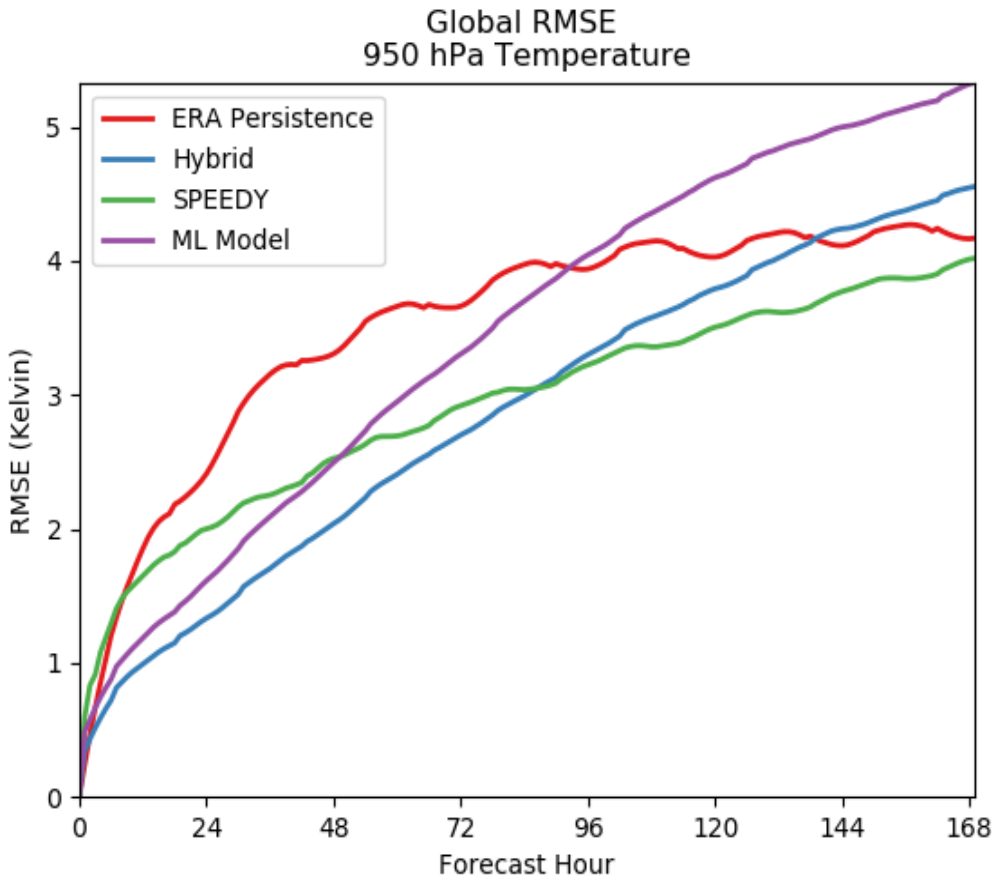
- Real runtime for training over 10 years and making predictions using TAMU's Ada cluster with 1152 cores and 2.8 Terabytes of total program memory is about 1 hour

Verification

- Comparing 20 hybrid forecasts to the regridded observation-based data not used for the training
- The 20 forecasts span from June 1990 to January 1991
- Forecast skill was compared to that of SPEEDY, persistence forecasts, and a reservoir computing based machine learning only model (trained using the same data as the hybrid)

Verification II





A lower value of the root-mean-square error (RMSE) indicates a more accurate forecast

Conclusion

- We built a prototype model that employs reservoir computing for ML-Informed numerical weather prediction (NWP)

- The hybrid system performs better than the numerical model out to 24 hours for all forecast variables
    - Atmospheric moisture and temperatures out to at least day 3

- Parallel IO can greatly improve runtime performance

- Reservoir computing algorithm with a parallel architecture allows for massively parallel training without a GPU , which is significantly faster than for a deep learning network