A Data-Driven Model for LoRaWAN Connection Quality and Coverage

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***Abstract*—LoRaWAN is a popular Long-Range Low-Power wireless communications protocol that is enabling many IoT applications worldwide, with more networks growing both in size and number around the world. To effectively plan and operate these networks, it is necessary to have tools that reliably quantify, measure, and predict the connection quality provided by LoRaWAN receivers. Being able to reliably quantify connection quality would allow LoRaWAN adopters to answer questions such as, "What does 'good coverage' mean?". Reliably measuring coverage would allow for questions like "What is the quality of network coverage in a given area?", to be answered, while predicting connection quality would allow adopters to answer questions such as "What would the coverage quality be if we deployed an additional wireless receiver in this location?" This paper proposes a novel data-driven approach to connection quality modeling that is tailored for LoRaWAN with the following features. First, connection quality is quantified by the packet reception rate (PRR), as opposed to the traditional received signal strength typical of generic radio planning tools. The PRR more closely captures what network operators and users ultimately care about. Next, we leverage a large set of original data to fit a model for PRR. This dataset is unique in two ways. First, it includes transmissions that were transmitted but not received by any gateway, eliminating an otherwise persistent source of bias in empirical estimates of wireless connectivity. Second, it includes features derived from high-fidelity terrain topology extracted from LiDAR point clouds. Our model includes both feature extraction and estimation. We evaluate our model out-of-sample, including in regions entirely disjoint from the training data, and show that it is considerably more accurate than common benchmark wireless propagation models. Finally, we demonstrate how our model can be used to provide coverage maps in a real-world network.**

***Index Terms*—IoT, LoRaWAN, data-driven, connection quality, machine learning**

I. Introduction

Low Power Wide Area Networks (LPWANs) are a type of wireless telecommunication network that offers low-power IoT and machine-to-machine (M2M) communication over large geographical areas and has seen rapid growth in recent years [1]. LPWANs are ideal for tasks that require small amounts of data, including near real-time monitoring of diverse data from flooding, temperature, humidity, infrastructure, power consumption, and other energy, environmental, and smart city applications, as well as other low data rate applications for both urban and rural areas [2]–[4]. A single LPWAN receiver, or *gateway*, can provide network coverage over distances ranging from 1-5km in urban areas to 10-40km in rural areas [5]. Moreover, one LPWAN gateway can serve up to thousands of compatible end devices [27]. This work focuses on long-range wide-area networks (LoRaWAN), one of the most popular LPWAN protocols. LoRaWAN differs from other LPWAN protocols in that (i) it allows for long-range communication with low power requirements and (ii) it is open-source, free to use, and accessible both in terms of cost and community-provided support. LoRaWAN uses the unlicensed industrial, scientific, and medical (ISM) radio band of the wireless spectrum, meaning there are no costs associated with its spectrum use.

As LoRaWAN adoption grows and more networks are implemented and expanded, accurately modeling LoRaWAN wireless connection quality is becoming increasingly important for informed gateway placement, network operation, and planning purposes. Being able to precisely identify areas of robust and poor network connectivity through signal propagation modeling allows LoRaWAN network adopters to optimize gateway placement locations and quantities to provide maximum coverage using minimal gateways. An accurate connection quality model also enables network adopters to identify areas where network redundancy from additional gateways might be necessary to ensure desired levels of coverage. Existing planning tools typically estimate network coverage based on propagation models that predict a received signal strength indicator (RSSI). Propagation models, including free-space path loss (FSPL) [6], Okumura-Hata [7], ITM [8], and ITWOM [9], are simple linear models

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that use features such as transmission and receiver heights, distances between them, and frequency of transmission to predict RSSI. Applying an RSSI threshold to predictions can also be used to estimate conditions for successful transmissions [10].

There are challenges with using existing RSSI-based propagation models for network planning in the context of LoRaWAN. For one, the accuracy of many models remains poorly tested for LoRaWAN. Secondly, estimating RSSI is challenging due to censoring; the received signal strength is observed only when it is above a theoretical minimum threshold for successful receptions, so special care is needed when estimating RSSI from data [10]. However, in practice, packet success is probabilistic instead of binary. For instance, a stationary transmitter may intermittently communicate with a stationary receiver over time if line-of-sight (LoS) obstructions or a considerable separating distance exist between the two, making the use of an RSSI threshold a weak indicator of packet success. Moreover, the minimum threshold is not exact. In fact, we routinely observe successful transmissions below the threshold. The threshold may also vary depending on the gateway model, antenna, and other factors. Additionally, RSSI itself is not of much interest; ultimately, it is not the signal strength that matters to the end user, but rather the rate at which transmissions are successfully received. Many existing RSSI models also make limited use of terrain-specific features, which can dictate the likelihood of successful signal transmission. Finally, many existing empirical RSSI models were not constructed using LoRaWAN-specific data but instead generalize signal propagation for large ranges of frequencies.

This paper develops an empirical model for the connection quality between LoRaWAN devices. The model eschews RSSI in favor of modeling the packet reception rate (PRR) directly. PRR is the ratio of the packets successfully transmitted to a gateway to the total packets transmitted. This can also be viewed as the probability of successful reception of a transmitted packet. PRR can be used to loosely estimate a minimum threshold for successful transmissions. However, PRR trumps RSSI in its ability to provide end-users with information on both successful and unsuccessful network transmissions.

The contributions of this work are threefold:

- We implement *(i)* a LoRaWAN testbed in Geneva, NY, consisting of 4 unique gateways and *(ii)* 3 GPS equipped LoRaWAN trackers for recording locations of successful and failed network transmissions, enabling the presentation of a real-world network transmission dataset consisting of 21,027 total attempted transmission links
- We develop a novel methodology for LoRaWAN adopters to use for predicting LoRaWAN network coverage based for their location
- We offer an alternative to existing RSSI models based on a developed PRR logistic regression model that makes use of our collected transmission data as well as widely available terrain data

The rest of this work is arranged in the following order: Section II provides a review of related work. Section III summarizes our LoRaWAN transmission data collection and processing. Section IV discusses our regression model-building process and metrics used to compare propagation models. Section V details and discusses the results of our study. Section VI draws conclusions from our work, discusses limitations, and identifies future areas of work.

II. Background

LoRaWAN is an LPWAN protocol built on top of the LoRa physical layer (PHY), based on Chirp Spread Spectrum (CSS) technology. LoRaWAN operates on the unlicensed ISM band of the wireless spectrum from 902MHz to 928MHz frequency and spreading factor (SF) 7-10 in the United States. LoRaWAN architectures typically consist of end devices and gateways that take on a star-of-stars topology, where end devices only communicate with gateways, and gateways communicate with a central network server.

Existing studies have explored LoRaWAN signal propagation from different perspectives. Gaitan et al. [22] explore LoRaWAN signal fading dynamics over estuaries, where reflection from bodies of water directly impacts signal transmission. They compare time varying empirical recordings with RSSI model predictions and show close alignment between the two. However, this work only models RSSI and does not consider modeling PRR. Other works, including [11] - [14], compare RSSI predictions from existing or proposed LoRaWAN propagation models with empirical RSSI data in indoor and outdoor environments. Still, none consider how RSSI can be related to the more practical PRR measurement.

Most generic propagation models use features that include transmission and receiver heights, distances between them, and transmission frequency to estimate a link budget to predict signal losses. The link budget models the final received signal strength as a function of (i) transmitted power, (ii) losses and gains, and (iii) minimum received power [15]. Transmitted power describes the output power at which the signal is sent from the transmitter antenna. Losses and gains decrease or increase the transmitted power as the signal traverses from the transmitter to the gateway. Path losses are the most common losses and can be attributed to factors related to distance and physical obstructions along the transmission path. Gains are most commonly attributed to antennas. The received signal strength can be represented as the difference between the transmitted power and losses, defined as:

$$P_{rx} = P_{tx} - L \tag{1}$$

where P_{rx} is the received power, P_{tx} is the transmitted power, and L is the loss. There is a minimum received power, or device sensitivity, represented as P_{min}, which is the minimum power at which a gateway can successfully receive a signal [16]; incoming signals below the threshold are lost.

Using Equation 1, RSSI models typically estimate received power by adding a predicted total signal power loss with a known transmitted power.

The FSPL model describes the signal power losses between two antennas when transmitting in an unobstructed space. FSPL depends on the frequency of the signal and the distance between signal reception and transmission. This model assumes the transmitter and receiver antennas have no losses and no multipath interference effects [6]. When measured in decibels relative to one milliwatt (dBm), FSPL is formulated as follows:

$$\text{FSPL} = 20\log_{10}(d) + 20\log_{10}(f) - 27.55, \tag{2}$$

where FSPL is the free-space path loss (dBm), d is the distance between the base and mobile stations (m), and f is the transmission frequency (MHz).

The Okumura-Hata [7] propagation model predicts path loss based on empirical data originally collected in Tokyo, Japan, in 1968. It assumes a transmission frequency of 150-1,500MHz, a transmission height of 1-10m, a reception height of 30-200m, and a link distance of 1-10km. This model depends on transmission and reception heights, transmission frequency, an antenna height correction factor corresponding to the type of geographical environment, and the distance between transmission and reception. The Okumura-Hata model also captures the effects of diffraction, reflection, and scattering caused by city structures. By adjusting the antenna height correction factor, this model can be well suited to predict path loss in small, medium, and large cities, as well as in suburban and open environments. The model is formulated as:

$$\begin{aligned} L_U = 69.55 + 26.16\log_{10}(f)–13.82\log_{10}(h_b)–C_H \\ + [44.9–6.55\log_{10}(h_b)]\log_{10}(d) \end{aligned} \tag{3}$$

$$C_H = 0.8 + (1.1\log_{10}(f)–0.7)h_m–1.56\log_{10}(f), \tag{4}$$

where L_U is the path loss (dB), h_b is the height of the base station (m), h_m is the height of the mobile station antenna (m), f is the frequency of transmission (MHz), C_H is the antenna height correction factor for small or medium-sized cities, and d is the distance between the base and mobile stations (km).

III. Data

We established a LoRaWAN network in Geneva, New York, using four Multitech Multiconnect Conduit [17] gateways. Each gateway was installed indoors for protection against tampering and weather and channeled to a 10dBi Signalplus vertically polarized omnidirectional antenna mounted on the roof of their respective host site. Signals were configured to be received using The Things Network (TTN) and saved in a database located on a network server.

We designed and constructed three GPS-equipped LoRaWAN trackers for data collection. Our tracking devices were built using an Adafruit Feather M0 LoRa Radio and SparkFun Electronics GPS-15210 Breakout board. Each device made a LoRaWAN transmission once every 30 seconds containing latitude, longitude, RSSI, signal-to-noise ratio (SNR), elevation, transmission, and gateway-related metadata. Failed transmissions did not have an associated RSSI and were assumed to be less than -127dBm, which is the minimum RSSI for our gateways containing a Semtech SX1302 baseband LoRa chip and spreading factor of 7 [16]. The transmission power P_{tx} of our trackers was the maximum power for LoRa devices, 20dBm.

Critical to our approach was a hardware innovation to avoid censoring of transmissions that were not received by any gateway. Each tracker was built with 8 gigabytes of local storage capabilities so that each transmission, including those not received by any gateway, was logged. This ensured that the location, time, and transmission metadata were stored irrespective of the success or failure of the transmission. This hardware innovation was included as existing literature has demonstrated the importance of avoiding censoring of transmissions in predicting path loss [23]–[26].

We define a link as the linear path connecting a tracker and gateway. Uncensored link data were constructed by joining the stored transmission data of the trackers with the received transmission data collected by the gateways. Each transmission produced as many links as there were gateways. In theory, every gateway could have received every transmission. If a transmission-gateway pair had a corresponding record in the TTN database, it was a success; if not, it failed. Because all transmissions were stored, even ones not received by any gateway generated link observations.

Transmission data was collected by traversing Geneva by car. Data were also collected on foot in more densely populated residential and urban areas, as well as areas that could not be accessed by car. Fig. 1 depicts a mapping of the collected data. Blue dots indicate points at which a LoRaWAN transmission was made. Larger black dots mark gateway locations.

The collected data were used in combination with a digital surface model (DSM) raster to obtain elevations for each of our transmission locations. Publicly available LiDAR point cloud data from USGS [18] were used to generate a DSM raster of elevations of the area's terrain and structures.

We generate linear links between each transmission and receiving gateway. We discretize the links into 250 evenly spaced points and pair the elevation of each discrete link point with the elevation of the terrain above or below it to calculate a "degree-of-sight", or DoS, for each point. Fig. 2 demonstrates how the DoS was obtained from an example link.

The DoS represents the percentage of unobstructed length of each link. It is continuous and equal to 0 when there is

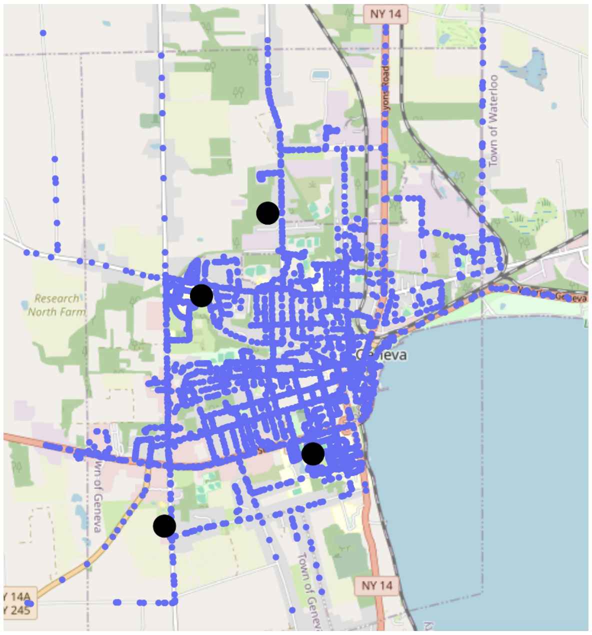

Figure 1: Mapping of LoRaWAN transmission data collected in Geneva, New York. Blue dots represent successful transmissions. Black dots represent gateway locations.

no free-space between the transmitter and receiver. Its value is 1 when there is only free-space.

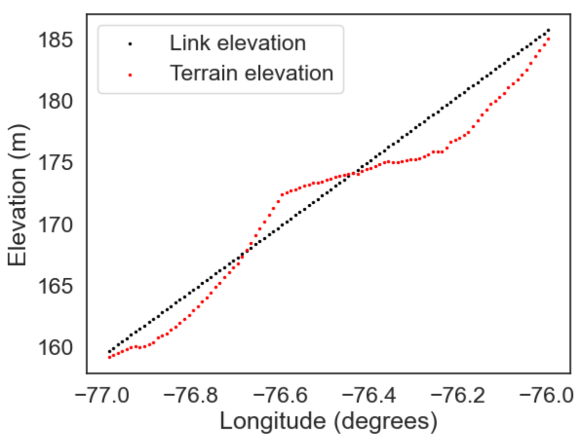

Figure 2: Example link and DoS calculation. The black line represents the elevation of the direct path (link) connecting the transmitter to the receiver. Red points indicate the elevation of the terrain along this path. Points above the black line indicate obstructions while points below it are free of obstructions. The percentage of points free of obstructions are used to calculate the DoS.

Statistics summarizing our training data are presented in Table I. 21,027 links were collected, with 20% being successful links and 80% being failed links.

Table I: Training data summary statistics

Parameters	Mean	Max	Min	Standard Deviation
Distance (m)	1,945.8	7,668.5	14.3	1,089.6
log(distance) (m)	7.4	8.9	2.7	0.7
DoS (%)	0.9	1.0	0.0	0.2

Total successful links: 4,163. Total failed links: 16,864. Total links: 21,027.

IV. Model and Experiments

Many signal propagation models, including the benchmark models in this study, make network transmission predictions using models comprised of linear combinations of features. Of these features, [21] determines distance and terrain-based features to hold the most importance in propagation modeling. Ref [21] also determines that modeling every physical phenomenon that impacts signal losses is infeasible, and instead relies on machine learning techniques to capture transmission propagation patterns. The goal of this work is to design a general modeling methodology for LoRaWAN adopters to easily predict connection quality and coverage in their respective geographical environment using few, easily obtainable yet important training features. For these reasons, we use a minimal logistic regression model consisting of a linear combination of three variables; (i) log-distance, (ii) DoS, and (iii) log-distance multiplied by DoS, passed through a logistic function, taking the form:

$$\text{PRR} = \sigma(w_1 \log_{10}(d) + w_2\text{DoS} + w_3 \log_{10}(d)\text{DoS} + w_0) \tag{5}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{6}$$

We implemented our models in Python using the statsmodels package [19], training on an nVidia RTX A6000 GPU with 48 GB of RAM using an 80:20 train-test split. We compare the prediction performance of our models with the benchmark propagation models FSPL and Okumura-Hata.

To assess the performance of our logistic regression model, we discretize our PRR predictions into binary outcomes using the following:

$$\text{PRR} = \begin{cases} 1, & \text{if PRR} > 0.5 \\ 0, & \text{otherwise} \end{cases}$$

To account for class imbalances in our dataset, we use the weighted F-score evaluation metric to assess the performance of our model.

We compare our PRR model performance with benchmark RSSI models that use a success threshold to predict PRR. To verify that the strength of our model is not driven by the thresholding, we also model RSSI. We use the link budget Equation 1 for each benchmark model and assume that the total loss L is equivalent to the path loss L_U. Combining L with our known transmission power P_{tx}, we calculate

P_{rx} by evaluating features obtained from our physical data collection on the benchmark models.

We compare the testing performance of our linear regression model with benchmark models exclusively on successful transmissions using the evaluation metrics Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Finally, we use our PRR model to generate smooth packet success predictions within the range [0, 1] and evaluate our model performance using the Brier-Score (BS) [20], formulated as follows:

$$\text{BS} = \frac{1}{n}\sum_{i=1}^{n}(f_i - o_i)^2 \tag{7}$$

where f_i is the i^{th} predicted probability of packet success, o_i is the i^{th} true binary packet success outcome, and n is the total number of examples.

V. Results and Discussion

This section presents and discusses the results of our LoRaWAN propagation modeling.

We first trained a logistic regression model on both transmission successes and failures to predict PRR directly. The model structure presented in Equation 5 was used in training the PRR model. The coefficients are provided in Table II:

Table II: PRR Logistic Regression Coefficients Statistics

Weights	Coefficients	Standard Error	Lower 95%	Upper 95%
w_0	-0.2842	0.0007	-0.2856	-0.2828
w_1	-3.7288	0.0120	-3.7523	-3.7054
w_2	0.3222	0.0013	0.3196	0.3248
w_3	2.9496	0.0115	2.9272	2.9721

The robustness of the model coefficients was ensured by training 1,000 bootstrap models of sample size 18,924, equal to the full training set size. The predicted mean value obtained from bootstrapping was used for each coefficient. The impact of distance is evident in that from the coefficients in Table II, the rate of successful transmissions decreases as the distance between transmission and reception increases. Additionally, as DoS increases, so does the rate of successful transmissions.

A confusion matrix depicting the performance of our PRR logistic regression model is depicted in Fig. 3. 69% of true unsuccessful transmissions are predicted correctly while 71% of true successful transmissions are predicted correctly, demonstrating the prediction capabilities of our PRR model.

Due to link class imbalances, a weighted F-score was used and determined to be $F_1 = 0.73$ for the test set, as presented in Table III. Weighted F-scores were then determined for both the FSPL and Okumura-Hata models by applying the -127dBm transmission success threshold to RSSI predictions from the same test set. FSPL and Okumura-Hata weighted F-scores were found to be $F_1 = 0.06$ and $F_1 = 0.10$, respectively. Our PRR logistic regression model resulted in a weighted F-score value of $F_1 = 0.73$, demonstrating superior performance compared to its FSPL and Okumura-Hata counterparts.

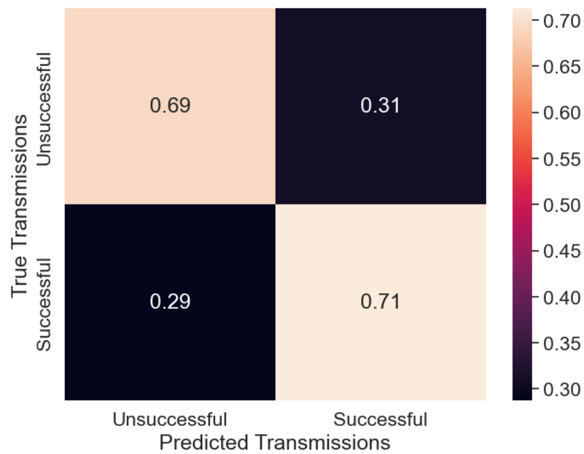

Figure 3: PRR logistic regression model confusion matrix. 69% of true unsuccessful transmissions are predicted correctly while 71% of true successful transmissions are predicted correctly.

Table III: Comparison of Linear Regression and benchmark RSSI prediction model performances

	MAE (dBm)	RMSE (dBm)	F-score
FSPL	41.9	44.4	0.06
Hata	13.5	17.6	0.10
Linear Regression	6.0	7.8	0.73

Table III depicts RSSI prediction performances for each model exclusively using data from successful transmissions. Our linear regression model has the strongest prediction performance, with an MAE and RMSE of 6.0 and 7.8dBm, respectively. The Okumura-Hata model has the second strongest prediction performance with an MAE and RMSE of 13.5 and 17.6dBm, respectively, while the FSPL model demonstrated the poorest performance with an MAE and RMSE of 41.9 and 44.4dBm, respectively, likely because neither makes direct use of terrain-based features like DoS. FSPL assumes an obstacle-free LoS path through free space, which omits any effects of transmission interference from LoS obstructions which may have contributed to observed FSPL errors. Additionally, the Okumura-Hata model was derived from data collection done in Tokyo, Japan, in [7], which may have been best fitted to Tokyo, contributing to observed errors for the Okumura-Hata model in Table III.

We then assess our PRR logistic regression model in a non-discretized setting, with transmission predictions between [0, 1]. Fig. 4 depicts a mapping of our PRR projections, which demonstrates the capabilities of our model to capture the effects of both (i) distance between transmitter and receiver and (ii) DoS on PRR. Yellow regions represent geographical areas of high PRRs, while blue regions represent areas of poor PRR. Regions of poor PRR generally result from shadowing effects and LoS obstructions from hills and valleys. To quantify our PRR model performance, we determine a Brier score of BS $= 0.21$ when assessed on our testing dataset. The captured impact of distance is evident in that, generally speaking, the rate of successful transmissions decreases as the distance from any gateway increases. The captured effect of DoS is evident in that some areas near gateway locations experience poor PRR predictions.

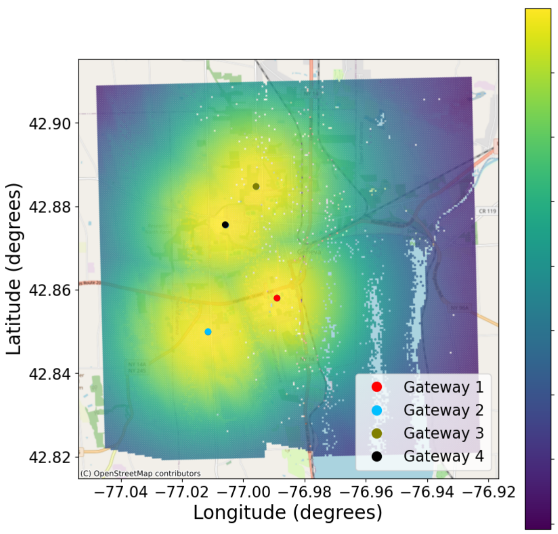

Figure 4: PRR projections for all gateways in Geneva, New York, LoRaWAN network. Network coverage predictions were made for each gateway. The maximum estimated transmission probability of all gateways was taken for each latitude/longitude pair.

VI. Conclusion and Future Work

In this work, we propose a modeling methodology for LoRaWAN packet reception rates designed to be used by LoRaWAN adopters of any geographical environment and demonstrate the effectiveness of our methodology using transmission data collected from Geneva, NY. We challenge traditional RSSI-based signal propagation models with one based on PRR. We show that when using a PRR model, we can accurately identify both successful and failed transmissions, as opposed to RSSI models, which can only identify successful transmissions. Moreover, we show that predicting probabilities, as opposed to binary outcomes, can also add value; we obtain a useful network quality model that LoRaWAN adopters can use to optimize gateway placement location and quantity for maximum network coverage. Accurately capturing the effects of DoS and distance between transmitter and receiver is essential for LoRaWAN network planning tools and optimizers, as these features provide guidance for optimized gateway placement.

Some limitations were met in conducting this work. First, a limited quantity of LoRaWAN gateways and trackers were used, making the collected data less diverse than ideal. Additionally, different materials can create different levels of obstruction–LoRaWAN signals may be able to travel through wood better than metal–but our model only considers the length of obstruction. We are also limited to how recent the terrain data is. Our DSM was created using 2019 LiDAR data, and newly constructed buildings may not be represented if the terrain data is outdated. Finally, all trackers used the same SF and antennas, limiting the extent of generalization of our PRR model. Future work will incorporate a wider variety of SFs and additional gateways and trackers.

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