Loss Exponent Modeling for the Hilly Forested Region in the VHF Band III

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Abstract  Modeling forest propagation loss over a vast area is challenging, particularly for the hilly terrain regions where canopy obstacle depth varies with region. To consider such vegetation impact, we present a novel forest cover classification well defined with the line-of-sight (LoS). Furthermore, we incorporated the mobile antenna site elevation angle, which showed significant influence within the target frequencies selected at 182.25 and 203.25 MHz (VHF Band III). We proposed a loss exponent dependent on the elevation angle and the vegetation-visibility classification, which is the basis of the model introduced in this paper. The resulting loss derived using this loss exponent showed a good agreement with the empirically derived loss variations. The proposed method offers easy forest classification approximations with precise determination of signal variation over a wide-ranging forested area.

Plain Language Summary  We discussed the influence of vegetation, line-of-sight (LoS), and elevation angle on the loss exponent of the observed data. We proposed a novel vegetation-visibility classification combined with the elevation angle to explain signal variation in a forest vegetation area. The results indicated that the proposed loss performs decently compared to the Egli, Hata, and Perez Vega model.

1. Introduction

Recently, Very High-Frequency Transmission (VHF) and Ultra High Frequency (UHF) initiate new interests, where efforts to exploit the under-utilized bandwidths in this spectrum are progressing with the digital-switch-over trend. A low-frequency wireless communication system has a potential solution for bridging the digitally divided areas (Chavez et al., 2015; Khamlichi et al., 2016; Nandi et al., 2016; Rahman & Safiullah, 2019; Zhao et al., 2019) with its range and operational advantages (Dagefu et al., 2015). Notwithstanding this, the global wireless subscribers are increasing rapidly, and it is essential to exploit these vacant bands for providing back-haul connectivity. Thus, understanding the propagation mechanisms of the low-frequency signal variation and their channel parameters deal with a necessary perspective for the future wireless communication system.

The signal propagation mechanism in a terrestrial radio system undergoes scattering, reflection, and diffraction (Ali et al., 2018). In a clustered environment, the propagated signal suffers multipath propagation (Lambrechts & Sinha, 2019) through reflection/refraction (Salous, 2013), and the channel-affecting factors remain elusive and complicated. As such, examining multiple aspects of the channel affecting factors is important for an accurate signal estimate, which is in particular required for the dense environment as opposed to open settings. In a wireless communication system, it is challenging to develop a model that explains the complete mechanism of the signal transmitted (Egi & Otero, 2019). Instead, path loss models were used to interpret the mean variation of the transmitted signal. There is a limited VHF-based empirical model (Faruk et al., 2019). Some reputed path loss models are the Okumura-Hata model (Hata, 1980), Egli model (Egli, 1957), Walfish and Bertoni model (Walfisch & Bertoni, 1988), and Perez Vega and Zamanillo model (Pérez-Vega & Zamanillo, 2002). Although these models provide a simple way to evaluate propagation loss (Jawhly & Tiwari, 2019), they are modeled from measurements made in particular settings and thereby are limited to a dynamic environment. Environment based propagation loss models have facilitated decent signal analysis in different studies (Azevedo & Santos, 2011, 2017; Erceg et al., 1999; Kurnaz & Helhel, 2014; Smith et al., 2016), and although the calculations are more demanding, such models are precise.
For the hilly forested region terrestrial communication system, it is common to have the base antenna located at the peak point to provide maximum coverage to the surrounding areas. For such settings with forest obstruction, the vegetation depth between the transmitter and receiver link is unique from site to site, owing to uneven terrain and forest distribution. As such, the lateral forest effect concept holds impractical for wide spatial coverage. Instead, the vegetation cover within a specified area surrounding the receiver can function to appraise such signal-related effects. As highlighted in many studies, the line-of-sight (LoS) and Non-line-of-sight (NLoS) sites have a clear distinction of the received signal quality, and the altitude of the receiving site can have a significant influence on the LoS clearance. Based on these concepts, we proposed vegetation-visibility classification and elevation angle-based loss exponent, which showed a good agreement with the empirical results. The proposed model does not predict the mean loss but predicts signal variation with change in the environment variables.

2. Related Works

2.1. Forest Attenuation Models

Studies have shown that signal suffers a loss when traversing a forested area. Forest attenuation, combined with other factors, can severely deteriorate signal propagation. Weissberger (1982) proposed a modified exponential decay model for the propagation channel through a dry, in-leaf temperate-latitude forest in the 230–95 megahertz (MHz) band. This model is particularly useful when the depth of trees is as large as 400 meters (m). ITU Recommendation (ITU-R), developed from measurement carried out in the UHF region, was later extended for the VHF band by Meng et al. (2009). This modified model is a function of frequency and foliage depth, which is applicable for the long-range propagation in the foliage area considering the lateral wave effect.

Studies conducted by Ibdah and Ding (2016) for the urban and forested region in the 2.1 GHz band have shown that the path loss exponents vary from 2.1 to 3.4 for the urban areas extends up to 8 for the forested region. While the reference loss also increases with the placement of the mobile antenna inside the vehicle. To find the foliage density of the tree canopy, authors in Azevedo and Santos (2017) used a background light shadowed by the tree canopy. They included the number of trees per square meter, the average canopy diameter as the signal influencing factor. Their model performance improved compared to the existing foliage model. Studies conducted by Adewumi and Olabisi (2018) in the UHF band for the forested region have highlighted a significant increase in attenuation corresponding to the thickness of the forest channel and proposed a model accordingly. They concluded that thicker leaves consist of more moisture reducing the permittivity of the transmitted signal. Shehadeh et al. (2019) have highlighted the strong impact of the foliage and tree trunk height on the received signal quality for the near ground link. Their three-optimization algorithm results indicated a sharp increase in path loss within a 2-km foliage depth and showed stability with a further increase in the foliage depth. Popov (2019) described a cross-polarization effect of VHF and UHF, while traversing forest vegetation causing a fading effect. This polarization effect, combined with the random change in attenuation forest coefficient, caused fluctuation of the received signal.

All these models comparatively consider the lateral-vegetation impact on the signal propagation defined by frequency and forest depth. In our study, since we consider a large coverage area with random LoS and NLoS vegetation-covered distribution, we cannot contemplate the same of the lateral vegetation effect. However, we highlighted the plausible signal variation due to vegetation cover in its propagation channel.

2.2. Topography Influence on Signal Propagation

It is challenging to take into account the full details of terrain roughness and interrelate them to the received-signal variation. Even in the absence of vegetation, the loss variation is dependent on both the transmitter-receiver separation and the terrain elevation variations (Ribero et al., 2019). Lu et al. (2013) developed a path loss model considering the terrain roughness, mean slope, and the mean difference of terrain elements. Their study showed that terrain scattering is more likely in longer links and that shorter antennas (1.8 m) have more significant terrain scattering compared to higher antennas (10 m). Loo et al. (2017) proposed a simulation-based 3D terrain model and three important observations: path loss between two nodes with the same separation, but the different location may vary; path loss depends on the number of obstacles
that block the Fresnel zone between the two nodes; base antennas highest position may not always reduce transmission loss.

In the case of our study area, it is a hilly terrain region with elevated antenna placement, whereas the measurement site altitude varies with location. Furthermore, the propagation channel consists of moderate to dense forest cover characterized by variation in topography. We cannot consider the influence of terrain alone without considering the impact of forest cover. Both these parameters have to be accounted for to understand signal variation across the region.

3. Data Collection Details

3.1. Measurement Survey

We performed a data measurement survey in Mizoram, North East India. We took the field strength measurements along the four cardinal directions (Kolasib-North, Keifang-East, Thenzawl-South, and Mamit-West) of the transmitter \( T_x \), as shown in Figure 1. The topographic feature for all directions was hilly with moderate-to-heavy forest cover. For the majority of the site, the vegetation height roughly ranges from 1 to 8 m, with varying density.

3.2. Experimental Details

We recorded a continuous wave (CW) signal (182.25 and 203.25 MHz) propagating from the Doordarshan transmitter located at Durtlang Aizawl, Mizoram, using Anritsu Site Master coupled with the standard Anritsu dipole antenna. The base antenna or the transmitter \( T_x \) height \( h_T \) for the \( f_1 \) and \( f_2 \) frequency is 32 and 40 m, respectively, while the mobile antenna/receiver \( M_x \) height \( h_M \) is 1.8 m above ground. Both the
transmitters share the same tower at a different height. The maximum transmitted power for the 203.25 MHz and the 182.25 MHz are 40 decibel-watt (dBW) and 30 dBW, respectively.

We recorded the signal strength through the spectrum analyzer, mounting the dipole antenna upon a clear ground, starting at a few meters away from the transmitter. We observed that signal strength showed not much variation (2–7 dBμVm) until at a 2 km distance from $T_x$. Therefore, we made the subsequent signal measurements at a rough separation interval of 2 km each. We preassigned each measurement site on Google-map and conducted our survey using the Google-map navigation system. This preassignment aids in approximating the separation interval as the hilly region winding roads and hairpin-turns limit performing this localization during the actual survey. The inbuilt Global Position System (GPS) of the spectrum analyzer helps identify the actual coordinates for a precise $R_x$ estimate. Table 1 provides an overview of the measurement parameters.

We covered a total of 89 sites, with 32 locations in the North, 27 locations in South, 15 locations in West, and 15 locations in East. These sites are separated by a distance of 2 km each, with an initial data analysis point prepared at 2 km separation from the transmitter. In each of these sites, we took field strength measurements ranging from five to seven readings.

4. Propagation Loss Formulation

4.1. Transmitter-Receiver Separation

In each measurement site, we logged the GPS location through the inbuilt Site Master GPS, and the $T_x$ and $M_x$ separation was calculated using the Haversine formula (Jawhly & Tiwari, 2020a), which is expressed as

$$
T_i = \sin(A_i)\sin(A_2) \\
T_2 = \cos(A_1)\cos(A_2) \\
R_x = \arccos(T_1 + T_2\cos(Z_2 - Z_1))R_E
$$

Here, $A_1$ and $Z_1$ are the respective $M_x$ latitude and longitude, $A_2$ and $Z_2$ are the respective $T_x$ latitude and longitude (all in radians). $R_E$ is the earth’s radius (6,371 km), and $R_x$ is the $T_x$-$M_x$ separation in km.

4.2. Path Loss Model

We employed a logarithmic-based propagation loss model given by the relation

$$
L_i = L_0 + 10n\log_{10}(R_x / d_o)(dB)
$$

Here, $i = 1, 2$ denotes the index for the two respective frequencies ($f_1$ and $f_2$), where $L_0$ is free space loss at a reference distance ($d_o$) expressed as

$$
L_0 = 20\log_{10}\left(4\pi d_o / \lambda \right)
$$

$R_x$ is the transmitter-receiver ($T_x$-$M_x$) separation in meter, $\lambda$ is the transmitted signal wavelength in meter, and $n$ is the path loss exponent. To find the reference distance ($d_o$), we took a small sample signal measurement based on $R_x$. We observed that most of the propagation loss at 300 m is roughly equal to the free space path loss (70 dB) for both the signals ($s_1$ and $s_2$). Based on this concept, we set the reference distance at 300 m.
4.3. Observed Loss Exponent

To convert our measured signal strength $\text{dB}_\mu\text{Vm}$ to $\text{dBW}$, we employed the relation

$$P_{R(\text{dBw})} = E(\text{dB}_\mu\text{Vm}) + 20\log_{10}(AR) - 156.755$$

where $E$ is the received signal strength (dB$\mu$Vm) and $AR$ is the isotropic antenna gain ratio related to the antenna gain $Ag$ as

$$AR = 10^{(Ag/10)}$$

In our analysis, we assumed zero antenna gain ($Ag = 0$). We calculated the path loss exponent from our observed field strength by rearranging Equation 2 where

$$n_i = \frac{(L_i - L_o)}{10\log_{10}(R_i / d_o)}$$

$L_i$ is the path loss in dB deduced from our measurement, which can also be computed using the expression.

$$L = P_{T(\text{dBw})} - P_{R(\text{dBw})} (\text{dB})$$

Here, $L$ is the difference between the power transmitter ($P_T$) and the power received ($P_R$), which could be in dBW or dBm, but both must be in the same unit.

First, we calculated the observed loss ($L_1$ and $L_2$) using Equation 7 for the respective signals $s_1$ and $s_2$ at frequencies $f_1 = 182.25$ MHz and $f_2 = 203.25$ MHz. Substituting these observed losses and the free-space path loss Equation 3 in Equation 6, we obtained the observed loss exponents ($n_1$ and $n_2$), separately for the respective $s_1$ and $s_2$ signals.

5. Estimating the Predictor Variables

5.1. Elevation Angle

We obtained the elevation detail for each measurement site using Digital Elevation Model (DEM) (NASA Jet Propulsion Laboratory (JPL), 2013). Our analysis showed a wide-ranging elevation for all four directions. The transmitter ($T_x$) understudy is at an altitude of 1,377 m above sea level while the rest of the location settings vary contrarily.

We recorded a stronger signal for the significantly elevated $M_x$ sites as opposed to the lowly elevated sites with an average difference of 15.6 dB$\mu$Vm between terrain at ≥500 m and ≤900 m elevation for both $f_1$ and $f_2$ signals. This difference arises as antennas, on higher grounds, have improved clearance with the nonpenetrating signal obstructions. Instead of modeling $n$ along with this elevation factor, we learned that the elevation angle ($\theta$) (Figure 2), from $M_x$ to $T_x$ is an essential alternative determiner of channel influencing factor similar to most High Altitude Platform (HAP) models (Khawaja et al., 2018; Yan et al., 2019). Since the 32 and 40 m ($h_T$) elevation angle difference is small (0.22°) and showed a negligible overall impact, to make the calculation easier, we use the same elevation angle (40 m elevation angle) for assessing both the loss exponents. At a significance level (alpha) of 0.05, linear regression analysis showed that the elevation angle ($\theta$) has a significant statistical relationship with respect to each $n_1$ and $n_2$ variations.

5.2. Vegetation-Visibility Classification

Forest parameters like tree size, tree type, the density of the leaves, the frequency of the branches, and form affect the propagated signal (Azev-
do & Santos, 2017). We did not consider these factors discretely; instead, we simplified the rough aspect of the vegetation densities and made a categorical classification for each site, as shown in Figure 3. Our study assumed a nonlateral effect of vegetation attenuation and supposed that the propagation channel is influenced only by the near neighboring forest cover within a specified area. We classified the nonhomogeneous vegetation distribution within an approximate area of 314.15 m$^2$ for each measurement site. We categorize the low, moderate, and heavy forest features as type (a), (b), and (c), respectively. As depicted in Figure 3, the forest cover is open within the roadways, and the road direction is not straight throughout the signal measurement sites. Hence, some sites, irrespective of the forest cover, have a LoS link with $T_x$. As such, the LoS sites, irrespective of the vegetation cover type (a, b, or c), are assigned the value 1. We classified this forest cover and the LoS combination as the vegetation-visibility ($V_V$) and correspondingly assigned a categorical value of 2, 3, and 4 to respective type (a), (b), and (c) as shown in Table 3.

The vegetation density in type (a), (b), and (c) has an approximate 10, 50, and 80 percentage of vegetation cover, respectively, within the specified area. Most of the vegetation heights in (a) were shorter than the mobile antenna height ($h_M$), while predominantly higher in type (b) and (c). We did not collect data at every center of the roadway but few feet away from the tarred area of the road since signal strength data differs by $\sim1–3$ dB$\mu$V/m only. The dipole antenna orientation, however, does give 20–30 dB$\mu$V/m differences for the minimum and the maximum signal interception. No attempt was made to collect the signal data at different mobile antenna heights. Throughout the signal measurement survey, the mobile antenna height was maintained at 1.8 m above ground.

Most works of literature (Andersen et al., 1995; Benaissa et al., 2019; Zang & Wang, 2017) used loss exponent $n = 2$ for the free-space loss. However, since we are modeling $V_V$ along with uncertain categorical vegetation classification, we calculated each vegetation and visibility classification coefficient using dummy variable regression to estimate its impact.

### 5.3. Vegetation-Visibility and Elevation Angle Coefficients ($\gamma$ and $\theta$)

We have used 34 sample data to obtain the estimator variables, out of the total 89 observed loss exponent, consisting of every vegetation type classification. The remaining 55 data sets are used for evaluating the proposed predictor variable. To estimate the coefficients of the vegetation-visibility ($V_V$) classification, we created $(m - 1)$ dummy variable ($d_2$, $d_3$, and $d_4$) for the respective $V_V = 2$, $V_V = 3$, and $V_V = 4$ variables, where $m$ is the total number of the categorical variables. Here only three dummy variables are created ($V_V = 1$, is left out) to avoid the “dummy-variable-trap” (Bagchi et al., 2012) as given in (Table 2). Setting a significance level (alpha) at 0.05, multiple linear regression of the dummy variables with the loss exponent indicated that there was a significant relationship between the $V_V$ classification (dummy variables) with each $n_1$ and $n_2$ loss exponent variations.

Table 2

| $V_V$ | $d_2$ | $d_3$ | $d_4$ |
|-------|-------|-------|-------|
| 2     | 1     | 0     | 0     |
| 3     | 0     | 1     | 0     |
| 4     | 0     | 0     | 1     |

Figure 3. Illustration showing vegetation classification for different sites based on vegetation density within an approximate 10 m radial area. The mobile antenna is fixed at the height of 1.8 m above ground.
Table 3
Vegetation ($V_v$) Features, Type, and Vegetation-Visibility ($V_v$) Classification With Regression Exponent Coefficients Obtained From Equation 8

| $V_v$ features | $V_v$ type | $V_v$ | $\gamma_1$ | $\gamma_2$ |
|----------------|------------|------|-------------|-------------|
| LoS            | (a, b, or c) | 1    | 2.87        | 2.95        |
| Low cover      | (a)        | 2    | 3.61        | 3.89        |
| Moderate cover | (b)        | 3    | 4.28        | 4.07        |
| Heavy cover    | (c)        | 4    | 4.15        | 4.06        |

A regression equation between either observed loss exponent ($n_i = 1, 2$) and the dummy variables with the elevation angle ($\theta$) can be expressed as

$$n_i = J_i + d_2c_2 + d_3c_3 + d_4c_4 + B(\theta)$$  \hspace{1cm} (8)

In the above linear regression, the intercept $J_i$ is the referenced category, whose value corresponds to the vegetation cover type (a, b, or c) with the LoS condition ($V_v = 1$), whose loss exponent is not necessarily $n = 2$. While $c_2$, $c_3$, and $c_4$ are the differential intercept coefficients corresponding to $V_v = 2$, $V_v = 3$, and $V_v = 4$ respectively.

We denote the vegetation-visibility coefficients corresponding to the different $V_v$ features using $\gamma_i$. The $J_i$ value gives the $\gamma_i$ value for the LoS features, while $J_i + c_2, J_i + c_3$, and $J_i + c_4$ give the $\gamma_i$ values for the respective low, moderate and dense forest features. In this way, the $\gamma_1$ and $\gamma_2$ coefficients are calculated using the sample observed loss exponents ($n_1$ and $n_2$) as the outcome variables, and provided in Table 3. The $B$ value is the angle coefficient, which is equal for both the $n_1$ and $n_2$ exponents.

We learned that $V_v$ type (c) has a loss exponent lower than expected from the type (b) cover. Due to large-scale area analysis, we did not consider this effect explicitly. Basing on the statistical concept, we attribute this effect explicitly to the majority of the type (c) sites having a clearer link with $T_v$. Furthermore, the diffraction effect could also play a significant role in this effect. However, this effect is not examined in this manuscript.

6. Results

6.1. Proposed Loss Exponent

Predicated on the above analysis, we proposed a simple linear loss exponent relationship $\hat{\beta}_i$, which is a function of ($\gamma$) and elevation angle ($\theta$) and is expressed as

$$\hat{\beta}_i = \gamma_i + B\theta \left( i = 1, 2 \right)$$  \hspace{1cm} (9)

Here, $\gamma_i$ is the vegetation-visibility coefficient, whose values are provided in Table 3 and $B$ is the angle coefficient. We calculated $B = 0.20$ for both $s_1$ and $s_2$ signals.

6.2. Assessment of the Predictor Variables

Pursuant to the elevation angle and vegetation-visibility classification analysis, we performed a multiple linear regression analysis to test if $\hat{\beta}_i$ significantly predicted the remaining observed $n_i$. The regression results indicated that the proposed loss exponent ($\hat{\beta}_i$) significantly explained 42% of the $n_1$ variance ($F(1, 53) = 38.75, p < 0.00, R^2 = 0.42$). And that the proposed loss exponent ($\hat{\beta}_i$) significantly explained 65% of the $n_2$ variance ($F(1, 52) = 98.72, p < 0.00, R^2 = 0.65$). Since we have chosen an alpha level of 0.05, the $F$ ratio determines the likelihood of occurrence by chance at a significance level of 0.05. Also, the $p$ value is statistically significant when it is lesser than 0.05. $R^2$ indicates the coefficient of determination value. For both the analysis, the overall regression test was statistically significant. A regression plot of the proposed $\hat{\beta}_i$ and $n_i$ is presented in Figure 4 and Figure 5 for the respective $f_1$ and $f_2$ signals.
To check the above multiple linear regression assumptions, we obtain a probability plot of the predicted and observed loss exponent residual. First, we standardized the residue of $\hat{\beta}_1$ and $n_o$ which is pretty straightforward

$$\kappa = \text{residue} / \sigma_{\text{res}}$$

The residue here is the difference between predicted ($\hat{\beta}_i$) and observed ($n_i$) loss exponents ($\beta - n$), and $\sigma_{\text{res}}$ represents the standard deviation of this residue. (A separate standardized residue $\kappa_1$ and $\kappa_2$ is calculated for the respective $\beta_1$ and $\beta_2$).

Next, we sorted the $\kappa_i$ values (here $i$ is the order of the data) in ascending order, whose cumulative distribution function (CDF) is denoted by $F$. We construct the corresponding plotting position given by Hazen's formula (Boylan & Cho, 2012)

$$p(x) = x - 0.5 / n_o$$

Here $x = 1, 2, 3, \ldots \ (n_o = 55)$. Where $n_o$ is the total number of the remaining observed losses not included in $\hat{\beta}$ formulation. Note that there are different plotting position methods proposed (Looney & Gulledge, 1985). The probability plot is obtained by plotting the $F^{-1}(p(x))$ on the Y-axis, and $\kappa_i$ order data in the X-axis. In the graph, instead of the scores ($F^{-1}$), a probability-scale represents the Y-axis, which is the probable position of getting values less than $\kappa$ fit line, while the X-axis represents the $x$ data. The Probability-Plot corresponding to $\hat{\beta}_1$ and $\hat{\beta}_2$ residue is given in Figure 6 and Figure 7, respectively, where almost all data falls closely within a straight line. This analysis indicates that the proposed loss exponents ($\hat{\beta}_1$ and $\hat{\beta}_2$) error terms are normally distributed, and this substantiated the above multiple-linear regression assumptions.

### 6.3. Main Results

As discussed in the aforementioned analysis, we have calculated the $T_v-M_v$ separation, estimated the elevation angle ($\theta$) and classified the Vegetation and visibility ($V_v$). Based on this, we have computed the ($\gamma$) variables and accordingly proposed a regression-based loss exponent ($\hat{\beta}$), which is a function of the $\delta$ and $\gamma$ function. The resulting log-distance path loss model based on the proposed loss exponent $\hat{\beta}$ can be expressed as

$$L_{p_1} = L_o + 10\hat{\beta}_1 \log_{10}(R_e / d_o)$$

where $L_{p_1}$ is the predicted loss based on the proposed loss exponent $\hat{\beta}_1$. The other parameters are well defined in 2. The expression Equation 12 is the resultant loss based on vegetation-visibility and elevation. Here the loss exponent ($\hat{\beta}$) treats signal variation as a function of vegetation-visibility ($V_v$) and elevation angle ($\theta$). As such, the proposed $\hat{\beta}_1$ showed variations similar to the change in these channel variables. We calculated the predicted loss separately for $f_1$ and $f_2$ signals using their respective $\hat{\beta}_1$ and $\hat{\beta}_2$, marking them as $L_{p_1}$ and $L_{p_2}$ respectively.
6.4. Comparison with Empirical Loss Models

The observed loss \( L_i \) and predicted loss \( L_{Pi} \) showed logarithmic scattered variations with separation. A separate fit line for both \( L_i \) and \( L_{Pi} \) is calculated with respect to the \( T_x \) and \( M_x \) separation \( (R_x) \) using the relationship

\[
L_{i(fit)} = X + Y \log_{10} R_x
\]

where the coefficients \( X \) and \( Y \) are obtained through each respective data regression and provided in Table 4. To evaluate the performance of our proposed model, we compared it with the empirical propagation loss models, which are applicable in the VHF frequency range, using the \( R^2 \)-squared analysis. The coefficient-of-determination \( (R^2) \) for analyzing the nonlinear data set (Jawhly & Tiwari, 2020b) is given by

\[
R^2 = 1 - \frac{\sum (o - p)^2}{\sum (o - \overline{o})^2}
\]

where \( o \) and \( \overline{o} \) represents the corresponding observed loss data and the mean observed loss data, while \( p \) represents the predicted loss data.

In our previous work, we have compared different empirical models like the Egli, Hata, and Perez Vega and Zamanillo model using the preliminary signal data collected over 28 km in the South and 12 km in the Northern region. The details of the models are provided in (Jawhly & Tiwari, 2019).

6.4.1. Egli Model

The Egli model is expressed as

\[
L_p(dB) = 20 \log_{10}(f_c) + 40 \log_{10}(R) - 20 \log_{10}(h_b) + \begin{cases} 
76.3 - 10 \log_{10}(h_m) & h_m < 10 \\
85.9 - 20 \log_{10}(h_m) & h_m \geq 10
\end{cases}
\]

Here, \( f_c \) indicates the transmitted frequency (MHz), \( h_b \) is the transmitter \( (T_x) \) height in meter (m), \( h_m \) is mobile antenna \( (M_x) \) height (m), \( R \) is \( T_x-M_x \) separation in kilometers (km).

6.4.2. Hata Urban Area Model

There are three different areas in the Hata propagation model. The optimal performing model for the study area is the Urban area propagation model, which is expressed as

\[
L_u(dB) = 69.55 + 26.16 \log_{10} f_c + (44.9 - 6.55 \log_{10} h_t) \log_{10} R \\
- 13.82 \log_{10} h_t \left( \frac{1.1 \log_{10} f_c - 0.7}{h_m} - \left( 1.56 \log_{10} f_c - 0.8 \right) \right)
\]

Table 5
Coefficient of Determination \( (R^2) \) With the Observed Loss Variations \( (L_i \) and \( L_{Pi} \))

|       | \( L_{Pi} \) | \( L_{i} \) | \( L_{Pi(fit)} \) | Hata | Egli | Perez |
|-------|--------------|-------------|------------------|------|------|-------|
| \( i = 1 \) | 0.41         | 0.28        | 0.22             | 0.23 | 0.06 | −0.33 |
| \( i = 2 \) | 0.66         | 0.36        | 0.35             | 0.34 | 0.16 | −0.27 |
where \( f_i \) is the frequency (MHz), \( h_i \) is the \( T_x \) height (m), \( h_m \) is the \( M_x \) height (1–10 m), and \( R \) is the \( T_x-M_x \) separation.

### 6.4.3. Perez-Vega and Zamanillo Model

The Perez-Vega and Zamanillo model is given by the relation

\[
L_p(dB) = 10n \log_{10}(R) + L_v
\]  

(17)

\( R \) is the \( T_x-M_x \) separation (m), \( L_v \) is the propagation loss at 1 meter in free space, and \( n \) is the path loss exponent deduced from the Federal Communication Commission (FCC) F(50,50) curve.

We compared the remaining observed losses with our proposed model Equation 12 and the above listed empirical models. The coefficient of determination showed that the nonfitted proposed loss models \( (L_{nf}) \) and \( (L_{f}) \) obtained using Equation 12 accounts for 41% and 66% of their respective observed loss variations \( (L_1 \) and \( L_2 \)). A plot of this variation is shown in Figure 8 and Figure 9. It is important to note that the empirical models predict the mean loss data. As such, to evaluate the performance of the proposed model alongside these models, we obtained the predicted model fit \( (L_{pfit}) \) using Equation 13. From the \( R^2 \) analysis (Table 5), we observed that the predicted model fit and the Hata model surpasses the Egli and the Perez model performance for both the \( f_1 \) and \( f_2 \) signal. Both the predicted model fit and the Hata model are almost analogous, where the Hata model has a better performance for the \( f_1 \) signal and the predicted fit for the \( f_2 \) signal. Note that we also compared observed fit \( (L_{of}) \) with the observed data to show how much of the observed data variations are explained by its logarithmic fit \( (L_{olf}) \) obtained using Equation 13. A plot of this is given in Figure 10 and Figure 11.

Furthermore, since the loss analysis is over a vast area, we started the initial plotting position from 2 km aerial distances to account for the loss over a larger spatial area. While the initial small sample signal measurements up to 300 m distances \( (R_x) \) are only used for finding the reference distances \( d_x \). In Figures 10 and 11, we present a scattered plot of the observed loss and the predicted loss alongside their respective fit \( (L_{olf}) \) and \( L_{of} \) for comparative loss variations analysis. From the graphical plot, the proposed model Equation 12 roughly lies within the variations of the observed losses.

The observed fit \( L_{olf} \) for both frequencies \( f_1 \) and \( f_2 \) showed a higher correlation with the observed loss at a closer separation distance \( (R_x) \) compared to the predicted fit \( L_{Pfit} \). This arises due to the sites nearer to \( T_x \) characterized by an urban area consisting of fewer vegetation cover, where the proposed loss exponent is dependent on the statistical outcome of the vegetation cover and the elevation angle. We infer from the above analysis that the proposed model gave a decent performance compared to the empirical models or the observed losses over a large spatial area. More importantly, the dynamic signal loss variation due to the environmental variables (forest and terrain) is accounted for, which is particularly essential for precise and detailed loss estimates when dealing with the changing channel influencing parameters.

### 7. Discussion

In this manuscript, we found vegetation classification within a specified area to be an appropriate approximation technique for modeling the non-lateral forest signal attenuation. Different studies have indicated a bet-
ter signal reception with higher mobile antennas. Here, the elevation angle significantly exhibited related effects. In this terrain analysis, we have used the DEM to estimate the terrain profile while recording the LoS and vegetation details during the measurement survey. Incorporating more satellite data can help in remote investigation of the LoS areas and vegetation cover. Such data could support analysis without in-site measurements and expand the overall accuracy of signal estimation. However, the proposed method does not consider the diffraction effect due to terrain, which is one critical factor in terrain region signal analysis. Furthermore, since the proposed method considers vegetation and visibility conditions to arrive at the loss exponent, the model would be deemed inapplicable in settings devoid of vegetation.

8. Conclusion

A study of the different foliage loss models indicates that the lateral foliage effect is impractical when the propagation channel is over the hilly forested region. This manuscript proposes a novel vegetation-visibility classification that addresses one critical aspect of vegetation attenuation modeling in the hilly forested environment. The resulting loss model Equation 12 considers the loss due to the dynamic variations of the propagation channel parameters, where it explained 41% and 66% of the respective $f_1$ and $f_2$ signal variations. The logarithmic fit of the predicted loss also displayed a decent performance compared to the Egli, Hata, and Perez Vega model. The predicted loss model Equation 12 can be used for finding how the signal varies while traversing the hilly forested region, while the proposed model fit ($f_{P_1 \text{fit}}$) provides the predicted mean loss variations. The method proposed has potential applications for future wireless communication deployment or planning in the hilly forested environment. Future work requires incorporating the diffraction effect due to terrain for improved prediction accuracy.

Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability Statement

Data sets for this research are available in these in-text data citation references: Jawhly, Thaisa (2021), “Signal strength data,” Mendeley Data, V1, doi: 10.17632/yn37495cdr.1, [License:CC by 4.0]

References

Adewumi, A. S., & Olabisi, O. (2018). Characterization and modeling of vegetation effects on UHF propagation through a long forested channel. Progress in Electromagnetics Research Letters, 73, 9–16. https://doi.org/10.2528/PIERL17092004

Ali, Z., Henna, S., Islam, S. U., & Akhunzada, A. (2018). Evaluation of propagation path delay using 3D scattered model in LoRaWAN. Ad-hoc and sensor wireless networks (p. 255–274).

Andersen, J. B., Rappaport, T. S., & Yoshida, S. (1995). propagation measurements and models for wireless communications channels. IEEE Communications Magazine, 33, 42–49. https://doi.org/10.1109/35.339680

Azevedo, J. A., & Santos, F. E. (2011). An empirical propagation model for forest environments at tree trunk level. IEEE Transactions on Antennas and Propagation, 59, 2357–2367. https://doi.org/10.1109/TAP.2011.2143664

Azevedo, J. A., & Santos, F. E. (2017). A model to estimate the path loss in areas with foliage of trees. AEU-International Journal of Electronics and Communications, 71, 157–161. https://doi.org/10.1016/j.aeue.2016.10.018

Bagchi, B., Chakrabarti, J., & Roy, P. B. (2012). Influence of working capital management on profitability: A study on Indian FMCG companies. International Journal of Business and Management, 7. https://doi.org/10.5539/ijbm.v7n22p1

Benaisa, S., Plets, D., Nikolayev, D., Deruyck, M., Verloock, L., Vermeeren, G., et al. (2019). Experimental characterization of in-to-out-body path loss at 433 MHz in dairy cows. Electronics Letters. https://doi.org/10.1049/el.2018.8150

Boylan, G. L., & Cho, B. R. (2012). The normal probability plot as a tool for understanding data: A shape analysis from the perspective of skewness, kurtosis, and variability. Quality and Reliability Engineering International, 28, 249–264. https://doi.org/10.1002/qre.1241

Chavez, A., Littman-Quinn, R., Ndukou, K., & Kovarik, C. L. (2015). Using TV white space spectrum to practise telemedicine: A promising technology to enhance broadband internet connectivity within healthcare facilities in rural regions of developing countries. Journal of Telemedicine and Telecare, 22. https://doi.org/10.1177/1357633X15595324

Dagefu, F. T., Verma, G., Rao, C. R., Yu, P. L., Fink, J. R., Sadler, B. M., & Sarabandi, K. (2015). Short-range low-VHF channel characterization in cluttered environments. IEEE Transactions on Antennas and Propagation, 63, 2719–2727. https://doi.org/10.1109/TAP.2015.2418346

Egi, Y., & Otero, C. E. (2019). Modeling tree canopy signal power path loss (SPPL) for deployment of wireless communication systems (WCS) using point cloud and sensor fusion. In 2019 IEEE international systems conference (SysCon) (pp. 1–5). https://doi.org/10.1109/JRPROC.1957.270224
Erceg, V., Greenstein, L. J., Tjandra, S. Y., Parkhoff, S. R., Gupta, A., Kulic, R., et al. (1999). Empirically based path loss model for wireless channels in suburban environments. *IEEE Journal on Selected Areas in Communications, 17*, 1205–1211. https://doi.org/10.1109/49.778178

Faruk, N., Surajudeen-Bakinde, N. T., Abdulkarim, A. I., Popoola, S., Abdulkarim, A. A., Olawoyin, L., & Atayero, A. (2019). ANFIS model for path loss prediction in the GSM and WCDMA bands in urban area. *ELEKTRIKA-Journal of Electrical Engineering, 18*, 1–10. https://doi.org/10.1113/elektrika.v18n1.140

Hata, M. (1980). Empirical formula for propagation loss in land mobile radio services. *IEEE Transactions on Vehicular Technology, 29*, 317–325. https://doi.org/10.1109/T-VT.1980.23859

Ibdah, Y., & Ding, Y. (2016). Path loss models for low-height mobiles in forest and urban. *Wireless Personal Communications, 92*, 455–465. https://doi.org/10.1007/s11277-016-3551-y

Jawahly, T., & Tiwari, R. C. (2019). Characterization of path loss for VHF terrestrial band in Aizawl, Mizoram (India). Lecture notes in electrical engineering (pp. 53–63). Springer. https://doi.org/10.1007/978-981-13-1642-5_5

Jawahly, T., & Tiwari, R. C. (2020a). Path loss modeling: A gis-based approach. *2020 international conference on computational performance evaluation (CoMPE) (pp. 054–058).*

Jawahly, T., & Tiwari, R. C. (2020b). The special case of Egli and Hata model optimization using least-square approximation method. *SN Applied Sciences, 2*, 1–10. https://doi.org/10.1007/s42452-020-3061-0

Khamlichi, B. E., Abdelaal, C., Ahmed, L., & Abbadi, J. E. (2016). A quantitative investigation of spectrum utilization in UHF and VHF bands in Morocco: The road to cognitive radio networks. *Sita 2016: 11th international conference on intelligent systems: Theories and applications (pp. 1–6).* https://doi.org/10.1109/SITA.2016.7772293

Khwaja, A. A., Chen, Y., Zhao, N., Alouini, M. S., & Dobbins, P. (2018). A survey of channel modeling for UAV communications. *IEEE Communications Surveys and Tutorials, 20*, 2804–2823. https://doi.org/10.1109/COMST.2018.2856587

Kurnaz, O., & Heheli, S. (2014). Near ground propagation model for pine tree forest environment. *AEU-International Journal of Electronics and Communications, 68*, 944–950. https://doi.org/10.1016/j.aeue.2014.04.019

Lambrecht, W., & Sinha, S. (2019). Terrestrial and millimeter-wave mobile Backhaul: A last mile solution. *Lecture notes in networks and systems.* https://doi.org/10.1007/978-3-030-20957-5_5

Loo, Z. B., Chong, P. K., Lee, K. Y., & Yap, W. S. (2017). Improved path loss simulation incorporating three-dimensional terrain model using parallel coprocessors. *Wireless Communications and Mobile Computing, 2017*, 5492691. https://doi.org/10.1155/2017/5492691

Looney, S. W., & Gullelde, T. R., Jr (1985). Use of the correlation coefficient with normal probability plots. *The American Statistician, 39*, 75–79. https://doi.org/10.2307/2683917

Lu, J. S., Han, X., & Bertoni, H. L. (2013). The influence of terrain scattering on radio links in hilly/mountainous regions. *IEEE Transactions on Antennas and Propagation, 61*, 1385–1395. https://doi.org/10.1109/TAP.2012.2231919

Meng, Y. S., Lee, Y. H., & Ng, B. C. (2009). Empirical near ground path loss modeling in a forest at VHF and UHF bands. *IEEE Transactions on Antennas and Propagation, 57*, 1461–1468. https://doi.org/10.1109/TAP.2009.2016703

Nandi, S., Thota, S., Nag, A., Divyasukhanchanda, S., Goswami, P., Aravindakshan, A., & Mukherjee, B. (2016). Computing for rural empowerment: Enabled by last-mile telecommunications. *IEEE Communications Magazine, 54*, 102–109. https://doi.org/10.1109/MCOM.2016.7498095

NASA Jet Propulsion Laboratory (JPL). (2013). NASA shuttle radar topography mission DEM 1 arc second. Version 3. NASA EOSDIS Land Processes DAAC. https://doi.org/10.5067/MERASURE/SRTM/SRTMGL1.003

Pérez-Vega, C., & Zamanillo, J. M. (2002). Path-loss model for broadcasting applications and outdoor communication systems in the VHF and UHF bands. *IEEE Transactions on Broadcasting, 48*, 91–96. https://doi.org/10.1109/TBC.2002.1021273

Popov, V. (2019). Cross-polarization effect of radio waves propagation by forest vegetation in wireless communication systems on transport. *Procedia Computer Science, 149*, 195–201. https://doi.org/10.1016/j.procs.2019.01.123

Rahman, M., & Saifullah, A. (2019). A comprehensive survey on networking over TV white spaces. *Pervasive and Mobile Computing, 59*, 101–1072. https://doi.org/10.1016/j.pmcj.2019.101072

Ribero, M., Heath, R. W., Vikalo, H., Chizhik, D., & Valenzuela, R. A. (2019). Deep learning propagation models over irregular terrain. *ICASSP, IEEE international conference on acoustics, speech and signal processing - proceedings (pp. 4519–4523).* https://doi.org/10.1109/ICASSP.2019.8682491

Salous, S. (2013). Radio propagation measurement and channel modelling (pp. 422). https://doi.org/10.1002/9781118302280

Shehadeh, H. A., Idris, M. Y. I., Ahmedy, I., & Hassan, H. R. (2019). Optimal placement of near ground VHF/UHF radio communication network as a multi objective problem. *Wireless Personal Communications, 110*, 1169–1197. https://doi.org/10.1007/s11277-019-06780-6

Smith, D. P., Messier, G. G., & Wasson, M. W. (2016). Boreal forest low antenna height propagation measurements. *IEEE Transactions on Antennas and Propagation, 64*, 4004–4011. https://doi.org/10.1109/TAP.2016.2583490

Walisch, J., & Bertoni, H. L. (1988). A theoretical model of UHF propagation in urban environments. *IEEE Transactions on Antennas and Propagation, 36*, 1788–1796. https://doi.org/10.1109/8.14401

Weissberger, M. A. (1982). *An initial critical summary of models for predicting the attenuation of radio waves by trees* (Tech. Rep.). 10.21236/ada118343

Yan, C., Fiu, L., Zhang, J., & Wang, J. (2019). A comprehensive survey on UAV communication channel modeling. *IEEE Access, PP*. https://doi.org/10.1109/ACCESS.2019.2933173

Zang, J., & Wang, X. (2017). Measurements and modeling of path loss over irregular terrain for near-ground and short-range communications. *Progress in Electromagnetics Research M, 57*. https://doi.org/10.2528/PIERM17032806

Zhao, Z., Vuran, M. C., Batur, D., & Ekici, E. (2019). Shades of white: Impacts of population dynamics and TV viewership on available TV spectrum. *IEEE Transactions on Vehicular Technology, 68*, 2427–2442. https://doi.org/10.1109/TVT.2019.289267