

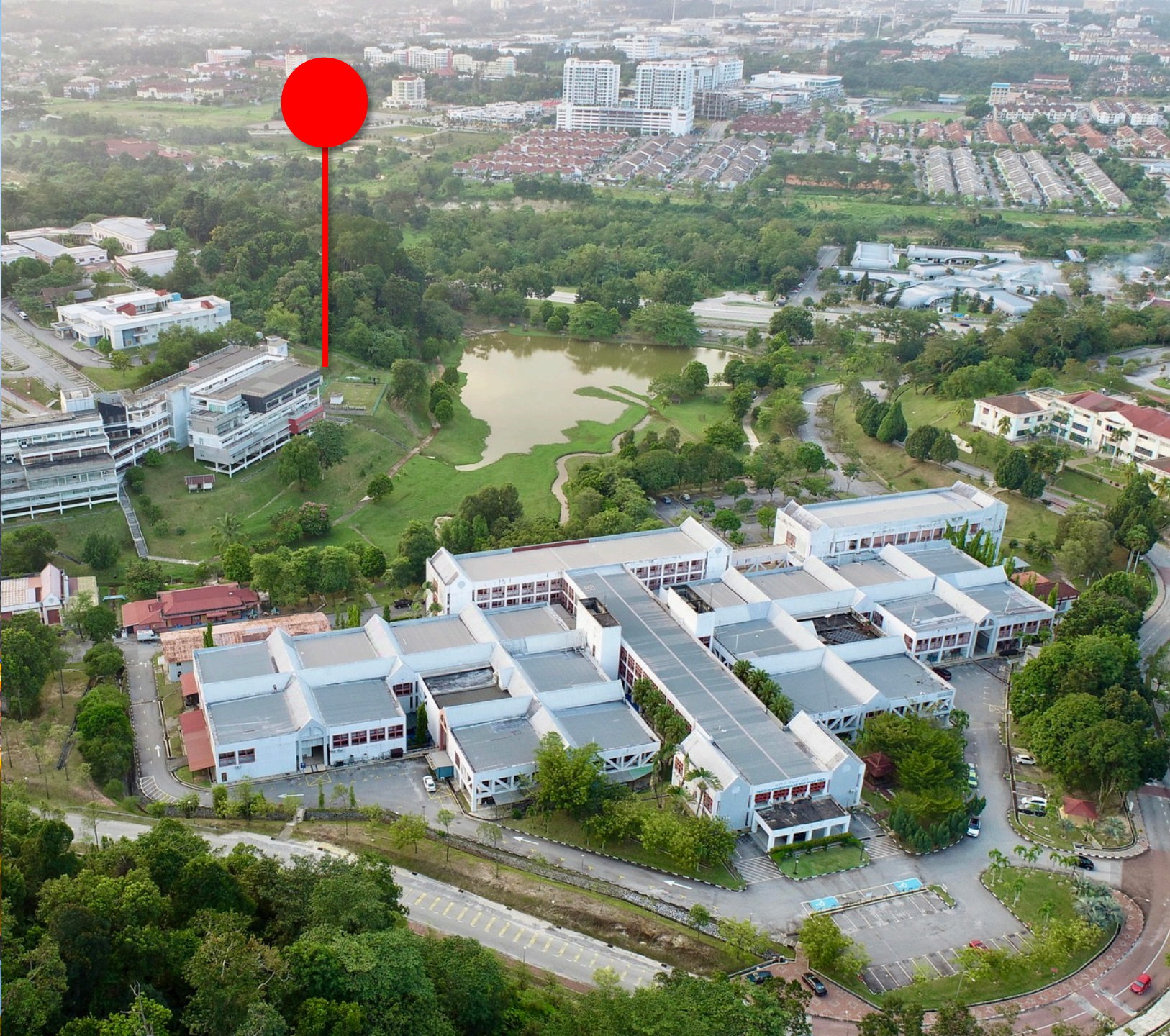


# Accurate Wireless LoRa Path Loss Prediction with Machine Learning for Airborne Internet of Things Networks (AIN) in Rural Tropics

Rosdiadee Nordin, Nor Fadzilah Abdullah, Asma' Abu-Samah, Haider A. H. Alobaidy, Mehran Behjati

*Workshop on Communication in Extreme Environments for Science and Sustainable Development*

Haider A.H. Alobaidy, Rosdiadee Nordin, J. S. Mandeep, Nor Fadzilah Abdullah, Azril Haniz, Kentaro Ishizu, Takeshi Matsumura, Fumihide Kojima, and Nordin Ramli, "Low Altitude Platform-based Airborne IoT Network (LAP-AIN) for Water Quality Monitoring in Harsh Tropical Environment", *IEEE Internet of Things Journal*, 9(20): 20034-20054



# Focus



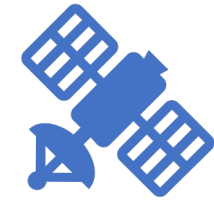
Design and  
Implementation of AIN



Path Loss Prediction  
with Machine Learning



Lesson Learned from  
AIN



Rekindle Interest  
Towards Non-  
Terrestrial Network

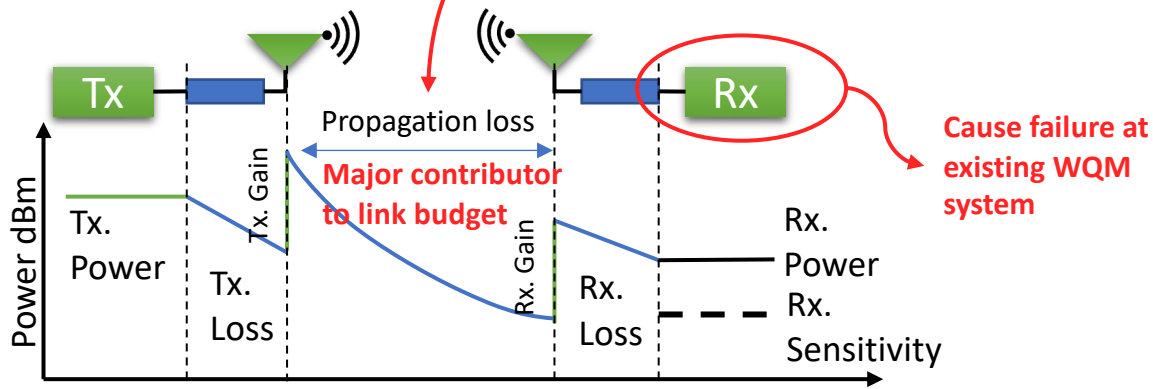
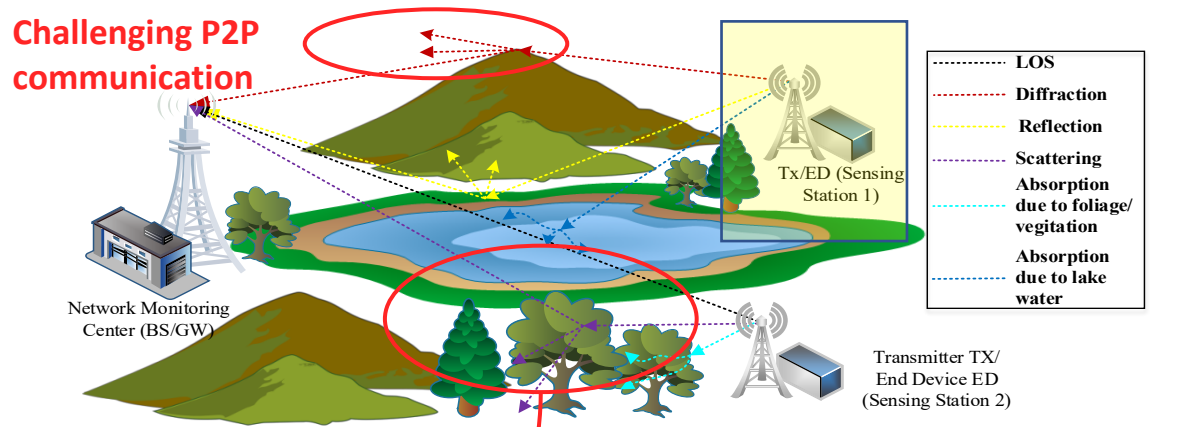


- Seven (7) stations to monitor the water quality across the Chini Lake
- Measuring various water quality parameters; pH, turbidity, dissolved oxygen, etc.



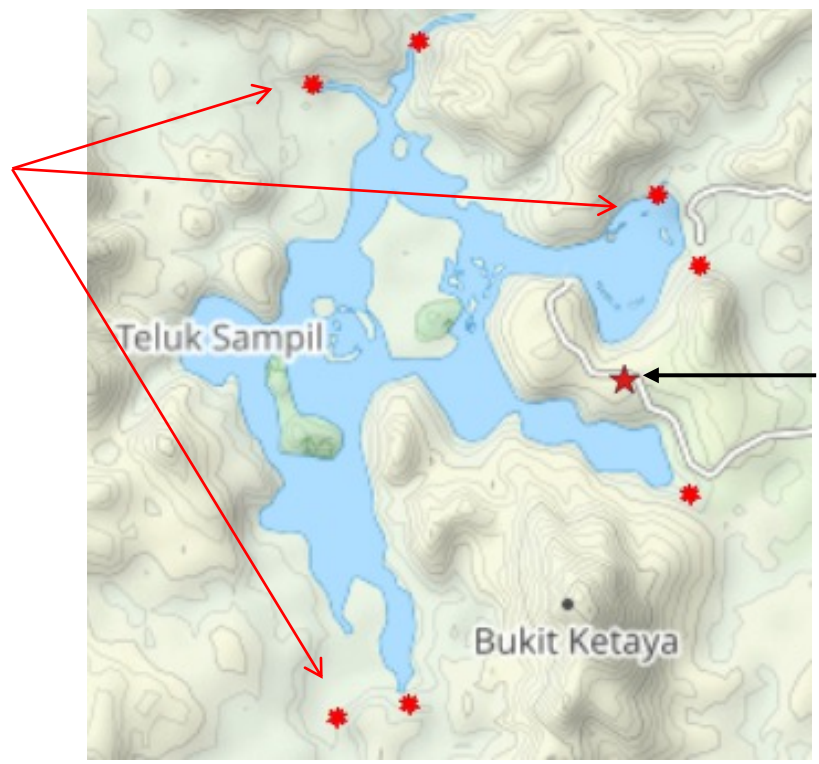
Pusat Penyelidikan Tasik Chini (PPTC) is Tasik Chini Research Centre

# Critical Challenges Facing Water Quality Monitoring at Chini Lake



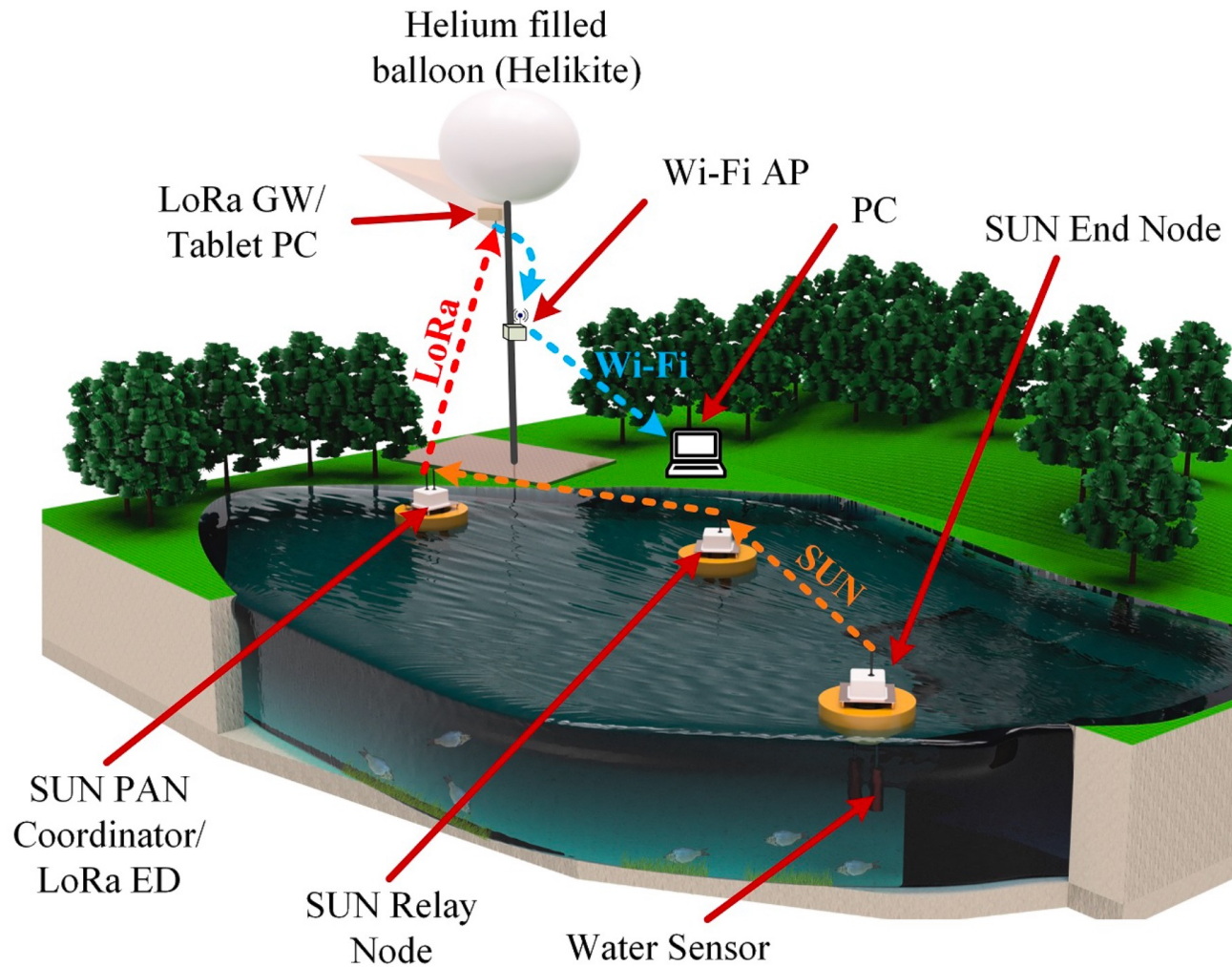
A Basic Wireless Signal Transmission with Various Attenuation Scenarios due to Channel Imperfection, Impacting Link Budget.

Current WQM stations

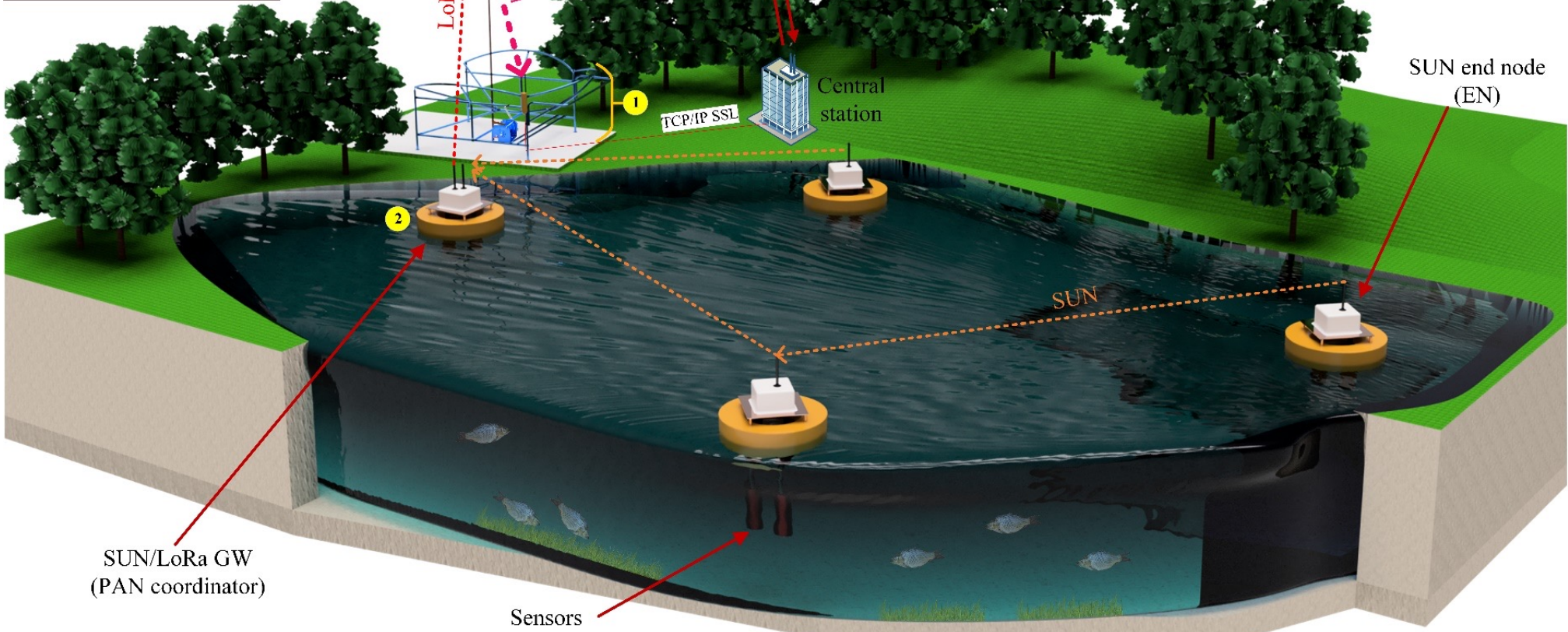
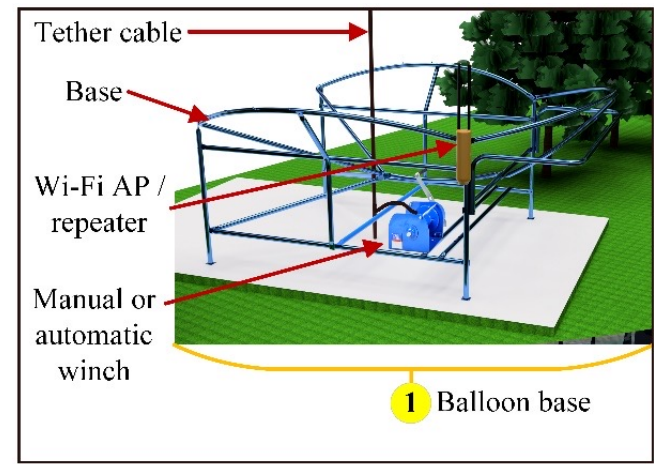
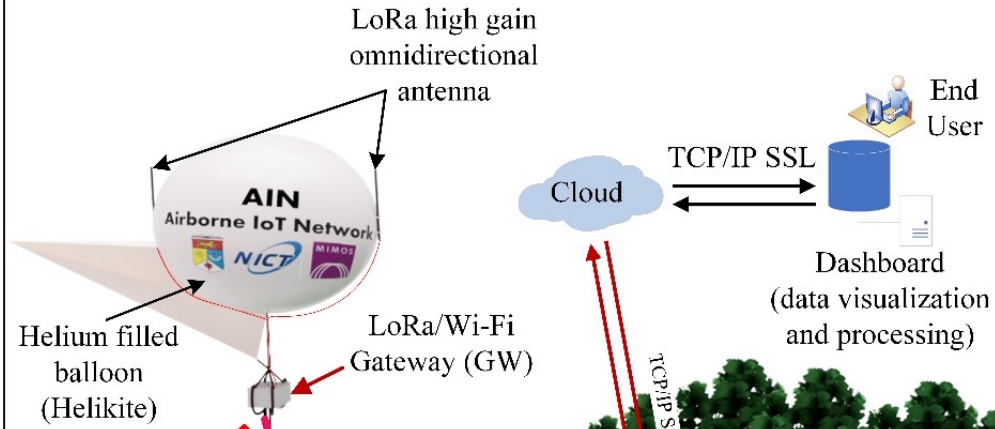
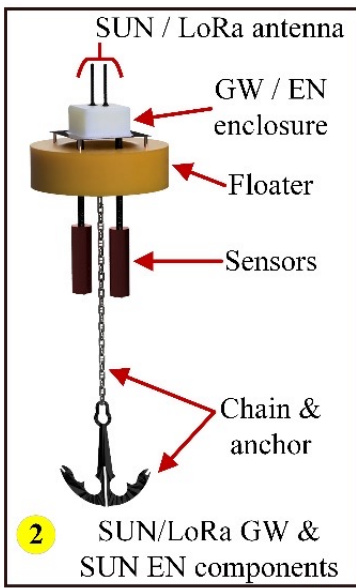


Chini Lake Map Showing Existing WQM Stations

# AIN Deployment



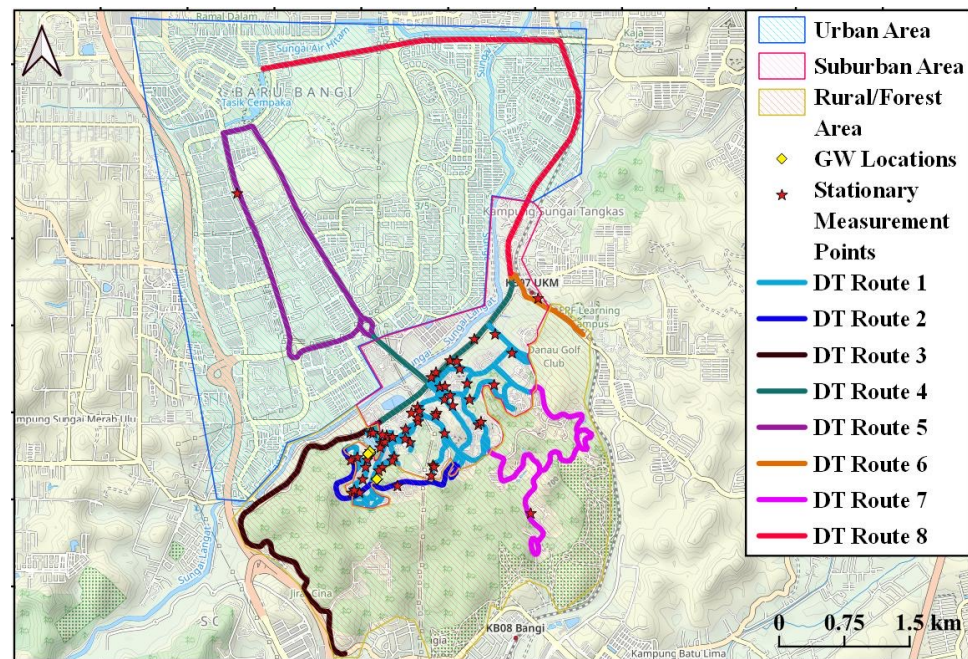




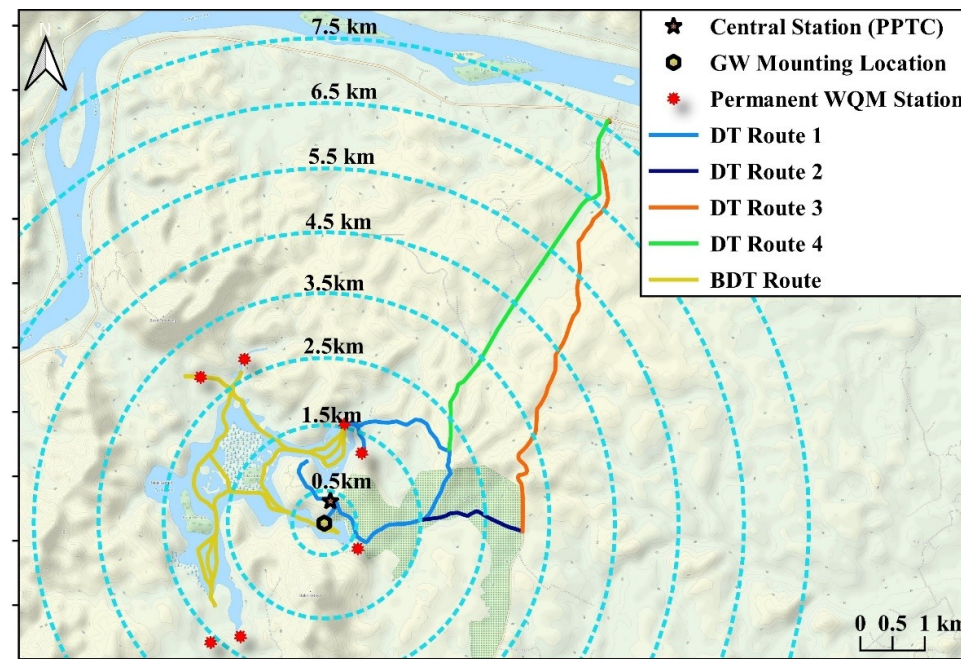


# LoRa Propagation Characterization using Hybrid Machine Learning: Reliability, Coverage, and PL Limits

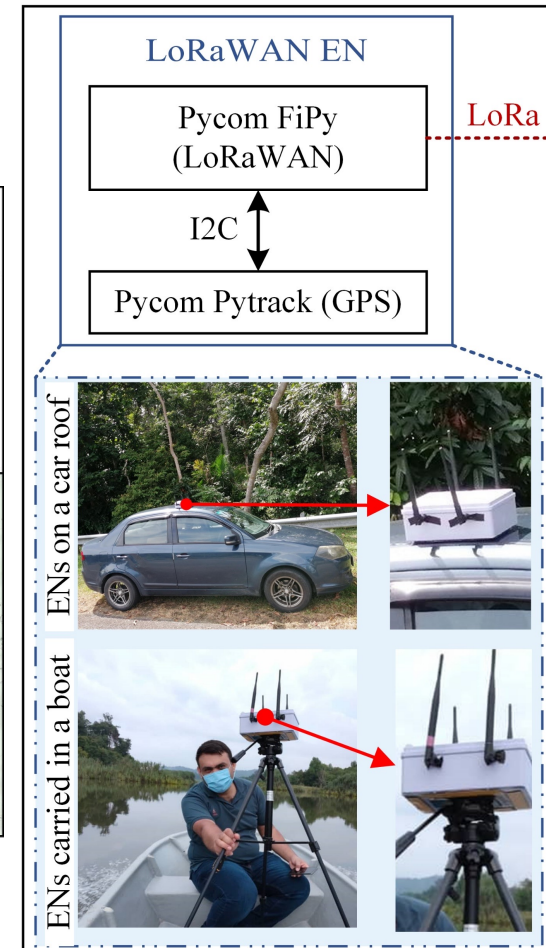
- Area types: Urban, rural, suburban (at UKM campus) and rural (at Lake Chini and surrounding)
- LoRa performance metrics: (1) **communication reliability**, (2) **coverage**, and (3) **path loss limits** via DT (car drive test), BDT (boat drive test)

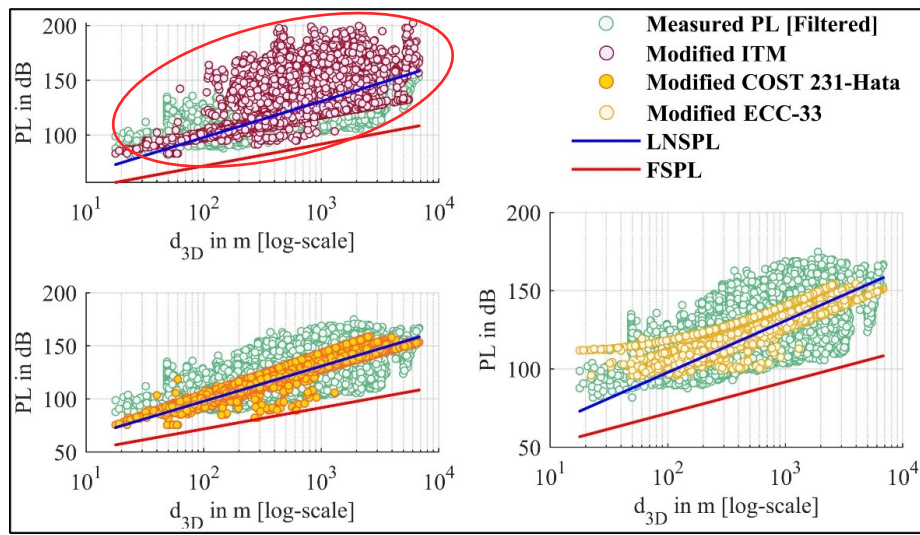


Measurement route/points at UKM, Bangi campus



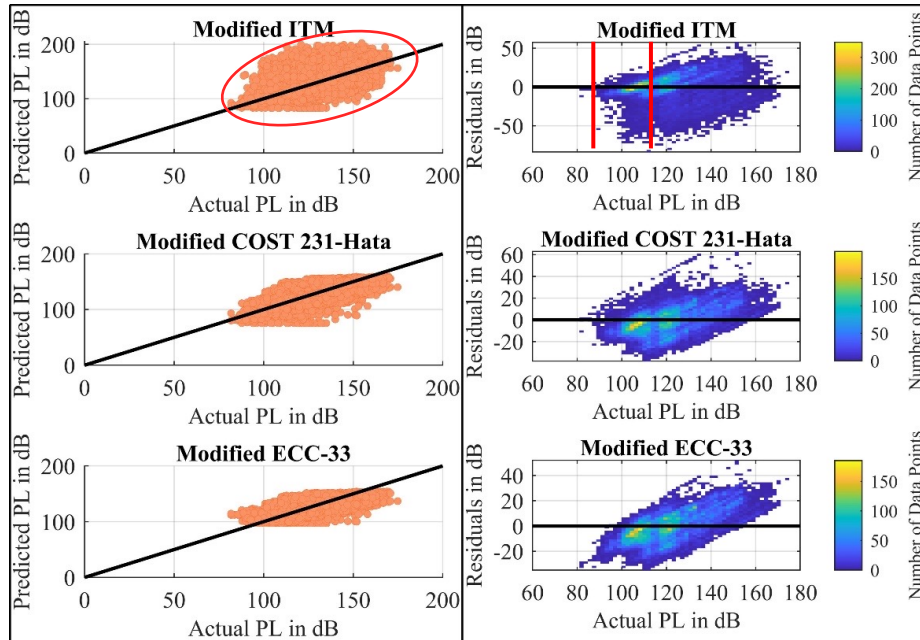
Measurement route at Lake Chini





- None of the well-known PL models are suitable for PL prediction in the study area under consideration
- Indicated the need for additional research to address this issue and propose new models that fit well in such harsh tropical areas

Measured PL vs. predicted PL plots from FSPL (baseline), LNSPL, and Cloud-RF<sup>®</sup>-based models



Modified Cloud-RF<sup>®</sup> based models performance. (a) Actual vs. predicted PL correlation. (b) Residuals vs. actual PL scatter plot

### Accuracy evaluation in terms of different metrics

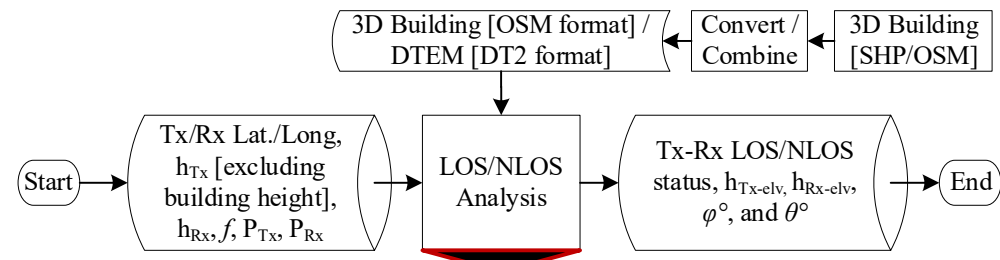
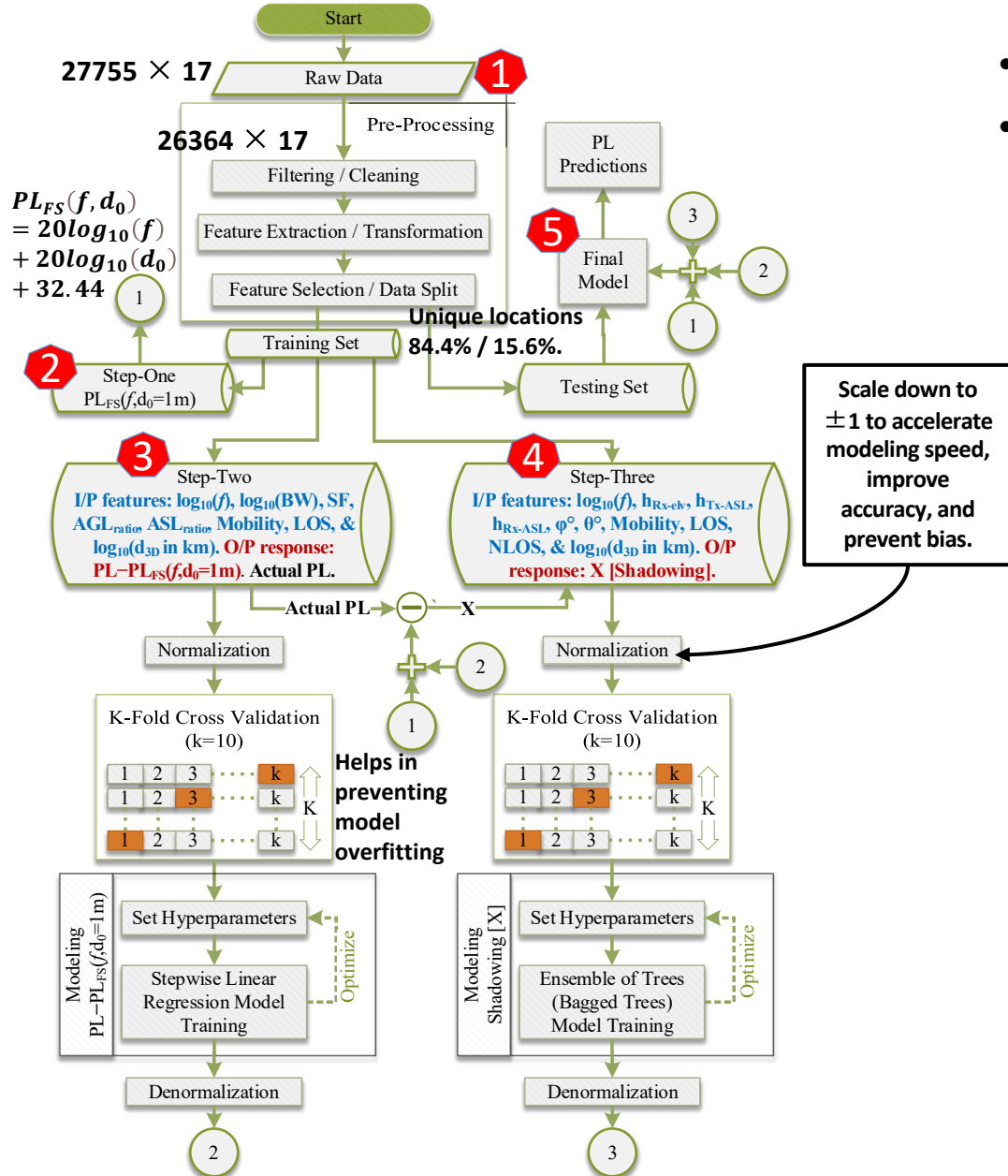
Model	MSE	RMSE	MAE	MAAPE	R	R <sup>2</sup>
FSPL	1458	38.18	36	28.04	0.54	-5.36
LNSPL	189.74	13.78	10.994	8.84	0.54	0.17
ITM	743.97	27.27	24.31	19.47	0.58	-2.25
Cost 231-Hata	888.55	29.81	27.03	21.38	0.62	-2.88
ECC-33	386.94	19.67	16.404	12.79	0.63	-0.69
Modified ITM	279.37	16.71	12.28	9.65	0.58	-0.22
Modified Cost 231-Hata	160.47	12.67	10.07	8.18	0.62	0.299
Modified ECC-33	141.23	11.88	9.62	7.82	0.63	0.383

Still performing poorly

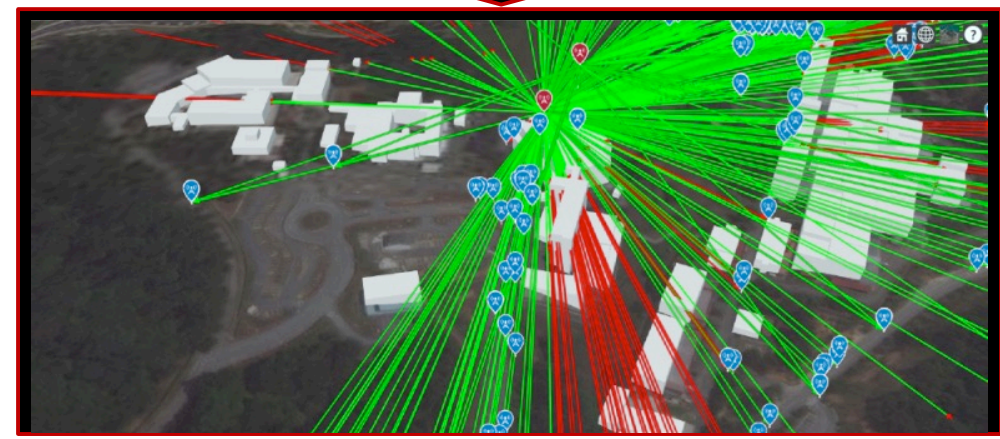
# Propagation Characterization using Hybrid Machine Learning

- The proposed model comprises of three stacked models.
- Compared to the popular LNSPL model, the proposed model can be represented as follows:

$$PL_{Proposed}[dB] = PL_{FS}(f, d_0 = 1m) + PL_{StWi}[dB] + X_{Ens}[dB]$$



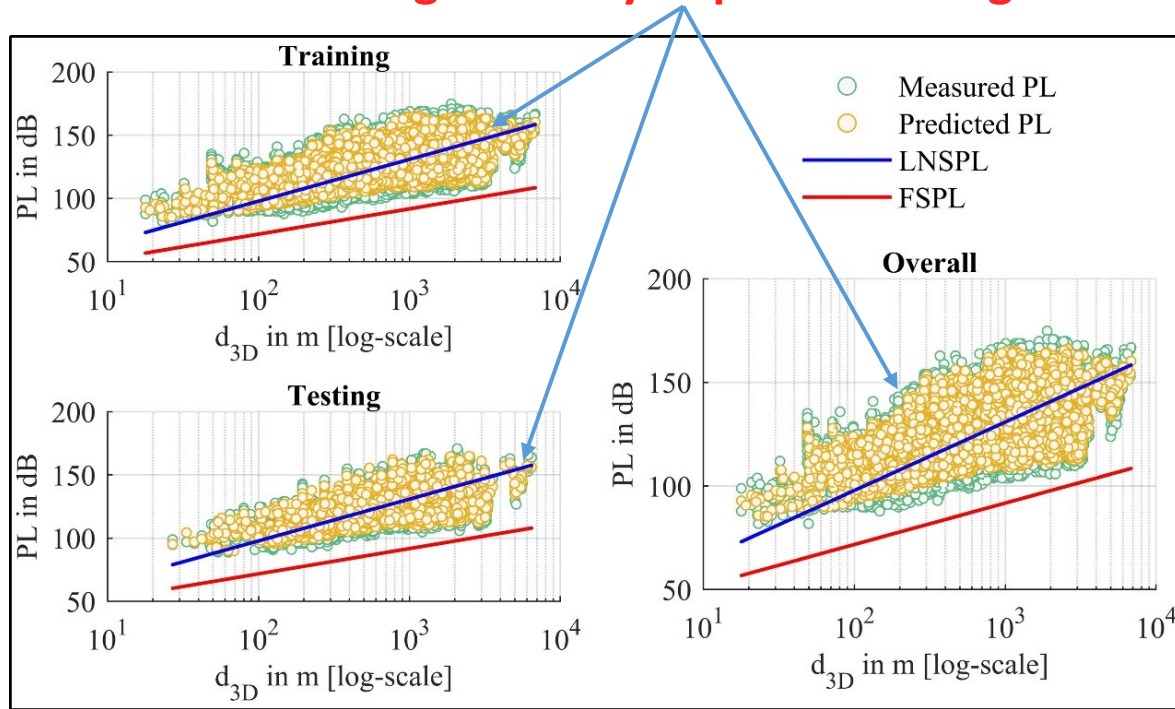
Extract geographical features, important for calculating large-scale fading



Flowchart of the raytracing simulation for LOS/NLOS analysis and geographical features extraction.

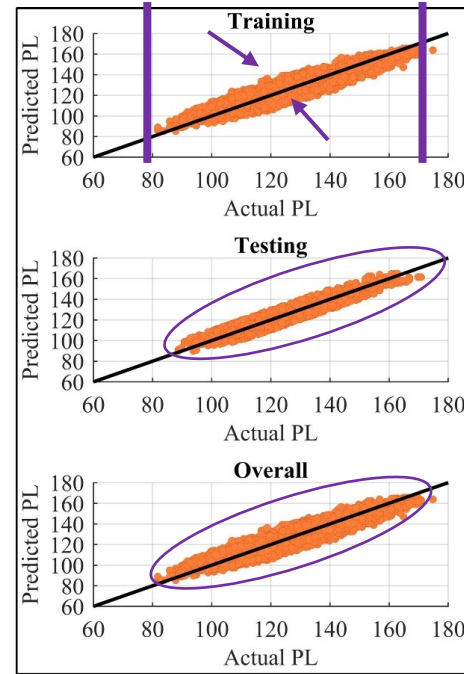
# Propagation Characterization using Hybrid Machine Learning

Significantly improved fitting



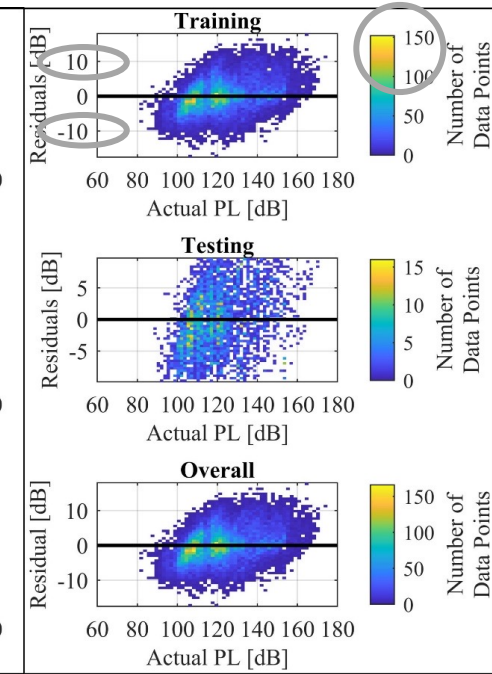
Measured vs. predicted PL from FSPL (baseline), LNSPL, and the proposed model for training, testing, and overall dataset

High correlation



(a)

Uniformly distributed residuals



(b)

Proposed PL model performance. (a) Actual vs. predicted PL correlation scatter plots. (b) Residuals vs. actual PL scatter plot with a 2D histogram, showing the density of the residuals spread across the range of actual PL.

# Propagation Characterization using Hybrid Machine Learning

The proposed model outperforms other conventional PL models as it is more flexible and provides the highest prediction accuracy, especially in rural and suburban areas.

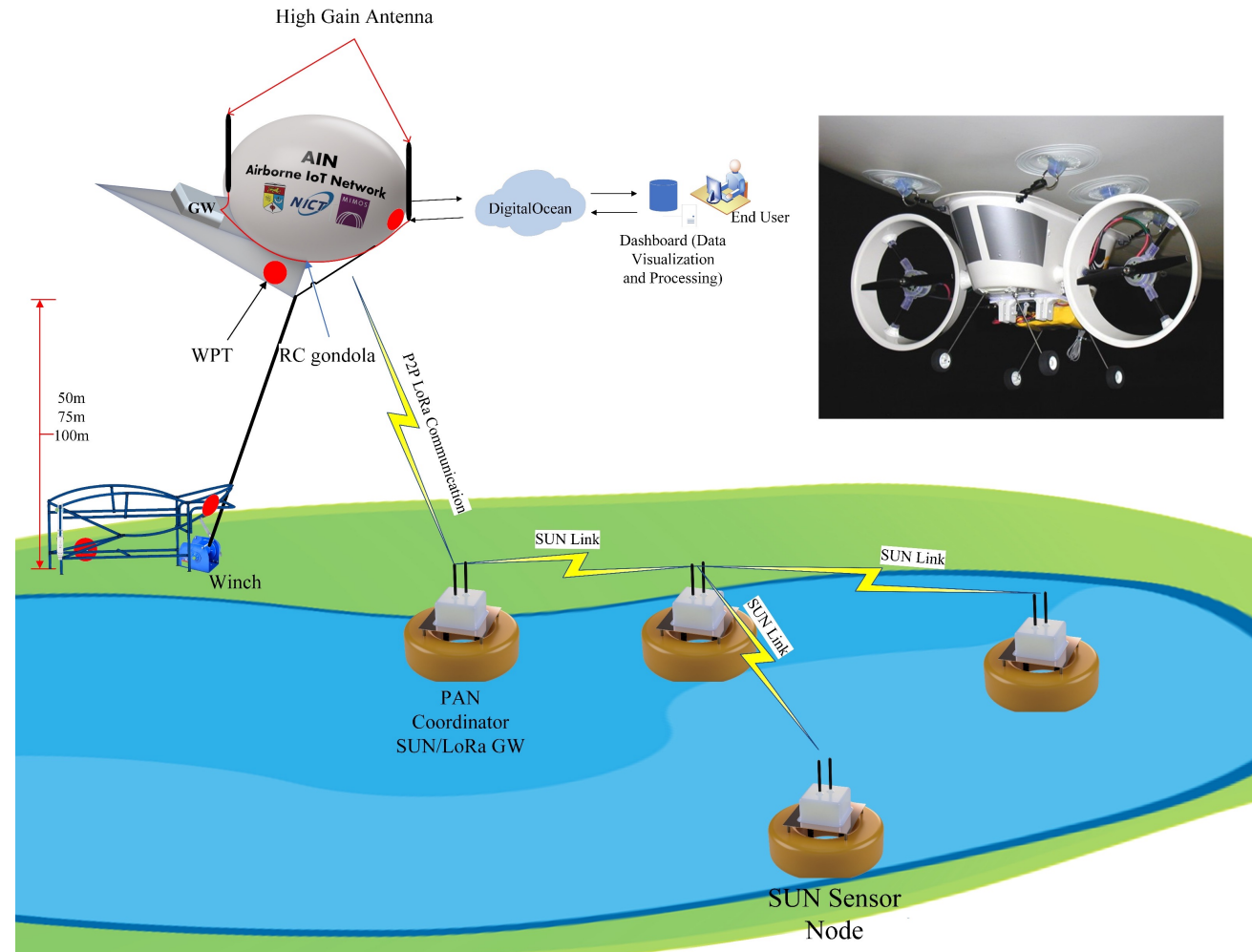
Set	MSE	RMSE	MAE	MAAPE	R	R <sup>2</sup>
Training	19.13	4.37	3.38	2.79	0.958	0.918
Testing	21.76	4.67	3.87	3.24	0.945	0.892
Urban training	21.32	4.62	3.64	2.82	0.918	0.834
Urban testing	22.15	4.71	3.84	3.01	0.885	0.779
Suburban training	17.16	4.14	3.18	2.69	0.96	0.92
Suburban testing	22.07	4.7	3.91	3.3	0.938	0.879
Rural campus training	22.9	4.79	3.73	3.11	0.935	0.871
Rural campus testing	21.81	4.67	3.84	3.25	0.921	0.847
Rural forest (Chini) training	26.56	5.15	4.15	3.07	0.939	0.877
Rural forest (Chini) testing	22.74	4.77	3.97	2.97	0.937	0.869
Rural lake (Chini) training	19.69	4.44	3.44	2.71	0.973	0.947
Rural lake (Chini) testing	19.5	4.42	3.68	2.97	0.971	0.941
Rural training	22.37	4.73	3.69	2.98	0.957	0.915
Rural testing	21.16	4.6	3.8	3.12	0.955	0.911
Rural all	22.19	4.71	3.71	3.01	0.957	0.914
All	19.51	4.42	3.45	2.86	0.957	0.915

Annotations:

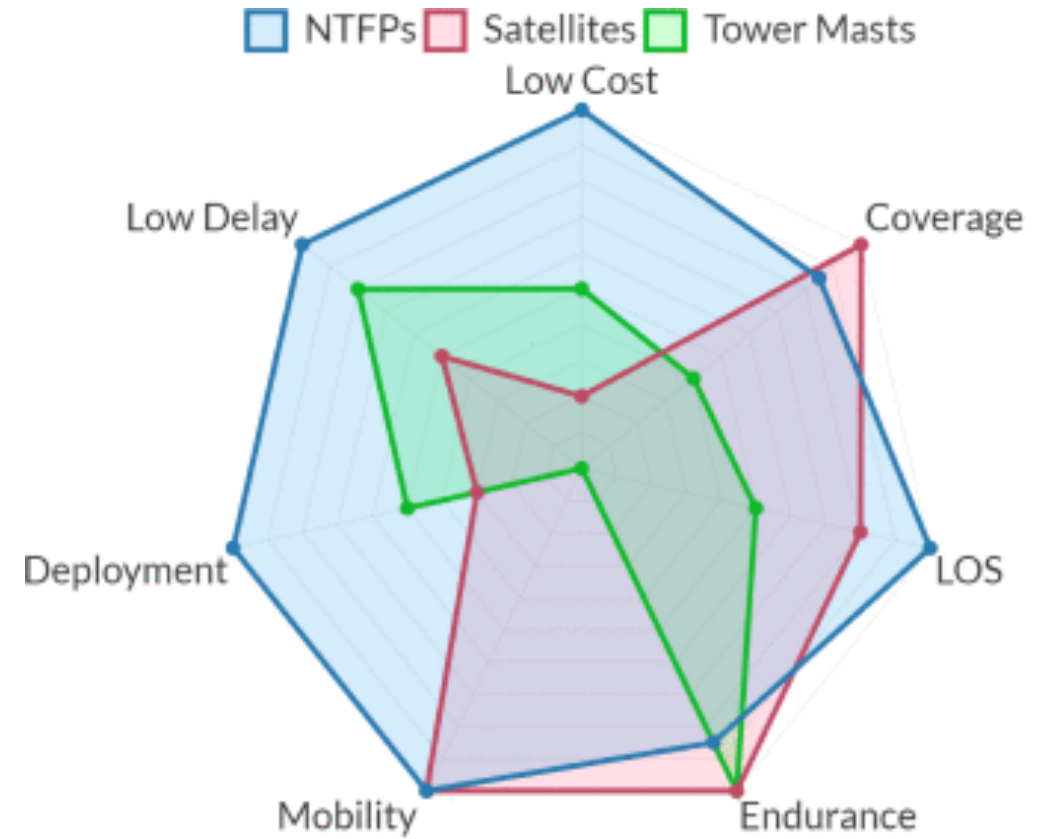
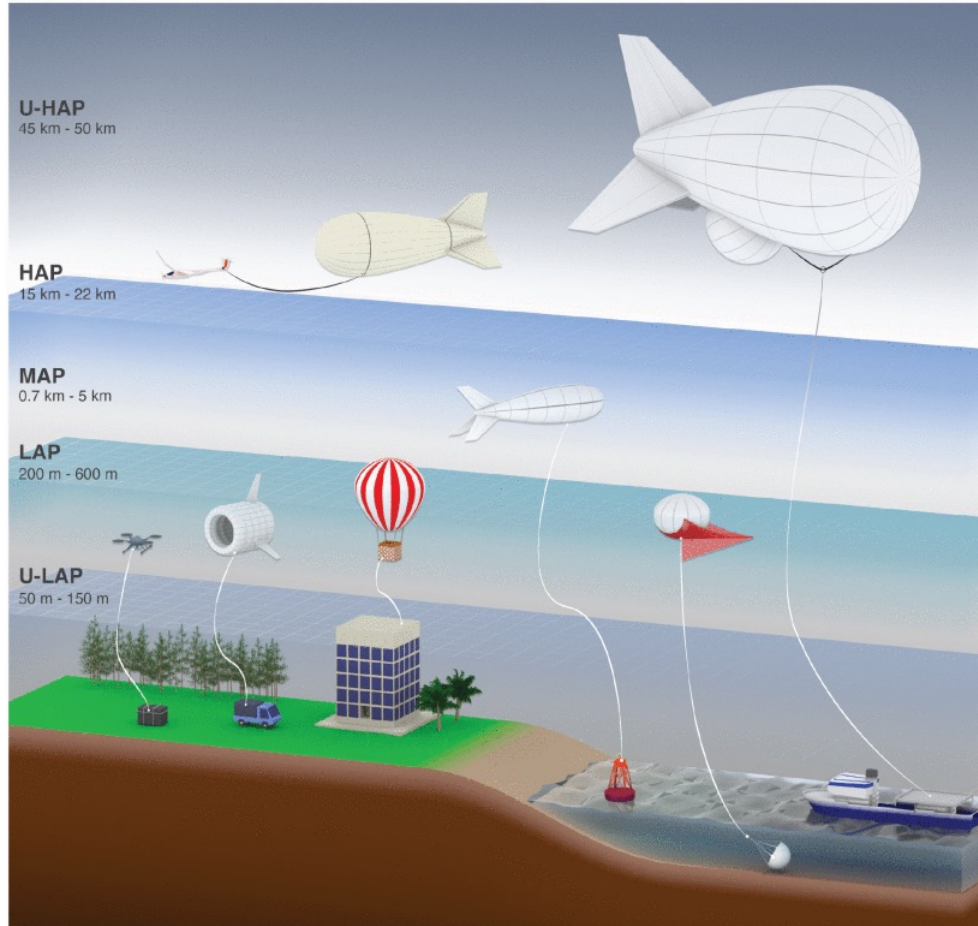
- Highest prediction accuracy 94% (points to Training R<sup>2</sup> = 0.918)
- Best performance 91.8% (points to Rural testing R<sup>2</sup> = 0.911)
- 91.8% (points to Training R<sup>2</sup> = 0.918)
- 89.2% (points to Testing R<sup>2</sup> = 0.892)
- 91.5% (points to Rural training R<sup>2</sup> = 0.915)
- Low error across all metrics (bracketed under MSE, RMSE, MAE, MAAPE for the 'All' row)

# Lesson Learned & Opportunities

- Limited availability & accessibility of helium gas with high operation cost in remote areas
- Alternative solutions that do not heavily rely on helium or explore more sustainable lifting gases
- Helikite balloon may be further stabilized remotely by using an RC gondola
- Increase the helium retention period by coating the balloon surface with nanomaterials or use other materials, such as aerogel
- Expanding the LAP system usage by adapting other sensors onboard



# LAP Communications in Rural & Underserved Area



(a) NTFPs, satellites, and tower masts.

B. E. Y. Belmekki and M. -S. Alouini, "Unleashing the Potential of Networked Tethered Flying Platforms: Prospects, Challenges, and Applications," in *IEEE Open Journal of Vehicular Technology*, vol. 3, pp. 278-320, 2022

# Key Takeaways

The challenge to push wireless connectivity in tropical setting based on rural lake forest and tough climate in Malaysia via AIN, a form of LAP-IoT

Explore opportunity to introduce a path loss model for LPWAN communications, based on combination of empirical and deterministic using Machine Learning

The implementation of AIN in rural area encountered with several challenges, such as technical, practical and cost

With the surging interest on NTN in 6G, will there be an opportunity to rekindle interest of LAP for rural or sustainable development?





# Thank You!

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