Bias correcting weather models with machine learning

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Methods

1. Perform a hindcast GCM run with a linear relaxation “nudging” term added to prognostic equations:

   \[
   \frac{dX}{dt} = \ldots - \frac{X_{\text{nudging}}}{T}
   \]

   time

   nudging tendency

   Model evolution

   Observational analysis

2. Train an ML model to predict the tendencies \(-\frac{X_{\text{nudging}}}{T}\) from above run given only the model state.

3. Now make a forecast using same model as step 1 and at each timestep apply corrective tendencies predicted by the ML algorithm trained in step 2.

Atmospheric model details

- FV3/GFS at C48 (~200km) resolution (https://github.com/NOAA-EMC/v3atm)
- Nudging temperature, specific humidity, surface pressure and horizontal winds
- 6-hour nudging timescale
- Reference dataset for nudging is GFS analysis at approximately 1° resolution
- Two-year nudged simulation initialized on 1 January 2015
- Training data comes from 2015 year; 2016 is used for testing and verification

Machine learning details:

- Random forest (RF) used to predict nudging tendencies
  - A single RF is trained to predict a column of tendencies given column profiles of the model state
  - Inputs: temperature (T), specific humidity (q), eastward wind (u), northward wind (v), land-sea mask, surface geopotential, cosine of zenith angle
  - Outputs: temperature nudging tendency, specific humidity nudging tendency, eastward wind nudging tendency, northward wind nudging tendency
- Training data is 160 timesteps worth of column profiles; 16 million samples, 16 individual trees, with max depth of 13

Coupling of machine learning and GCM:

- We use a python wrapper of the Fortran FV3/GFS code to allow calling python code during model simulation
- At end of each timestep, RF makes prediction of tendencies given current state of model and these tendencies are applied to the state
- The column-integrated drying induced by the nudging or machine learning is assumed to be converted to rainfall and is added to the surface precipitation rate felt by the land-surface model
- A limiter is applied to the specific humidity tendencies predicted by the RF so that the resulting specific humidity is non-negative

Key points

- A random forest (RF) can make skillful predictions of the nudging tendencies from a hindcast GCM simulation nudged toward observational analysis.
- Coupling a conventional GCM to this RF results in marked improvements in 1- to 10-day forecasts of Z500 and other variables.
- The root mean squared error of annual-mean precipitation is reduced by 24% in the RF-assisted GCM.

Improved weather and climate forecasts

The large positive bias of precipitation over Himalaya and Andes in baseline run is significantly smaller in rf-control run

Future work

- How much of an improvement does this method provide if the baseline model is higher resolution than 200km?
- Some temperature/moisture biases emerge in coupled GCM-RF simulations on monthly timescales, particularly in polar regions. How to avoid this?
- Use a neural network? RFs require significant memory which is a drawback. Have successfully trained a NN which produces stable simulations if it predicts heating/moistening. Instabilities if it predicts wind accelerations.
- How best to account for ML moistening tendencies in terms of soil moisture changes? Small land surface biases can emerge with current setup.

References