

Indigenous Community Connectivity: Enhancing LoRa WAN Performance through Machine Learning in Palm Oil Plantations

**Nor Fadzilah Abdullah , Asma Abu Samah, Ammar Zaid Norabid, Nur
Hasinah Najiah Maizan, Haider A.H. Alobaidy, Rosdiadee Nordin**

**Universiti Kebangsaan Malaysia, Al-Nahrain University Iraq,
Sunway University Malaysia.**

Overview

- Introduction
- Motivation
- Objectives
- Literature review
- Methodology & measurement setup
- Results and discussion
- Conclusions



Introduction



- In precision farming/ agriculture, IoT applications involve connected sensors and devices that optimize irrigation, monitor soil conditions, and enhance overall crop management. Real-time data allows farmers to make informed decisions, improve yield quality, and reduce resource wastage.
- In Malaysia, palm oil plantation is the largest agricultural sector (around 5.65 million hectares area in 2023), which also offers jobs for indigenous communities in remote areas.
- LoRa (Long Range) facilitates long-distance and low-power communication, making it ideal for remote areas.
- LoRa WAN propagation model in plantation areas is important for planning network topology and performance → to identify the best locations of end nodes and gateways ($RSSI > \text{minimum GW sensitivity}$)



Motivation

Frequency

- There are 4 LoRa operating frequencies depending on regions. But lack of research on LoRa propagation characteristics at 923 MHz and tropical environment.
- Previous research using 433 MHz (Anzum et al. 2022) does not comply with Malaysia spectrum regulations.

Foliage

- LoRaWAN signal attenuation occurs in plantation areas due to dense foliage.
- There is lack of research on LoRaWAN signal attenuation in oil palm plantations.

Channel model

- Existing empirical/mathematical models do not consider wireless signal propagation affected by scatterers in a dense foliage environment.
- Machine learning avoids the need for complex mathematical models, but requires large datasets.

Objectives

To implement a prototype of a LoRa network at 923 MHz using RAK Gateway and RAK Field Tester.

To measure LoRa WAN P2P (point-to-point) signal attenuation at 923 MHz considering foliage profile of a palm oil plantation at various channel conditions & GW heights.

To develop a machine learning-based LoRa WAN signal attenuation model due to foliage effects in oil palm plantations.



Literature Review

FREQUENTLY USED PATH LOSS MODELS

MODEL	AUTHORS	EQUATION	NO	PARAMETER
WMED	(RAHEEMAH 2016; RAHIM 2017; SILVA 2018; ANSAH 2020; KO 2020)	$\begin{cases} PL_{W_MED} = \begin{cases} 1.33f^{0.284}d^{0.588} & \text{for } 14m < d \leq 400m \\ 0.45f^{0.284}d & \text{for } 0m < d \leq 14m \end{cases} \\ 230MHz \leq f \leq 95GHz \end{cases}$	2.1	f is the frequency in MHz (except for WMED, frequency is given in GHz), d is the tree depth in m
ITU-R	(RAHEEMAH 2016; RAHIM 2017; SILVA 2018; ANSAH 2020; ANZUM 2022)	$\begin{cases} PL_{ITU-R} = 0.2f^{0.3}d^{0.6} \\ 200MHz \leq f \leq 95GHz, d \leq 400m \end{cases}$	2.2	
FITU-R	(RAHEEMAH 2016; RAHIM 2017; SILVA 2018; ANSAH 2020)	$\begin{cases} PL_{FITU-R} = \begin{cases} 0.37f^{0.18}d^{0.59} & \text{for out of leaf} \\ 0.39f^{0.39}d^{0.25} & \text{for in leaf} \end{cases} \\ 10GHz \leq f \leq 40GHz, d \leq 400m \end{cases}$	2.3	
COST-235	(RAHEEMAH 2016; RAHIM 2017; SILVA 2018)	$\begin{cases} PL_{C235} = \begin{cases} 26.6f^{-0.2}d^{0.5} & \text{for out of leaf} \\ 15.6f^{-0.009}d^{0.26} & \text{for in leaf} \end{cases} \\ 9.6GHz \leq f \leq 57.6GHz, d \leq 200m \end{cases}$	2.4	
Chen & Kue	(SILVA 2018)	$\begin{cases} PL_{C-K} = \begin{cases} (0.001f + 0.2)d + 0.5f + 3 & \text{vertical polarization} \\ (0.002f + 0.2)d + 0.03f + 2 & \text{horizontal polarization} \end{cases} \\ 1GHz \leq f \leq 100GHz \end{cases}$	2.5	
WEISSBERGER	(ANZUM 2022)	$L_W(dB) = \begin{cases} 1.33f^{0.284}d^{0.588} & ; 14\text{ m} < d < 400\text{ m} \\ 0.45f^{0.284}d & ; 0\text{ m} < d < 14\text{ m} \end{cases}$ $230\text{ MHz} < f < 95\text{ GHz}$	2.6	

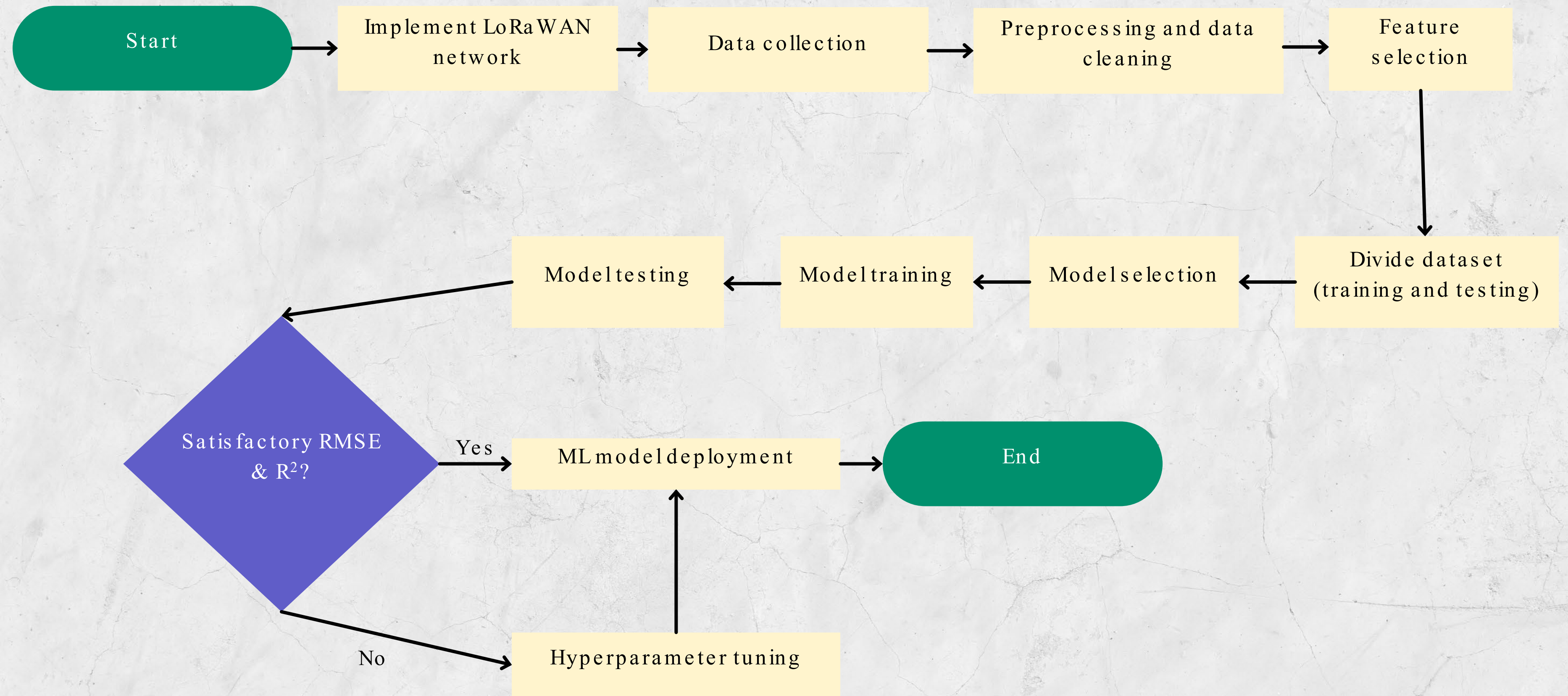
Literature Review

FREQUENTLY USED PATH LOSS MODELS

MA	(HEJSELBAEK 2018; KO 2020)	$ \begin{cases} PL_{MA} = A_m(1 - e^{-\left(\frac{\xi d}{A_m}\right)}) \\ A_m = A_1 f^{\alpha_1} \\ 30MHz \leq f \leq 100GHz \\ A_1 = 0.18, \alpha_1 = 0.752 \text{ for tropical trees at } 900 - 1800MHz \\ @h_{Rx} = 2.4m \text{ with } 15m \text{ average tree height} \\ A_1 = 1.15, \alpha_1 = 0.43 \text{ for mixed forest at } 900 - 2200MHz \\ @h_{Rx} = 1.6m \text{ and } h_{Tx} = 25m \text{ with } 15m \text{ average tree height} \\ A_1 = 1.37, \alpha_1 = 0.42 \text{ for mixed forest at } 105.9 - 2117.5MHz \\ @h_{Rx} = 1.5m \text{ with } 14m \text{ average tree height} \end{cases} $	2.7	A_m is the maximum attenuation in dB for a specific type of vegetation, ξ is the attenuation for a very short path via a specific type of vegetative in dB/m, d is tree depth in m (propagation distance through foliage), R_0 is the initial gradient of the attenuation curve, R_∞ is final attenuation in dB/m, k is final attenuation offset in dB, f is the frequency in GHz, w is the maximum effective width between Tx-Rx, a, b, and c are estimated constants
NZG	(HEJSELBAEK 2018)	$PL_{NZG} = R_\infty d + k(1 - e^{-\left(\frac{R_0 - R_\infty}{k}\right)})$	2.8	
DG	(HEJSELBAEK 2018; RAHEEMAH 2016)	$PL_{DG} = \frac{R_\infty}{f^a w^b} d + \frac{k}{w^c} (1 - e^{-\left(\frac{(R_0 - R_\infty) W^c d}{k}\right)})$	2.9	

Source : Alobaidy et al. 2022

Methodology



Measurement Setup

Hardware



RAK10701 Field
Tester



RAK7289 Series WisGate Edge Pro
Outdoor LoRaWAN Gateway

Software



The Things Stack/ The Things
Network



TTN Mapper



MATLAB



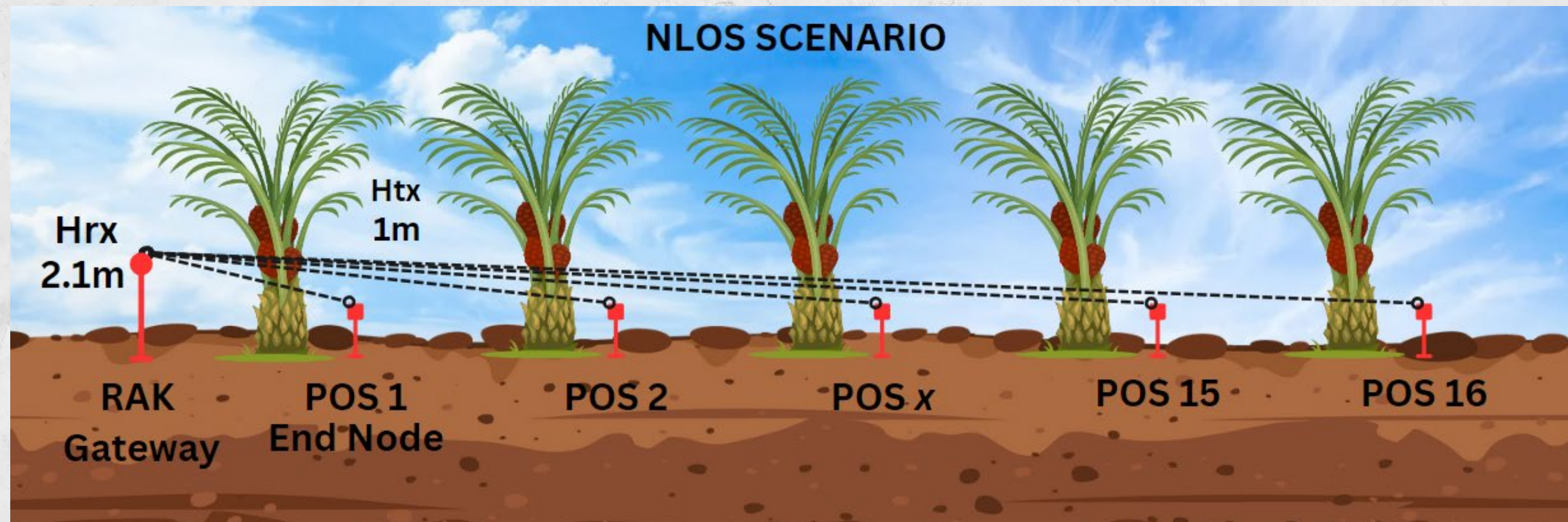
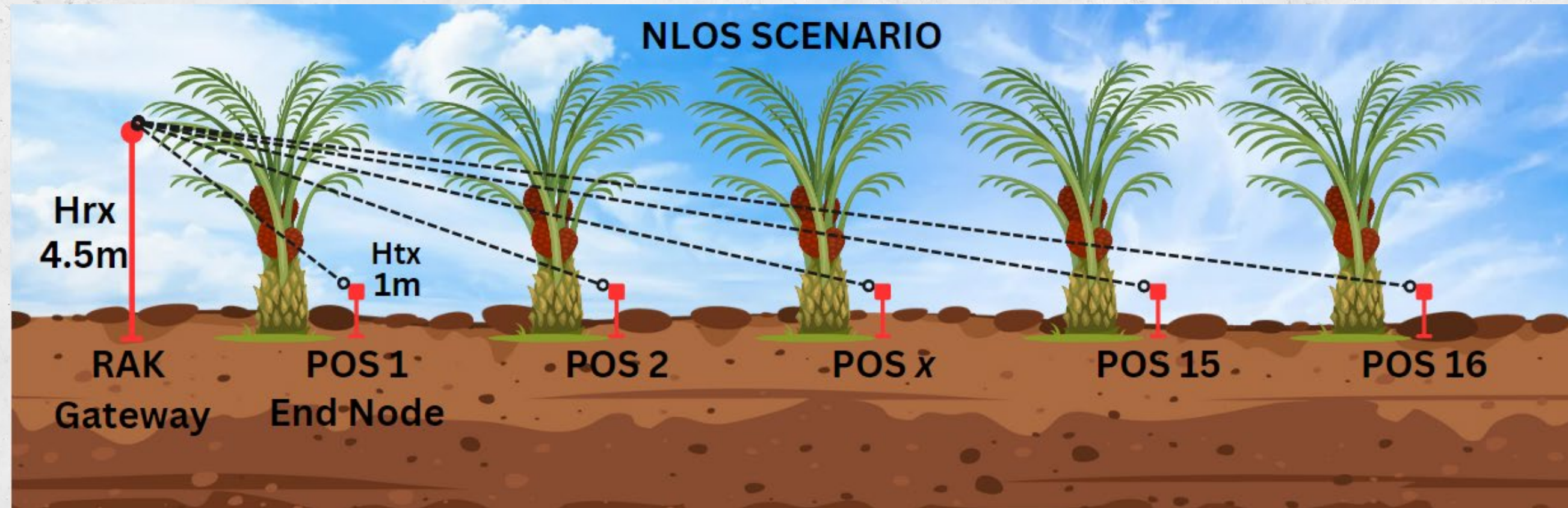
Excel

LoRaWAN parameters

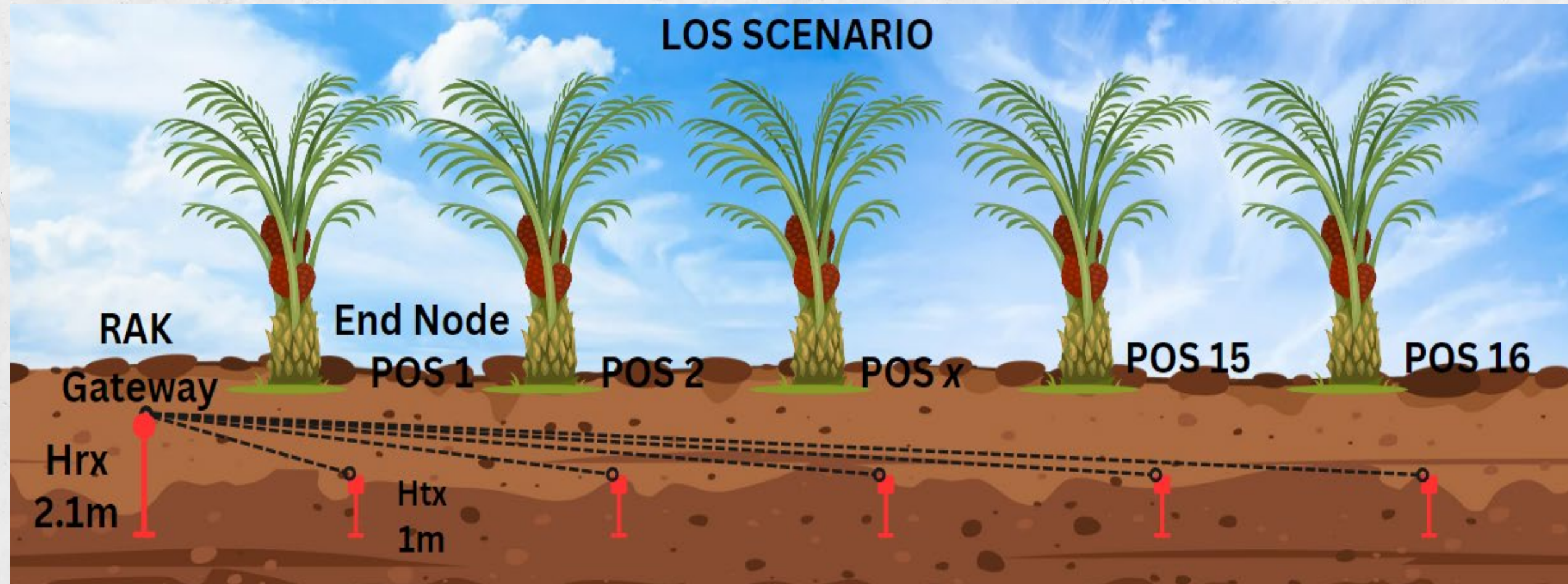
Parameter	Value
Frequency	923 MHz (AS923 -1)
Antenna gain	2.8 dBi (Field tester) & 8 dBi (GW)
Height	EN (1m), GW (2.1m & 4m)
Spreading factor	SF 10
Data rate	DR2 (980 bps)
Transmission interval	6 seconds
Transmission power	16 dBm
Receiver sensitivity	-142 dBm

Data rate (LoRaWAN)	Data rate (bps)	Spreading Factor	Time on Air (mS)	Gateway sensitivity (dBm)
DR0	290	SF12	1400	-147
DR1	530	SF11	740	-144.5
DR2	970	SF10	370	-142
DR3	1,760	SF9	200	-139.5
DR4	3,125	SF8	100	-137
DR5	5,470	SF7	56	-134.5
DR6	11,000	SF7HS	28	-131.5
DR7	50,000	FSK50	6	-116

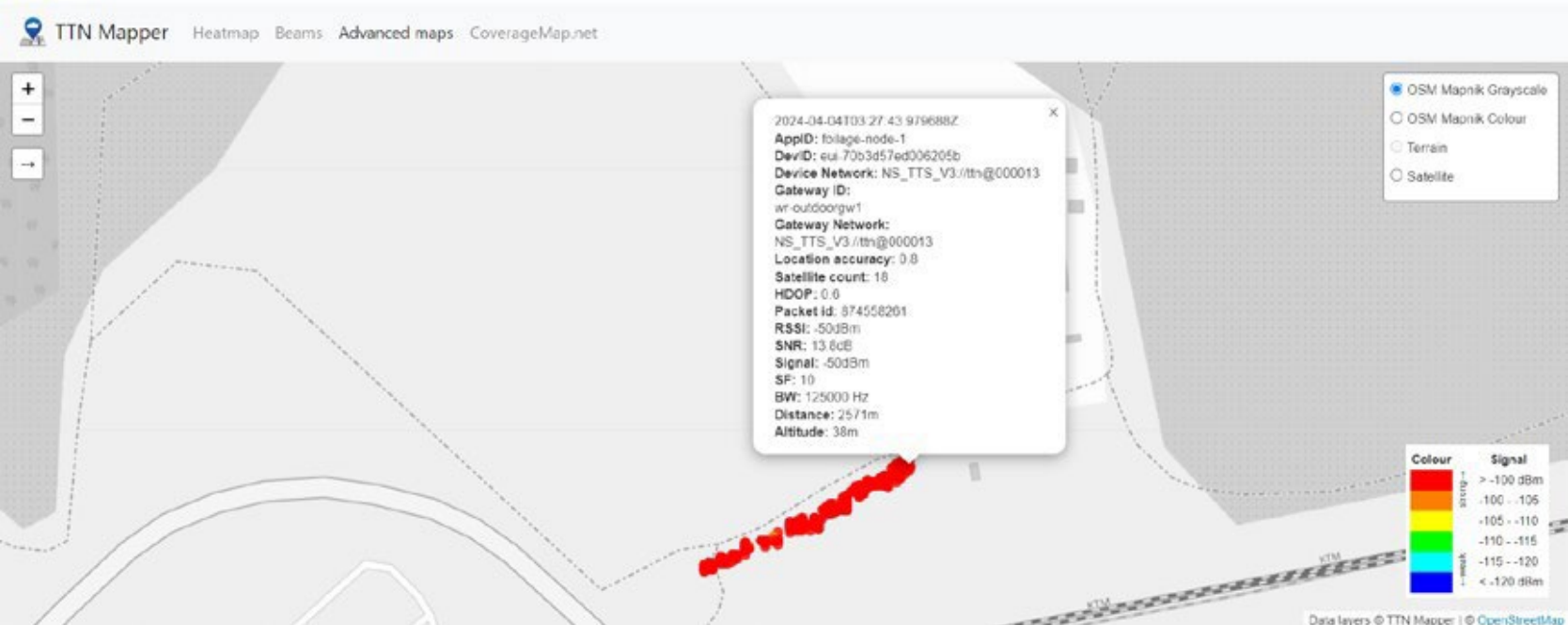
Measurement Setup (NLOS)



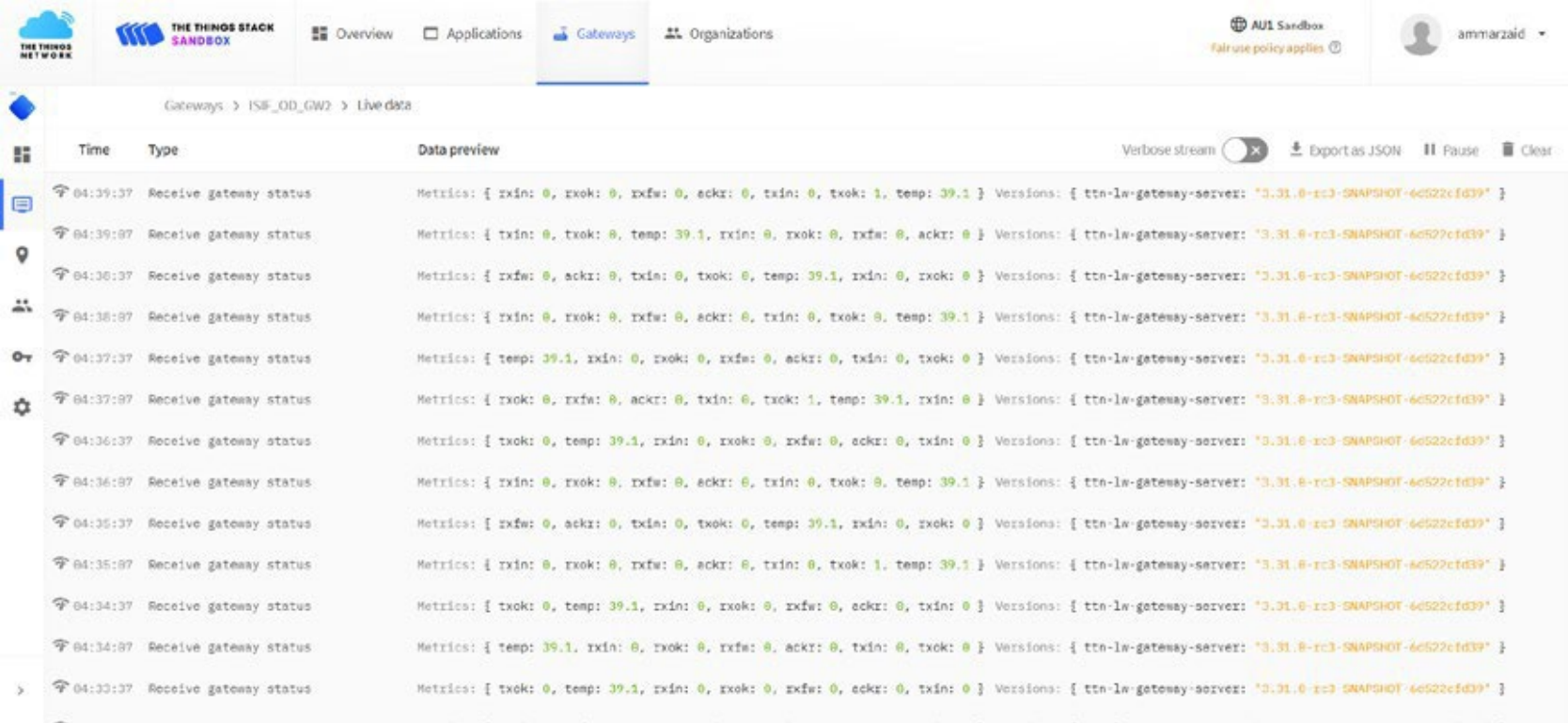
Measurement Setup (LOS)



TTN mapper



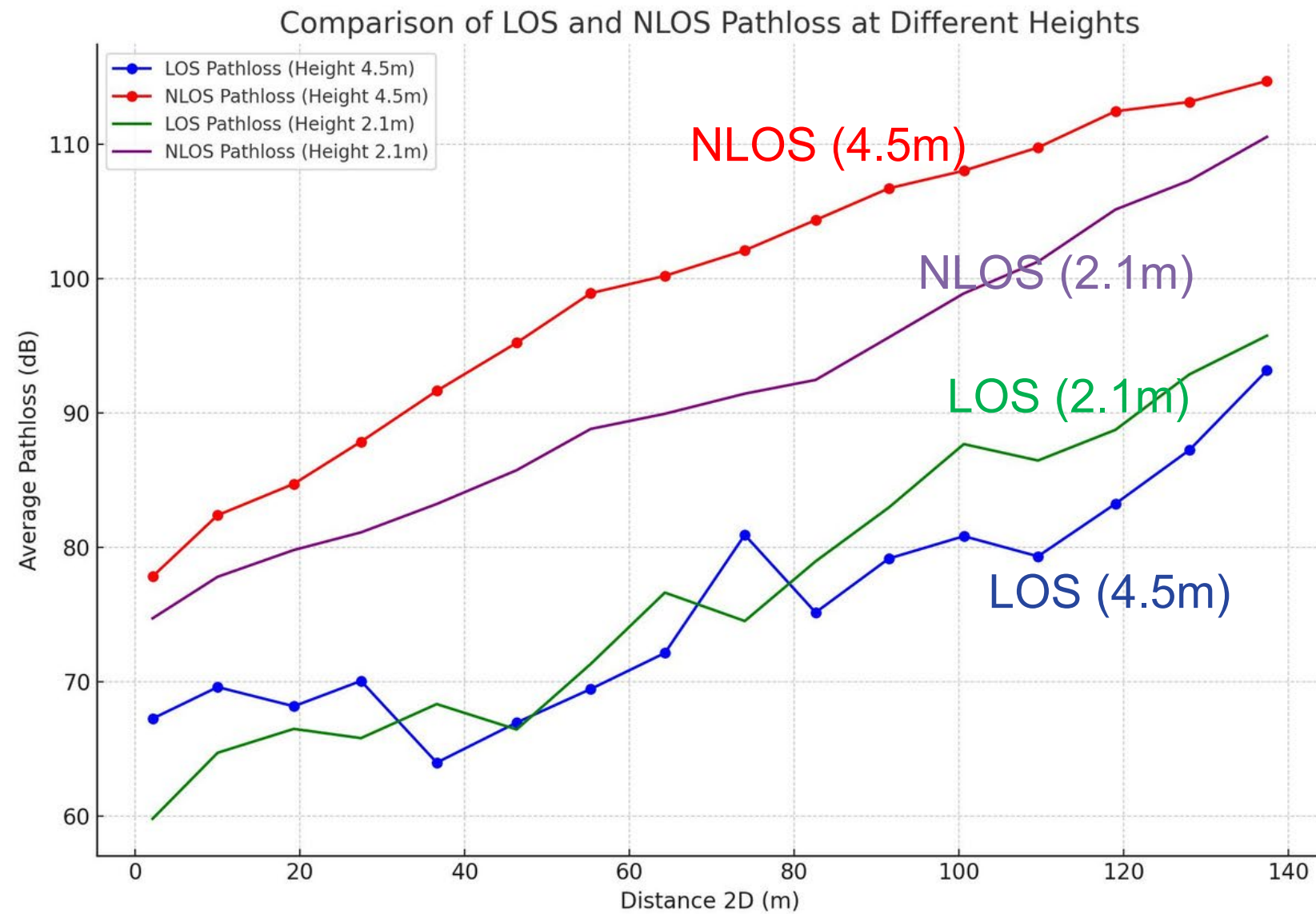
The Things Stack



Results (1): Pathloss

PATH LOSS MEASUREMENT

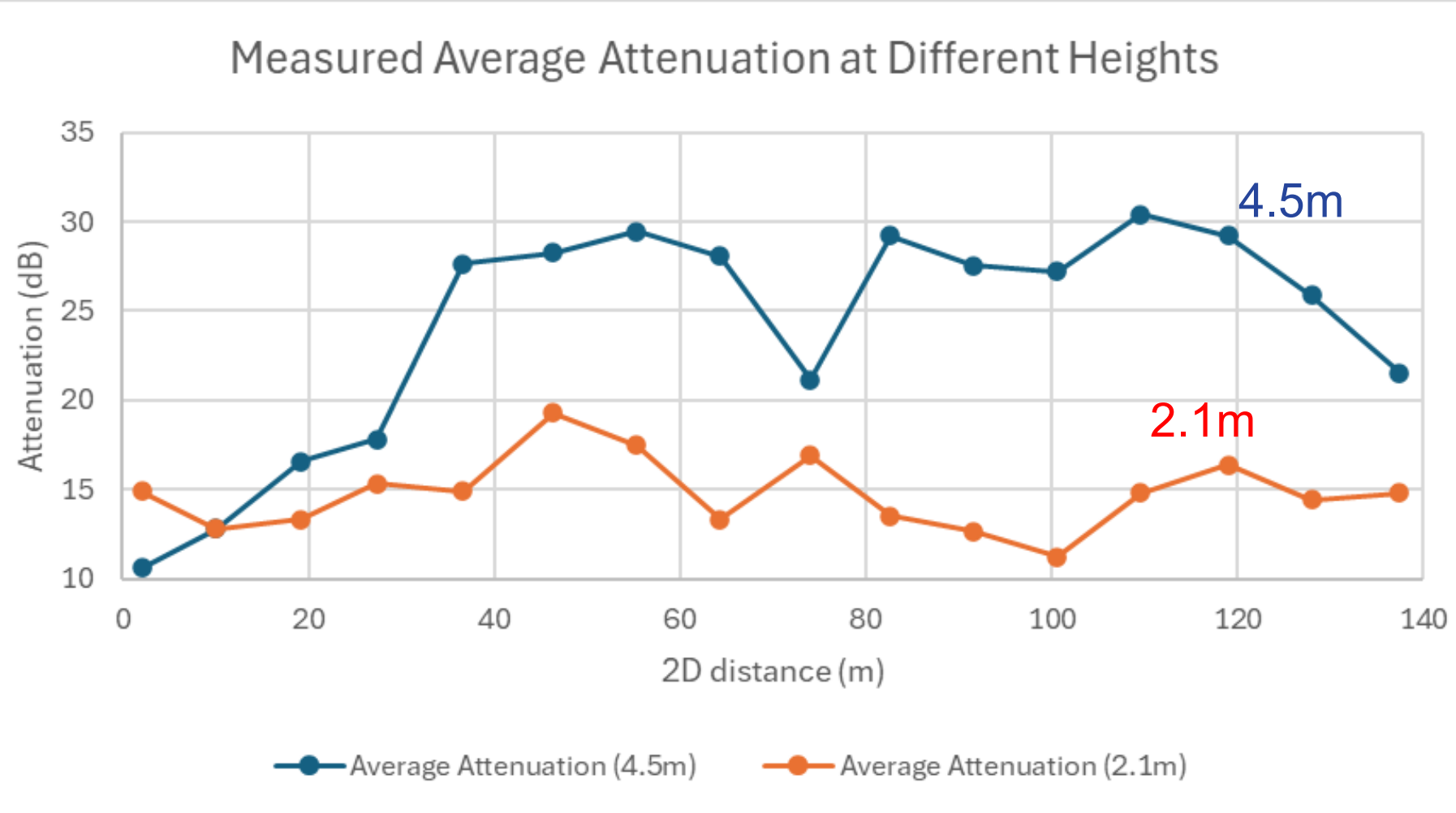
$$\text{Pathloss (dB)} = P_{tx} \text{ (dBm)} - P_{rx} \text{ (dBm)} + G_{rx} \text{ (dBi)} + G_{tx} \text{ (dBi)}$$



- Due to foliage effects, the pathloss is more significant at the gateway height of 4.5m (NLOS).
- The effect of uneven terrain is more prominent in 2.1m (LOS).

Distance 2D (m)	LOS Pathloss (4.5m)	NLOS Pathloss (4.5m)	LOS Pathloss (2.1m)	NLOS Pathloss (2.1m)
2.1	67.24	77.82	59.79	74.7
10.0	69.59	82.38	64.7	77.79
19.25	68.16	84.71	66.48	79.79
27.4	70.04	87.85	65.79	81.1
36.6	63.96	91.63	68.32	83.21
46.3	66.94	95.21	66.43	85.72
55.3	69.44	98.9	71.31	88.8
64.3	72.12	100.19	76.62	89.92
74.0	80.91	102.08	74.5	91.42
82.6	75.14	104.34	78.94	92.44
91.5	79.15	106.7	82.95	95.61
100.6	80.82	108.01	87.67	98.88
109.6	79.31	109.74	86.45	101.24
119.0	83.22	112.43	88.73	105.12
128.0	87.23	113.13	92.86	107.28
137.4	93.15	114.69	95.73	110.53

Results (2): Attenuation



Distance 2D (m)	Average Attenuation (4.5m)	Average Attenuation (2.1m)
2.1	10.58	14.91
10.0	12.79	12.79
19.25	16.55	13.31
27.4	17.81	15.31
36.6	27.66	14.89
46.3	28.26	19.29
55.3	29.45	17.49
64.3	28.07	13.31
74.0	21.17	16.92
82.6	29.2	13.5
91.5	27.55	12.66
100.6	27.2	11.21
109.6	30.42	14.79
119.0	29.21	16.39
128.0	25.9	14.42
137.4	21.54	14.8

- Due to foliage effects, the attenuation is more significant at the gateway height of 4.5m (NLOS).

Attenuation (dB)= LOS Pathloss (dB)- NLOS Pathloss (dB)

↙
↙
↙

Foliage factor
Distance factor
Distance + Foliage factors

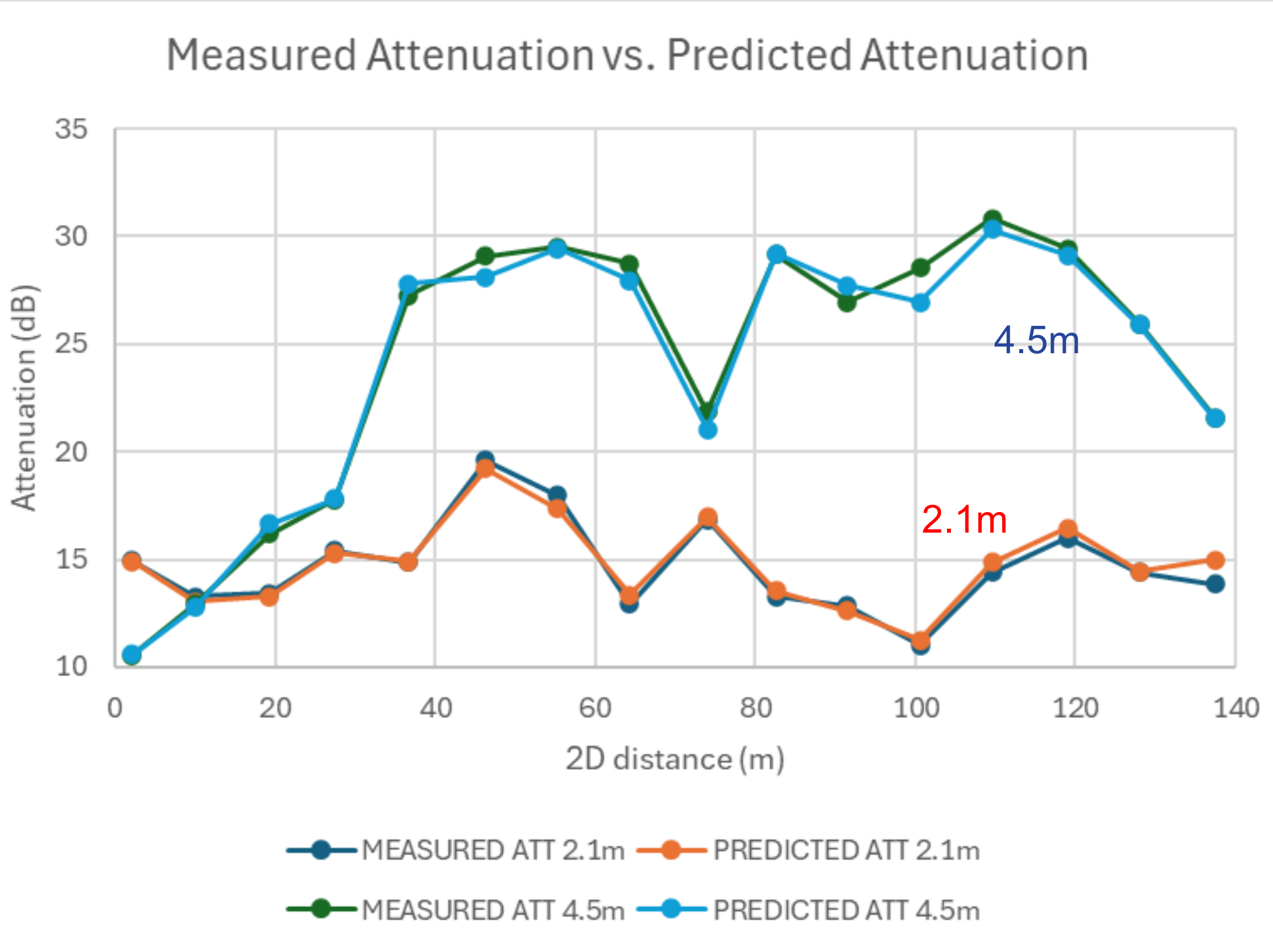
ML Model

Specification	Description
Type of model	Optimizable Tree
No. of features	8
Cross-validation method	10-fold cross-validation
Training/testing split	80% training, 20% testing
PCA (principal component analysis)	At least 95% variance
Optimization method	Bayesian optimization
Specification	Description
Type of model	Optimizable Tree

Measurement features

- 3 D distance
- 2 D distance
- Scenario type
- GW height
- Number of trees
- Average foliage depth
- Average branch diameter
- Average tree circumference

Results (3): ML model



Training vs. Testing

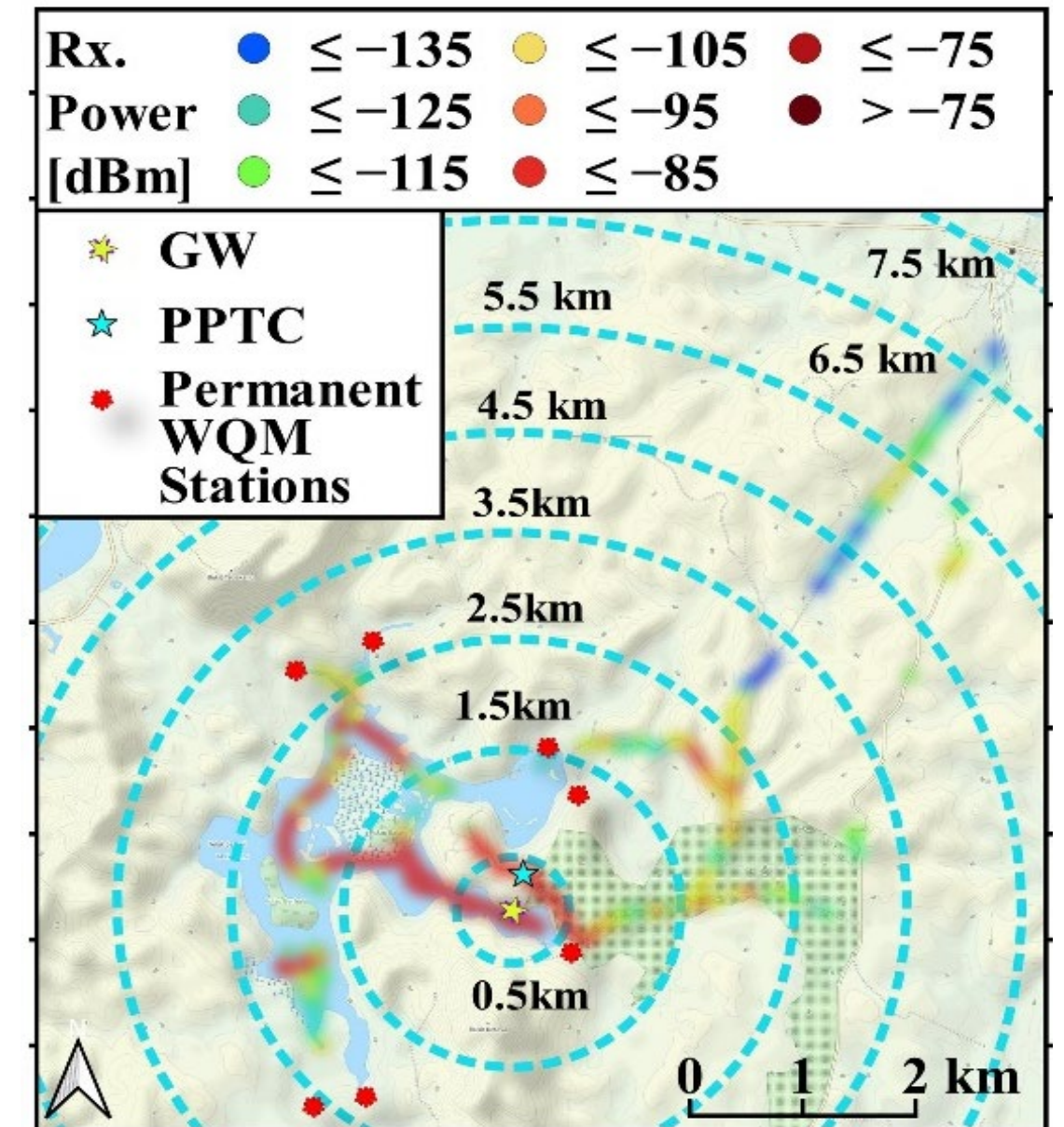
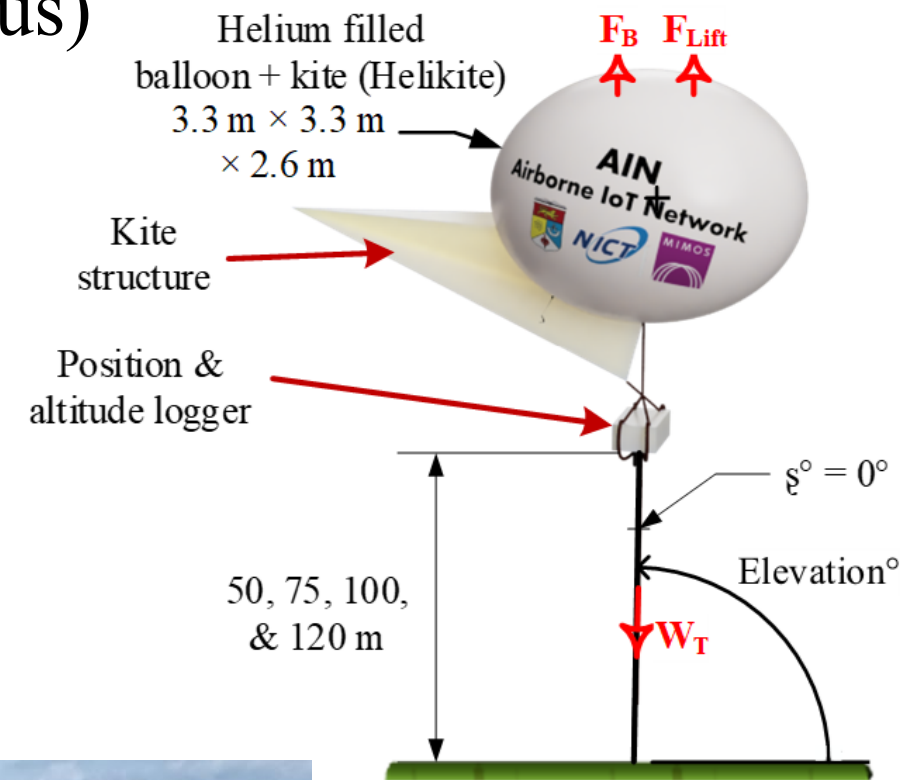
Dataset	RMSE (dB)	R-squared
Training	2.5378	0.8726
Testing	2.5721	0.8751

ML performance based on random data

HGW (m)	DISTANCE 2D (m)	ATTENUATION (dB)	PREDICTED ATTENUATION (dB)	ATTENUATION BY ITU-R (dB)
4.5	137.4	23.15	21.53	29.74
2.1	137.4	17.57	14.99	
4.5	128	27.79	25.88	28.5
2.1	128	15.77	14.43	
4.5	119	26.55	29.13	27.28
2.1	119	15.53	16.44	
4.5	109.6	32.76	30.33	25.97
2.1	109.6	13	14.87	
4.5	100.6	8.93	11.25	24.67
2.1	100.6	29	26.94	

Helium balloon: LoRa Measurement (Chini)

- Area types: suburban area (UKM campus)

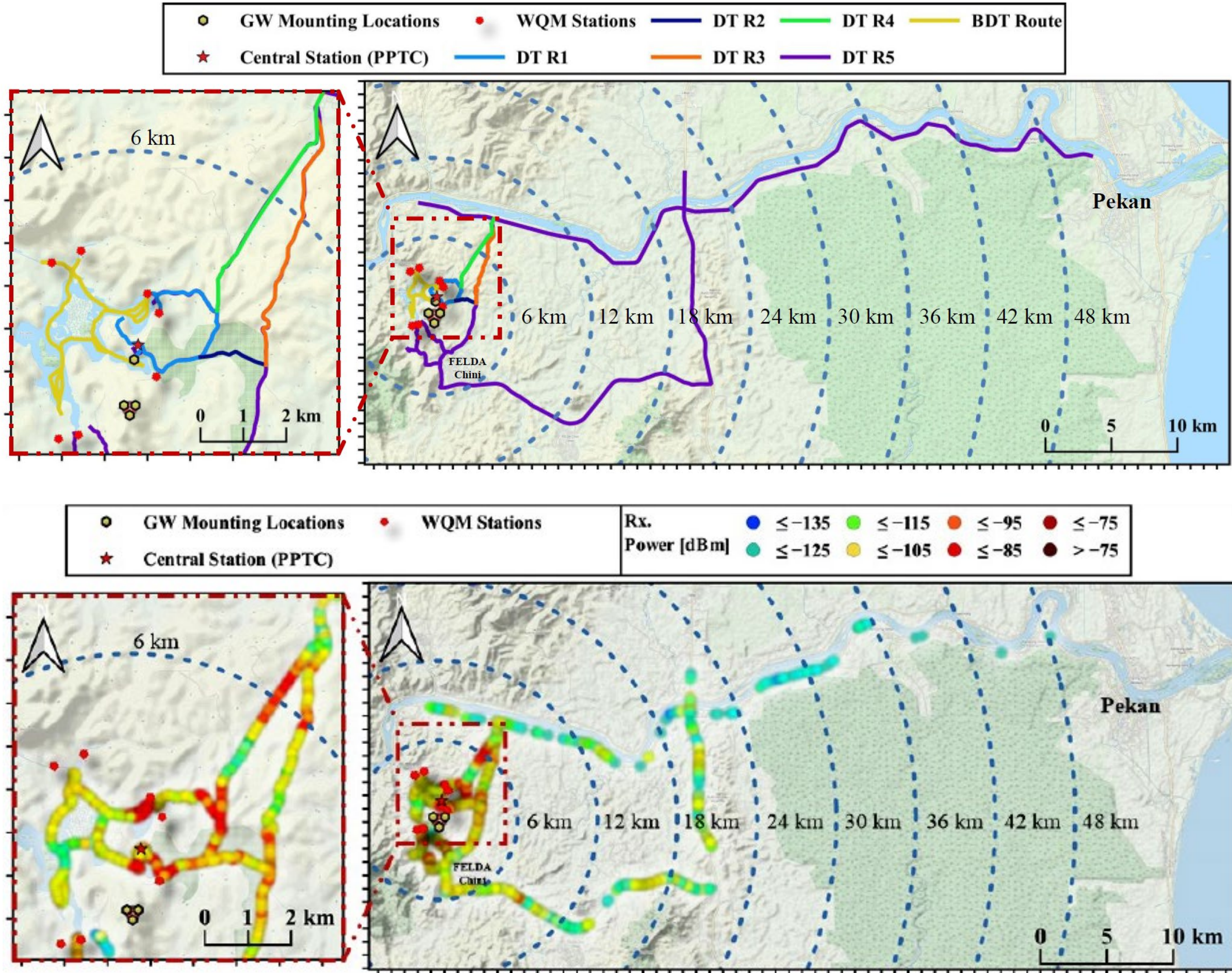


Heatmap of LoRa DTs and BDTs coverage at Chini Lake area for a GW at 120m with SF10 configuration.

Chini: Measurement

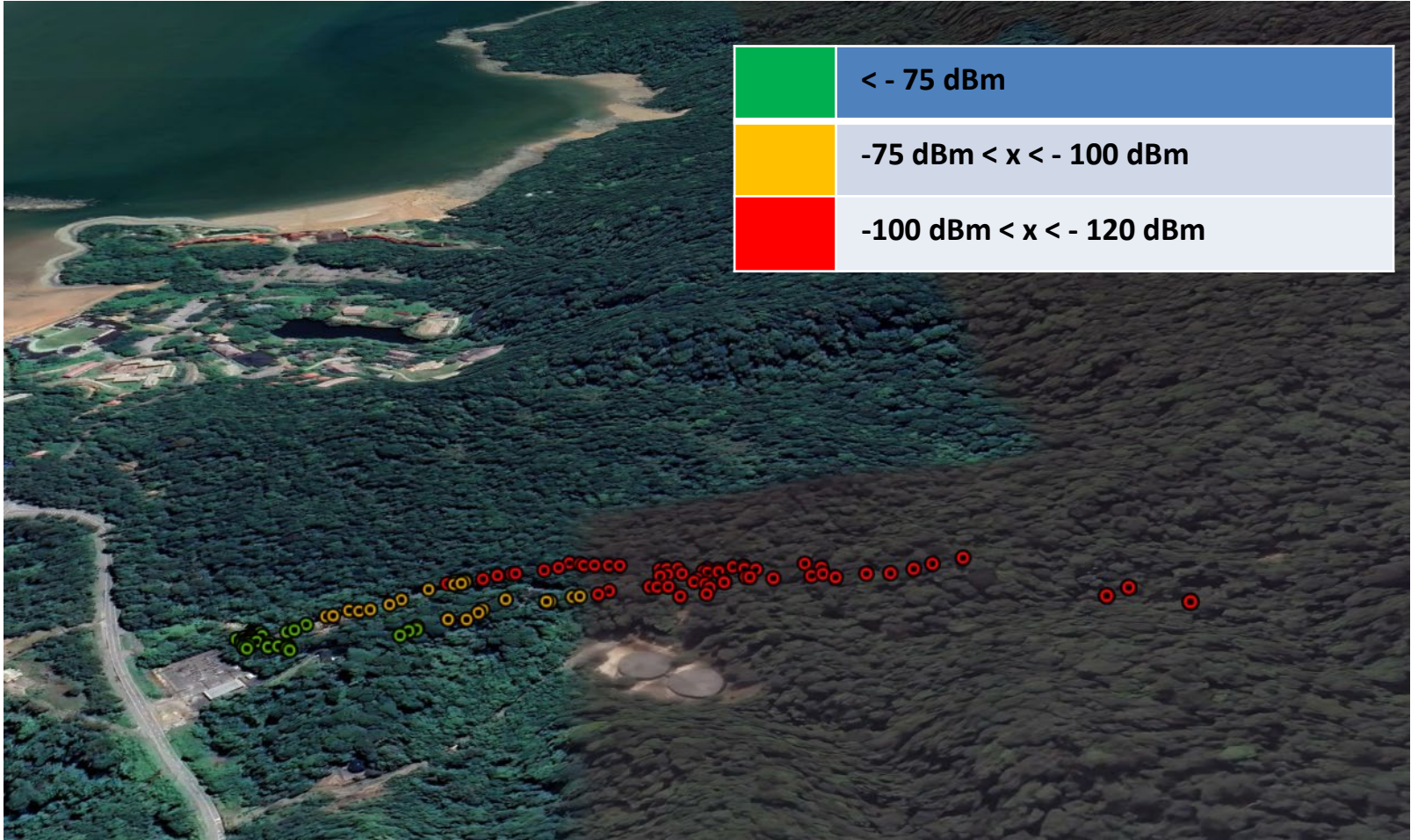


Fixed mounting structure:
Longer communication distances (up to 48 km) due to the higher mounting location at Bukit Ketaya (220m ASL) and the use of higher gain antennas for the GWs.

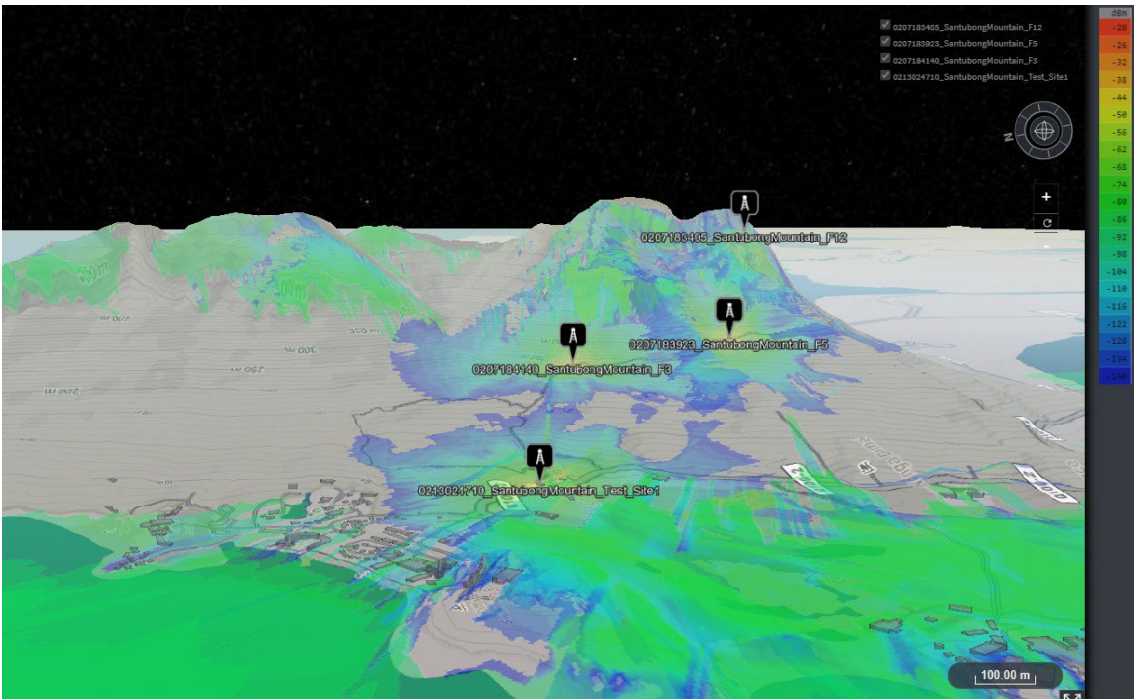
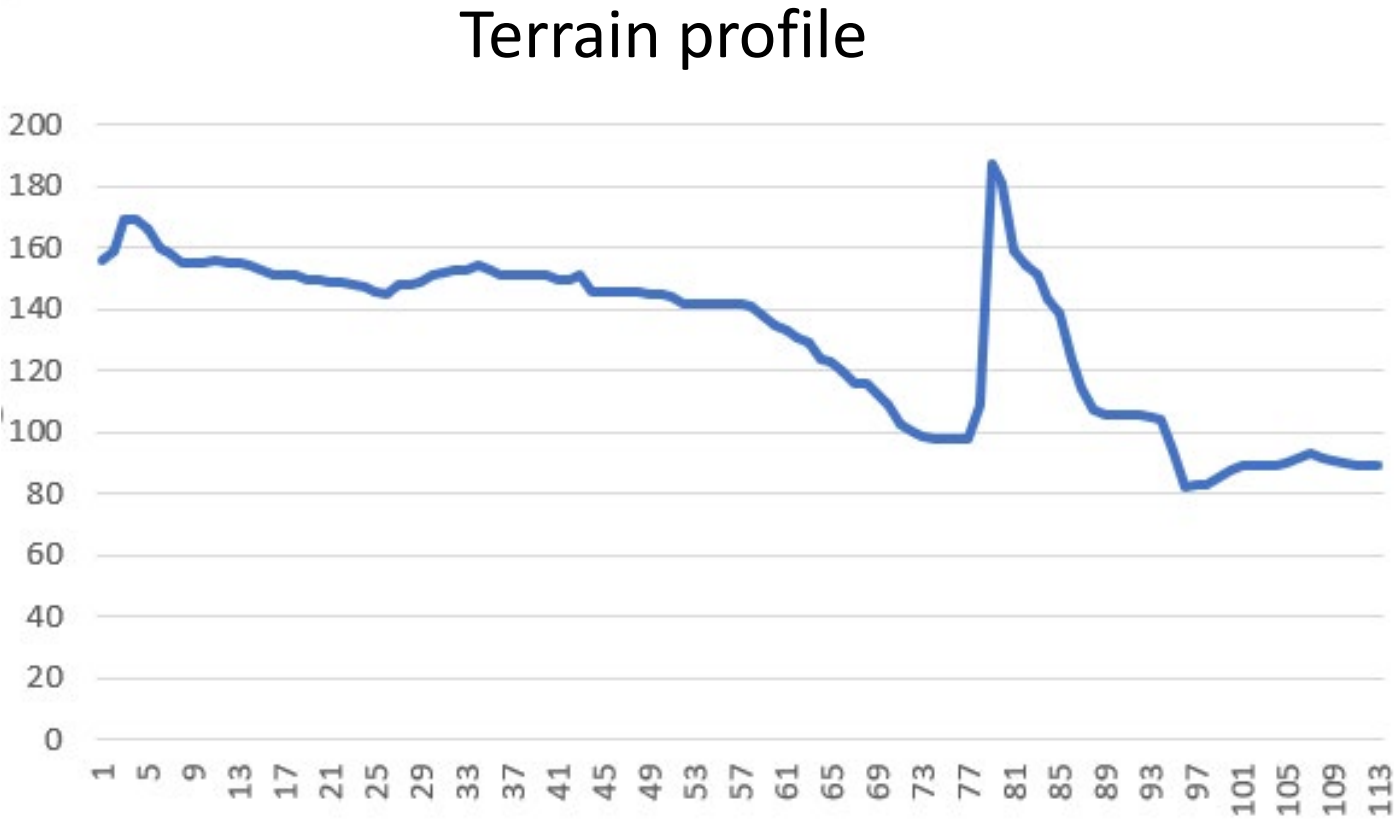


Field work @ Kuching, Sarawak (6-8 Feb 2023)

RSSI measurements in Mount Santubong, Sarawak



Coverage for 4 proposed GW locations



Conclusions

- LoRa signal is impacted by foliage and terrain effects.
- Measurement campaigns are essential for LoRa network planning.
- It is important to identify GW locations and heights. Coverage holes are inevitable in dense foliage, but can be compensated by integrating with other technology, e.g. Mesh LoRa.
- Improvement opportunity: dataset with more locations and scenarios.

Thank you!

fadzilah.abdullah@ukm.edu.my