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Using Numerical Weather Model To Predict Zenith Total Delay (ZTD) With Machine Learning and Improve Tropospheric Correction for InSAR

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G42D-0264

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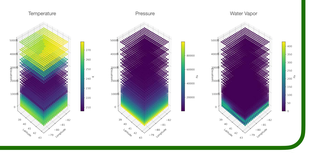
Can we use machine learning to improve tropospheric correction from weather model?

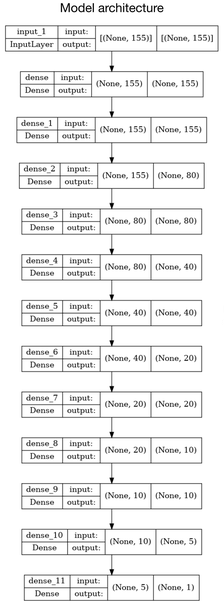
- Interferometric synthetic aperture radar (InSAR) is a powerful tool to detect deformation and movement of the Earth's surface.
- Machine Learning (ML) algorithm could extract or predict deformation. ML could detect spatial correlation and trend when input with large volume of data. (Brengman et. al. 2021, Anantrasirichai et. al. 2018)
- GPS can be used to estimate troposphere delays, but is is limited by spatial and temporal resolution. (Bekaert et. al. 2015)
- Incorporate spatial stochastic behavior when interpolating GAM data is known then to improve the estimated delays. (Cao et. al. 2021)
- Developing deep learning models from weather model parameters (Temperature (T), Pressure (P), and Water vapour (e)), and digital elevation model (DEM) without other auxiliary data (e.g. GNSS).
- From understanding the spatial correlation and using Deep Neural Networks (DNNs), we can improve the interpolation scheme and downscale the GAMs to InSAR resolution.
- We purpose GNSS station have high temporal resolution of TD (5 mins) but sparse spatially, and it hold high accuracy data which can be served as target in machine learning training.

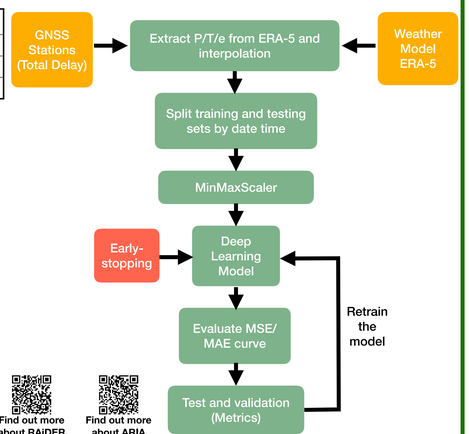


Method

Model architecture		
	Layers	11
	Epoch	150
	Batch	128
	Early stopping	10

Model architecture





Find out more about RAIDER

Find out more about ARIA

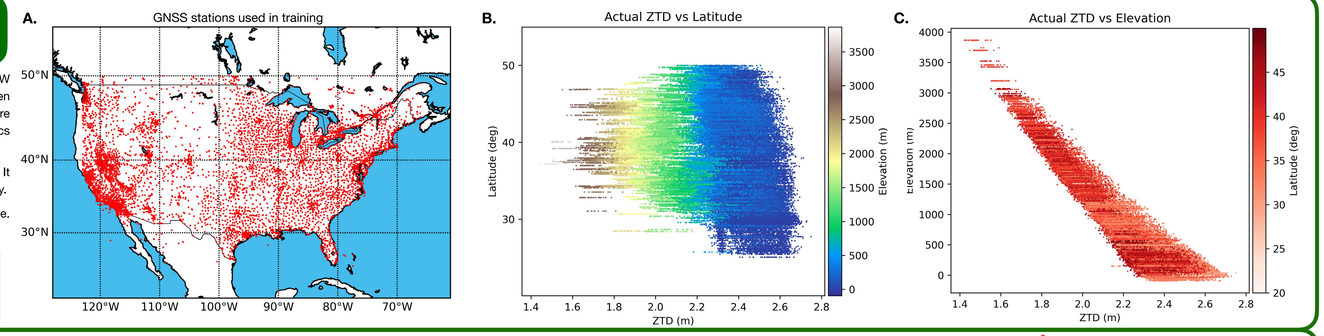
- Both GNSS station total delay and weather model (ERA-5) are downloaded through Raytracing Atmospheric Delay Estimation for RADAR (RAiDER)
- Utilize the total delay product from GNSS in the US ~ 8000 stations as target.
- Filter out low quality GNSS the 'sigZTD' column by a cut off at 0.01.
- Interpolate weather parameters P/T/e into 51 elevation levels and location for each GNSS station.
- MinMax Scaler is used for preprocessing input data and allow easier convergence.
- Early-stopping is set up for call backs to prevent overfitting.

Result

Training of ML model with GNSS

- Figure A: Training area is between the latitude of 50 N and 25 N, and longitude 123 W and 66 W in the region of United States. A total 7620 GNSS stations in the US between 2017 and 2022 at UTC 11:00:00 with a total of more than 7.5 million data points. Data are download with RAiDER and process from Nevada Geodetic Laboratory. Model Metrics see Table below.
- Figure B: The distribution of zenith total delay (ZTD) are in the range of 1.4 m to 2.6 m. It varies in latitude and elevation. It shows that ZTD has strong correlation with topography.
- Figure C: The distribution of ZTD varies much with elevation compare with latitude. Higher elevation will have lower ZTD due to the lack of water vapor in atmosphere.

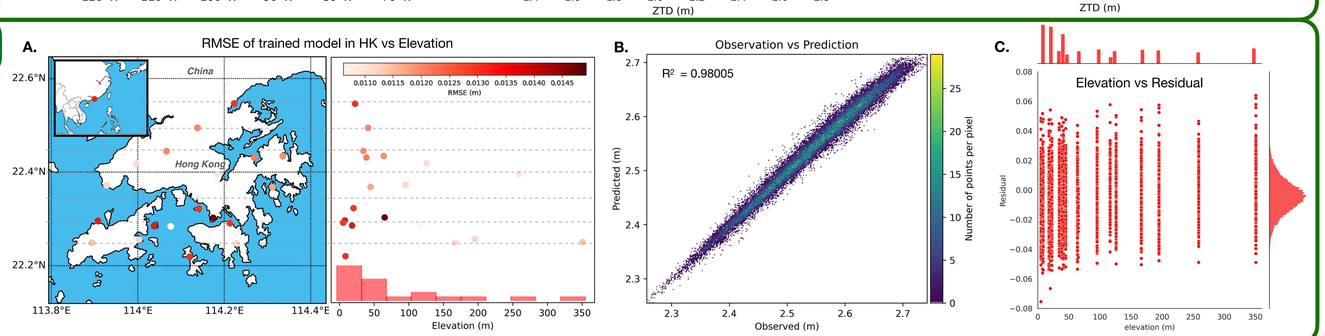
DNN model		
	MSE	0.00007702 m
	R^2	0.9979
	RMSE	0.00878 m
	Average error	0.00587 m



Testing on a new unseen area

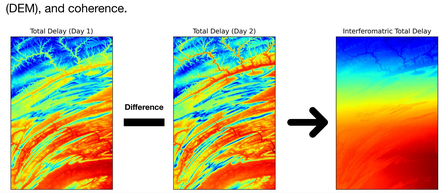
- Figure A: 20 stations with continuous data between 2012 and 2019 at UTC 10:00:00. Validation test is done at this location to validate model performance in generalization and specifically at a subtropical area. Most stations are located below 150m and near to the coast shows high RMSE which can be resulted from high variability in water vapor.
- Figure B: Observation vs prediction plot. There is a good linear trend between observation and prediction shows model predict very closely to the actual value.
- Figure C: Residual vs Elevation plot. The majority of the residual normally distributed at zero and spread between -0.03 and 0.03. At higher elevation, there is an increase in the positive direction.

Model performance in Hong Kong		
	MSE	0.000152 m
	R^2	0.98005
	RMSE	0.01235 m
	Average error	0.00959 m

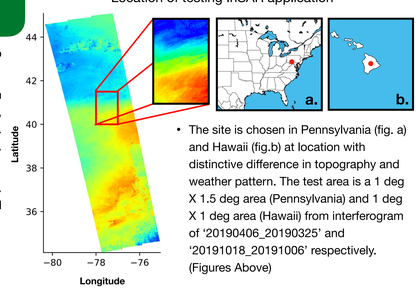


Application to InSAR

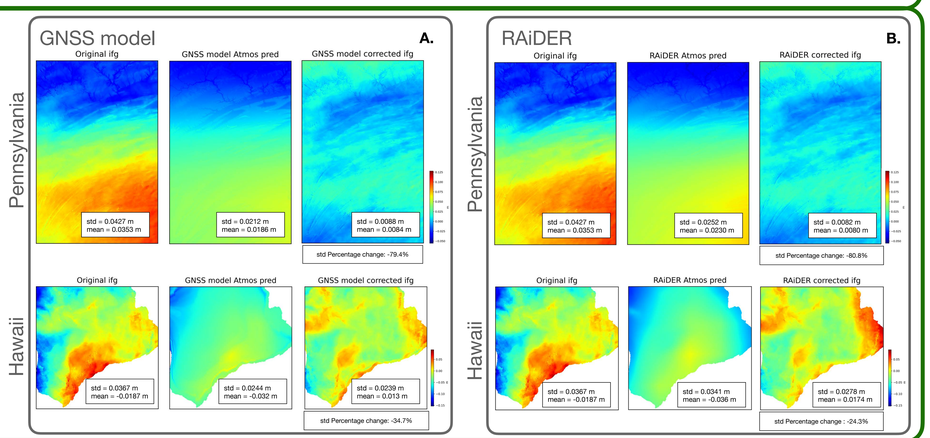
- GNSS model can predict ZTD with low error, we can implement such into tropospheric correction for InSAR.
- To obtain the interferometric delay, first, predict the total delay (TD) from both acquisition date (slave & master date) and by the hour of the interferogram. Then, get the difference of the TD to obtain interferometric delay (tropospheric delay). Last, take the difference the interferometric delay from original interferogram. (Figures below)
- Interferograms downloaded from ARIA are preprocessed and unwrapped. Extracted data consist files such as line of sight (LOS), digital elevate model (DEM), and coherence.



Location of testing InSAR application



- The site is chosen in Pennsylvania (fig. a) and Hawaii (fig.b) at location with distinctive difference in topography and weather pattern. The test area is a 1 deg X 1.5 deg area (Pennsylvania) and 1 deg X 1 deg area (Hawaii) from interferogram of '20190406_20190325' and '20191018_20191006' respectively. (Figures Above)
- Comparing the performance of GNSS model and traditional method (such as RAiDER). In Pennsylvania, GNSS model (ML model) was able to predict tropospheric delay as close as traditional method shows. In Hawaii, GNSS model performs better than traditional method in corrected ifg by approximate of ~15.8% (from std 0.0278 m to 0.0239 m) (Figure A and B)



Discussion

- Model perform well in predicting total delay with RMSE in the range of 1-2 cm.
- Both traditional method and machine learning model are able to correct ifg at ~ 80%. Performance varies at area of high topography and climate change (e.g. Hawaii)
- Even though GNSS model achieves low RMSE from predicting ZTD, but error in predicting interferometric delay could resulted with more than 2 times larger than ZTD RMSE.

Future Work

- Expand the region of training data, area such as Europe and Asia.
- Include different time of day into training data.
- Implement other optical data to fill the gaps between weather model nodes.
- Study the use of other Machine learning algorithm such as GAN, CNN, and RNN etc.

Reference

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https://github.com/dbekaert/RAIDER

https://github.com/aria-tools/ARIA-tools

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