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Retrieval of All-weather Precipitable Water Vapor over Land Using Remote Sensing Passive Microwave Observations

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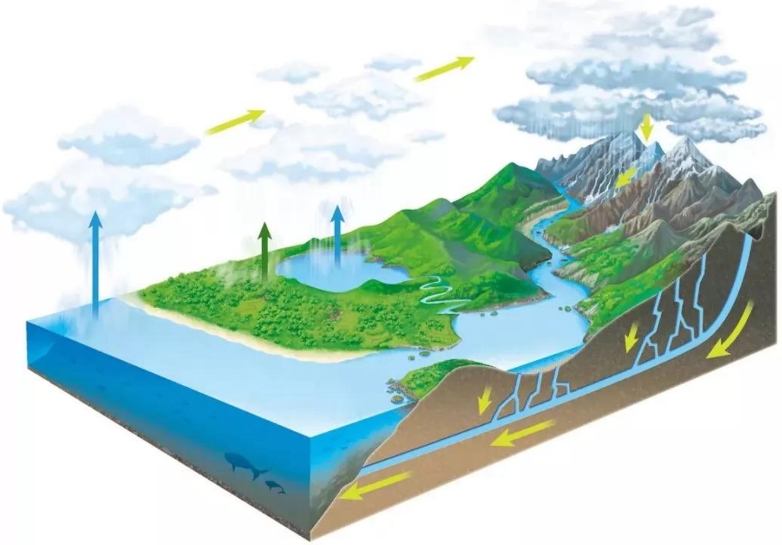
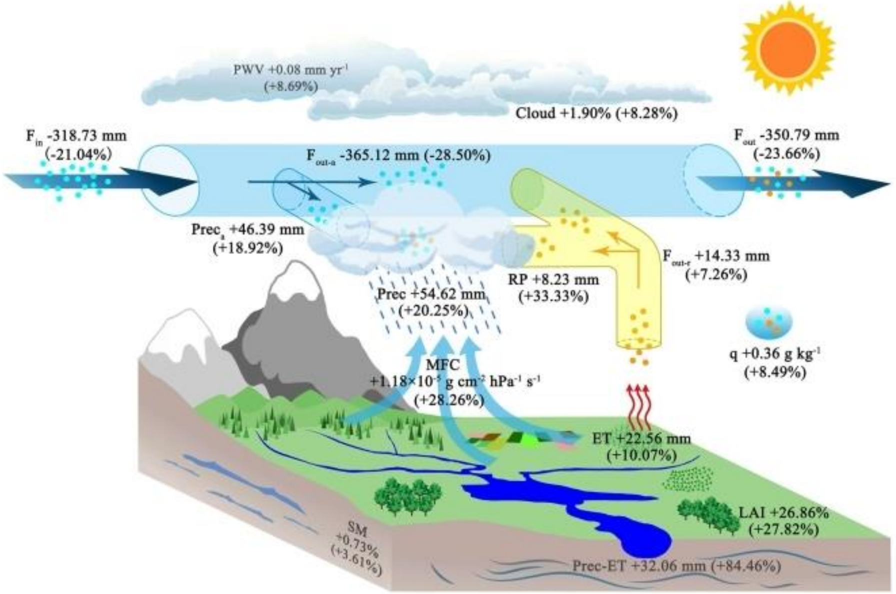
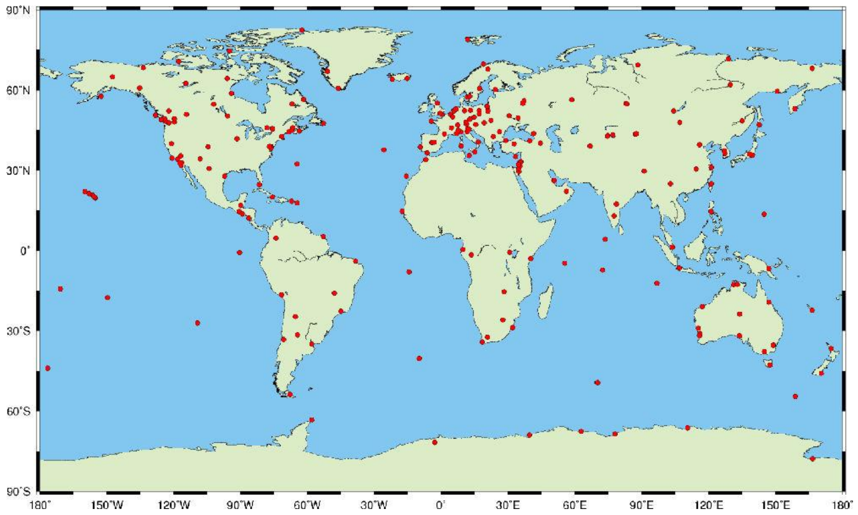
1. INTRODUCTION

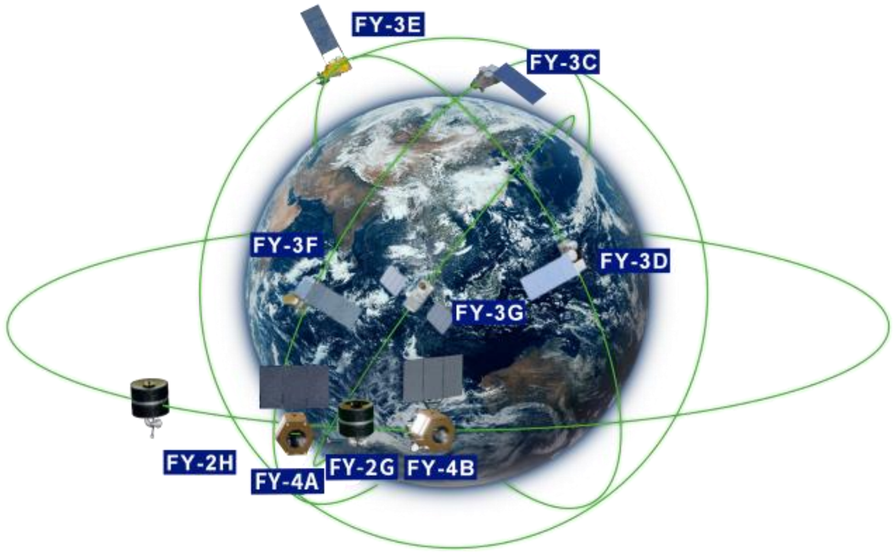
Atmosphere total precipitable water vapor (PWV) serves as a key indicator of column-integrated atmospheric moisture, tightly linked to precipitation dynamics and climate feedback mechanisms. Studies show that abrupt PWV increases often precede precipitation events within 2 hours, while its role as the most abundant greenhouse gas contributes ~70% of atmospheric radiative absorption, driving global warming processes. Consequently, PWV plays a fundamental role in weather forecasting, climate modeling, and remote sensing atmospheric correction, underscoring the need for continuous, high-quality monitoring.





Current PWV monitoring employs ground- and space-based approaches. Ground instruments—including radiosondes, GPS networks, microwave radiometers, sun photometers, and Raman lidars—offer high accuracy but suffer from sparse spatial coverage, particularly over deserts, oceans, and lakes. Satellite platforms with near-infrared (NIR), thermal-infrared (TIR), and passive microwave sensors can provide global coverage.





However, NIR/TIR retrievals are ineffective under cloudy skies due to clouds cover. Microwave observations overcome this limitation by penetrating clouds, enabling all-weather PWV retrieval.

2. DATA——2018 and 2019

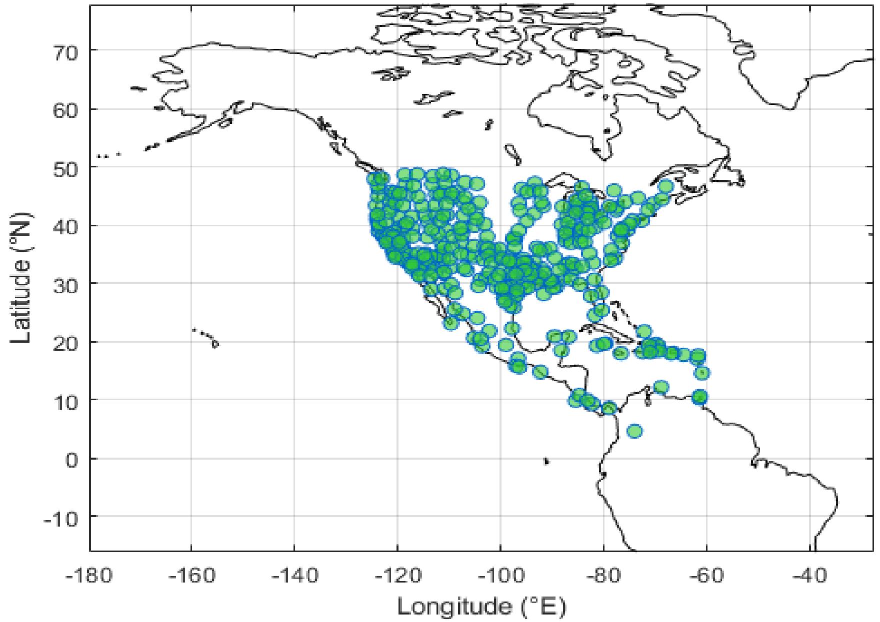
- FY-3D MWRI brightness temperature data as main input data.
- DEM and land cover types data as auxiliary input data.
- Passive microwave brightness temperature index.
- SuomiNet PWV data as validation data.

Microwave Atmospheric Water Vapor Index:

$$\mathrm{MAWVI} = \Delta T_{b,23.8}/\Delta T_{b,18.7}$$
$$\Delta T_{b,23.8} = T_{b,23.8v} - T_{b,23.8\mathrm{h}}$$
$$\Delta T_{b,18.7} = T_{b,18.7v} - T_{b,18.7\mathrm{h}}$$

Vegetation Transmissivity Index:

$$Fh = \bar{T}_{b,23.8\mathrm{h}}/T_{b,18.7\mathrm{h}}$$



Geographic distribution of SuomiNet stations.

3. METHOD——Physical and machine learning methods

$$T_{b,i,p} = T_{a,i}^{\uparrow} + \tau_i \cdot \varepsilon_{i,p} \cdot T_S + (1 - \varepsilon_{i,p})\tau_i \cdot T_{a,i}^{\downarrow}$$

$$\tau_i = e^{-(a_v \times PWV + b_o)}$$

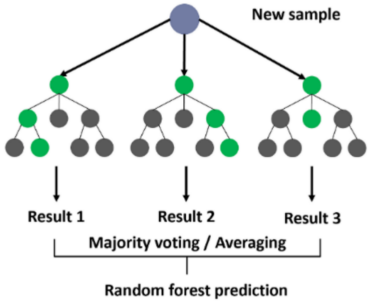
$$T_{a,i}^{\uparrow} \approx T_{a,i}^{\downarrow} = (1 - \tau_i)(a_T \cdot PWV^2 + b_T \cdot PWV + c_T)$$

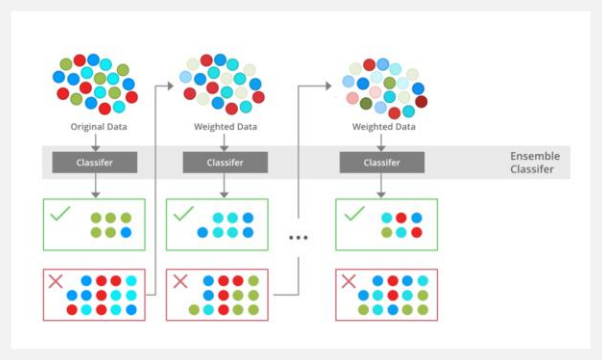
$$PWV = f(T_{b,i,p}, \varepsilon_{i,p}, T_S)$$

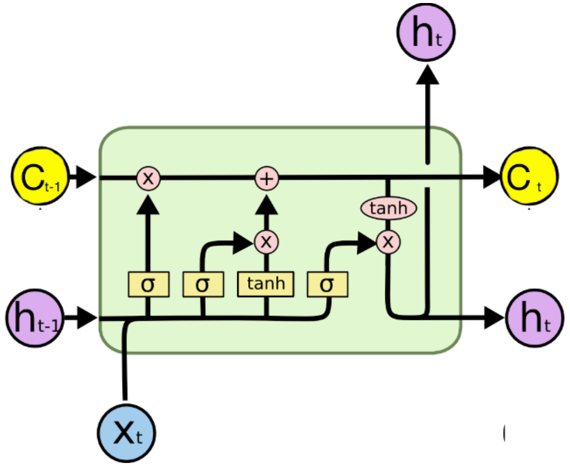
$$PWV = f(T_{b,i,p}, \varepsilon_{i,p}, T_S, H, LU)$$

$$PWV = f(T_{b,i,p}, PR_{18.7}^2, PR_{18.7}, \mathrm{MAWVI}, Fh, DEM, LU)$$

- Random Forest Model.
- Light GBM.
- XGBoost.

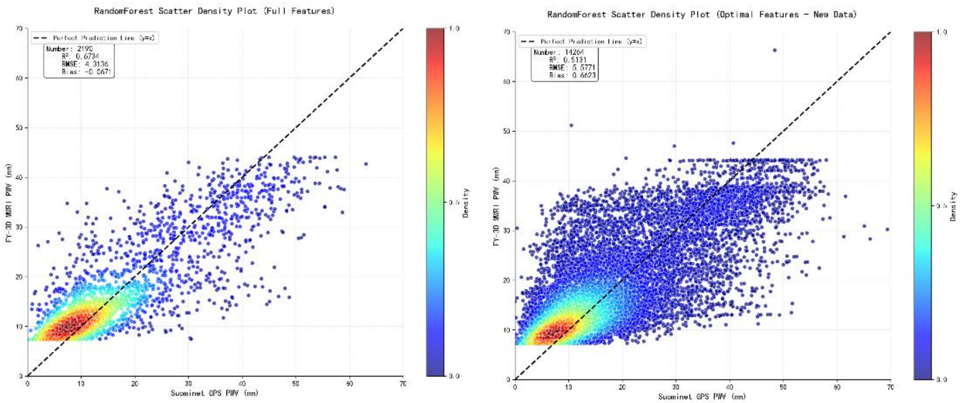




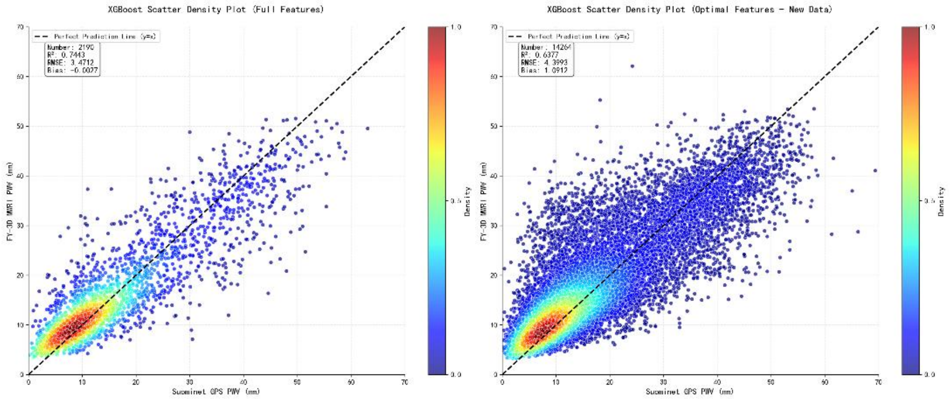


4. RESULTS AND DISCUSSIONS

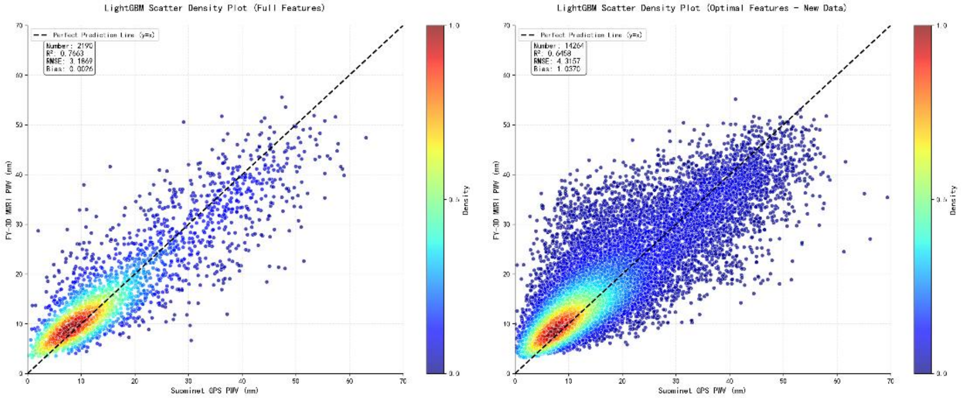
Random Forest



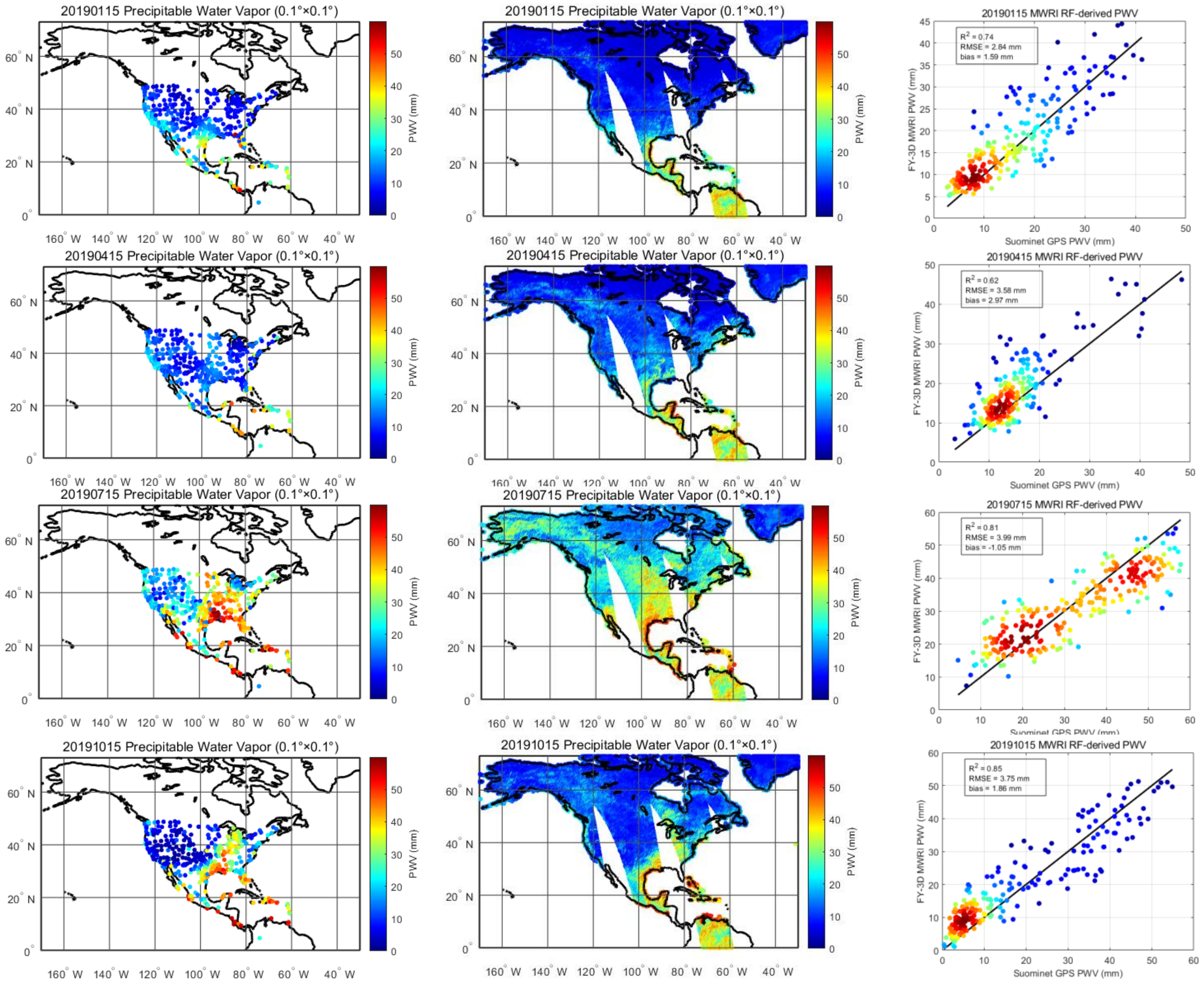
XGBoost



LightGBM



Method	RMSE(mm)	R2	Bias(mm)
RF	5.5771	0.5131	0.6623
Light GBM	4.3157	0.6458	1.037
XGBoost	4.3993	0.6377	1.0912



These pictures show the all-weather PWV distribution maps over the study area on the 15th day of January, April, July, and October 2019. The left column shows the measurements from SuomiNet stations, the middle column presents the retrieval results from FY-3D MWRI, and the right column displays the scatter density plots comparing the station measurements with the retrieval results. Notably, the passive microwave remote sensing-based land PWV monitoring (middle column) achieves spatially continuous coverage (excluding gaps), offering distinct advantages for enhancing weather forecasting accuracy and advancing global climate change research compared to the discrete SuomiNet station observations.

5. CONCLUSIONS

This study presents an all-weather PWV over land retrieval method using FY-3D microwave data. Firstly, through the transformation and approximation of the Radiative Transfer Model, it was found that channel brightness temperature, LST, and LSE were the main factors affecting PWV. Meanwhile, combining the achievements of previous studies, DEM, land use types, microwave brightness temperature indices, etc. are used as the input parameters in three machine learning methods, validated against SuomiNet-measured PWV as ground-truth values. Comparative analysis reveals that Light GBM achieves the highest accuracy, with an average RMSE of approximately 4 mm throughout 2019. Predictions and mapping were performed using the Light GBM model for the 15th day of January, April, July, and October 2019, and the results show excellent agreement with the distribution trends of SuomiNet data, demonstrating robust performance.

This research provides an all-weather PWV retrieval framework with improved accuracy and spatial coverage, offering valuable insights for microwave remote sensing applications in meteorology and climate research.

Thank you for your attention!