Forecasting the magnetic disturbance-storm-time (*Dst*) index using machine-learning

Manoj Nair, Patrick Alken and Arnaud Chulliat

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ISCWSA

Speaker Bio

- Manoj Nair
  - Research scientist and Operational science-lead
  - University of Colorado and
    US National Oceanic and Atmospheric Administration
  - 17+ years research experience in geomagnetism
  - PhD in Geophysics
  - Boulder, CO
  - Specialized in
    - Geomagnetism
      - Signal-processing, research-to-operations
        - Machine-learning

Geomagnetism group of University of Colorado and US National Oceanic and Atmospheric Administration

- Conducts original research on geomagnetism
- Develops and distributes magnetic reference models (HDGM, WMM, IGRF)
- Real-time modeling of magnetic disturbance field
- Magnetic survey data repository (GEODAS)
- CrowdMag citizen-science project

https://geomag.colorado.edu/
https://www.ngdc.noaa.gov/geomag/

CIRES

University of Colorado Boulder

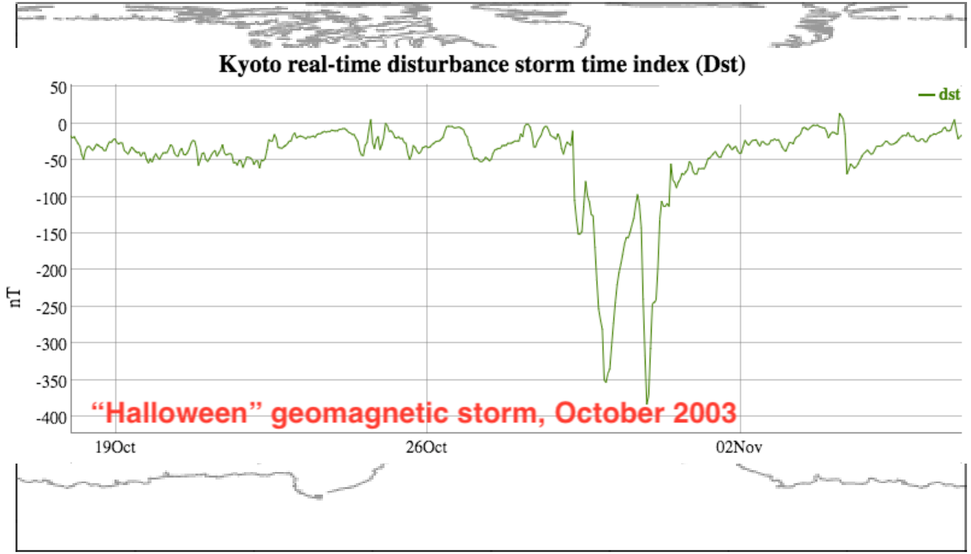
NOAA

Roadmap

- Disturbance-storm-time (*Dst*) index: what and why
- Solar-wind based forecast of *Dst*
- Machine-Learning and artificial neural networks
- Modeling of *Dst*
- Results and conclusion

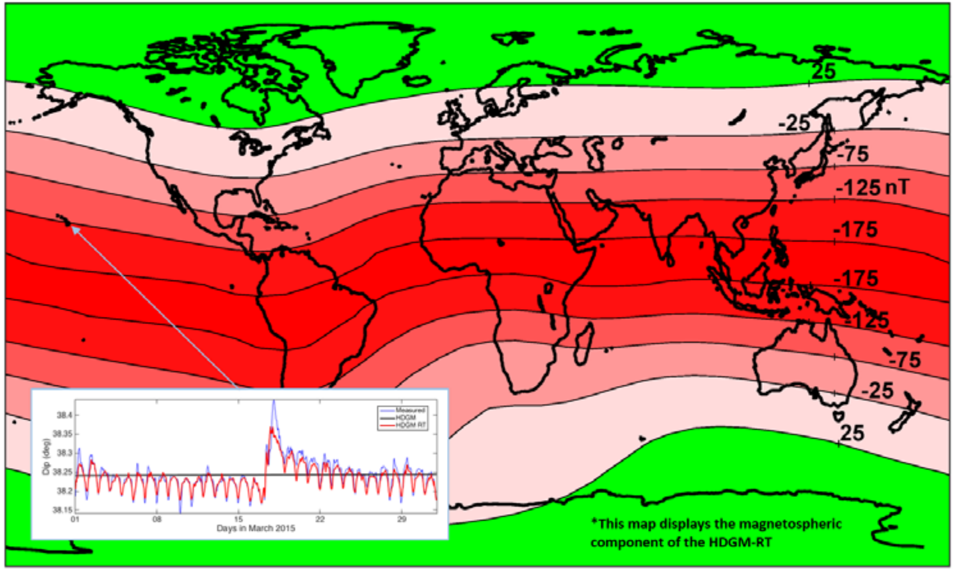
Disturbance-storm-time (*Dst*) index
A measure of magnetic disturbance

- Solar-wind interaction with Earth's magnetic field generate electric currents
- *Dst* index is a measure of "ring-currents" in the magnetosphere
- Hourly *Dst* index is calculated using four geomagnetic observatories
- Different flavors: Kyoto *Dst*, USGS *Dst*, *Rc* index



Why to predict *Dst*?
Important space-weather specification

- Ring-current is one of the major current systems in the magnetosphere
- Critical input to magnetospheric specification models
- Operational *Dst* forecast provides early warning
- Augment NOAA/CIRES real-time magnetic disturbance modeling



Forecasting of *Dst* using solar-wind data

- Solar-wind forecasting
  - Less-accurate
  - Lead-time
  - Observatory data not needed
- Empirical relationship
  - Burton et al (1975), Temerin and Li (2002), O'Brien and McPherron (2000)
- Physics-based models
  - University of Michigan's Geospace model
- Machine-learning approach

The $dst1$, $dst2$, and $dst3$ terms are calculated as follows:

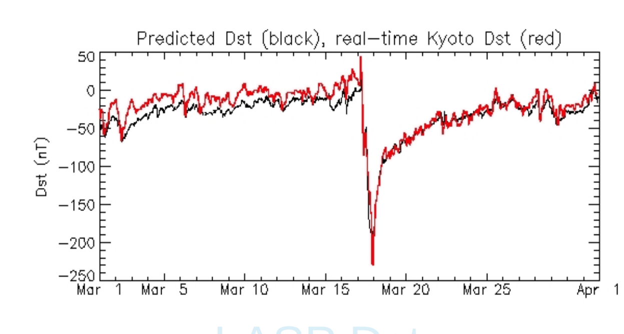
$$dst1(t+dt) = dst1(t) + \{a_1 \cdot [-dst1(t)]^{a_2} + fe1(t)[1 + \frac{a_3 \cdot dst1(t-\tau_1) + a_4 \cdot dst2(t-\tau_1)}{1 - a_5 \cdot dst1(t-\tau_1) - a_6 \cdot dst2(t-\tau_1)}]\}dt \quad (5)$$

$$dst2(t+dt) = dst2(t) + \{b_1 \cdot [-dst2(t)]^{b_2} + fe2(t)[1 + \frac{b_3 \cdot dst1(t-\tau_2)}{1 - b_3 \cdot dst1(t-\tau_2)}]\}dt \quad (6)$$

$$dst3(t+dt) = dst3(t) + \{c_1 \cdot dst3(t) + fe3(t)[1 + \frac{c_2 \cdot dst3(t-\tau_3)}{1 - c_2 \cdot dst3(t-\tau_3)}]\}dt \quad (7)$$

where $a_1 = 6.51 \cdot 10^{-2}, a_2 = 1.370, a_3 = 8.4 \cdot 10^{-3}, a_4 = 6.053 \cdot 10^{-3}, a_5 = 1.21 \cdot 10^{-3}, a_6 = 1.55 \cdot 10^{-3}$, $\tau_1 = 0.14$ days, $b_1 = 0.792, b_2 = 1.326, b_3 = 1.29 \cdot 10^{-2}, \tau_2 = 0.18 days$, $c_1 = -24.3, c_2 = 5.2 \cdot 10^{-2}, \tau_3 = 9 \cdot 10^{-2} days$, $fe1 = -4.96 \cdot 10^{-3}(1 + 0.28 \cdot dh)[2 \cdot exx + abs(exx - th1) + abs(exx - th2) - th1 - th2]v_x^{1.11} n^{0.49} \sin^{6.0}(\phi)$, $fe2 = 2.02 \cdot 10^3 \cdot \sin^{3.13}(\phi) \cdot df2/(1 - df2)$, $df2 = -3.85 \cdot 10^{-8} \cdot v_x^{1.97} b_t^{1.16} \sin^{5.7}(\theta) \cdot n^{0.41} \cdot (1 + dh)$, $fe3 = 3.45 \cdot 10^3 \cdot \sin^{0.9}(\phi) \cdot df3/(1 - df3)$ $df3 = -4.75 \cdot 10^{-6} \cdot v_x^{1.22} \cdot b_t^{1.11} \sin^{5.5}(\theta) n^{0.24}(1 + dh)$, $exx = 10^{-3} \cdot v_x \cdot b_t \sin^{6.1}(\theta)$, $\theta = -(acos(-\frac{b_z}{b_t}) - \pi)/2$, $b_t = (b_y^2 + b_z^2)^{\frac{1}{2}}$, $th1 = 0.725 \sin^{-1.46}(\phi)$, $th2 = 1.83 \sin^{-1.46}(\phi)$, $dh = b_p \cdot \cos(atan(b_x, b_y) + 6.10)(3.59 \cdot 10^{-2} \cos(2\pi t/yr + 0.04) - 2.18 \cdot 10^{-2} \sin(2\pi t - 1.60))$, and $b_p = (b_y^2 + b_x^2)^{\frac{1}{2}}$. Time (t, dt) is in days, magnetic field in nT, solar wind velocity in km/s and density in cm^{-3}. Here v_x is the magnitude of x-component of the solar wind velocity.

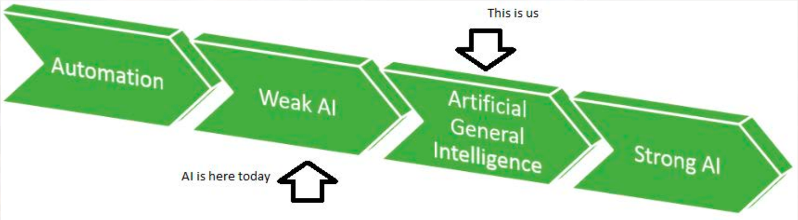
Temerin and Li (2002) – LASP model



LASP Dst prediction

Artificial Intelligence

- An “AI”, or Artificial Intelligence is an intelligent code/machine made by human.
- AI performs cognitive functions such as learning, problem solving, Planning.
- AI progression
  - Artificial Weak Intelligence
  - Artificial General Intelligence
  - Strong AI
- Practical applications are limited to Weak-AI
  - Machine-Learning



Source: https://vincentlauzon.com/2015/09/16/strong-ai-existential-risks/

Machine-Learning
Deep Neural Networks

Artificial Neural Networks

- Mimics the function of brain
- Weights and transfer function
- Unversal non-linear approximator
- Back-propagation training
- Supervised learning

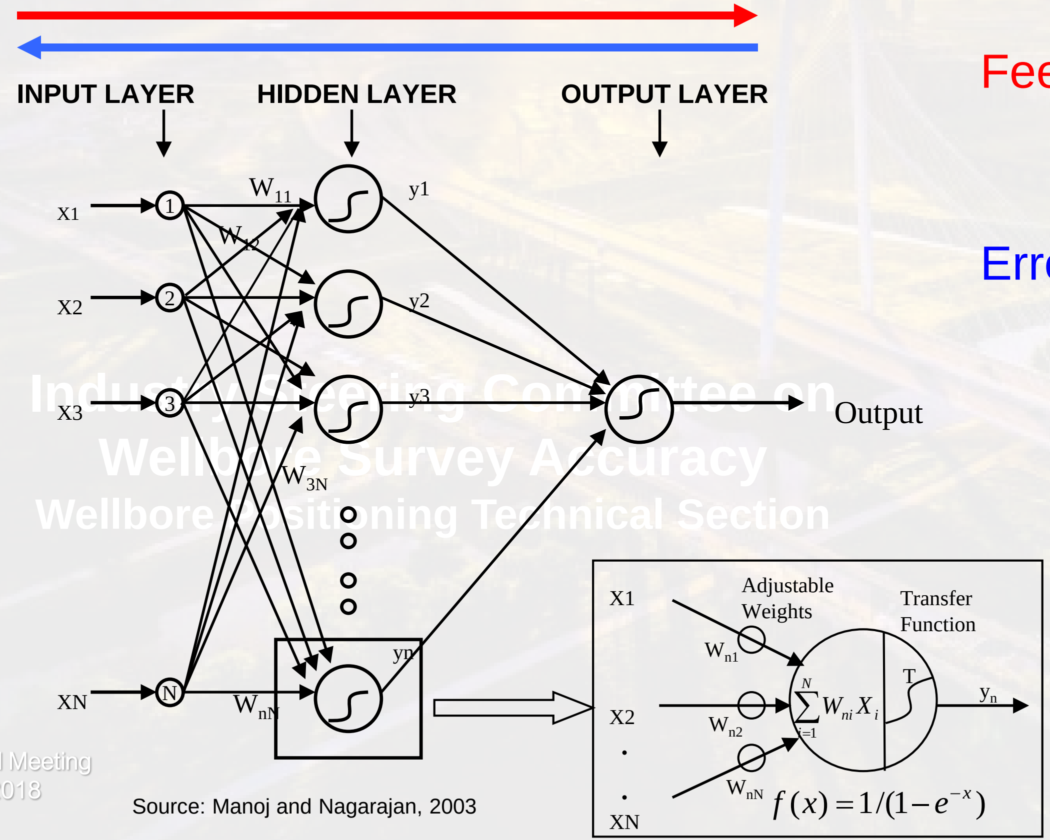
Recurrent Neural Networks

- A variation of ANN
- For predicting temporal (sequential) information
- Squence-to-sequence processing

ML frameworks

- Bring your own software
- Tensorflow (Google)
- PyTorch (Facebook)

Training
Deep Neural Networks



Source: Manoj and Nagarajan, 2003

Feed forward

$$y_j = f\left(\sum W_{ji} x_i\right)$$

$$f(x) = 1/(1-e^{-x})$$

Error Backpropagation

$$\delta_j = \partial E / \partial W_{ij},$$

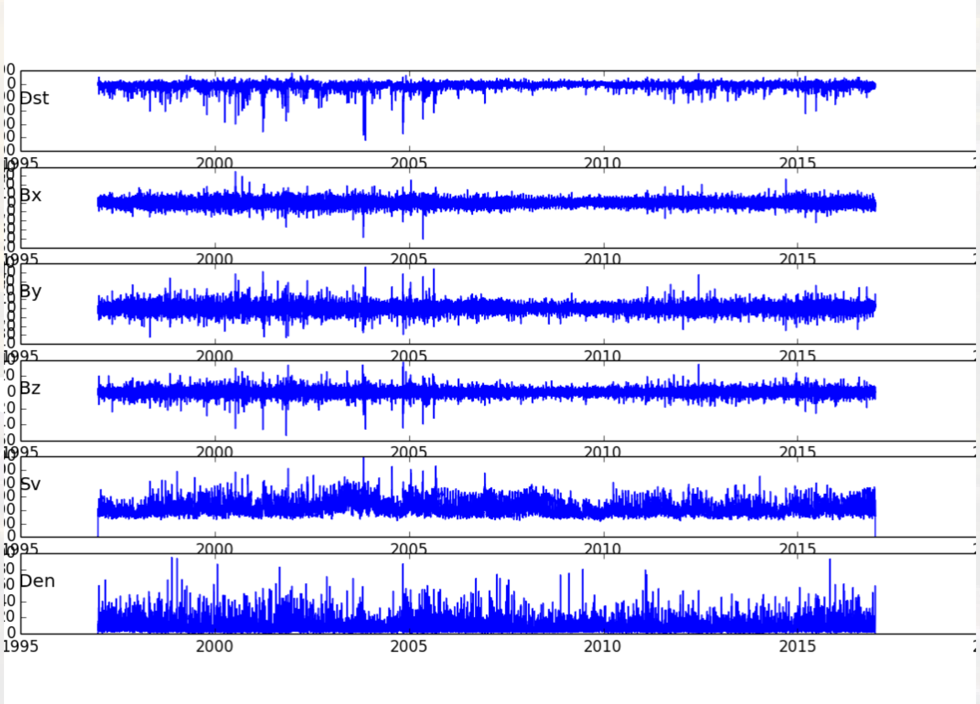
$$E = 0.5 \sum (d_j - o_j)^2$$

$$\Delta W_{ji} = \eta \delta_j o_i$$

$$\Delta W_{ji}(n+1) = \eta \delta_j o_i + \beta \Delta W_{ji}(n)$$

Data used for machine-learning

- Observerved *Dst* values (Kyoto WDC)
- Observed solar-wind data (NASA-OMNI)
- 1997-2016 (175,200 hourly values)
- Divided into training and testing segments
- Normalized



Training the model

- Aim: one-step (hour) ahead forecast of *Dst* using current and historical solar-wind data

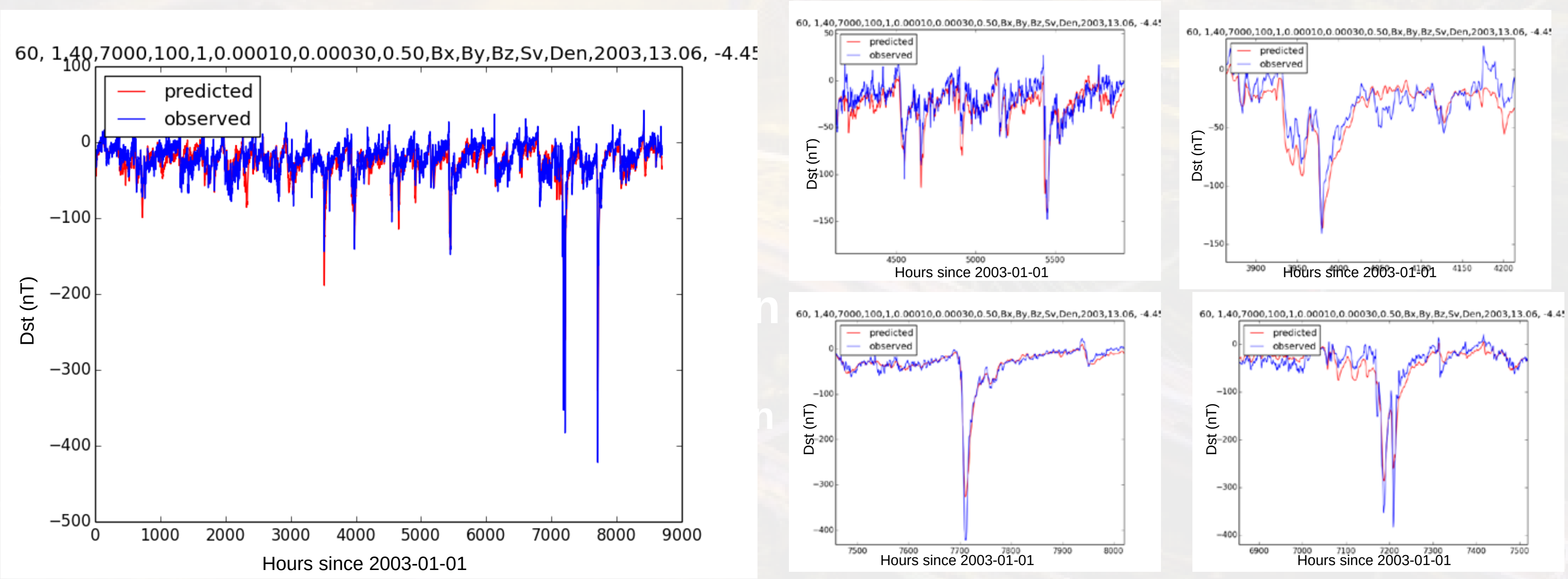
- Optimizing hyperparameters

- Minimizing the loss-function versus generalizing the model

- CPU versus GPU

- Final weights and biases saved for production.

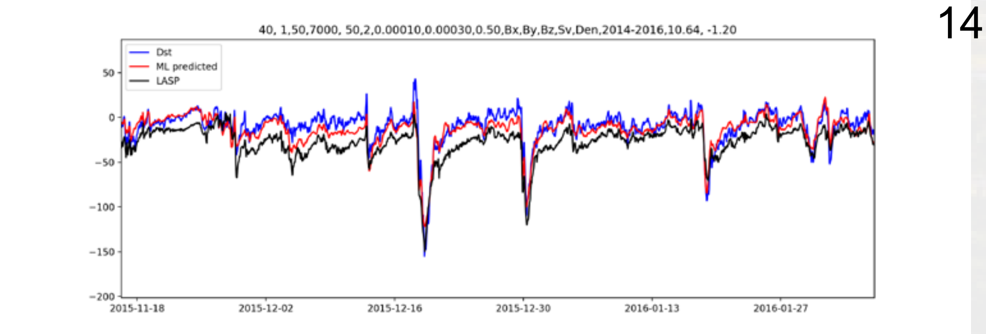
Results

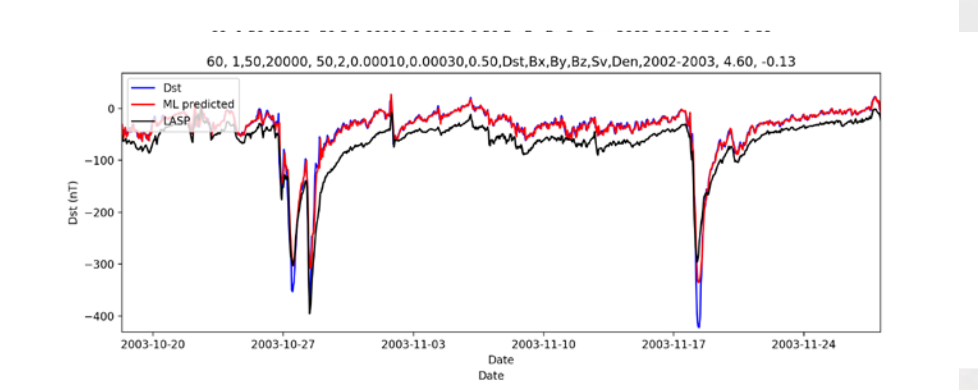


One-step ahead forecasting of *Dst* for 2003

Benchmarking ML prediction

- Compared ML model against LASP model using test data.
- ML and LASP predictions are very similar
- Extreme geomagnetic storm of Nov-2003 is better predicted by ML
- Further improvement to prediction is achieved by ingesting past *Dst* data





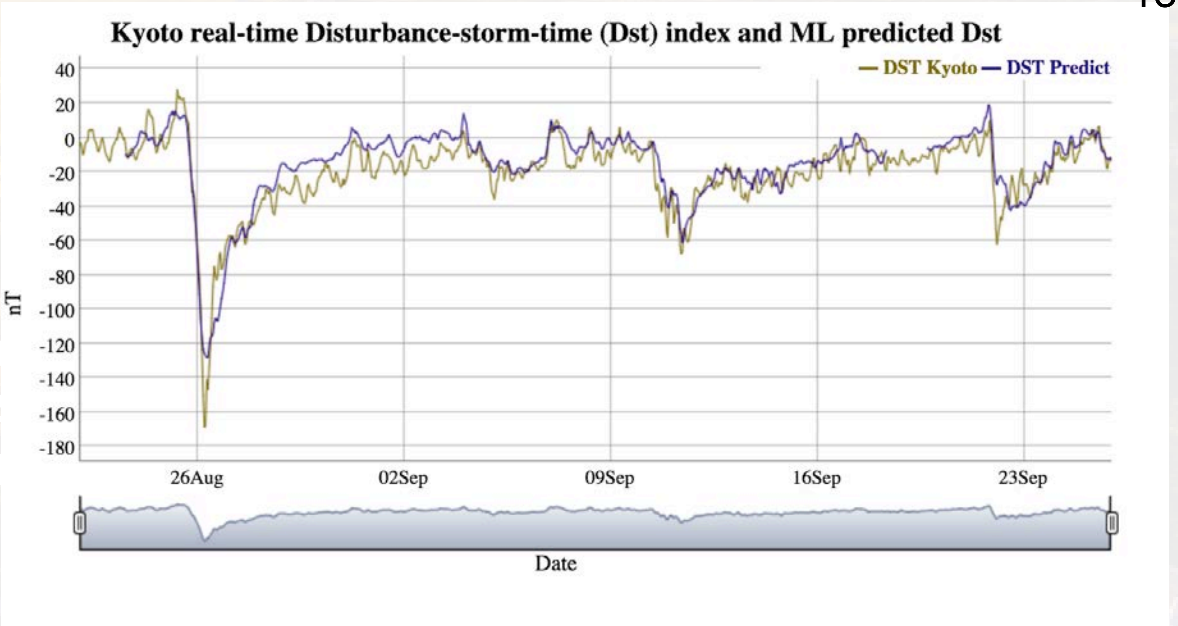
Real-time prediction service

- We use the trained ML model to predict *Dst* in real-time
    - Satellite only
    - Satellite + past *Dst*

- Uses NOAA's DSCOVR satellite data
    - Operational upstream solar-wind measurements

- 1-hour advance prediction of *Dst*

- Real-time validation against observed data



Will be available at https://geomag.colorado.edu

Conclusion

- Machine-learning (ML) is a powerful tool to develop predictive models
- Disturbance-storm-time (*Dst*) index is an important specification of magnetic disturbance
- Using historical *Dst* and satellite data, we developed a ML model to forecast *Dst* data
- Our predictions compare favorably with observed data
- Potential for modeling other electric-current systems in the space.