A Proposed Mid-band Statistical Clutter Propagation Model utilizing Lidar Data

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***Abstract*—This paper proposes a mid-band statistical propagation model where objective clutter metrics derived from LiDAR data provide the means to predict the distribution of clutter loss. Model performance is compared with 3.5 GHz propagation measurements performed in Boulder, Colorado at two different antennas heights. Results demonstrate that this approach provides improved accuracy when compared to traditional modeling approaches that use subjective clutter categories such as urban, suburban, and rural.**

***Index Terms*—propagation, clutter, measurements, mid-band.**

I. Introduction

A statistical propagation model is a mathematical model that predicts the probability distribution of basic transmission loss for a well-defined set of assumptions concerning the specified propagation environment. Statistical models, in general, are based on experiments and regression analyses to estimate model distribution and parameters. The focus of this paper is on a statistical clutter propagation model (SCPM), where clutter is defined as vegetation and man-made structures on the surface of the Earth. We limit the scope of this study to scenarios where terrain has negligible effect on propagation.

Traditionally, SCPMs require a classification of the environment into subjective categories, e.g., 'urban', 'suburban', and 'rural'. Such SCPMs are typically based on the regression analysis of large amounts of measurement data [1]–[3], where it is assumed that the measured data is representative of the subjective clutter category. This assumption can be difficult to validate, and not all environments clearly fall into subjective categories. For example: Does the downtown neighborhood of a medium-size town get categorized as urban or suburban?

Additionally, terrestrial SCPMs typically do not consider elevation angle as a prediction parameter. In many common analysis use-cases, e.g., broadcast coverage and interference analysis with radar systems, terminals can be well-placed high above the surrounding clutter to maximize their operational area. Elevation angles from a ground-based receiver to the well-placed terminal can be large and the resulting clutter loss can be significantly reduced.

In this paper, we propose a new mid-band SCPM for scenarios where there is no loss due to terrain. We describe objective clutter metrics derived from LiDAR data as a means to predict the distribution of clutter loss. Model parameters are estimated based on 3.5 GHz propagation measurements performed in Boulder, Colorado at two different antennas heights.

II. Model Definition

The propagation scenario that we aim to model is illustrated in Figure 1. It is assumed that there are no terrain losses and in the absence of clutter the two terminals would be line-of-sight (LOS) with respect to each other. In addition, we restrict ourselves to a suburban environment where the receiver (RX) is enmeshed within the clutter. The transmitter (TX), meanwhile, is located both above the height of the clutter and such that there exists no clutter within its immediate foreground. By the geometry, the impact of clutter can be considered an end-point phenomena, although the percentage of the path that is within clutter at the receiver can be sizable for low elevation angles.

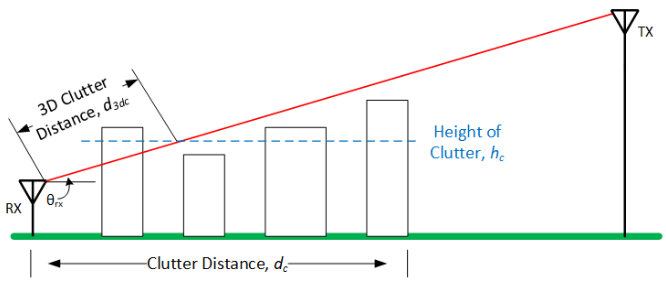


Fig. 1. Illustration of the propagation scenario.

We propose that the basic transmission loss for this scenario can be modeled as

$$L_{btl} = L_{fs} + L_c \tag{1}$$

where $L_{fs} = 20\log_{10}(4\pi r/\lambda)$ is free space basic transmission loss, r is the distance between terminals, and c is the speed of light.

The distribution of clutter loss is described as

$$L_c = L_{c,m} + Y(p) \tag{2}$$

where $L_{c,m}$ is the median clutter loss, $Y_L(p)$ is location variability modeled as a log-normal distribution, and p is percentage of locations. All propagation losses are given in dB.

We construct the median clutter loss formulation as

$$L_{c,m} = a\log_{10} r_c + b \tag{3}$$

where a is an exponent term and b is an intercept term to be estimated from measured data. The distance of the propagation path through clutter can be estimated from LiDAR data via

$$r_c = MIN\left(d_c, \frac{h_c}{\sin\theta}\right) \tag{4}$$

where d_c is the horizontal distance through clutter, h_c is the representative clutter height, and θ is the elevation angle for the direct ray path from RX to TX.

III. Measurements

Statistical model parameters are based on measured data. To illustrate, in this section we provide results from mobile clutter measurements performed in the Martin Acres suburban neighborhood of Boulder, Colorado located immediately East of the Department of Commerce (DoC) Labs. Martin Acres is comprised of single family homes with mature trees throughout. The terrain can be approximated as a flat plane with no terrain variations, such that all measurement points were at the same relative height above mean sea level (approximately 1650 meters MSL).

A 3.5 GHz continuous wave (CW) signal was transmitted from two different locations (i.e., low TX and high TX). The low TX location was the roof of Wing 4 on the Radio Building at the DoC Labs (approximately 1660 meters MSL). The high TX location was at the top of Green Mesa at the western portion of the DoC Labs (approximately 1800 meters MSL). Figures 2(a) and 2(b) show the measured clutter loss along the drive route for the low and high antenna location, respectively.

The receiver system was a mobile system as described in [4]. Measured data was acquired and processed to estimate the local mean received signal level according to best practices [5].

From the measurements, we estimate clutter loss as

$$\hat{L_c} = \hat{L}_{btl} - L_{fs} \tag{5}$$

Figure 3 presents the cumulative distribution function (CDF) of the measured clutter loss for the two transmitter locations. Summary statistics for the low and high transmitter measurement data are shown in Tables I and II, respectively.

TABLE I
SUMMARY STATISTICS FOR LOW TRANSMITTER MEASUREMENTS.

	Min	Max	Mean	St Dev
Path length (km)	0.20	2.01	1.16	0.50
RX elevation angle (deg)	0.20	3.20	1.07	0.73
Clutter loss (dB)	-1.07	39.66	29.36	5.07

TABLE II
SUMMARY STATISTICS FOR HIGH TRANSMITTER MEASUREMENTS.

	Min	Max	Mean	St Dev
Path length (km)	1.31	2.88	2.11	0.44
RX elevation angle (deg)	2.97	6.41	4.30	0.96
Clutter loss (dB)	1.67	33.83	22.61	5.07

IV. Parameterization of Clutter

We look to parameterize a clutter environment in an objective manner based on physical characteristics of the environment, replacing subjective terms with objective, statistical parameters. This approach requires a balancing of two overarching goals:

1) If LiDAR data is available, an algorithmic definition exists to compute the numeric clutter parameters in a deterministic fashion.
2) If LiDAR data is not available, or processing of LiDAR is not practical or desirable for the analysis, a user can estimate the clutter parameters, though visual inspection of overhead satellite imagery or personal familiarity with the environment.

The first item above ensures objectivity in the definition of clutter environments through clear definitions of clutter parameters and their values. This leads to the ability to analyze the similarity of clutter environments (such as two suburban neighborhoods) in a clear manner. The second item above addresses the strength of the intuitiveness of current urban/suburban/rural classifications. It is clear that the desired behavior of such a model utilizing a set of defined clutter parameters is that it is able to be localized to an individual environment, yet not be so sensitive to the clutter parameter values themselves that a user's error in estimation results in large prediction errors.

To support our analysis of the measurement data, we define two clutter parameters:

- μ_c: mean clutter height, in meters above ground level
- σ_c: standard deviation of clutter height, in meters

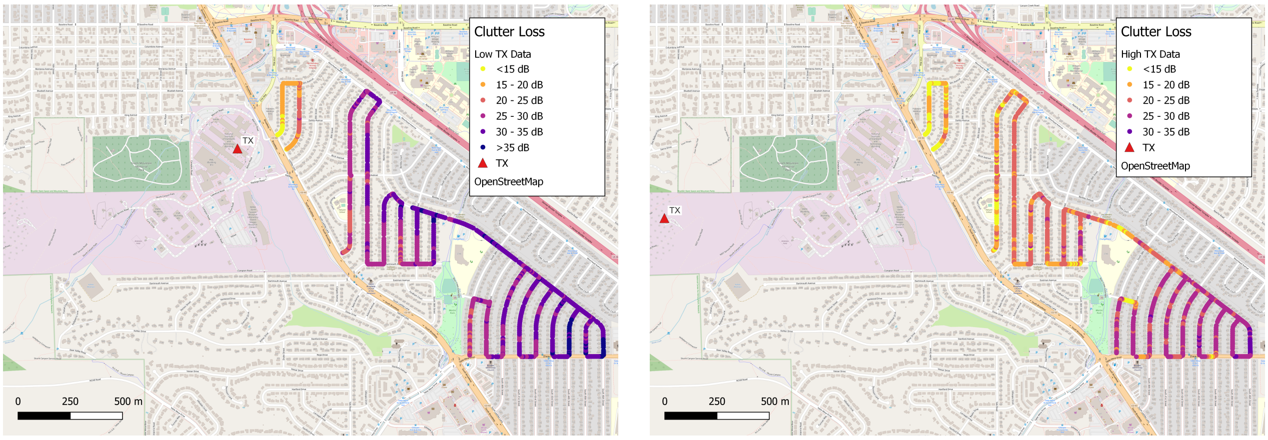
For the Martin Acres neighborhood, we utilize quality level 2 (QL2) LiDAR PointCloud data captured in 2013 and made available by the United States Geological Survey (USGS). The PointCloud data was processed into a digital terrain model (DTM), representing bare earth, and a digital surface model (DSM), representing the height of the top of the clutter canopy. The DTM was then subtracted from the DSM, resulting in a clutter height histogram as show within Figure 5. The statistics of the histogram were computed resulting in $\mu_c = 8.71$ meters and $\sigma_c = 4.92$ meters.

V. Estimation of Median Clutter Loss

A. Development of 3D Clutter Distance

Figure 4 shows the relationship between the measurement data and clutter loss. The data has no obvious correlation due to the presences of elevation angles between approximately 0 and 6.5 deg across the two transmitter locations. Elevation angles of this magnitude are reasonable for a variety of real-world terrestrial paths, in particular for well-placed terminals on elevated terrain features or structures (such as radar systems).

In addition, clutter is not evenly distributed across the entire path. As previously described, clutter only appears at the end-point of the receiver. In this measurement scenario, Broadway, the road separating the DoC Labs from the Martin



(a) (b)

Fig. 2. Map of measured clutter loss along drive route in the Martin Acres neighborhood of Boulder, CO for (a) low transmitter location, and (b) high transmitter location. Base map and data from OpenStreetMap and OpenStreetMap Foundation, www.openstreetmap.org/copyright

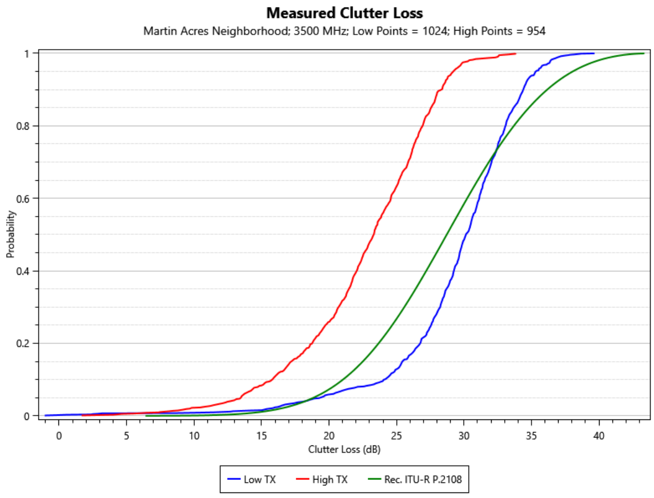


Fig. 3. Measured clutter loss CDF.

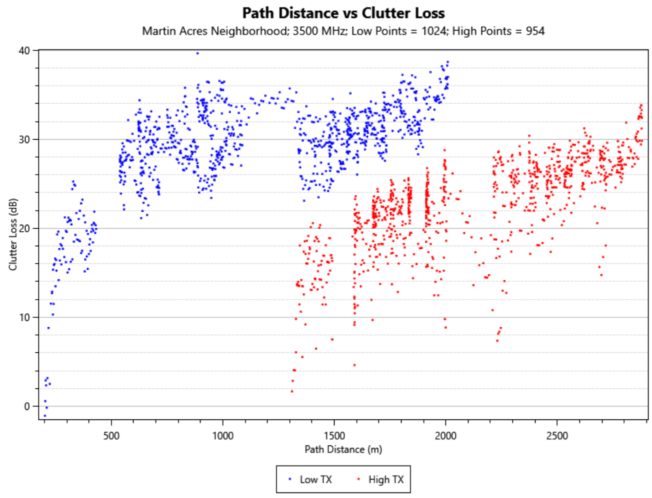


Fig. 4. Relationship between path distance and clutter loss for low and high transmitter location measurement data.

Acres neighborhood, acts as a environmental boundary. To the east of Broadway is the clutter environment of Martin Acres neighborhood. To the west is the DoC Labs, which is essentially free space.

We therefore model the clutter as a slab residing atop the terrain in the Martin Acres neighborhood. The clutter slab is bound horizontally along the measurement paths by Broadway. The slab is also bound vertically by the representative height of the clutter, h_c, and an unknown value which we will derive from the measurement data.

The result of this construction is that we can define the 3D distance through the clutter environment, as shown in Figure 1. We define the clutter distance, d_c, as the horizontal distance along the great circle path between the receiver and the boundary of the clutter environment. The clutter distance, r_c, is then defined as the minimum of the clutter distance and the slant path distance through the clutter, as defined in Equation 4. Such a construction allows us to account for both the distance of the path through clutter and the impact of the elevation angle.

B. Regression model

The definition of clutter distance allows the measurement data for the low and high TX to be aggregated into a single measurement dataset. A regression-based clutter model can then be fit to this aggregate dataset with dependence on r_c, as illustrated in Equation 4. This formulation relies on knowing h_c, from which r_c is dependent upon. We want to define h_c as a function of the clutter parameters μ_c and σ_c, to support extensions of the formulations to various clutter environments. To do so, we perform an optimized regression analysis by sweeping across a range of values for h_c and generating a regression model in the form of Equation 3. The Root Mean Square Error (RMSE) of the resulting model is computed and plotted for the specified value of h_c. Figure 5 plots the result of this optimized regression analysis.

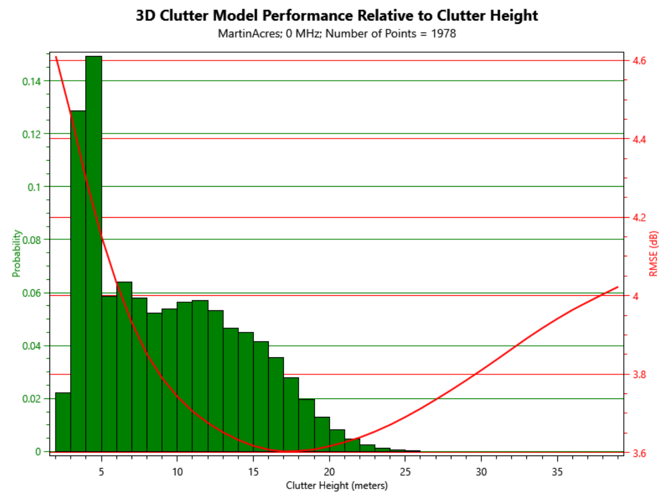


Fig. 5. Results of optimized regression analysis of clutter height, h_c, with respect to RMSE. Overlaid with clutter statistics of Martin Acres.

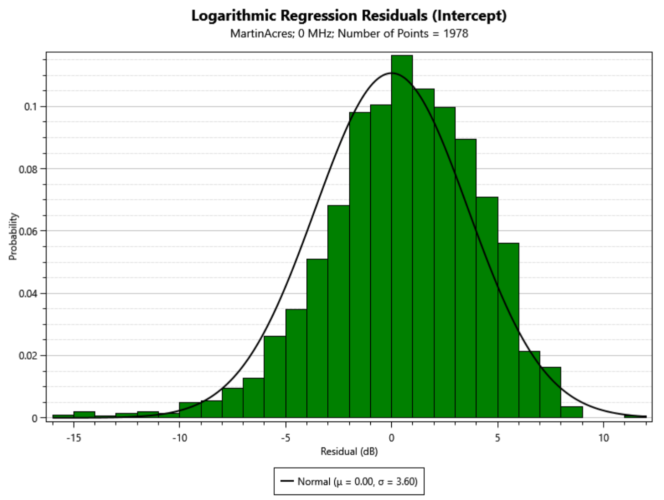


Fig. 6. Residuals of regression model and measurement data for Martin Acres.

The results of the regression analysis is that the height of the clutter that results in a minimum RSME is $\approx$ 18 meters. Defining h_c with respect to the clutter parameters results in $h_c \approx \mu_c + 2\sigma_c$. Importantly, aside from the resulting local minimum of the analysis, it is clearly shown that while the regression model supports parameterization for future localization based on the clutter parameters, the model is not overly sensitive such that estimation errors of a few meters by a user would result in large prediction errors relative to the minimum RMSE.

With h_c defined, the median clutter loss is defined as,

$$L_{c,m} = 14.6 \log_{10} r_c - 12.289 \tag{6}$$

VI. Estimation of Location Variability

The residuals of the regression model and the measurement data are approximately log-normally distributed as shown in Figure 6. These statistics are formed to represent the location variability of the predicted clutter loss, $Y_L(p)$.

The result of this formulation is shown in Figure 7 where the measurement data is plotted as the relationship between 3D clutter distance and clutter loss. Unlike in Figure 4, there is a clear relationship between these values. Plotting 10%, 50%, and 90% curves of the L_c demonstrates their resulting fit.

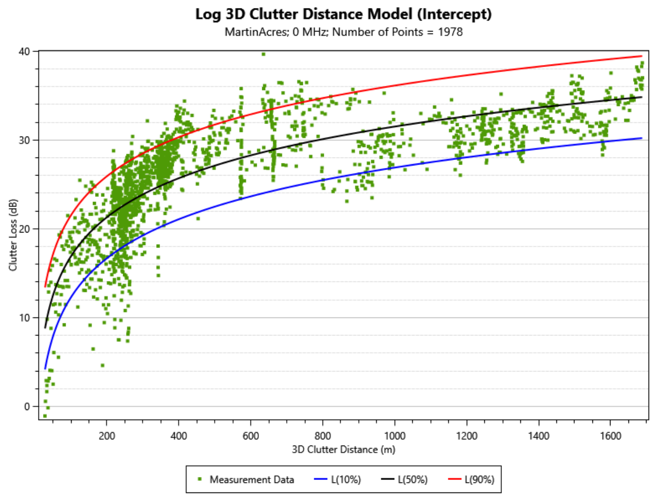


Fig. 7. The 10%, 50%, and 90% prediction curve for clutter loss.

VII. Conclusions and Future Work

This paper presents 3.5 GHz measurement data of two transmitter locations from a suburban environment in Boulder, Colorado. The measurement data is used to develop a statistical regression model from which both median and location variability can be predicted. The model was developed through the concept of parameterizing the clutter, in which a local, homogeneous clutter environment is statistically represented and input into the prediction model. The resulting model shows good agreement across the two transmitter location datasets and is able to account for the impact of elevation angle in the prediction results.

We plan on further developing our approach, starting with acquisition of additional measurement data in a variety of suburban neighborhoods. These new datasets will allow us to validate and improve the basis for the clutter parameterization approach presented and test its generality. In addition, the a term in Equation 2 should be further developed such that it is a function of the clutter parameters. Lastly, we plan to incorporate losses due to terrain effects.

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