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Bridging the Microwave Data Gap: Using Bayesian Deep Learning to "See" the Unseen

NeurIPS 2022 Workshop
Tackling Climate Change with Machine Learning

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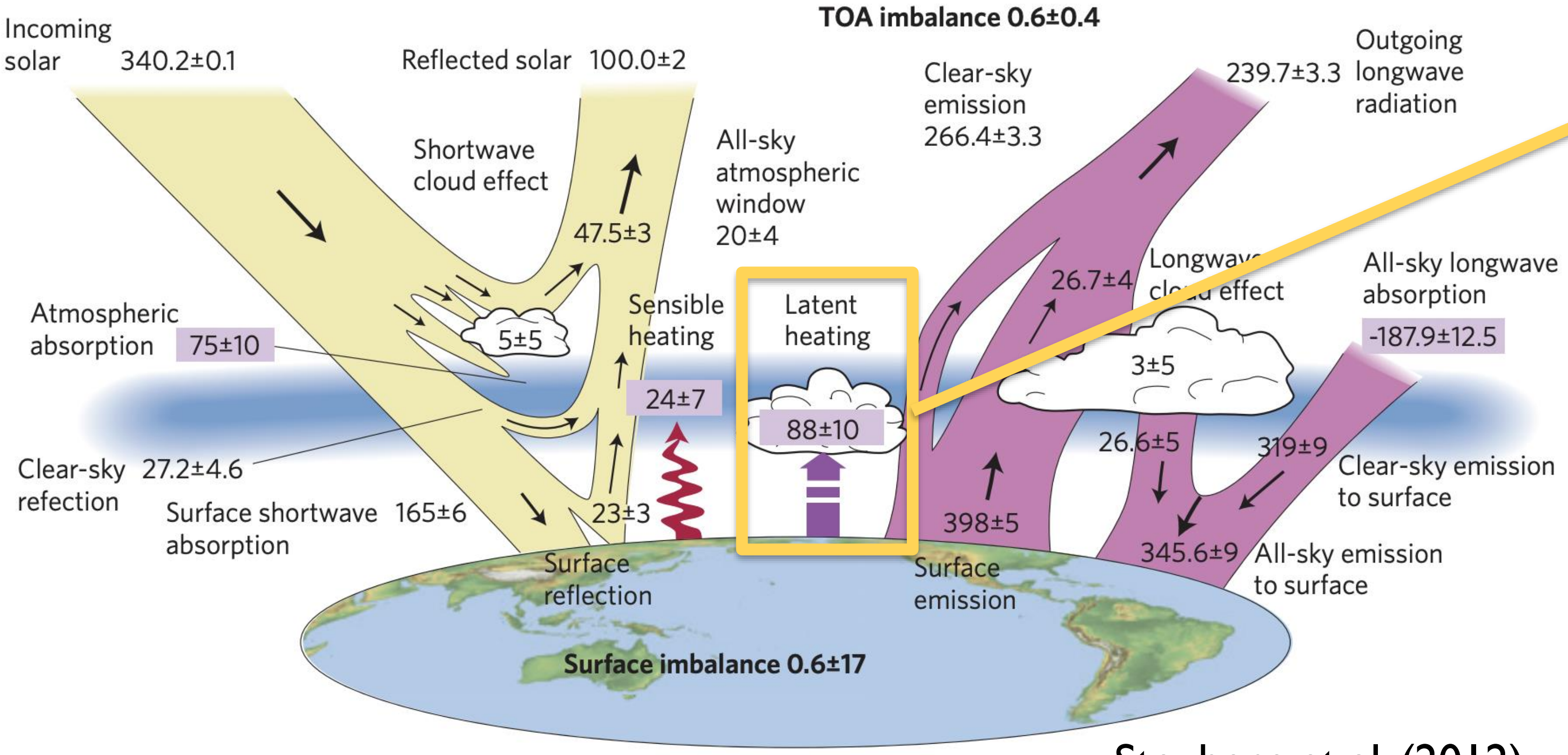
On Climate Scales, Energy In ≈ Energy Out

Energy transfers within the atmosphere:

Solar Energy In

Infrared Energy Out

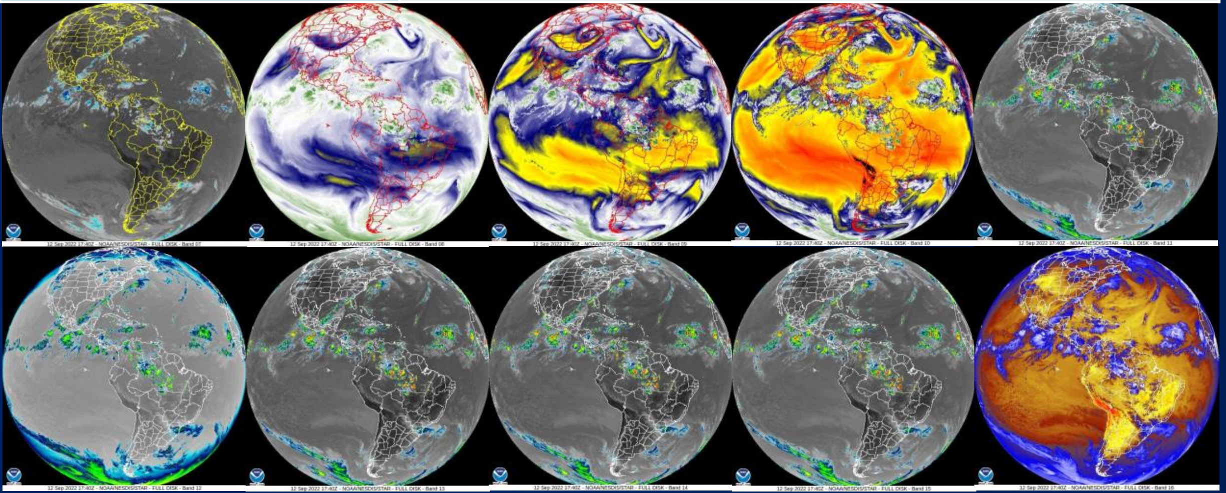


Stephens et al. (2012)

There is large uncertainty on how much energy is transferred within clouds in the global annual mean energy budget because it's difficult to remotely sense inside clouds around the globe without large data gaps

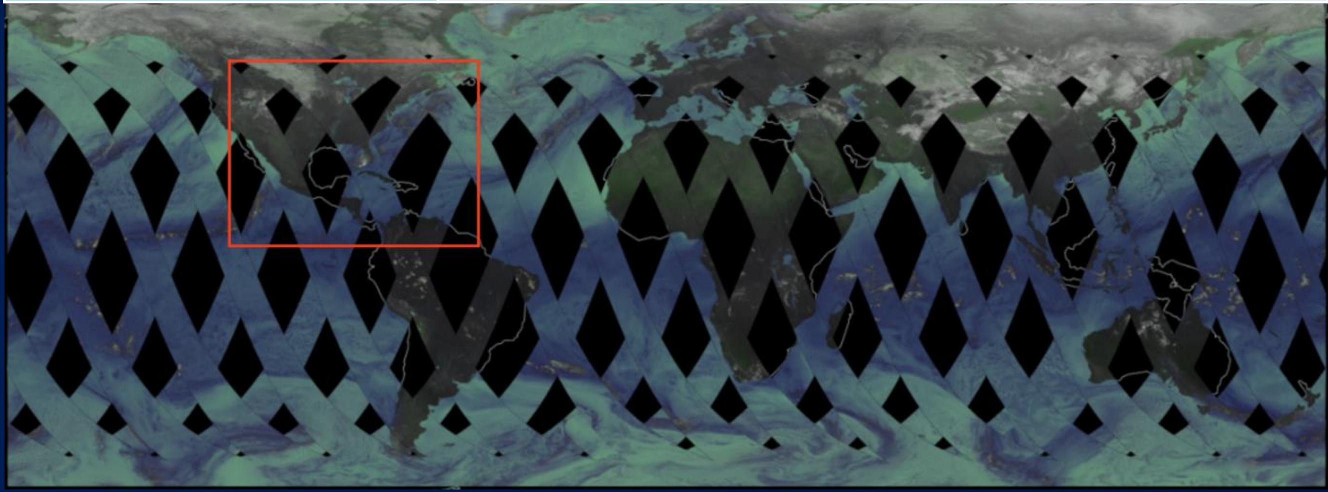
Features

Data	GOES-16 ABI Bands 7-16 (Near IR and IR) TBs
Spatial Resolution	1 km^2 at Nadir
Temporal Resolution	Full Disk picture every 10-15 min



Labels

Data	GMI TBs for each channel
Spatial Resolution	Channels range from 32 km^2 to 624 km^2 at Nadir
Temporal Resolution	Swath passes Equator every 45 min on avg.



Scientific Objectives and Methods

Use Bayesian Deep Learning to create a synthetic product of microwave data and variances with the spatial and temporal resolution of IR data

1. Collocate IR and microwave pixels that are sampled at the same place and time
2. Train a 56-layer Bayesian ResNet with convolutional Flipout Layers and the ELBO loss function
3. Output both Microwave TBs and variance at IR resolutions
4. Decompose resulting variance into epistemic and aleatoric components

Impact: Atmospheric scientists can use the resulting product to learn more about our atmosphere and improve many models and forecasts

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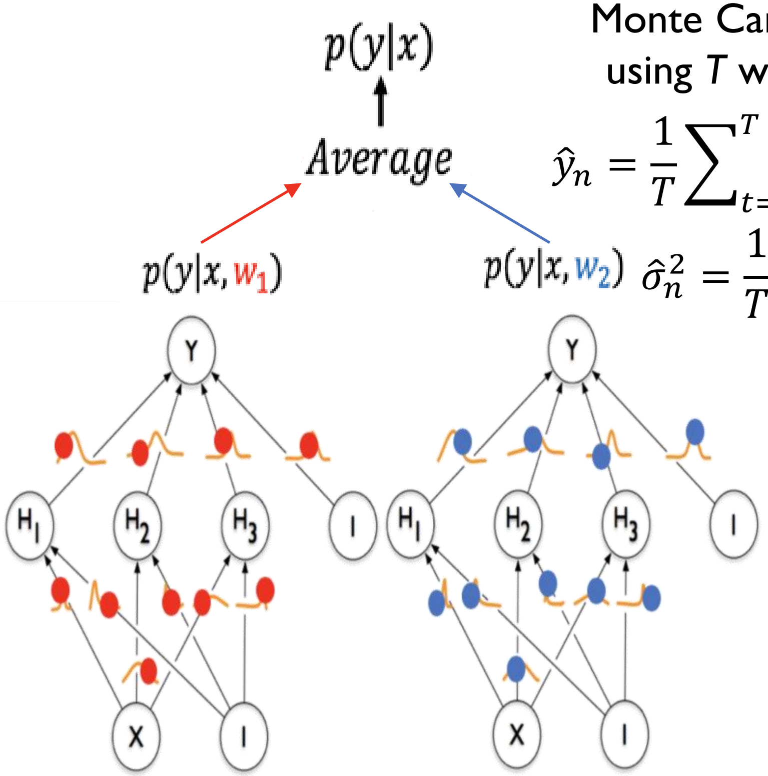
Why Bayesian Deep Learning?



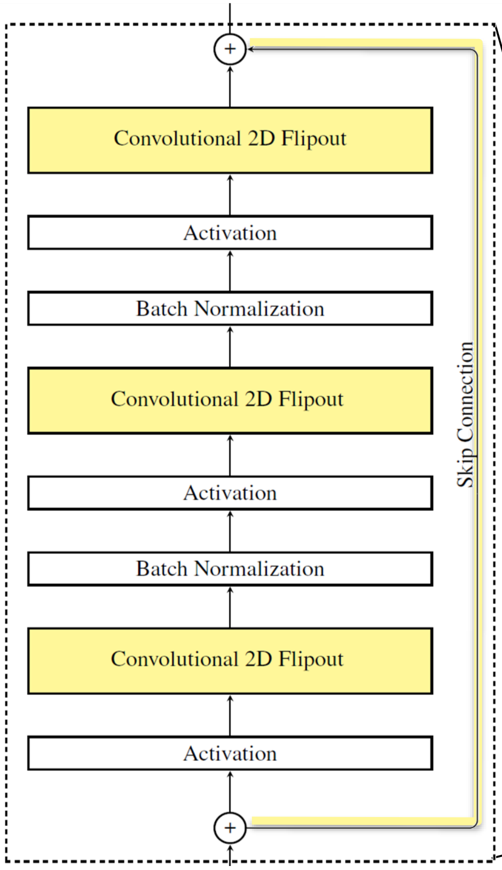
Monte Carlo Integration using T weight samples

$$\hat{y}_n = \frac{1}{T}\sum_{t=1}^{T} p(\hat{y}_t \mid x_n, w_t)$$

$$\hat{\sigma}_n^2 = \frac{1}{T}\sum_{t=1}^{T} (\hat{y}_n - \hat{y}_t)$$

Adapted from: McClure, P., Rho, N., Lee, J.A., Kaczmarzyk, J.R., Zheng, C.Y., Ghosh, S.S., Nielson, D.M., Thomas, A.G., Bandettini, P. and Pereira, F., 2019. Knowing What You Know in Brain Segmentation Using Bayesian Deep Neural Networks. *Frontiers in Neuroinformatics*, *13*, p.67.

Bayesian ResNet Block



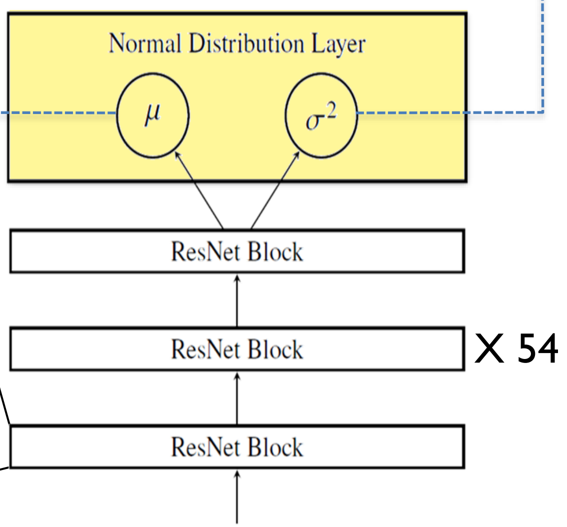
Monte Carlo Integration using mixture of Normal Distributions

$$\hat{y}_n = \frac{1}{T}\sum_{t=1}^{T} \mathcal{N}(\mu_t(x_n,\mathbf{w}_t),\sigma_t^2(x_n,\mathbf{w}_t)) = (\hat{\mu}_n,\hat{\sigma}_n^2)$$

$$\hat{\mu}_n = \frac{1}{T}\sum_{t=1}^{T} \hat{\mu}_t(x_n,\mathbf{w}_t)$$

$$\hat{\sigma}_n^2 = \frac{1}{T}\sum_{t=1}^{T} \underbrace{\hat{\mu}_t^2(x_n,\mathbf{w}_t) - \hat{\mu}_n^2}_{\text{Epistemic Uncertainty}} + \underbrace{\hat{\sigma}_t^2(x_n,\mathbf{w}_t)}_{\text{Aleatoric Uncertainty}}$$

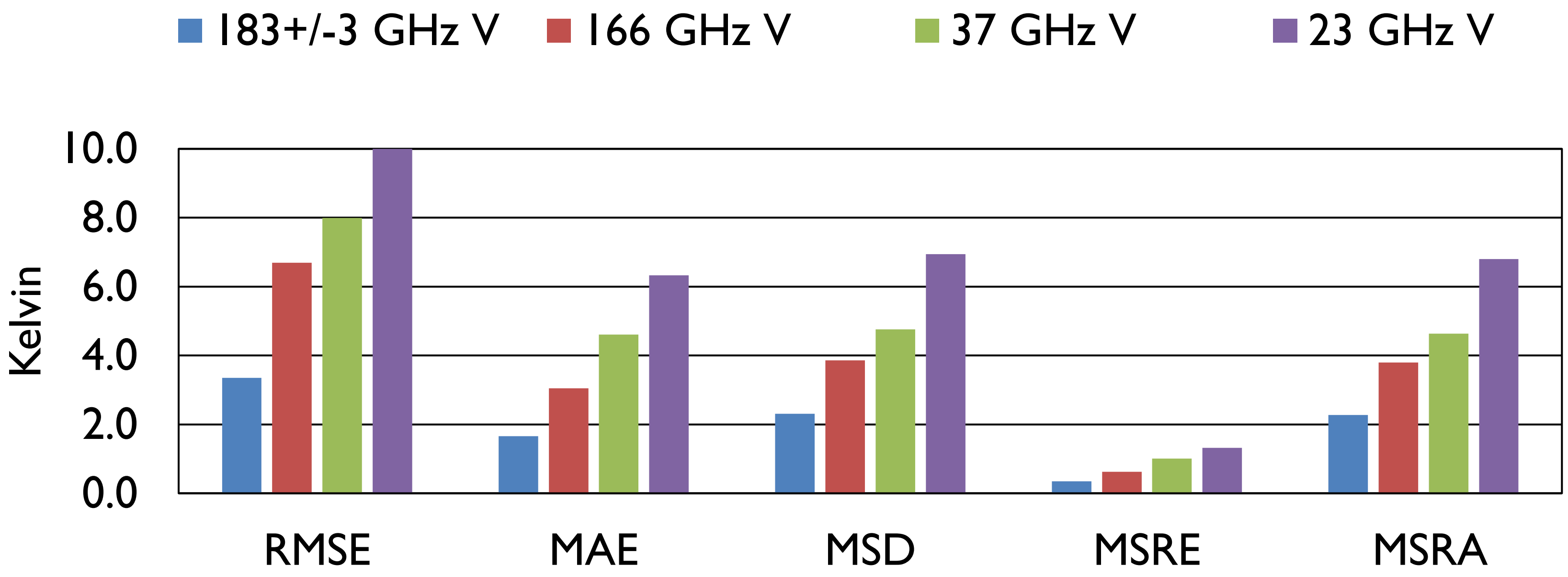
Bayesian ResNet with Normal Distribution Output



Results

Mean Absolute Percentage Error

183+/-3 GHz V	166 GHz V	37 GHz V	23 GHz V
0.7%	1.2%	2.1%	2.9%



RMSE = Root Mean Squared Error
MAE = Mean Absolute Error

MSD = Mean Standard Deviation
MSRE = Mean Square Root Epistemic
MSRA = Mean Square Root Aleatoric

- Higher frequency MW Tb easier to predict
- Relative level of uncertainty matches level of error
- Aleatoric component is the main source of uncertainty
- Epistemic uncertainty for lower frequencies may be reduced with more data to reduce error

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Scientific Impact of Product

Climate Scientists

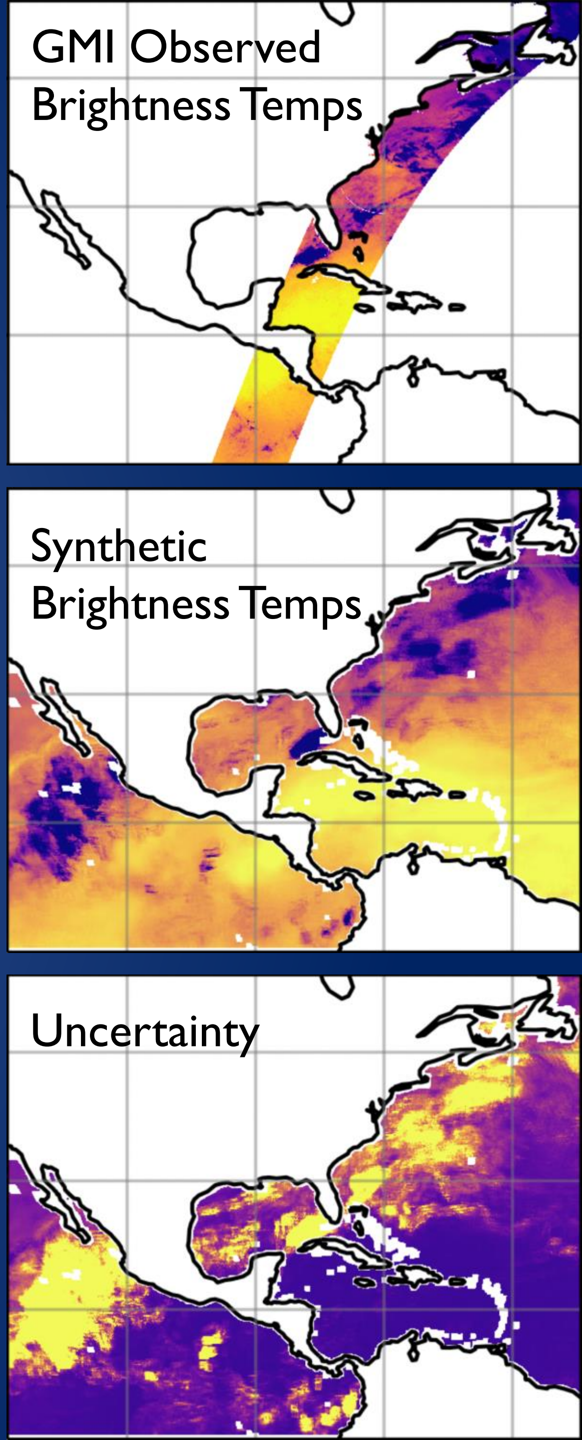
- Could reduce uncertainty in energy budget by using product to create less uncertain cloud and precipitation climatologies

Real-Time Forecasters

- Could finally track evolution of oceanic deep convection in near-real-time
  - E.g. Hurricanes

Data Assimilation

- Could assimilate more microwave data into weather models and potentially increase forecast skill



Questions?

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