National Aeronautics and Space Administration

Maximize Europa Clipper Data Return by Accurate Prediction of Atmospheric Noise Temperature Using Machine Learning

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Program: FY21 R&TD Topics   Strategic Focus Area: RF and Optical Communications

Objectives

- The objective of this project is to develop a customized real-time prediction system for atmospheric noise temperature (T_{atm}), which is the input to the telecommunication link model, for Deep Space Network (DSN) tracking sites using machine learning (ML).
- We focus on Ka-band (32 GHz) communication links that will be demonstrated for possible use by the Europa Clipper mission.
- The prediction system of zenith T_{atm} with uncertainty quantification (UQ) will be developed, with forecast lead time of 1-16 days.
- In FY21, we focused on developing the forecast system at Goldstone, CA.
- This forecast system will be adopted to other tracking sites and expanded to predict other atmospheric variables when in-situ observations become available.

Background

- Ka-band (32 GHz) communications links are far more sensitive to weather degration than X-band (8.4 GHz).
- Current models for the Ka-band downlink data rates are quite conservative, accounting for 90% weather availability. The Europa Clipper mission is using a 3 dB margin. This approach can result in wasted downlink capacity.
- Recent studies showed that using real-time weather forecasting can increase data return and the reliability of the communication links.

Significance/Benefits to JPL and NASA

- This project proposes to provide direct support to the operation of the Europa Clipper mission and other flight projects using the DSN.
- This project is aligned with JPL's strategic goals to achieve "seamless, higher rate, larger volume data and information delivery" and enable more productive and impactful space missions for the ultimate quest of life beyond Earth and other scientific investigations.
- The ML model for predicting T_{atm} can be generalized to many other missions in which data communications are essential. It could serve as a universal component of future onboard data prioritization protocol.

Publications

[A] Longtao Wu, David D. Morabito, Lei Huang, Joaquim Teixeira, Hai Nguyen, Hui Su, Melissa Soriano, Lei Pan, and Daniel Kahan, "Prediction of Atmospheric Noise Temperature at the Deep Space Network with Machine Learning," abstract submitted to *AGU Fall meeting 2021,* New Orleans, LA, 2021.

[B] David D. Morabito, Daniel Kahan, Meegyeong Paik, and Longtao Wu, "A Study of Twenty Years of Advanced Water Vapor Radiometer Data at Goldstone, California," abstract submitted to *AGU Fall meeting 2021,* New Orleans, LA, 2021.

Acknowledgement

We would like to acknowledge Alan Tanner and Stephen Keihm for their methodological recommendations for calibration of the AWVR data.

Approach

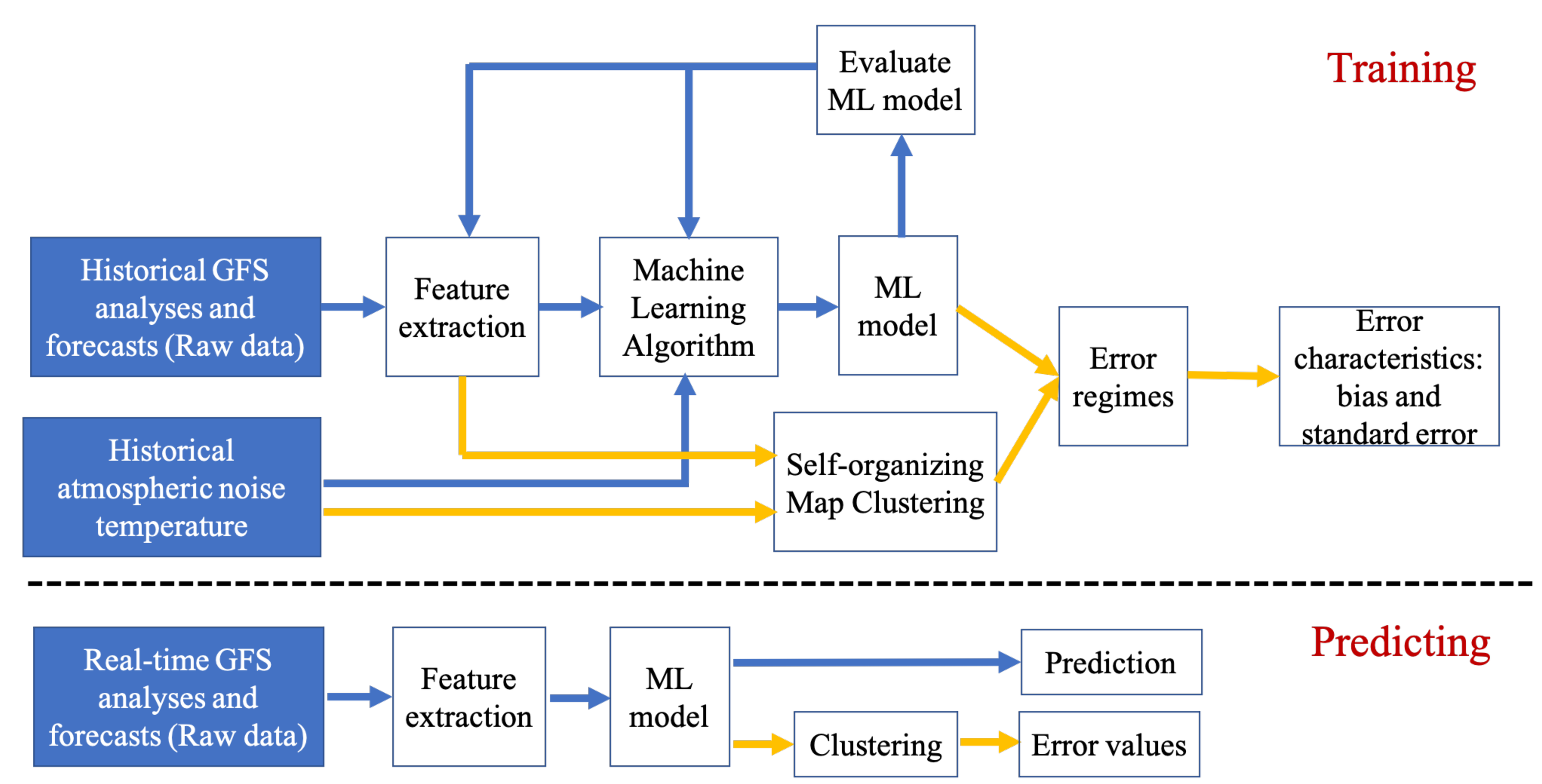

Figure 1. Workflow of the Machine Learning-based forecast system.

Table 1. List of T_{atm} predictors used in the machine learning forecast model.

Variable name	Variable type	Correlation	Description
PWV_f024	24 hr forecast	0.46	Precipitable water vapor
CW_f024	24 hr forecast	0.39	Cloud water
qv2_f024	24 hr forecast	0.38	2-m specific humidity
Td_f024	24 hr forecast	0.35	2-m dew point temperature
AccRain_f024	24 hr forecast	0.35	6-hr accumulated precipitation
PWV_f000	analysis	0.32	Precipitable water vapor
RH2_f024	24 hr forecast	0.29	2-m relative humidity
qv2_f000	analysis	0.23	2-m specific humidity
Td_f000	analysis	0.22	2-m dew point temperature

- In FY21, we have trained a ML model with the historical weather forecasting data from NCEP Global Forecast System (GFS) and the in-situ observations of T_{atm} at Goldstone, CA from 2015 to 2020.
- 24-hour forecasts of T_{atm} are used as the demonstration case of the forecast system.

Results

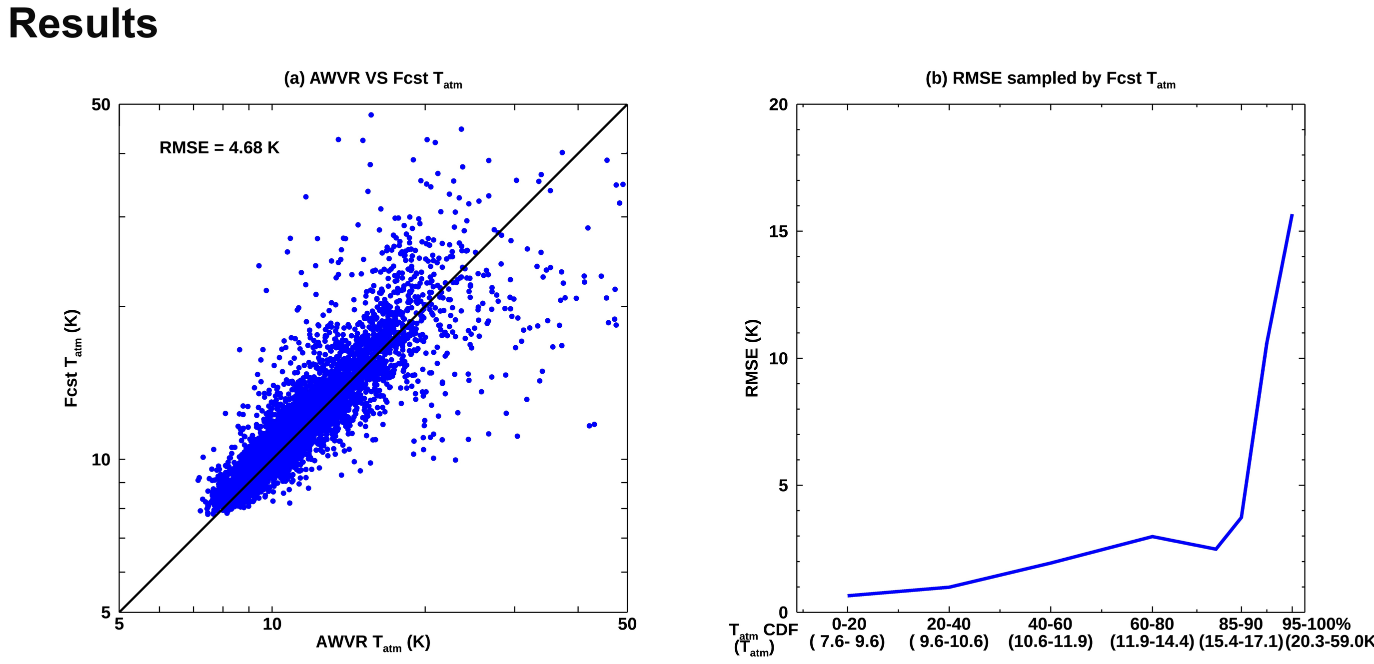

Figure 2. (a) Observed (AWVR) vs forecasted (Fcst) T_{atm} (K); (b) Forecast RMSE (K) sampled by forecasted T_{atm}. X-axis in Figure b is the percentile range (%) of the forecasted T_{atm}; values inside parentheses are the corresponding ranges of the forecast T_{atm} (K). Data from 2015 to 2020.

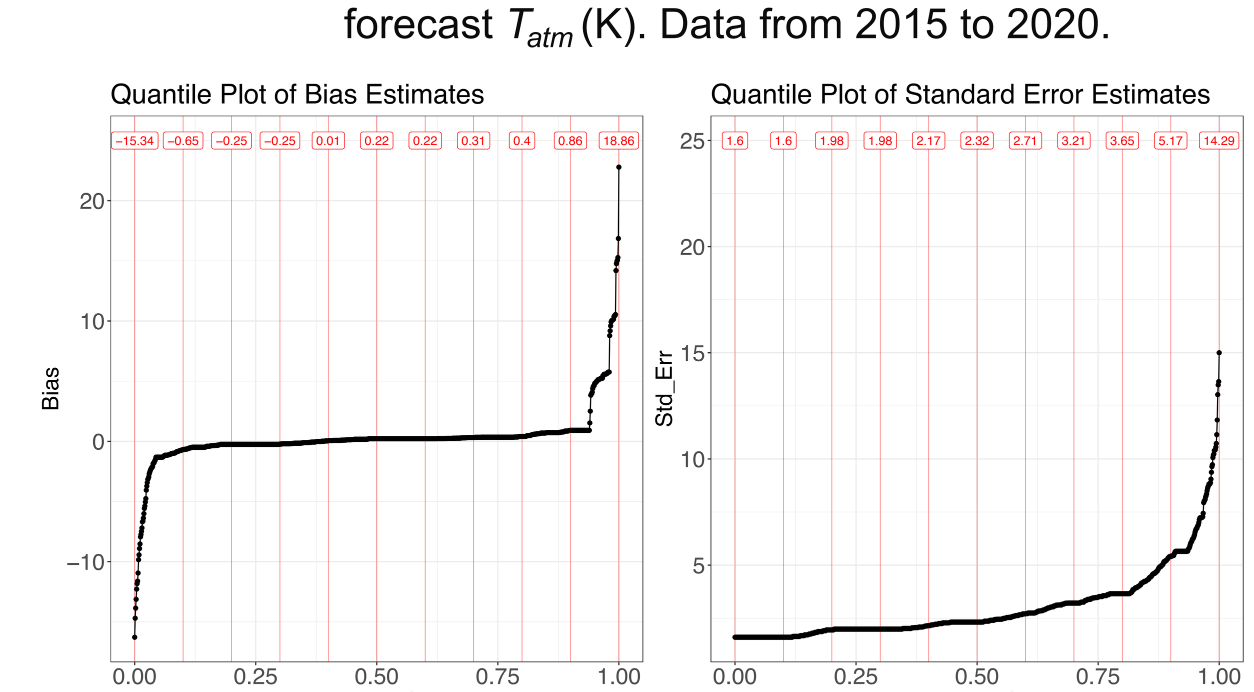

Figure 3. Quantile plot of (a) bias and (b) standard error from the Uncertainty Quantification model. The red numbers represent the value for each decile.

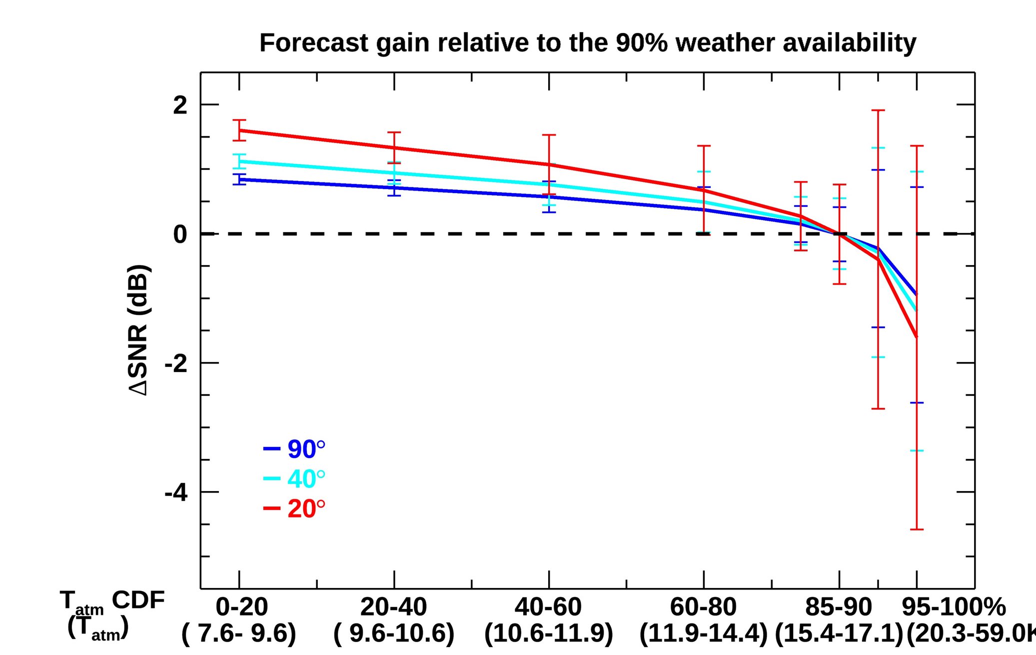

Figure 4. Forecast Gain ($\Delta E_b/N_0$, dB) relative to the 90% weather availability versus mean T_{atm} for different elevation angle cases at Goldstone, CA. Error bar represents the forecast error.

Summary

- The forecasted T_{atm} has good agreement with the observations, especially when the observed T_{atm} is less than 20 K (Fig. 2a).
- The RMSE of all the forecasts is 4.68 K.
- The RMSE increases with the increase of T_{atm}. 90% of the samples has RMSE less than 4 K (25% relative to the mean T_{atm}) for fair-weather conditions with T_{atm} < 17 K (Fig. 2b).
- Most of the forecasts have a bias lower than 1 K (Fig. 3a).
- At the low-end of T_{atm} = 9 K, one can realize a forecast gain of 1.6±0.16 dB (44% more data) at 20° elevation angle (Fig. 4).
- A real-time forecast system has been developed to produce 24-hour forecasts of T_{atm} at Goldstone, CA.

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