A Deep Learning Parameterization for Ozone Dry Deposition Velocities

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MIT ATMOSPHERIC CHEMISTRY

U.S. DEPARTMENT OF ENERGY

NSF

Silva et al. (GRL, 2019)

What is ozone dry deposition?

20-25% of all ozone loss in the troposphere

Varies with:

- Turbulence
- Plant Physiology
- Surface Chemistry
- More!

Credit: Danica Lombardozzi/NCAR

The loss of ozone to the surface of the earth.

Traditional models use physically-based resistance frameworks (e.g. Wesely 1989).

$$Loss = -V_d\left[O_3\right]$$

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Dry Deposition Velocity:

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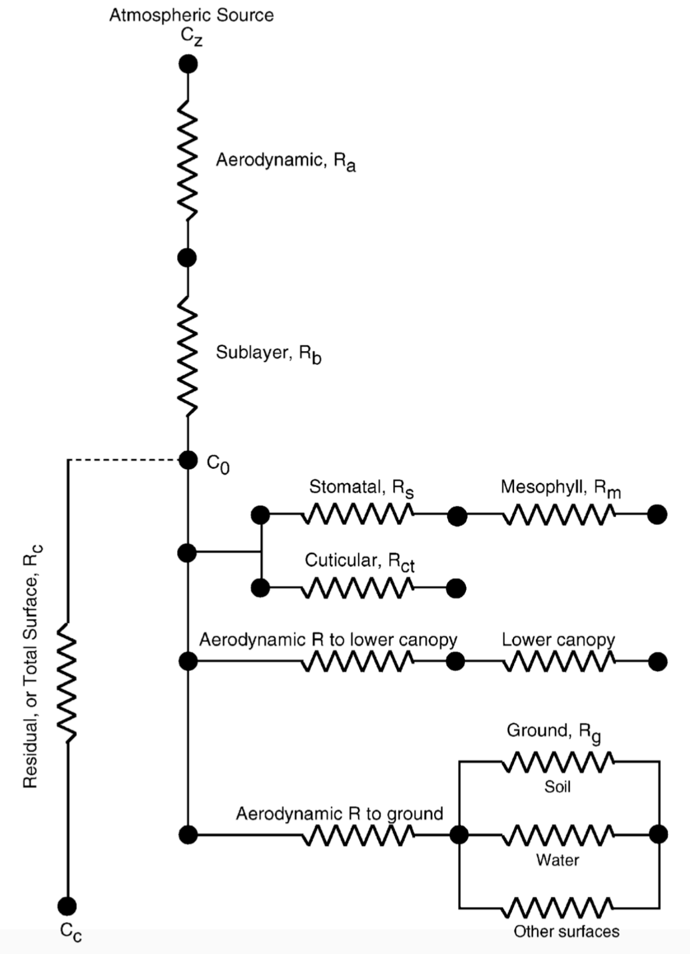

How does model V_d compare to observations globally?

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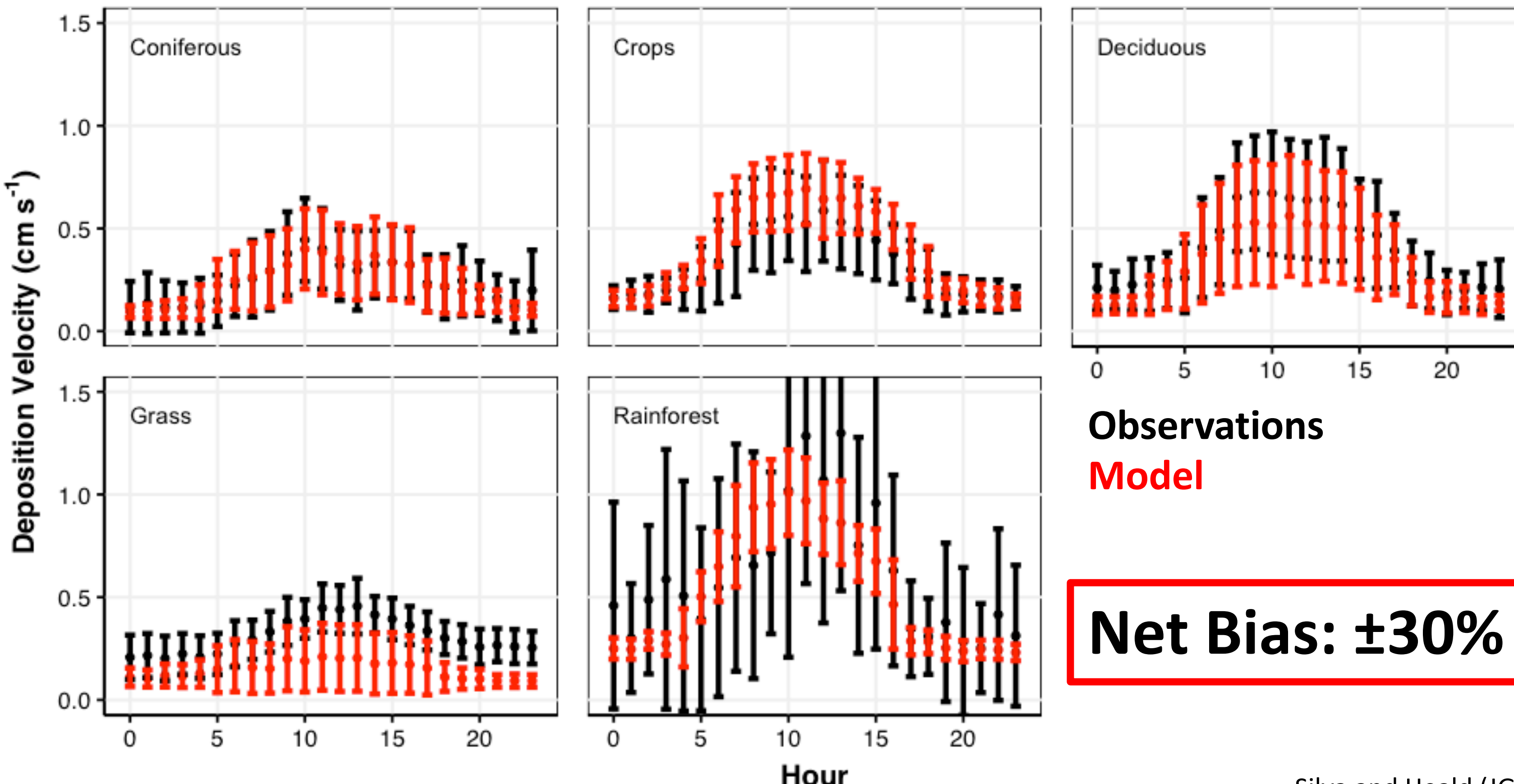
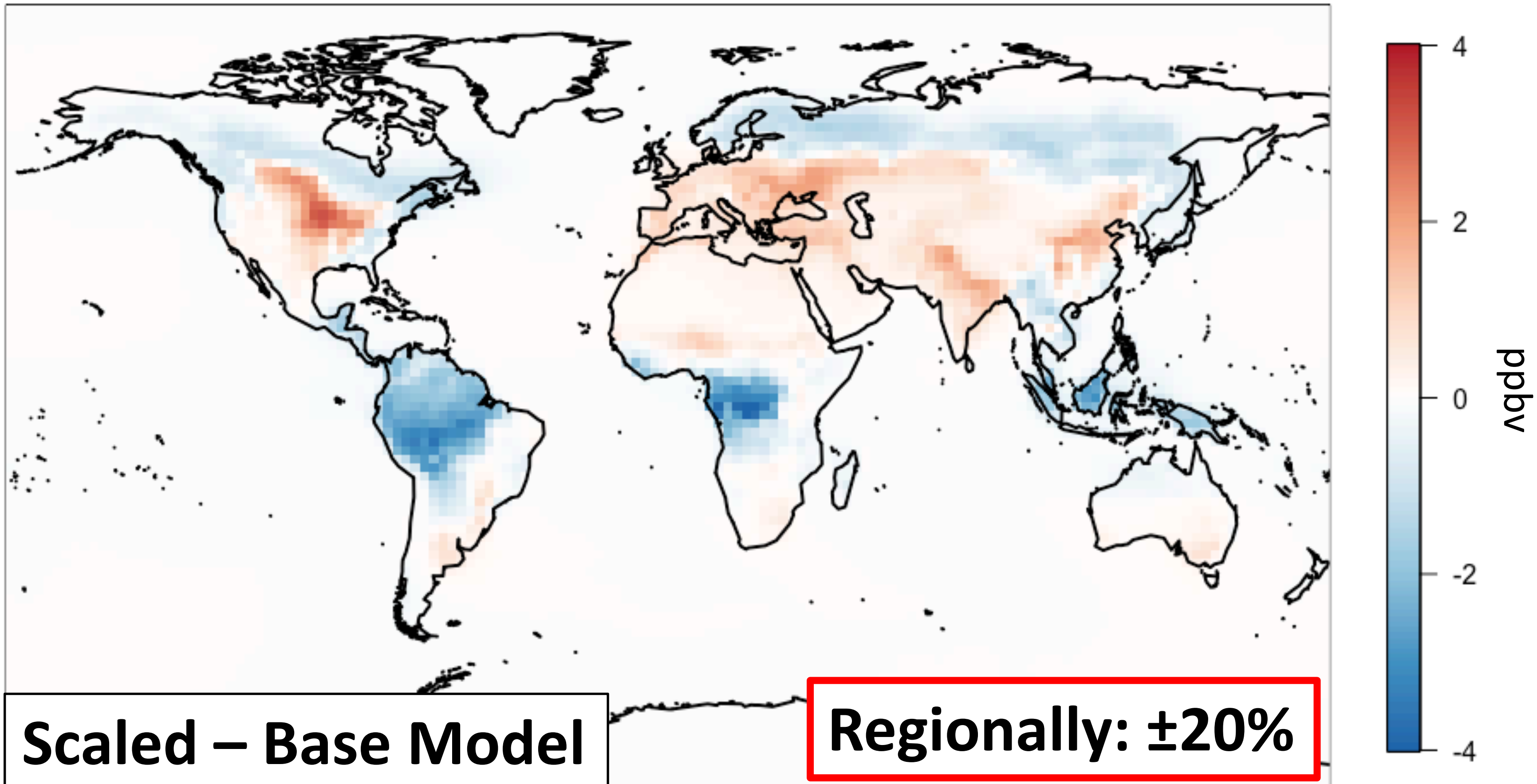


Net Bias: ±30%

Silva and Heald (JGR, 2018)

Impact of V_d biases on ozone is not small!



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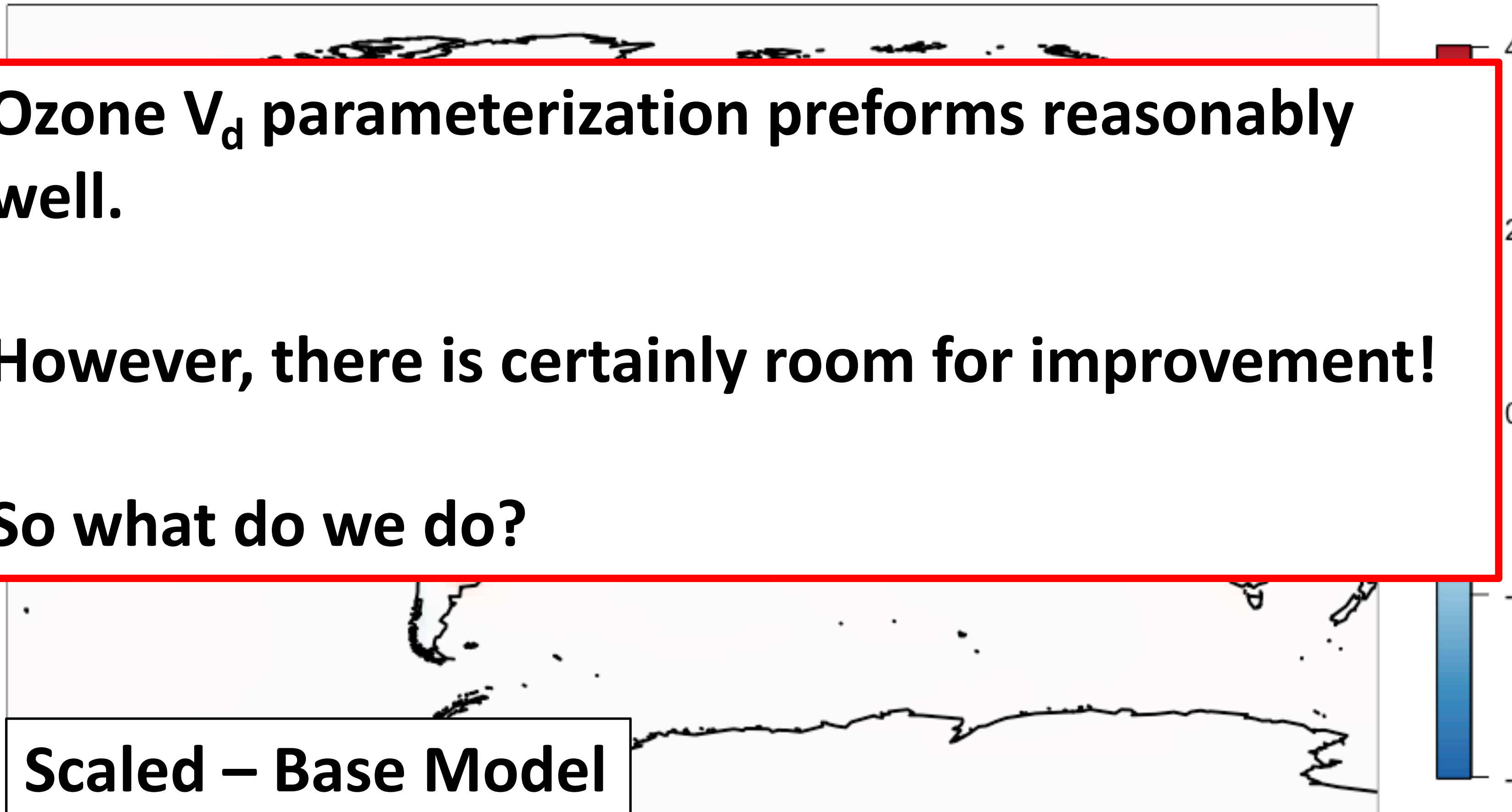

Ozone V_d parameterization preforms reasonably well.

However, there is certainly room for improvement!

So what do we do?

Silva and Heald (JGR, 2018)

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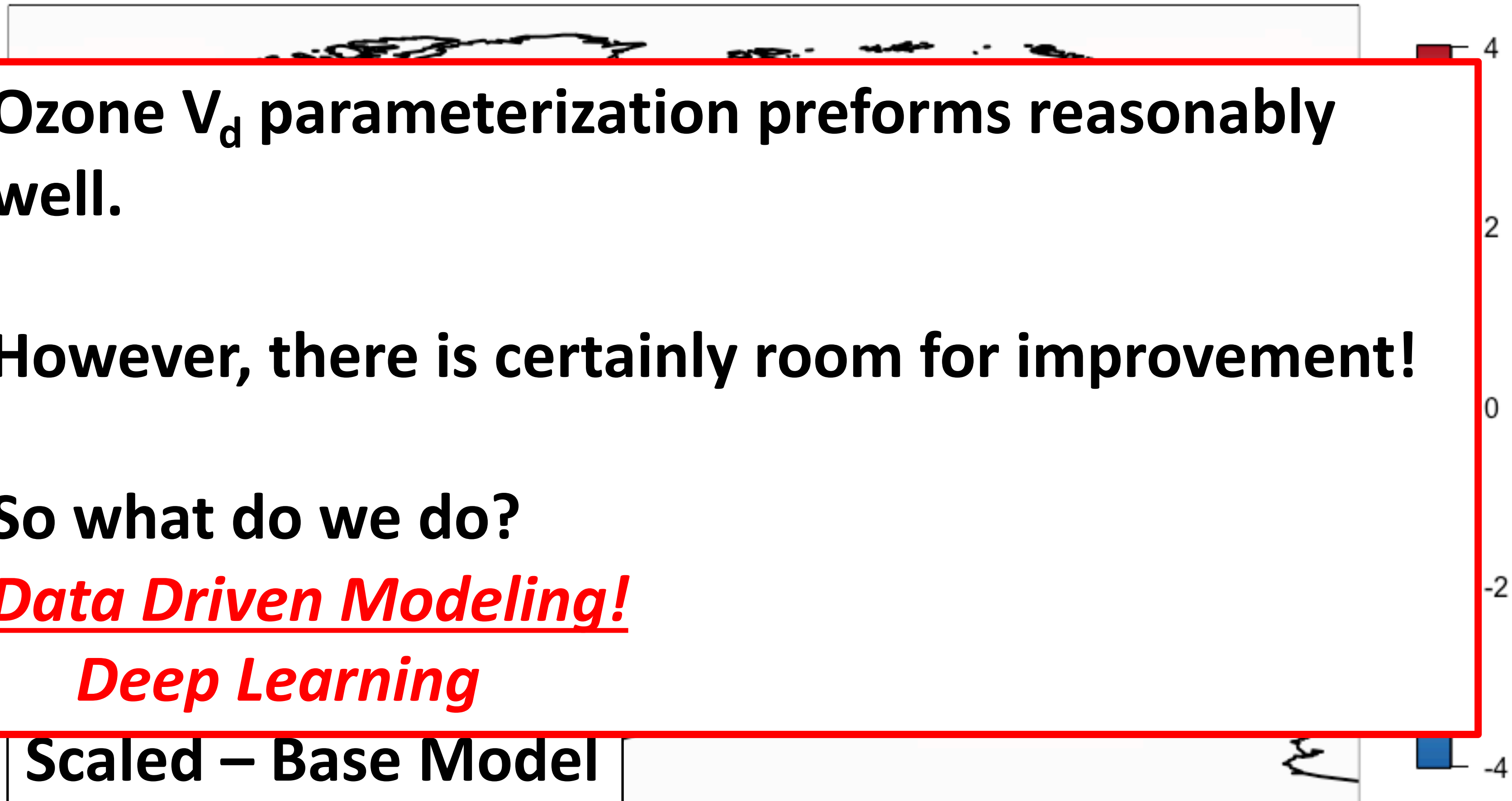

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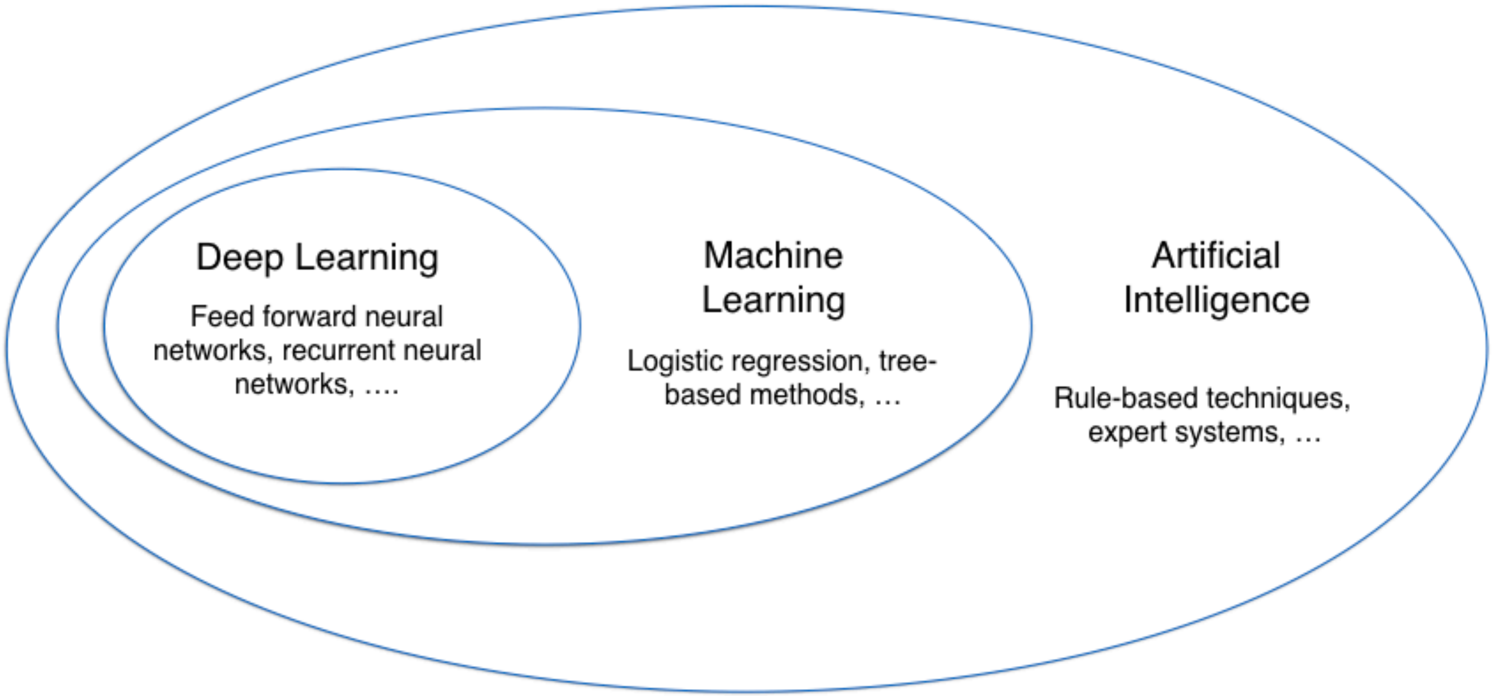
<u>Data Driven Modeling!</u>

Deep Learning

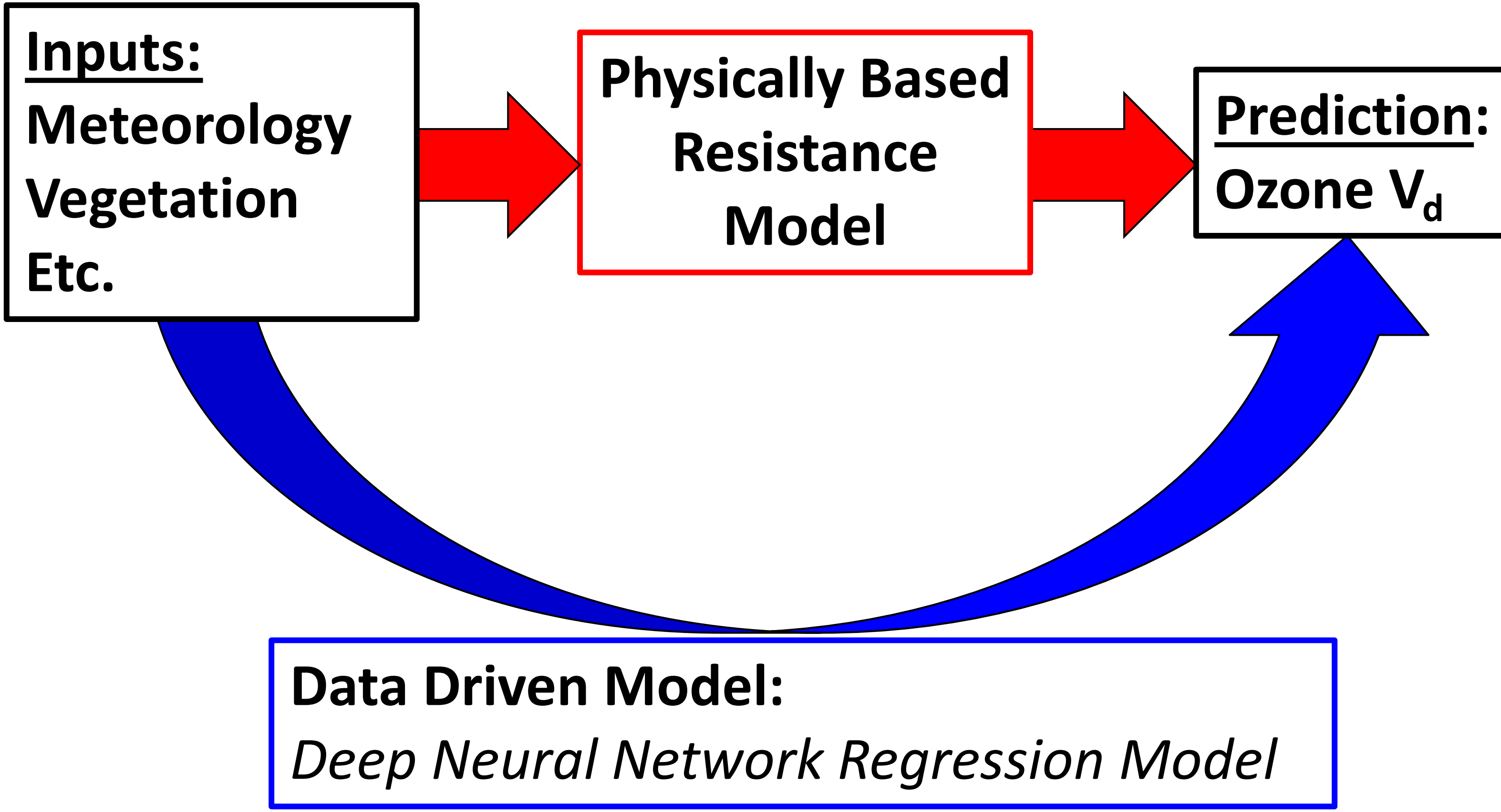
Silva and Heald (JGR, 2018)

What is Deep Learning?



A method of building empirical models from data

Deep Learning Regression Model

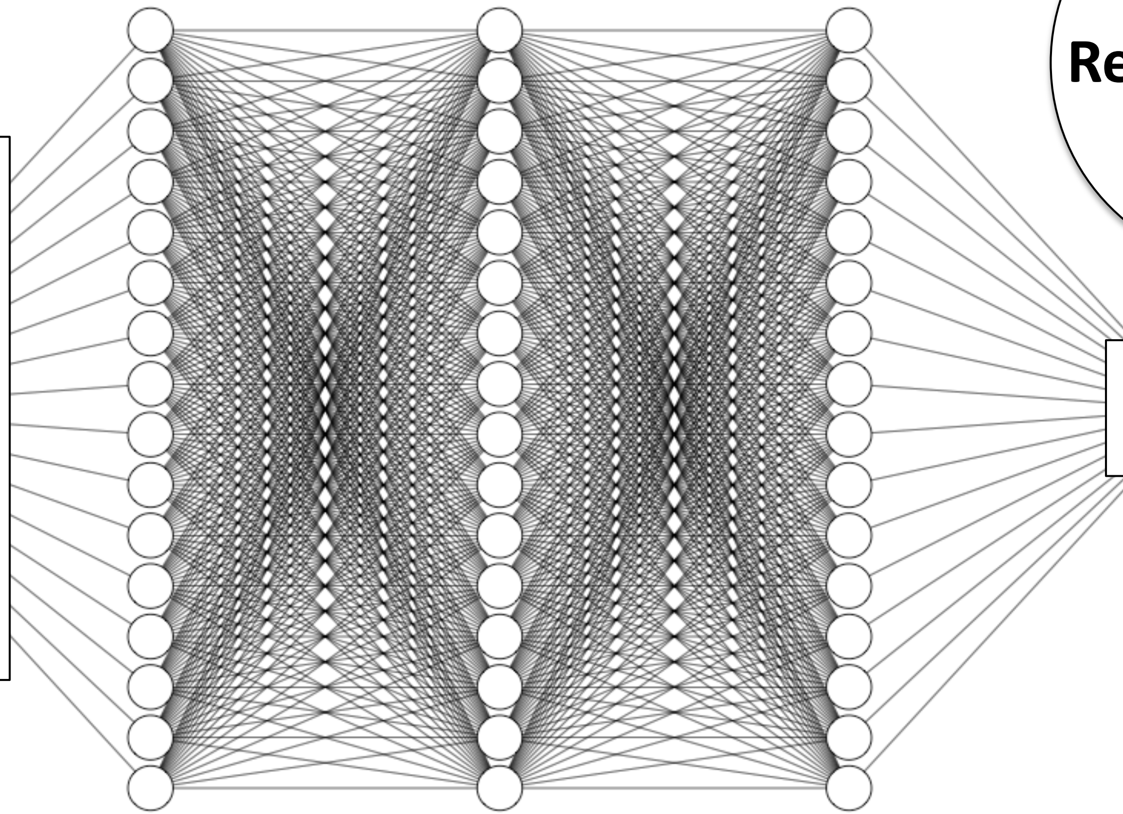


DNN Regression

ReLU(w*x + b)

Input Variables:

- Sensible Heat Flux
- Wind Speed
- Air Temperature
- Relative Humidity
- PAR
- Month
- Hour



Prediction:

- O_3 V_d

A set of linear operations, modulated by a nonlinear term.

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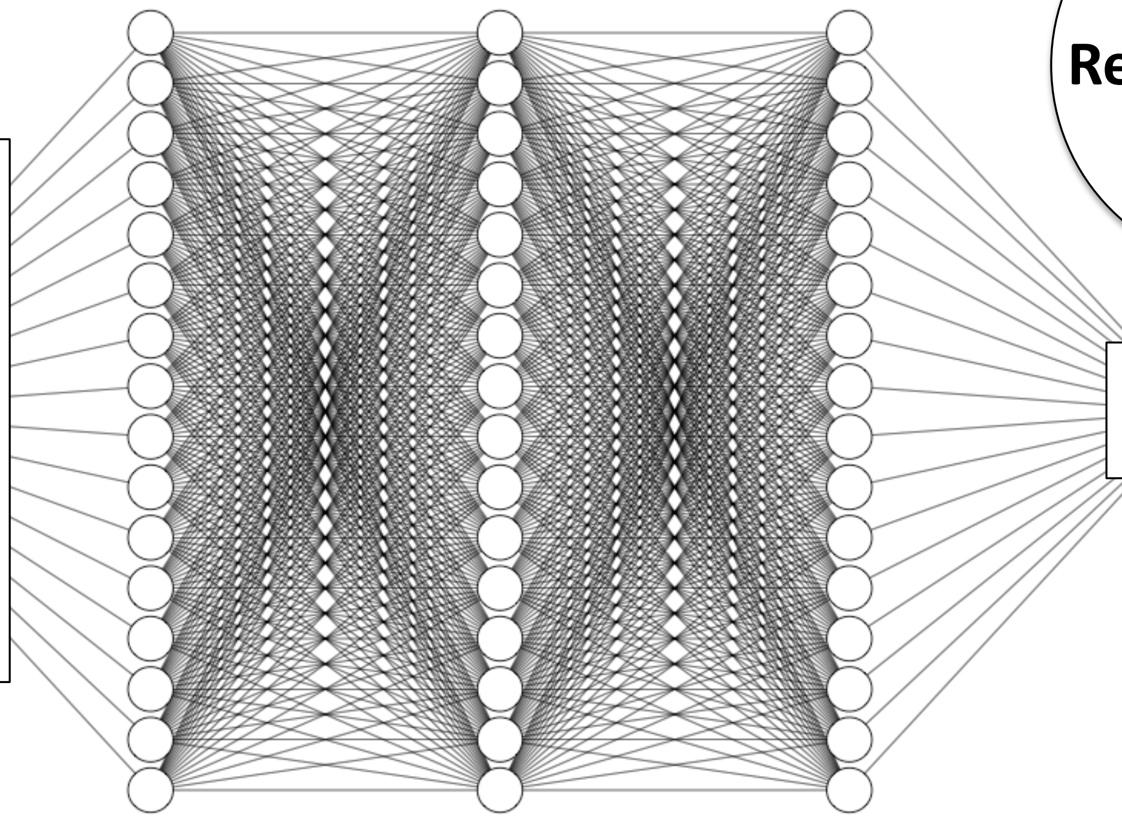

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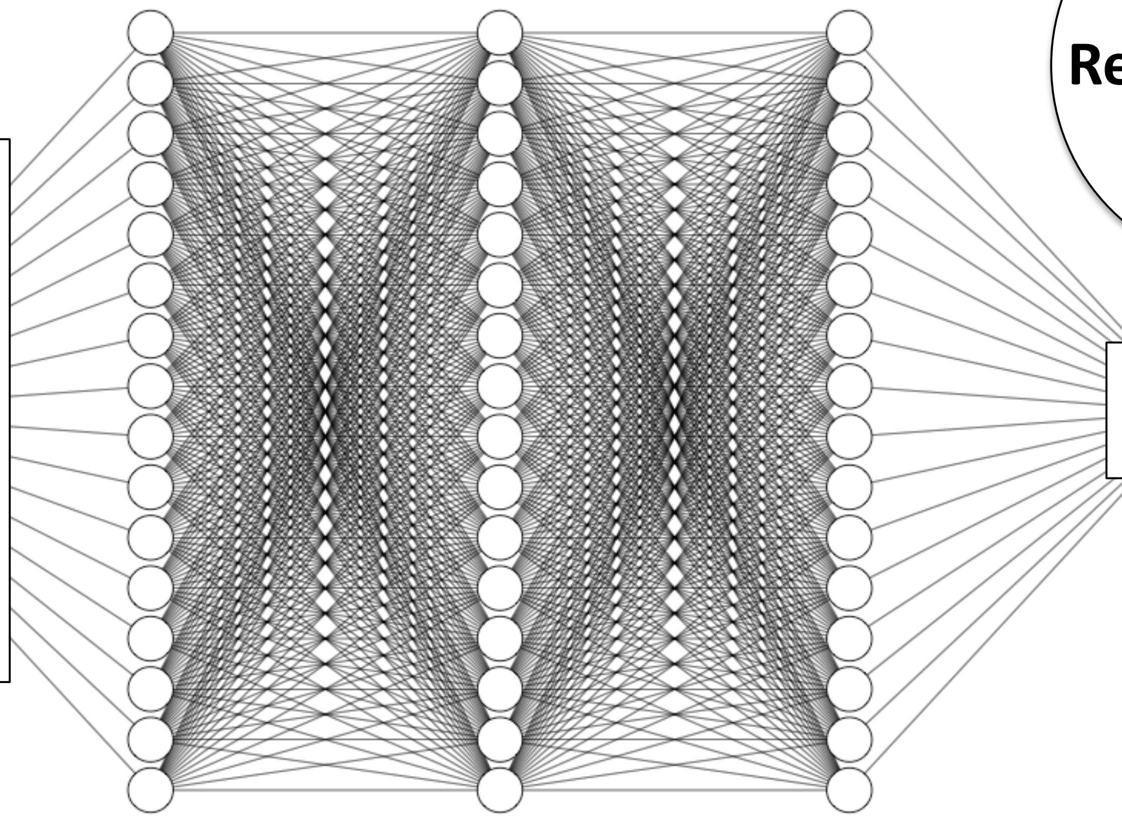

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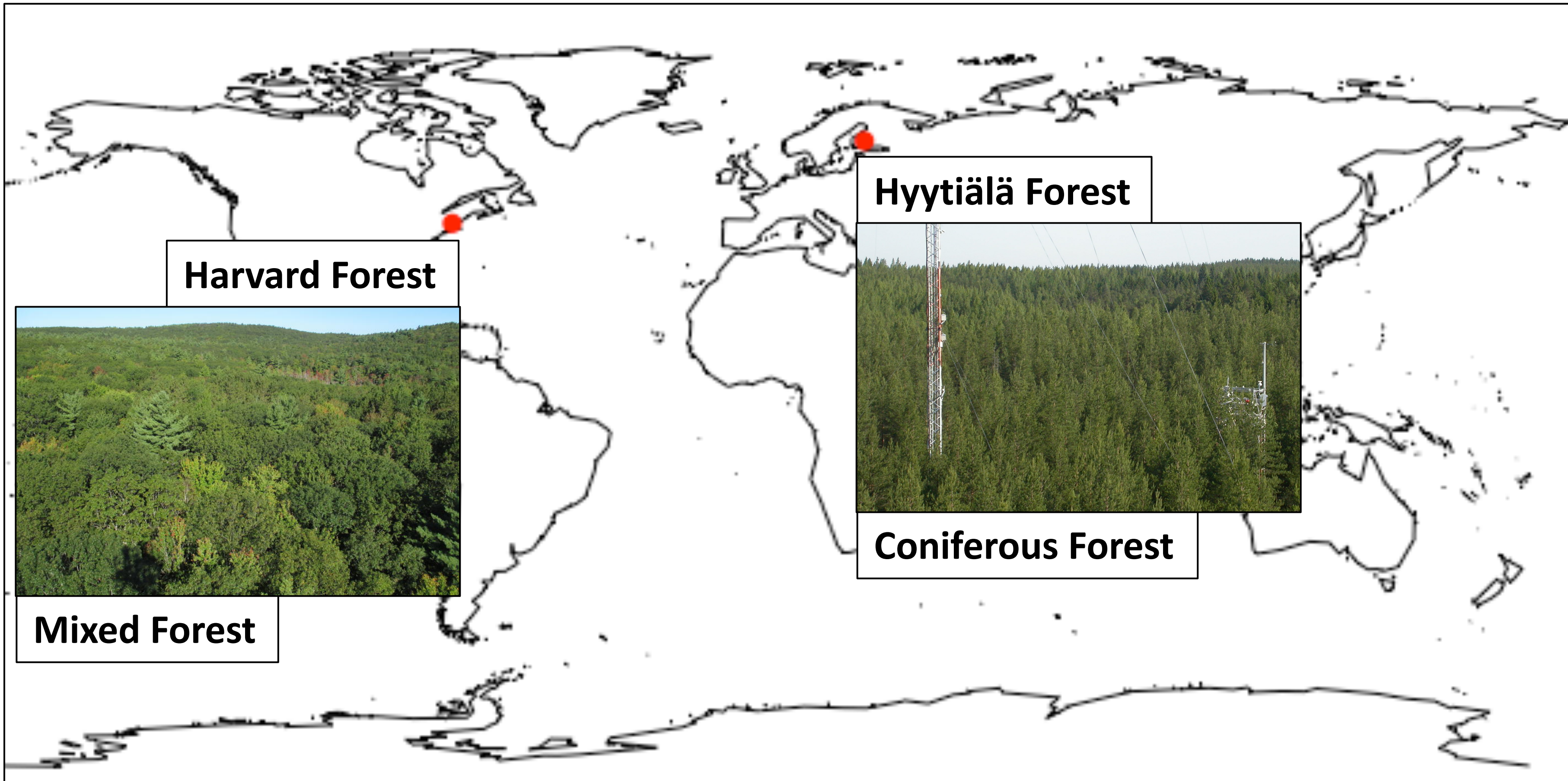
Requirements: Large sets of input data for parameter training

Long Term Observations



Silva et al. (GRL, 2019)

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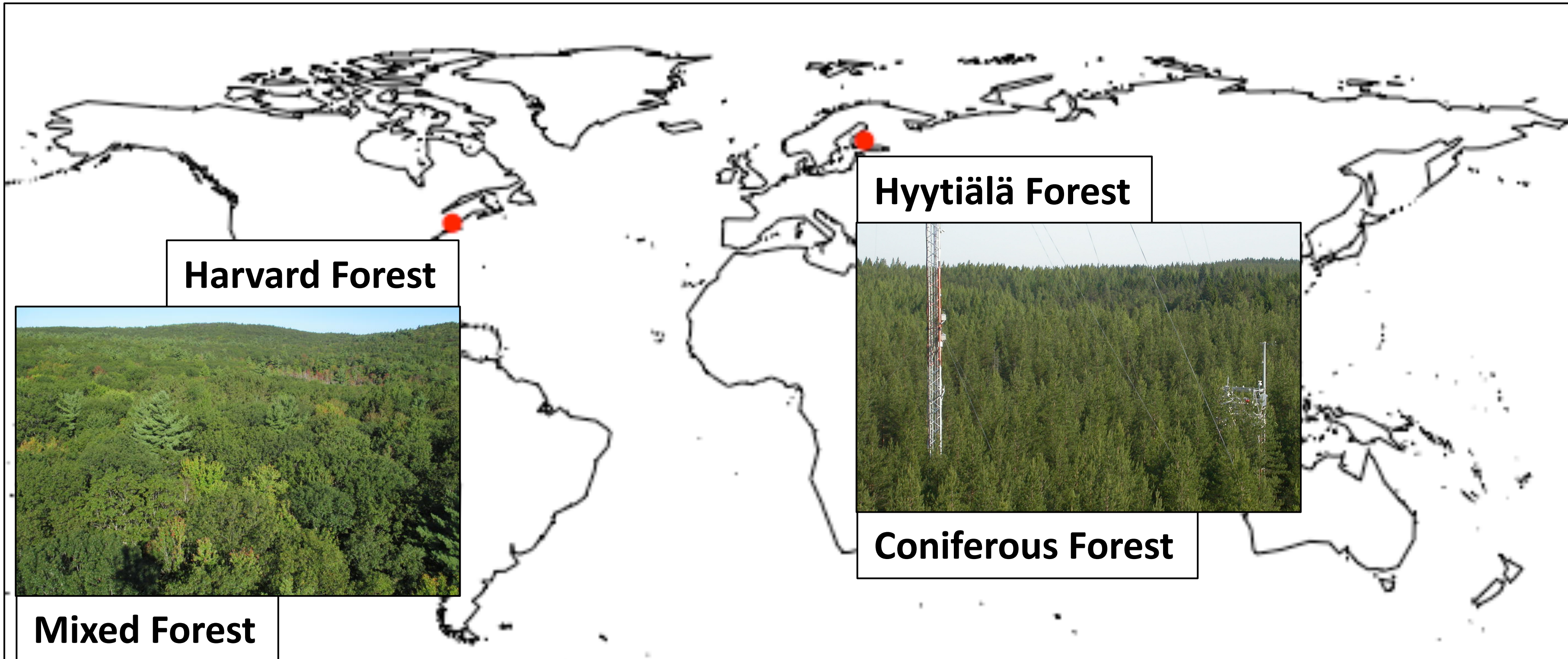
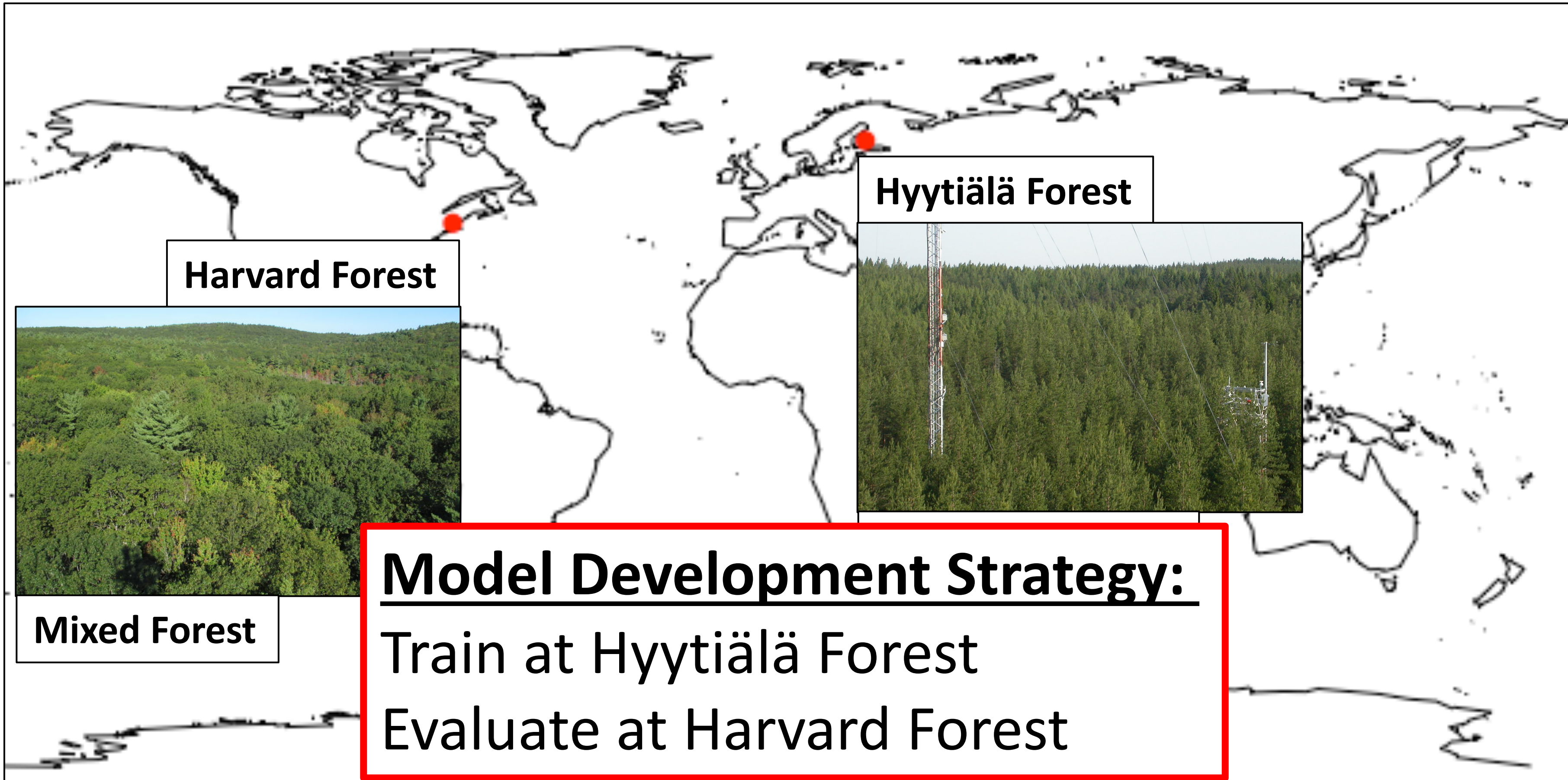


~10 years of V_d observations, with auxiliary measurements

Silva et al. (GRL, 2019)

Long Term Observations



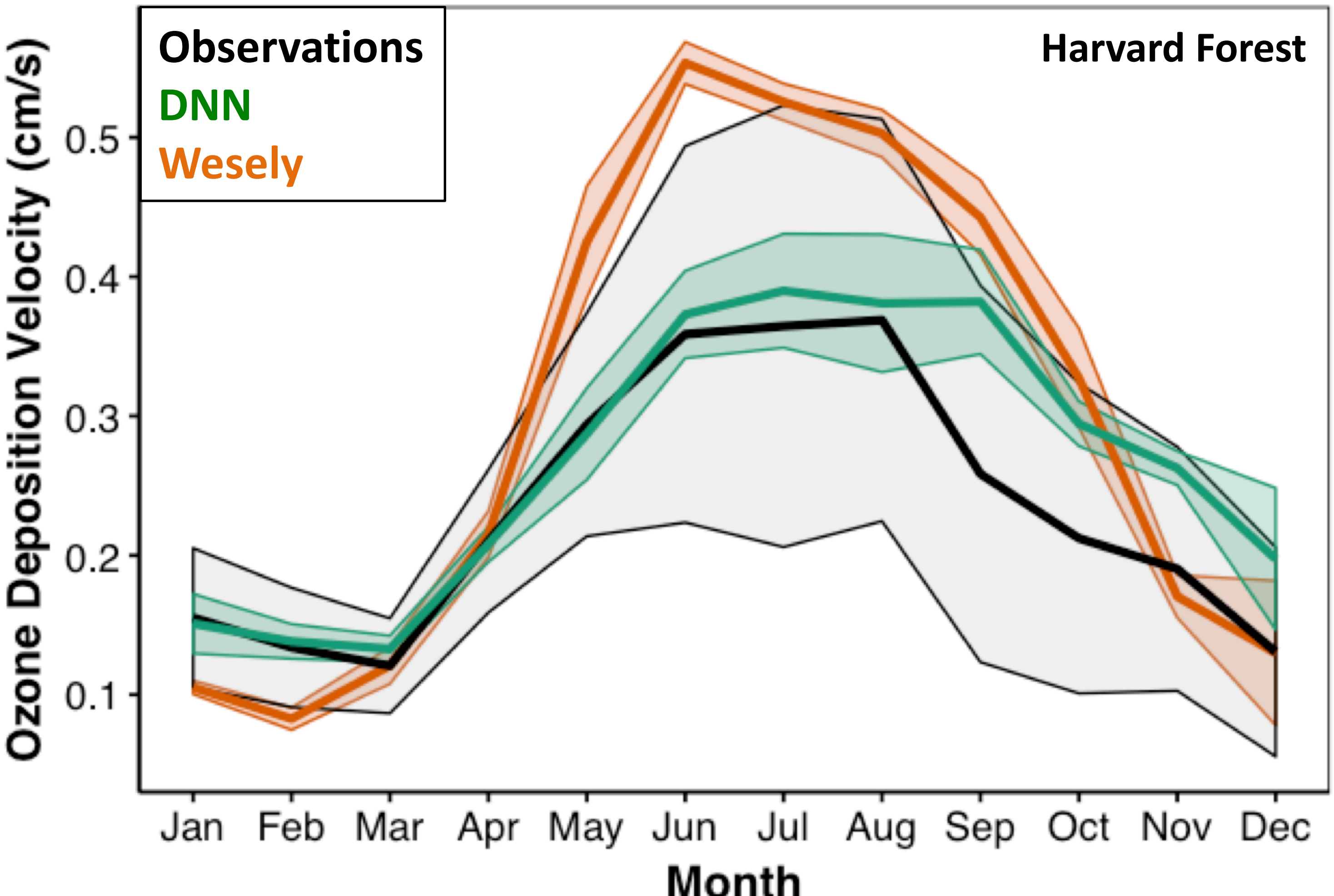
Model Development Strategy:

Train at Hyytiälä Forest

Evaluate at Harvard Forest

Silva et al. (GRL, 2019)

Monthly DNN Performance – Model Driven



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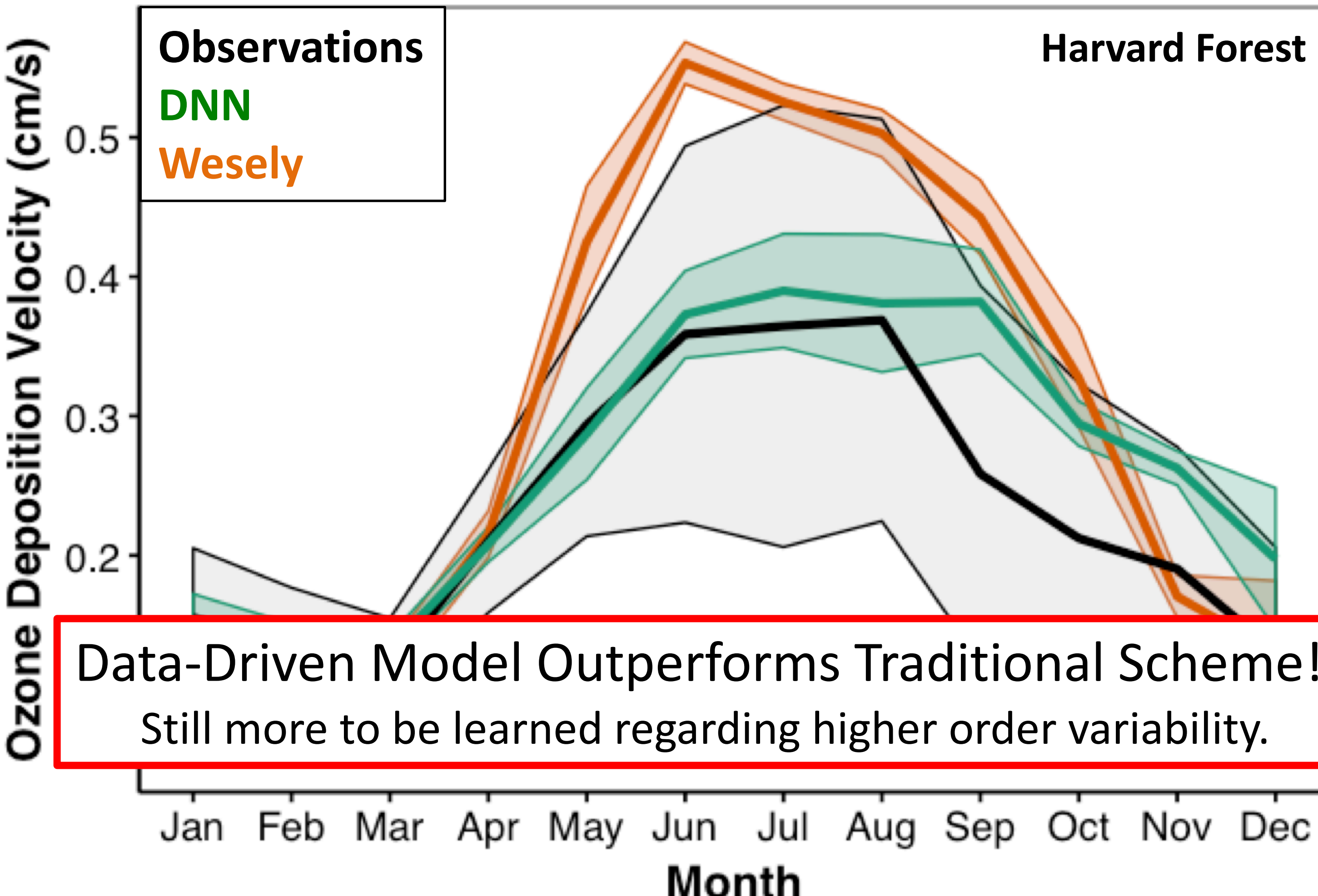
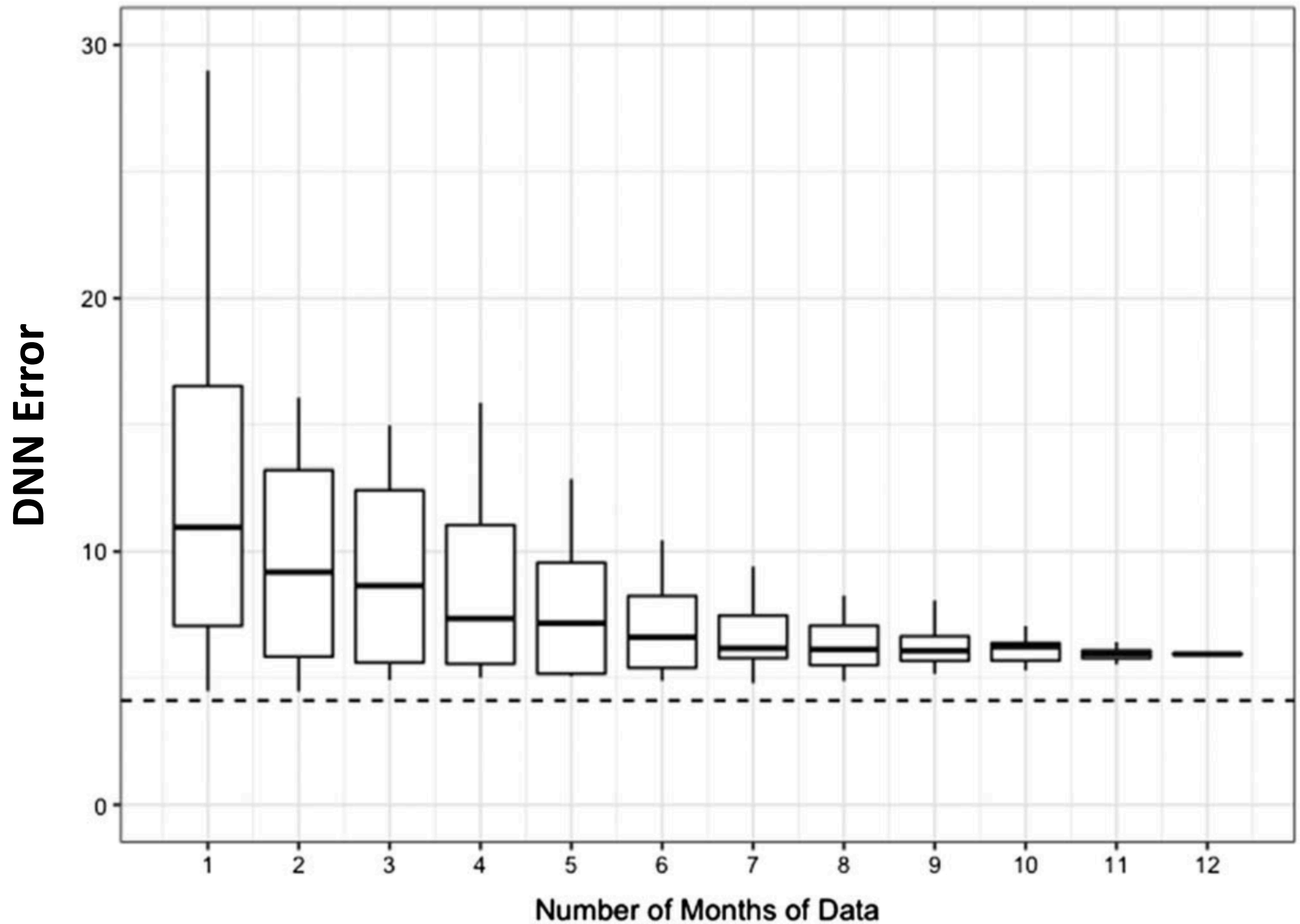


Data-Driven Model Outperforms Traditional Scheme!

Still more to be learned regarding higher order variability.

Silva et al. (GRL, 2019)

With ~6 months of observations, we can get similar accuracy over new vegetation types!



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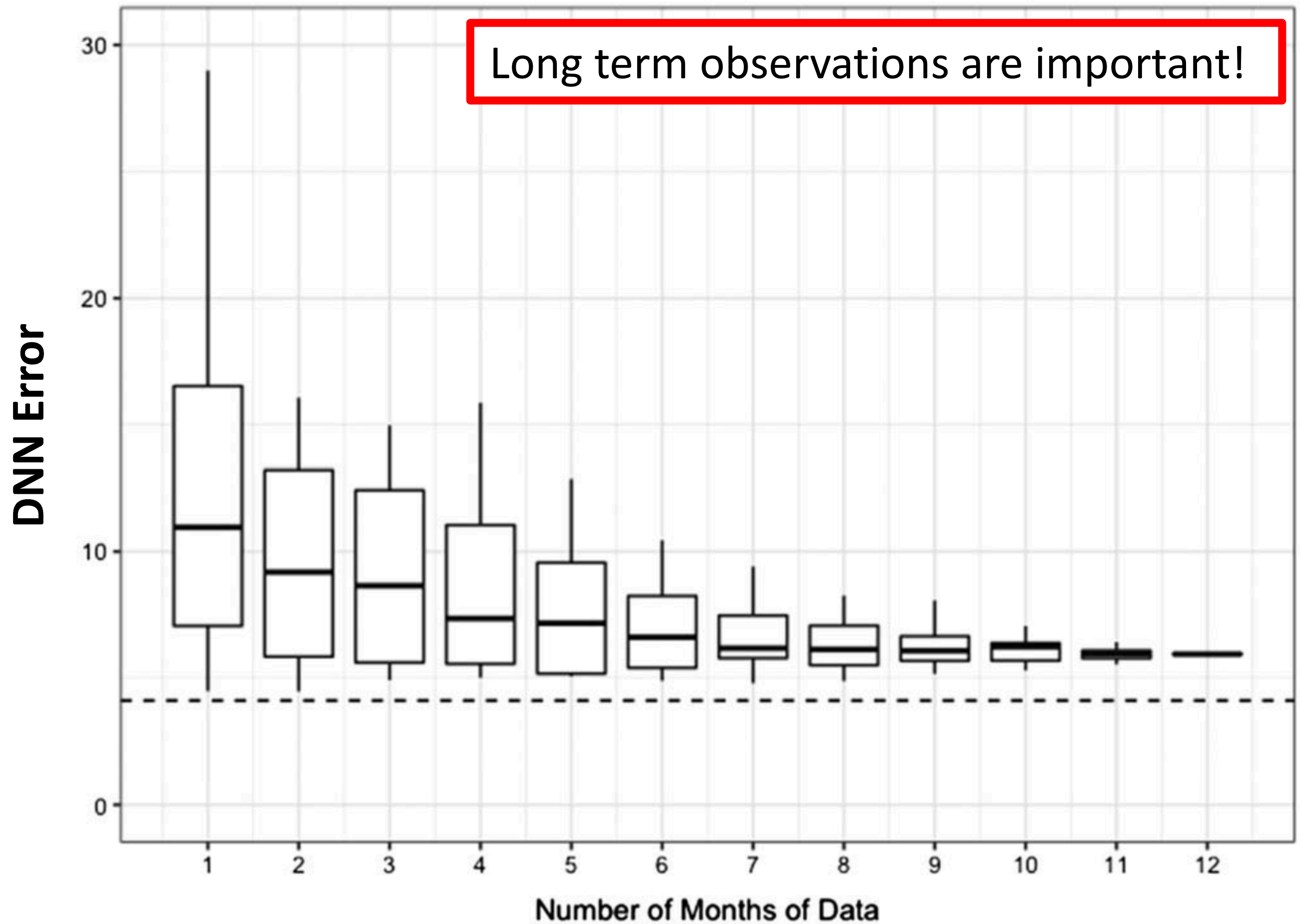

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Why use Deep Learning over any other fancy new machine learning method?

Geophysical Research Letters

Toward Data-Driven Weather and Climate Forecasting: Approximating a Simple General Circulation Model With Deep Learning

S. Scher[1]

PNAS

Deep learning to represent subgrid processes in climate models

Stephan Rasp[a,b,1], Michael S. Pritchard[b], and Pierre Gentine[c,d]

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Deep learning and process understanding for data-driven Earth system science

Markus Reichstein[1,2]*, Gustau Camps-Valls[3], Bjorn Stevens[4], Martin Jung[1], Joachim Denzler[2,5], Nuno Carvalhais[1,6] & Prabhat[7]

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Model	R	MSE	Time
DNN	$\boxed{0.35}$	$\boxed{0.20}$	$\boxed{1.00}$
Linear	0.22	0.52	< 0.01
Random forest	$\boxed{0.36}$	$\boxed{0.19}$	$\boxed{1.27}$
Ridge	0.33	0.43	0.07

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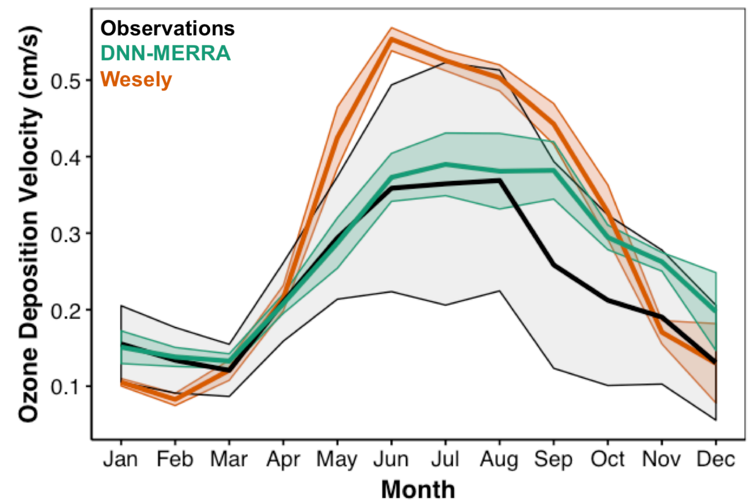
Conclusions

A.I. methods are powerful tools for modeling biosphere-atmosphere exchange

- Can be more accurate than traditional physically-based models
- No loss in computational speed

Costs

- Physical process-based insight
  - But not always!



Long term observations are extremely valuable!

Acknowledgements

C. L. Heald, S. Ravela, I. Mammarella , and J. W. Munger

Silva, S. J., Heald, C. L., Ravela, S., Mammarella, I., & Munger, J. W. (2019). A Deep Learning Parameterization for Ozone Dry Deposition Velocities. *Geophysical Research Letters*

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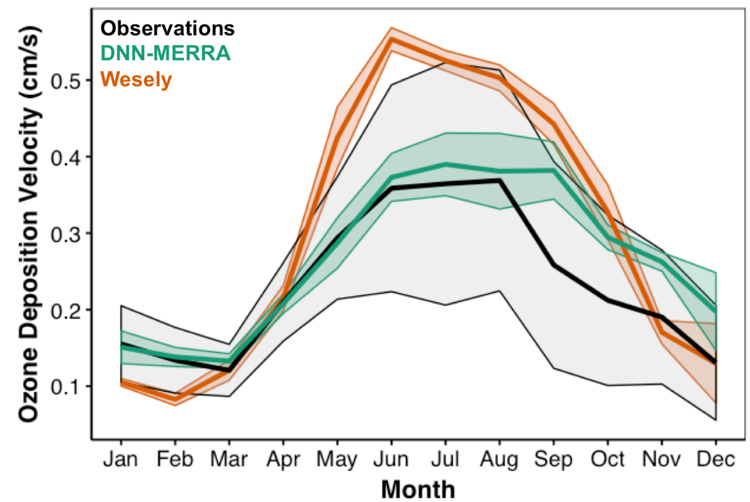

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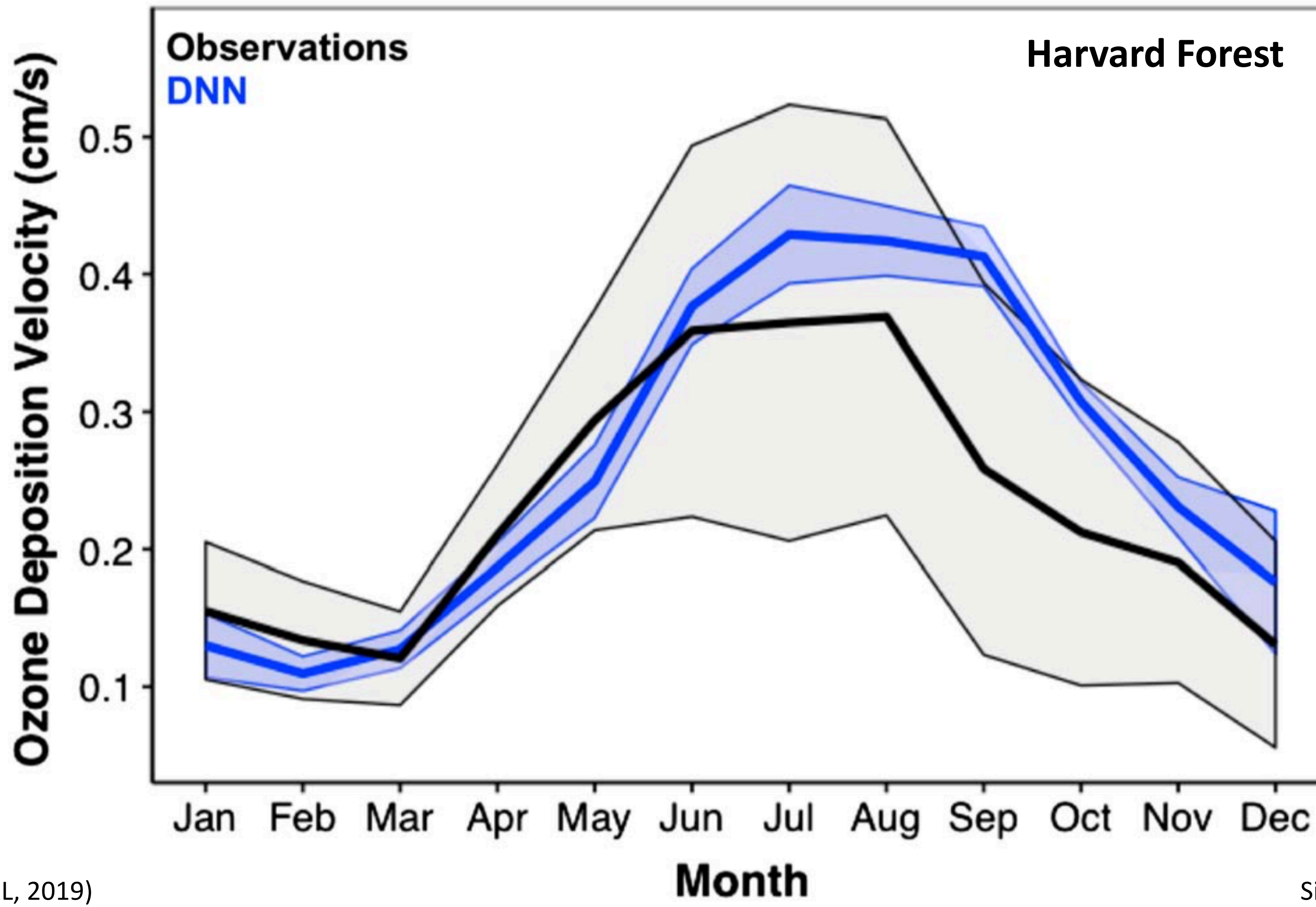
Extra Slides

Monthly DNN Performance – Observation Driven



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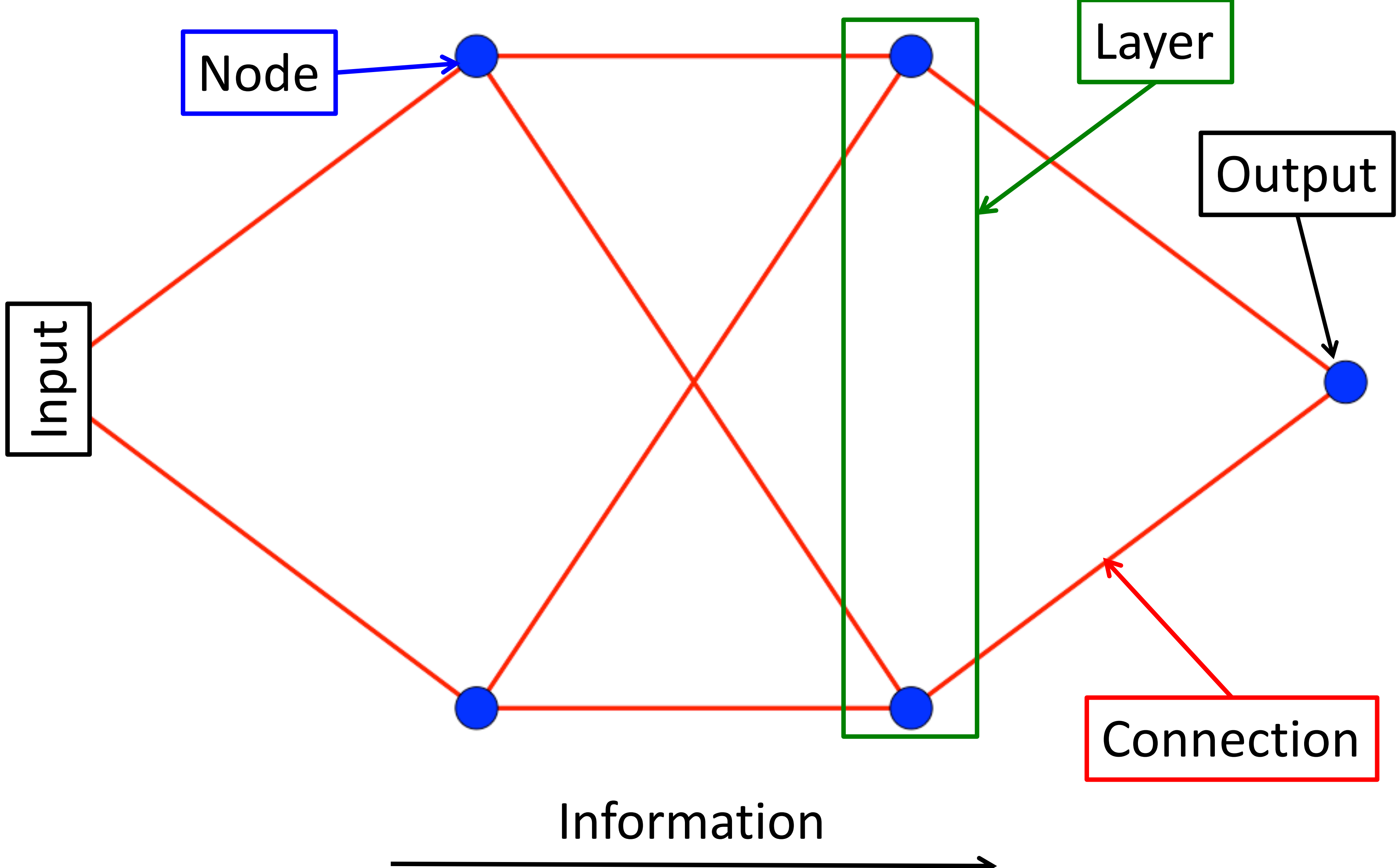
Node
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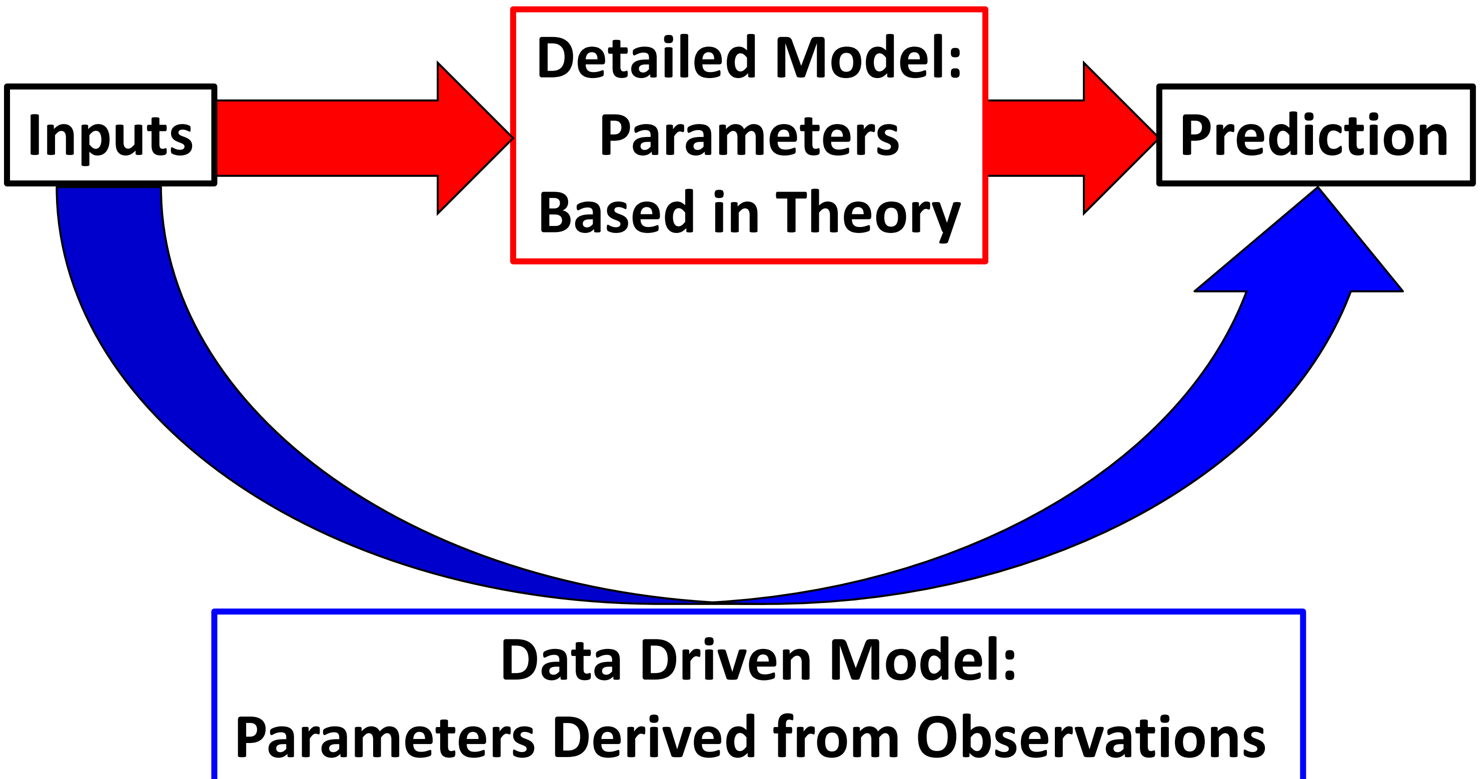
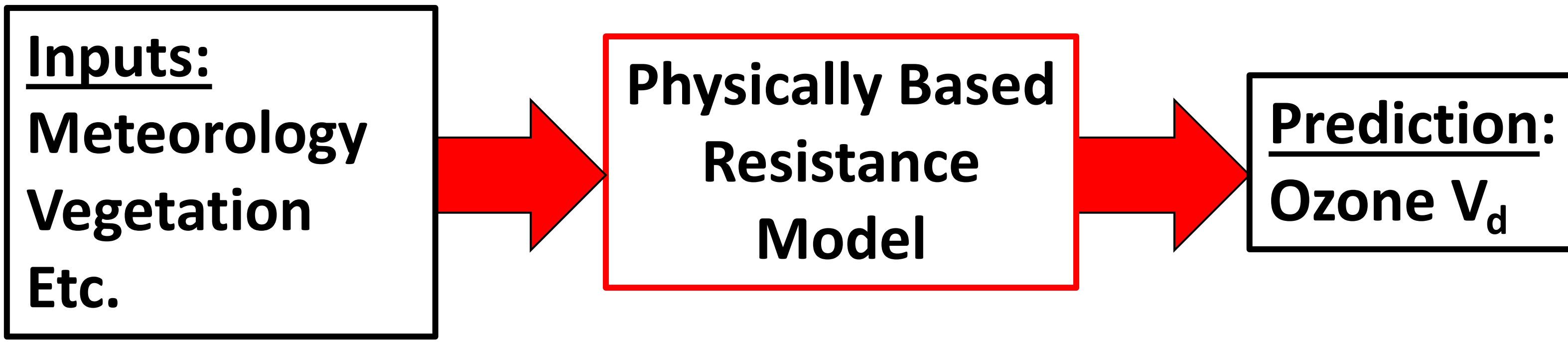
Theory Driven Modeling

Data Driven Modeling



Traditional V_d Resistance Model



Deep Learning Regression Model