Race to the Bottom Presentation

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Intoduction/Overview

Water vapor (WV) is one of the most influential gases in our atmosphere.

1. Arguably the most influential greenhouse gas (GHG) and is estimated to account for 50% of the total greenhouse effect (Trenberth, 2022).
2. Transport of WV in the atmosphere is an essential part of the weather we see everyday.

Plenty of instrumentation is used to measure **precipitable water vapor** (PWV) [e.g. Microwave Radiometer (MWR)]. However, not all the data retrieved is “good”.

Project Scope: A model that leverages concurrent **microwave and solar radiometry** to **calibrate the radiometry vs the microwave** and then **extend the radiometric retrievals** to the low end where microwave is signal challenged.

Hypothesis

Water vapor strongly absorbs at wavelength of **~900 nm**. High PWV reduces the downwelling direct beam irradiance near that frequency. Therefore we are expecting that the shortwave irradiance decreases with higher water vapor-

However **shortwave (SW) irradiance** is also affected by clouds and by Solar zenith angle- All these factors need to be accounted for in order to ensure that we properly train our model.

By using the MWR to train the SW irradiance we may be able to **extend the range of PWV availability** and also to **develop a secondary PWV monitor.**

Data

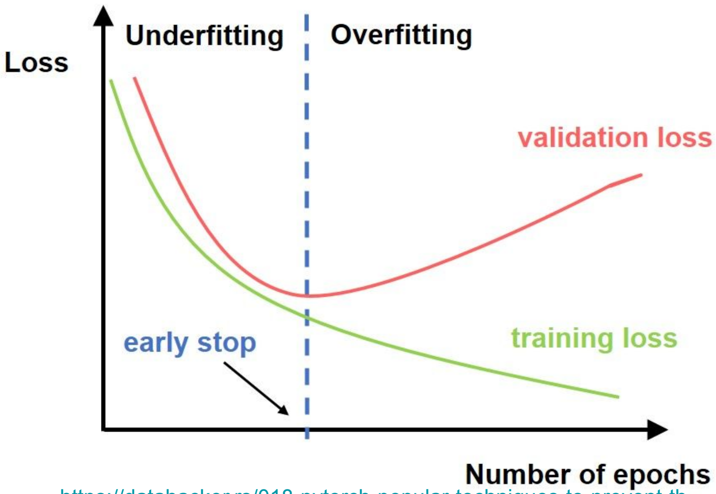
Using the ARM database, we can extract data from multiple instrumentation:

1. **Microwave Radiometer**
   - Precipitable water vapor - our target dataset
2. **Visible Multifilter Rotating Shadow Radiometer**
   - Downwelling direct beam at 940 nm (input data)
   - Remove when values are 0 (presumed night-time)
3. **Ceilometer**
   - First cloud base height
   - Remove values when clouds are detected below 5 km.

Other datasets we didn't get to use: **NIMFR** and **Cimel Sunphotometer**

Methodology

- We trained a simple three-layer neural network and an LSTM with:
  - **Early stopping -** Ceases training when model begins to overfit (e.g., fits training noise).
  - **Dynamic learning rate -** Reduces likelihood that model weights “get stuck” in local minima.



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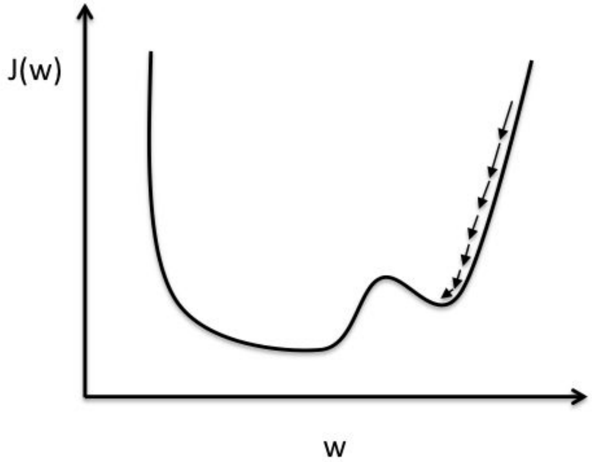

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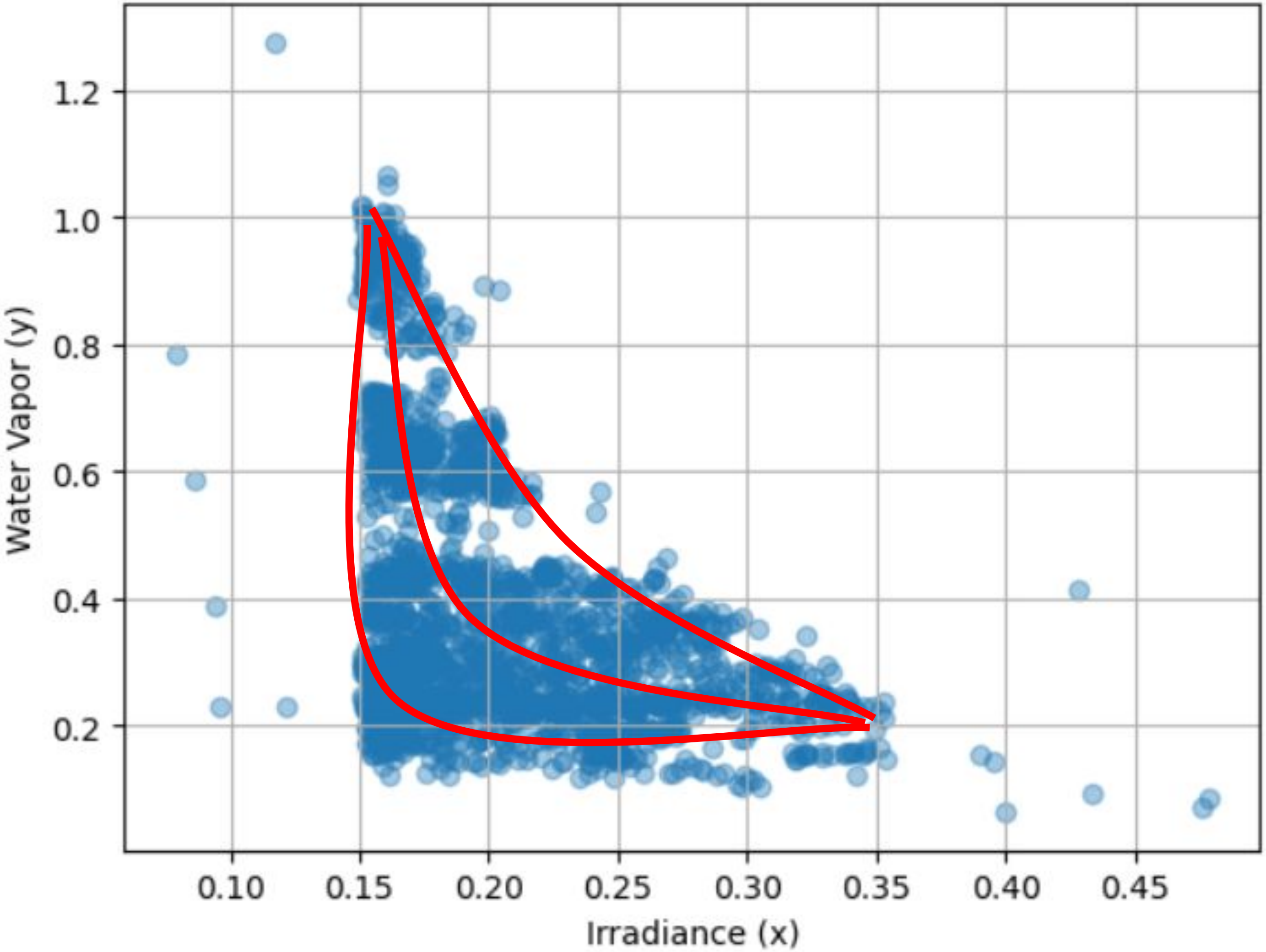

Conclusions/Future Work

- The biggest conclusion: we need more variables (and data)!
- Other methods of subsetting the datasets could reveal a more obvious relationship between variables
- In the future, we could run a model optimization scheme, create a deeper model, and use a more robust model architecture.

Work Cited

Trenberth, K. E. (2022). The changing flow of energy through the climate system. Cambridge University Press. https://doi.org/10.1017/9781108979030