

Deep Learning Based Rain Attenuation prediction modeling for Microwave and mmWave Band 基于深度学习的微波和毫米波频段雨衰预测模型

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Advisor: Prof. Xiong Lei(熊磊)

8/11/2024



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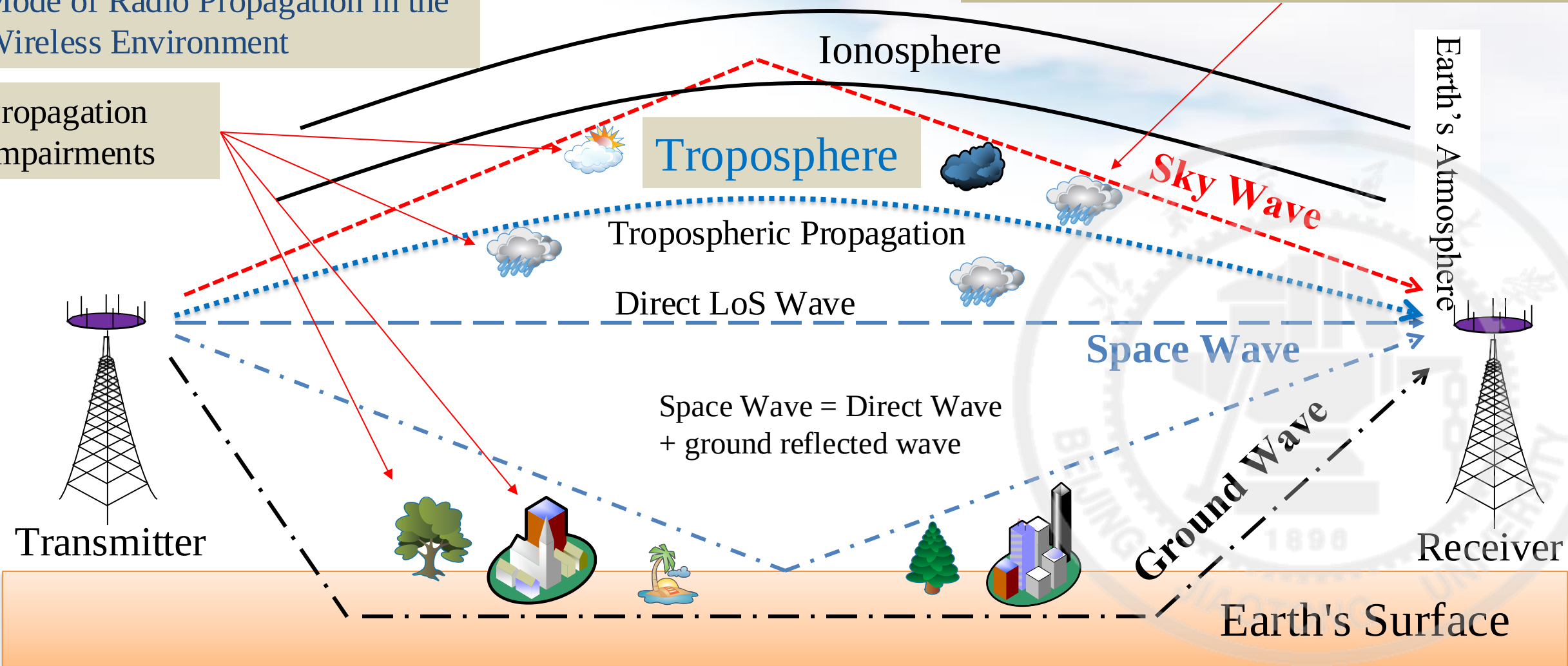
Background

Radio Propagation

Dominant Atmospheric Impairment!

Mode of Radio Propagation in the Wireless Environment

Propagation Impairments



Background

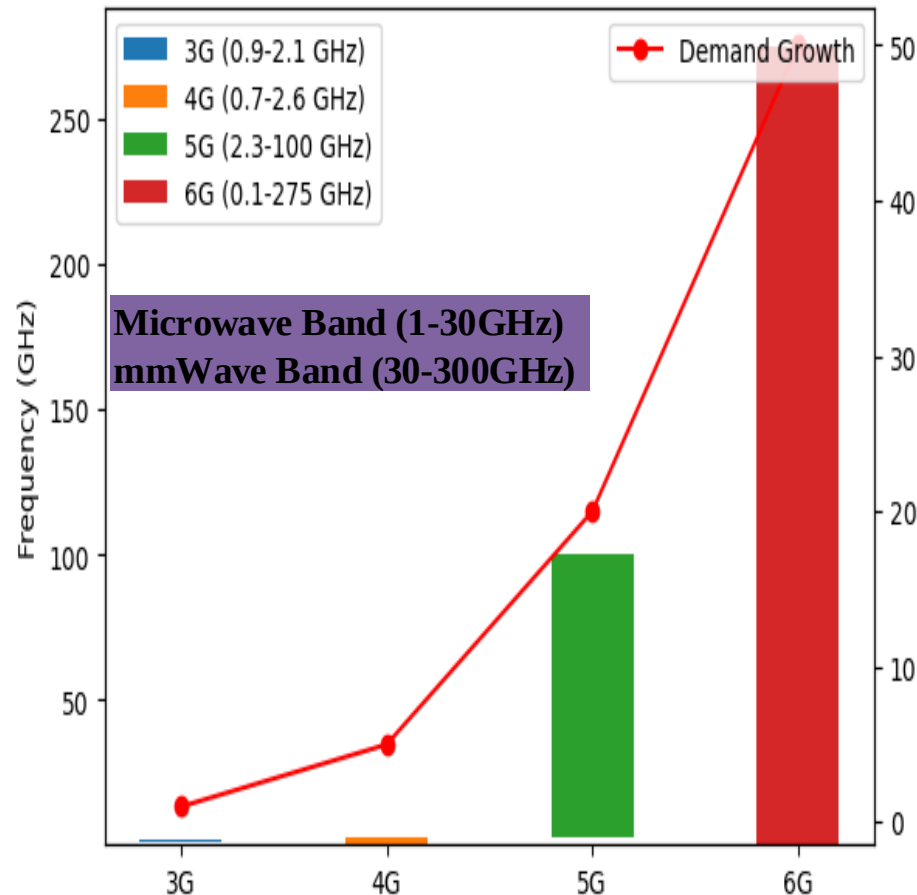
Problems and Motivations

The need for high frequency band increases

What is Rain Attenuation and how it shall be estimated?



Frequency Band Ranges and Demand Growth



Propagation Impairments such as **Rain** becomes critical at high frequency!

Rain Induced propagation fading has be estimated properly!

ITU-R Methods:

ITU-R P.530
ITU-R P.837
ITU-R P.838
...

Individual Researchers

AI-Assisted Methods

Background

LoS Propagations

The fundamental equation that governs the propagation of radio waves in free space:

Friis equation:
$$p_r = \frac{P_t G_t G_r \lambda^2}{(4\pi D^2)}$$

Before a microwave or mmWave link installed, an analysis and calculation of the link has be made first !

The analysis should **include** the following:

- Free space loss calculation $L_0 = 32.44 + 20\log f + 20\log D$
- Link budget calculation $p_r = P_t + G_t + G_r - L_0 - L_p$
- **Rain attenuation** $\gamma_R = kR_{0.01}^\alpha \text{ dB/km}$
- Multipath fading
- Fade margin $= p_r - \text{Rx Sensitivity}$
- Fresnel zones calculation $F_1 = \sqrt{\lambda \frac{d_1 \cdot d_2}{d_1 + d_2}}$

Medium Loss



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Research Methodology

Data Collection

- Rainfall data of 15-minute integration time of 8 years period is collect from National Metrology Agency of Ethiopia and Microwave Link information operating at 11 GHz in Addis Ababa city is collected from similar research work and Addis Ababa University
- Preprocess collected data using MS-Excel, Python and Matlab

ITU-R Methods

- Utilize ITU-R models (ITU-R P.530-17, ITU-R P.837-7 and ITU-R P.838-3) to calculate rain rate, specific attenuation and total path attenuation due to rain.
- Dataset containing of rain rate, specific attenuation and total path attenuation for 8 years is compiled.

Apply Deep Learning

- Develop an LSTM prediction model which use the compiled dataset and make prediction of rain attenuation.
- Compare the developed LSTM prediction model with other AI models and evaluate the performance.



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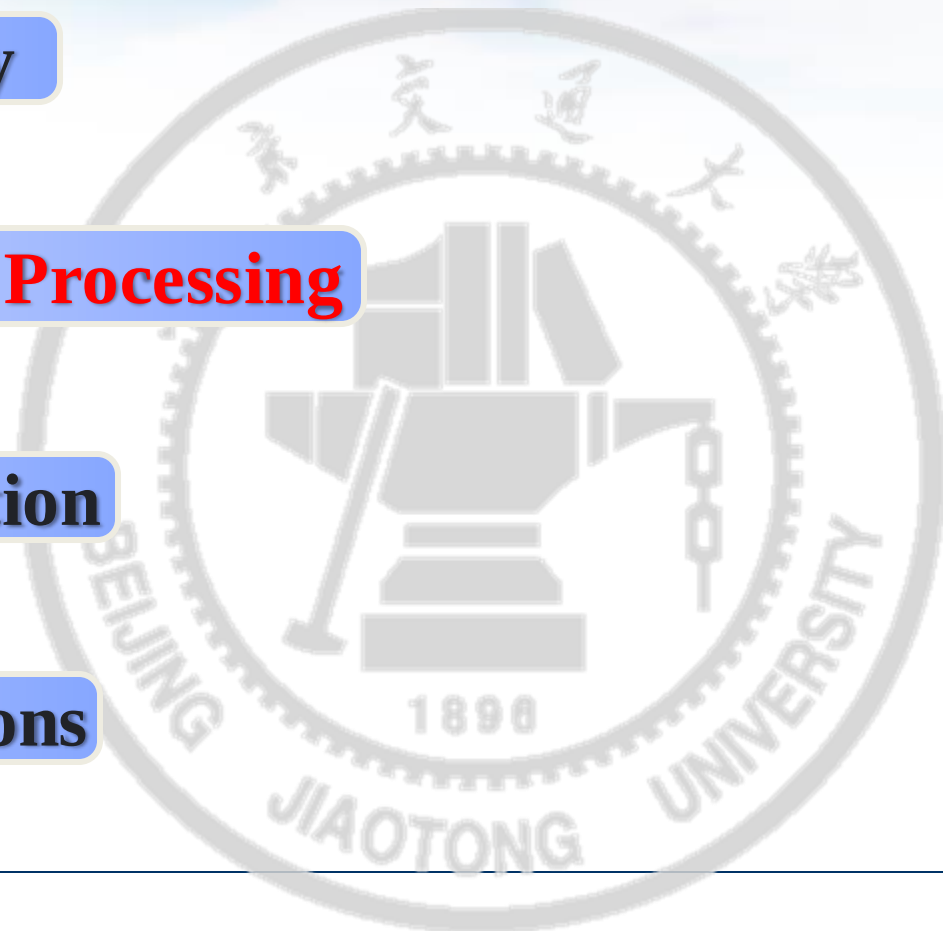
Data Collection and Processing

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Deep Learning Prediction

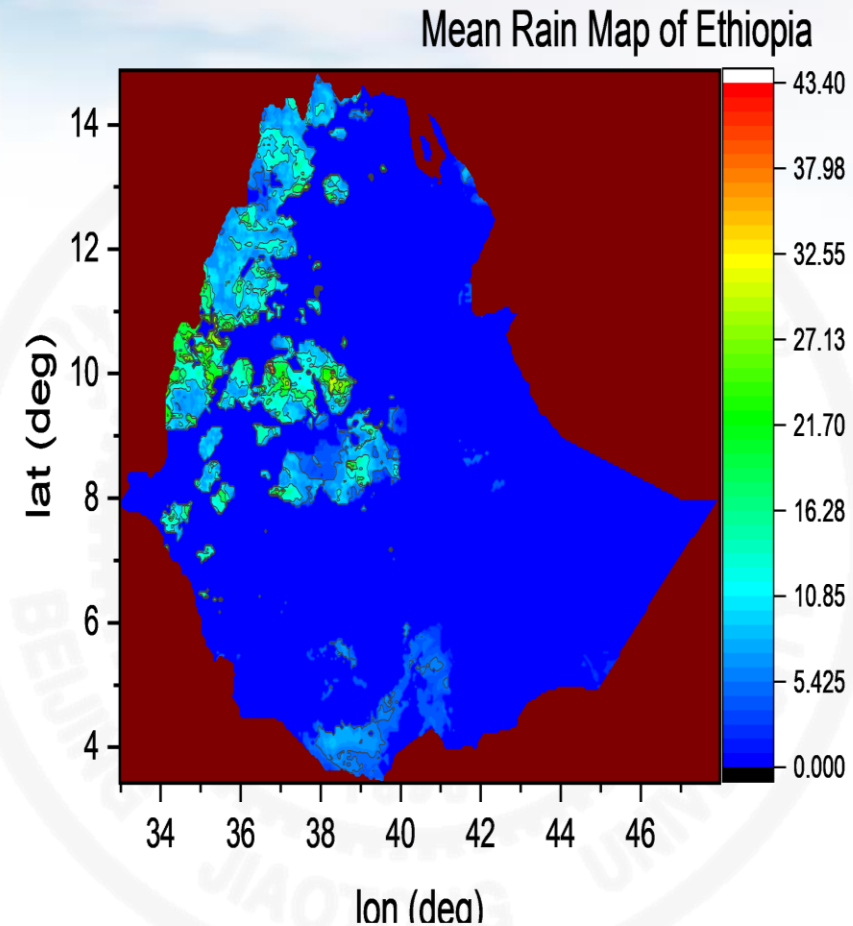
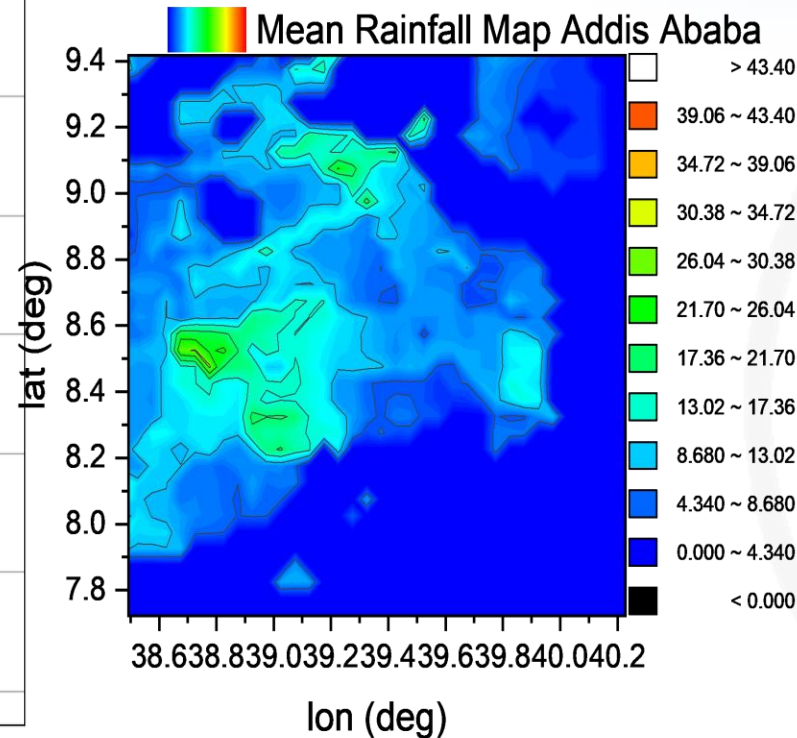
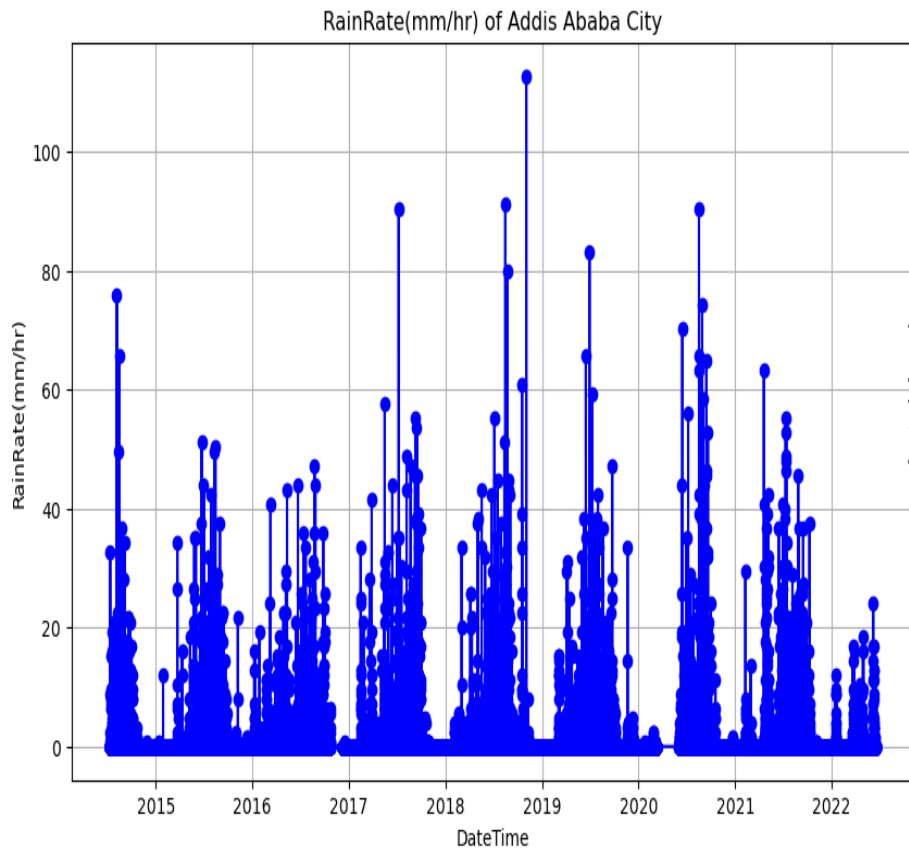
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Conclusion and Contributions

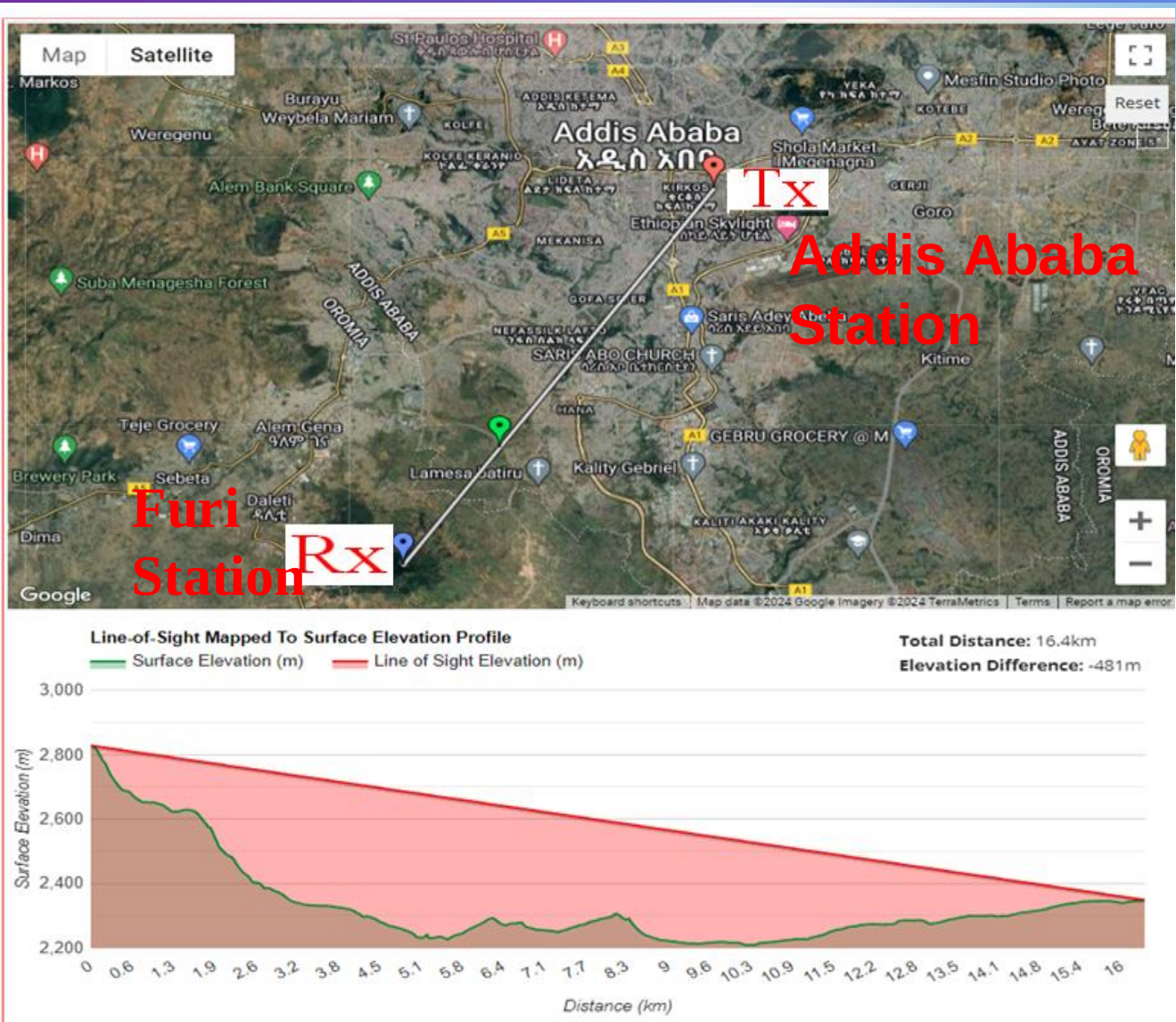


Data Collection

Rainfall and microwave link information collected for Addis Ababa,
Highest rainfall rate per hour = 112.8 mm/hr (Rainy)
Lowest rainfall rate = 0 mm/hr (Non-Rainy)



Data Collection



Parameters	AddisAbaba-Rx	MountFuri-Tx
Elevation(m)	2842	2401
Latitude	08.52582°N	09.01067°N
Longitude	38.41125°E	38.44504°E
Antenna gain (dBi)	42	42
Antenna height (m)	10	10
Frequency (GHz)	11	
True azimuth (°)	23.92	203.93
Vertical angle (°)	-1.59	1.48
Link length (km)	16.42	
Tx line loss (dB/100)	4.53	4.53
Tx line loss (dB)	0.91(dB)	0.91(dB)
Circuit branching loss	6.8(dB)	6.8(dB)
Tx power (dBm)	30	30
Free space loss (dB)	139.6	139.6
Rx threshold level(dBm)	-76.2	-76.2
Atmospheric absorption loss	0.35(dB)	0.35(dB)
Effective frequency spacing	21.7(MHz)	21.7(MHz)

The terrestrial LoS radio link was found between Addis Ababa station and Furi station the above link information. The radio link was using vertical polarization at a frequency of 11 GHz.

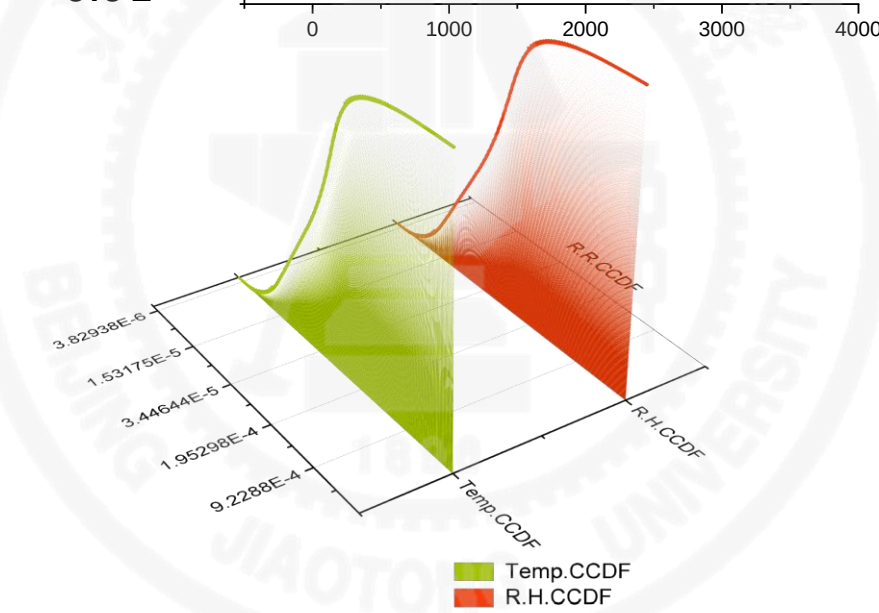
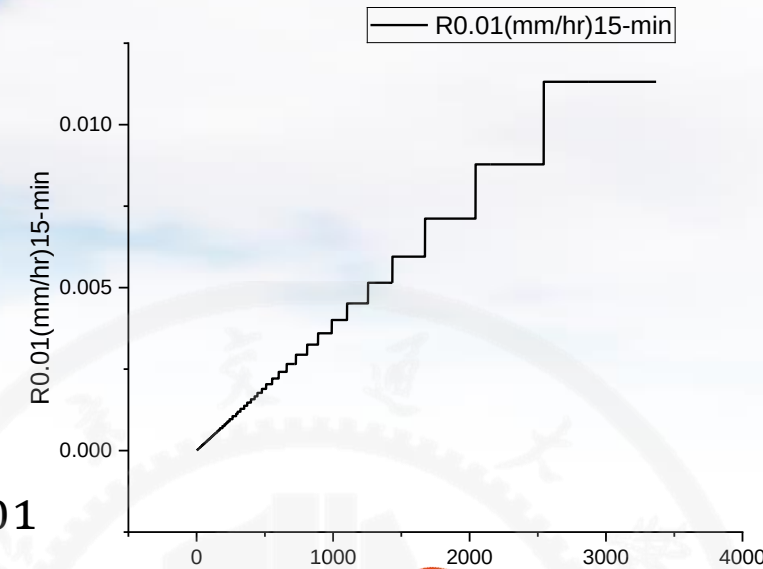
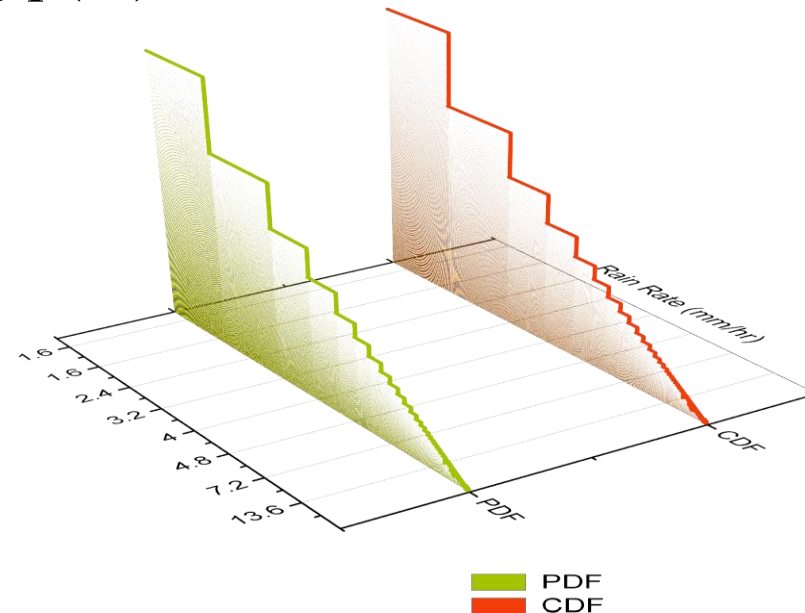
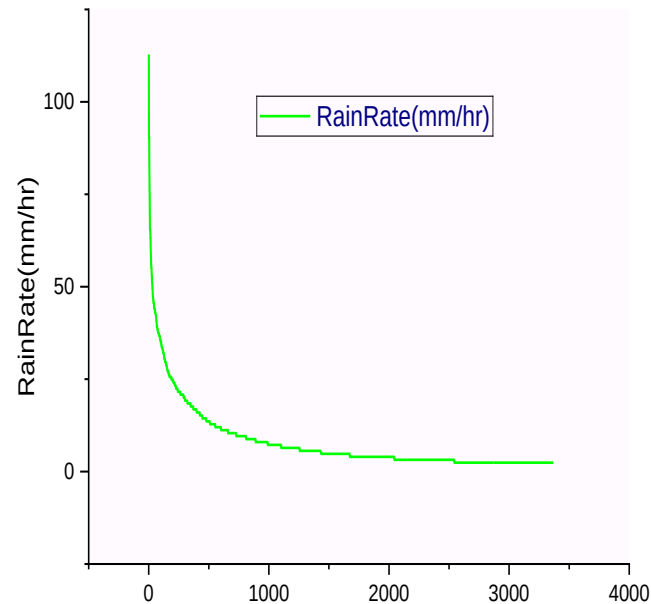
$$L_0 = 32.44 + 20\log f + 20\log D$$
$$= 139.6 \text{ dBm}$$

$$p_r = P_t + G_t + G_r - L_0 - L_p$$
$$= 30 + 42 + 42 - 139.6 - 0.9 - 6.8 - 0.35$$
$$p_r = -33.66 \text{ dBm}$$

$$\text{Fademargin} = p_r - \text{Rx Sensitivity}$$
$$= -33.66 \text{ dBm} - (-762) \text{ dBm}$$
$$= 42.54 \text{ dBm}$$

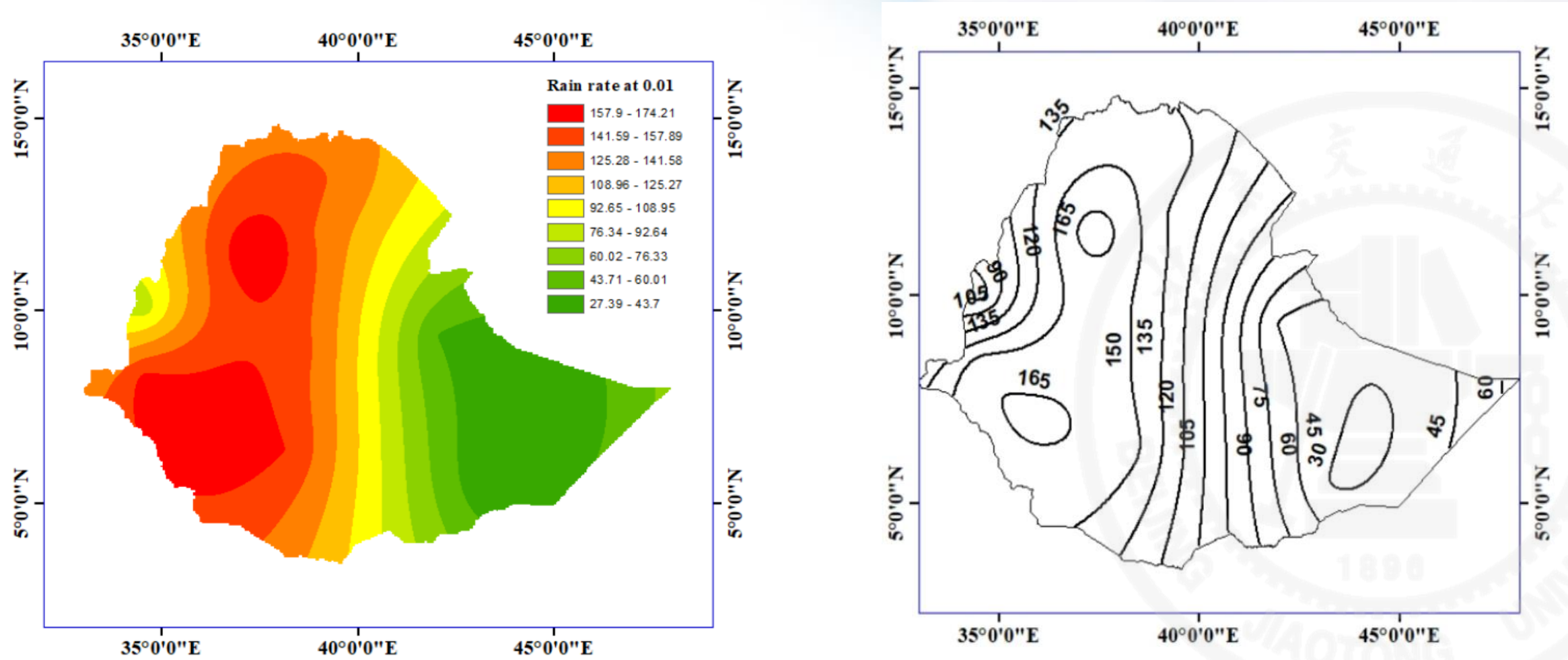
Determination of Rain Rate $R_{0.01}$

- Filter rain rate data raw data(zeros and non numerical values)
- Sort the rain rates in an ascending order
- Assign cardinal numbers n for rain rate values as $n = 1, 2, 3, \dots, N_r$
- Determine the number of non-zero recordings, N_r .
- Calculate PDF, CDF and CCDF
- Calculate the percentage $P(\%) = N_r - n / \text{Numberofminutsinayear} * 100$
- Read the rain rate value along $p(\%)=0.01$, which is the value of $R_{0.01}$



Determination of Rain Rate $R_{0.01}$

Plotting of $R_{0.01}$ distribution over Ethiopia



One-Minute Rain Rate Modeling

$$R_1(p) = a(R_t(p))^b$$

Power Law Method

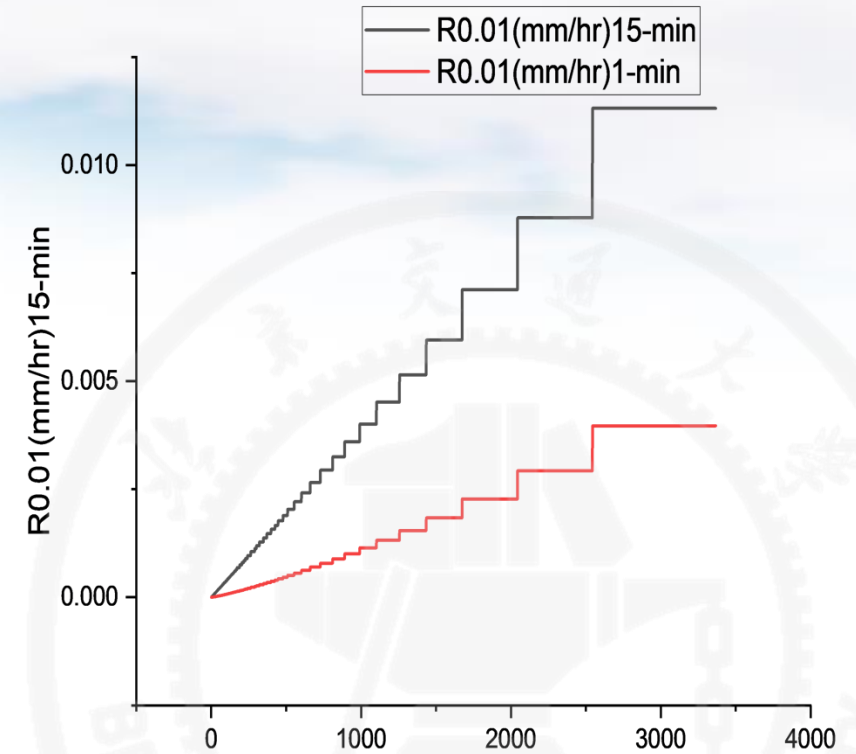
$R_1(p)$ is one-minute Rain Rate

$R_t(p)$ is t-minute Rain Rate, (t=15 for this study)

$$a = 0.0002t^2 - 0.0189t + 1.136$$

$$b = 0.0063t + 1.10366$$

where a and b represent the conversion variables obtained from a statistical analysis of rainfall data



[1] Emiliani, L.D., L. Luini, and C. Capsoni, *Analysis and Parameterization of Methodologies for the Conversion of Rain-Rate Cumulative Distributions from Various Integration Times to One Minute*. IEEE Antennas and Propagation Magazine, 2009. 51(3): p. 70-84.

[2] AlKhedhairi, K.I. and J. Din. *Conversion of 15-minutes to 1-minute rain attenuation derived from tropical rain attenuation measurement*. in *2011 IEEE International RF & Microwave Conference*. 2011.

Determination of Specific Attenuation(ITU-R P.838-3)

The ITU-R P.838 provides a method for calculating the specific attenuation of radio signals due to rain, using a power-law relationship between attenuation and rain rate for frequencies ranging from 1 to 1,000 GHz. It provides coefficients for different frequencies and polarizations, essential for designing terrestrial microwave communication links. This method is crucial for predicting signal loss in varied weather conditions, ensuring the reliability of communication systems.

$$\gamma_R \text{ (dB/km)} = k R_{0.01}^\alpha$$

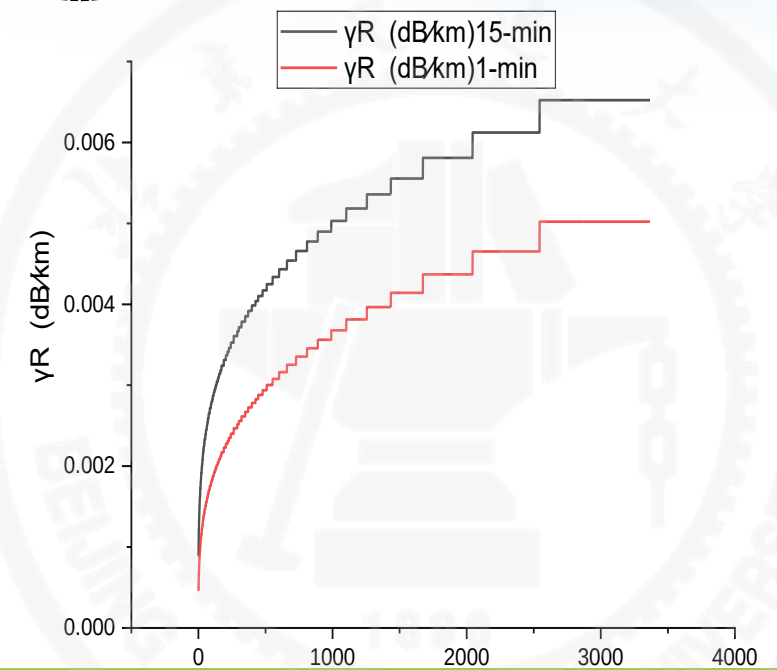
$$k = [k_H + k_v + (k_H - k_v) \cos^2 \theta \cos 2\tau] / 2 = \mathbf{0.02}$$

$$\alpha = \frac{[k_H a_H + k_v a_v + (k_H a_H - k_v a_v) \cos^2 \theta \cos 2\tau]}{2k} = \mathbf{0.25}$$

f	k_H	k_v	a_H	a_v
11GHz	0.01772	1.2140	0.01731	1.1617

$$\theta = \tan^{-1} \left(\frac{R_x \text{ height} - T_x \text{ height}}{d} \right) = \mathbf{-1.54}$$

$$\tau = \mathbf{0} \text{ (Vertical Polarization)}$$



$$\gamma_R \text{ (dB/km)} = 0.02 R_{0.01}^{0.25}$$

Determination of Rain Attenuation(ITU-R P.530-17)

The ITU-R P.530 provides a guide for designing LoS communication systems to predict radio wave behavior in various atmospheric conditions for frequencies between 30 MHz to 100 GHz. It addresses factors like free-space loss, atmospheric absorption, multipath fading, rain attenuation, refraction, and diffraction, which affect signal strength and quality. The document also outlines a method for estimating long-term rain attenuation statistics, crucial for the reliability of satellite and microwave communication links.

$$A(\text{dB}) = \gamma_R \left(\frac{\text{dB}}{\text{km}} \right) \times d_{\text{eff}}(\text{km})$$

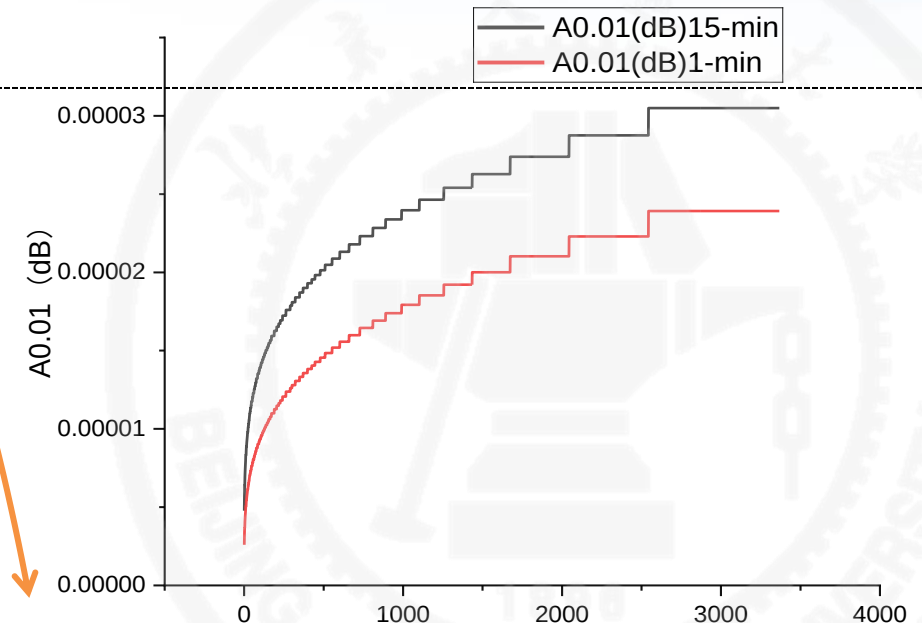
$$d_{\text{eff}}(\text{km}) = d(\text{km})r$$

Distance Factor

$$r = \frac{1}{0.477d^{0.633}R_{0.01}^{0.073}f^{0.123} - 10.579(1 - \exp(-0.024d))}$$

$$f = 11 \times 10^9 \text{ Hz}, d = 16.42 \text{ km}, \alpha = 0.25$$

$$d_{\text{eff}}(\text{km}) = \frac{16.42}{3818.99R_{0.01}^{0.018} - 10.579} \text{ km}$$



$$A(\text{dB}) = \frac{0.33R_{0.01}^{0.25}}{3818.99R_{0.01}^{0.018} - 10.579}$$



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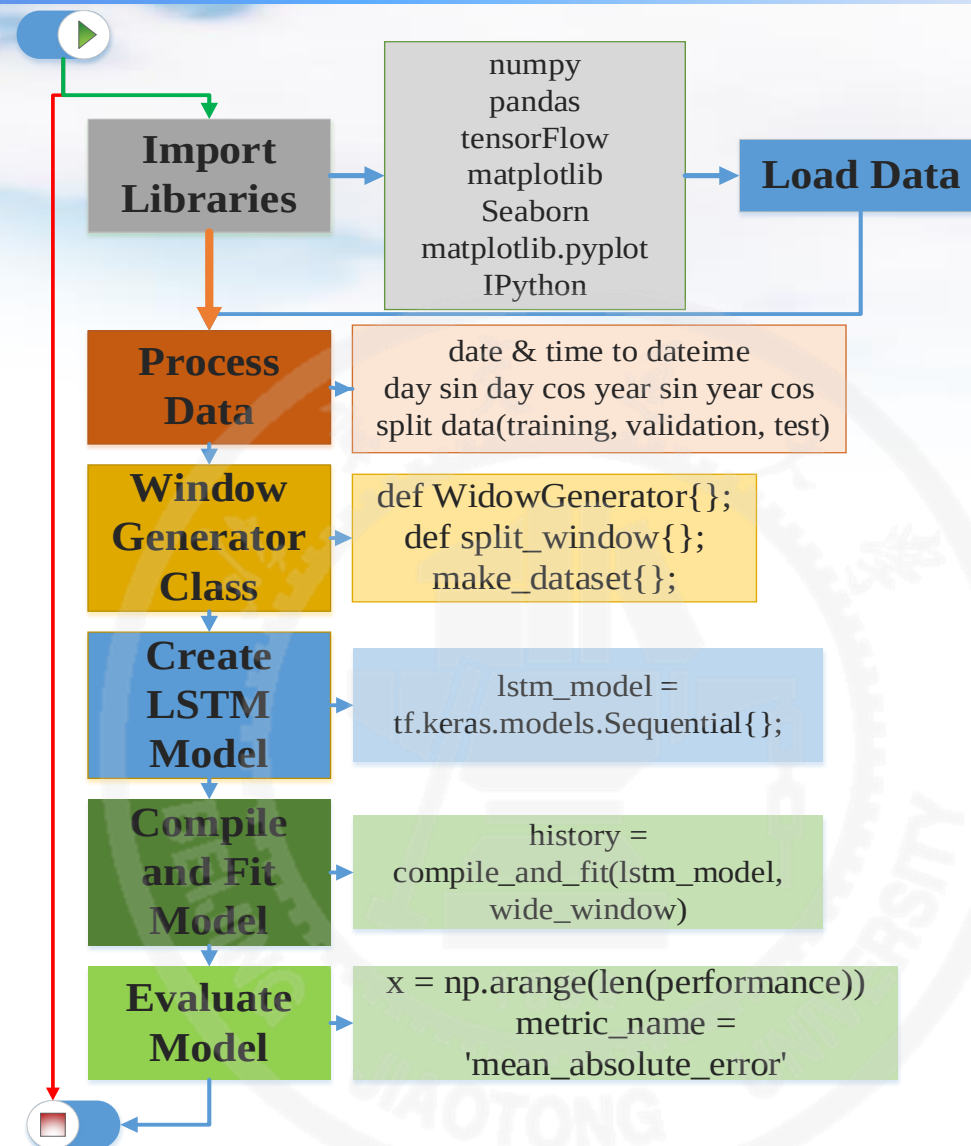
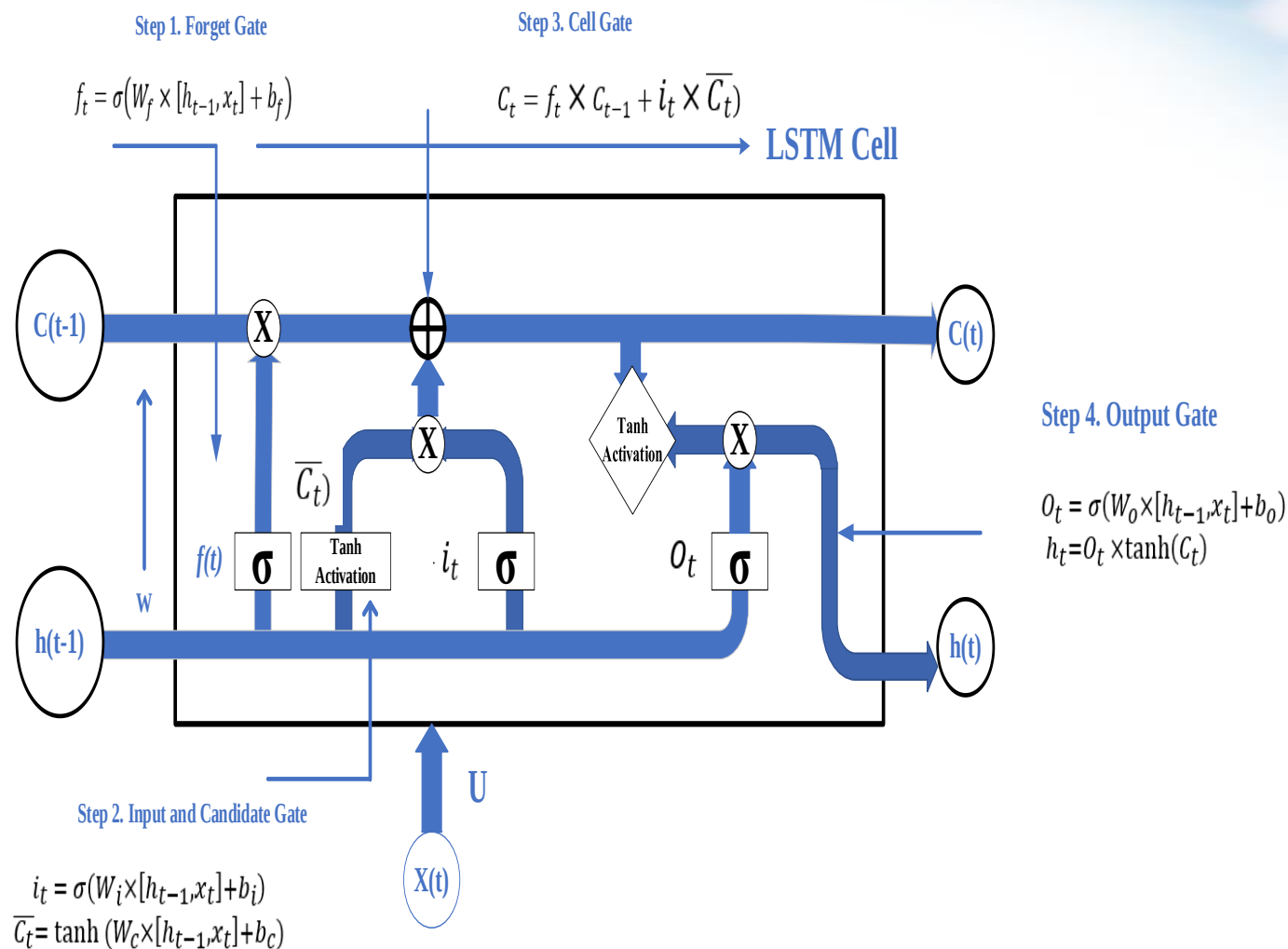
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Deep Learning Prediction

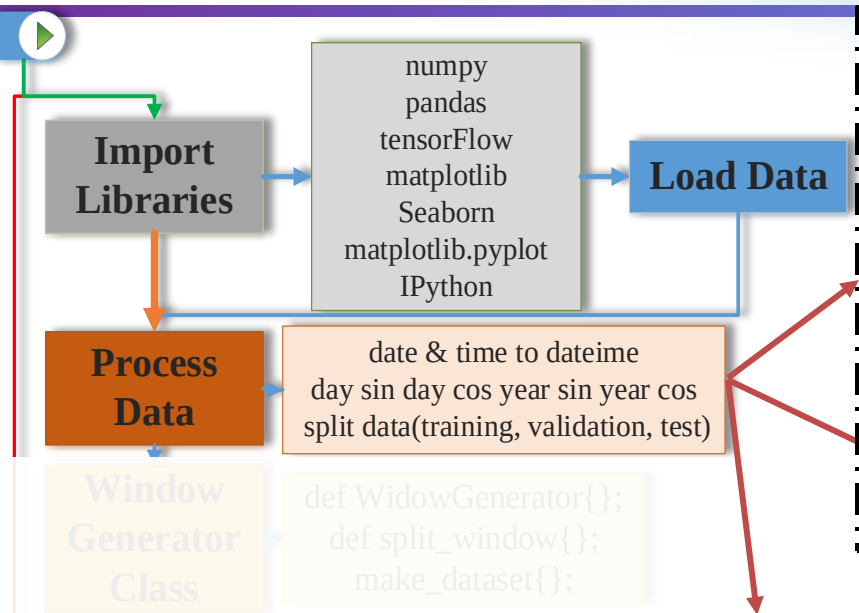
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Conclusion and Contributions

LSTM Based Rain Attenuation Prediction

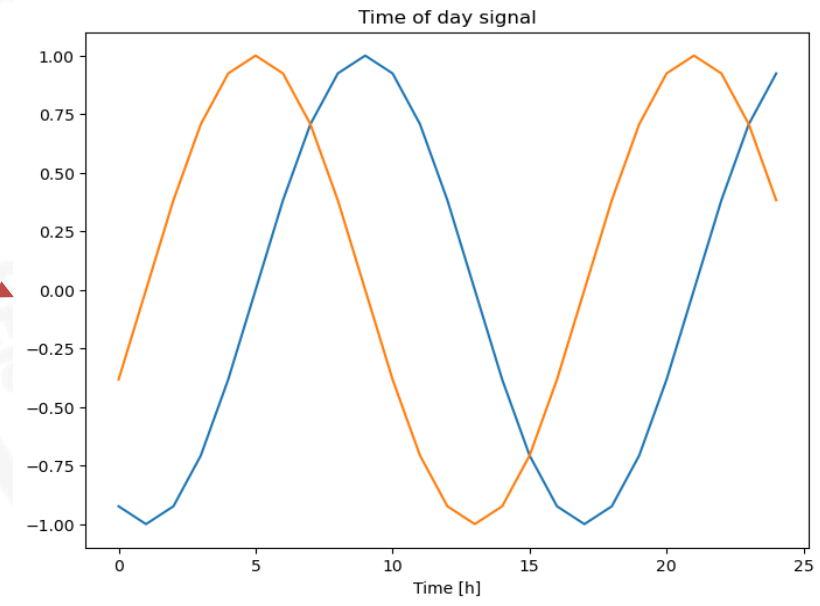


LSTM Based Rain Attenuation Prediction

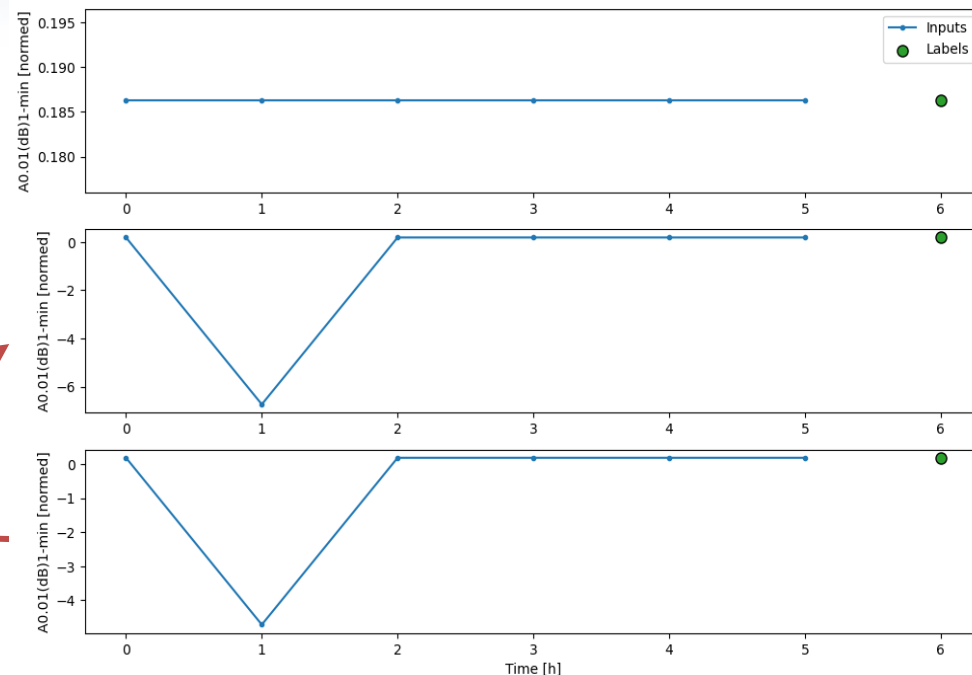
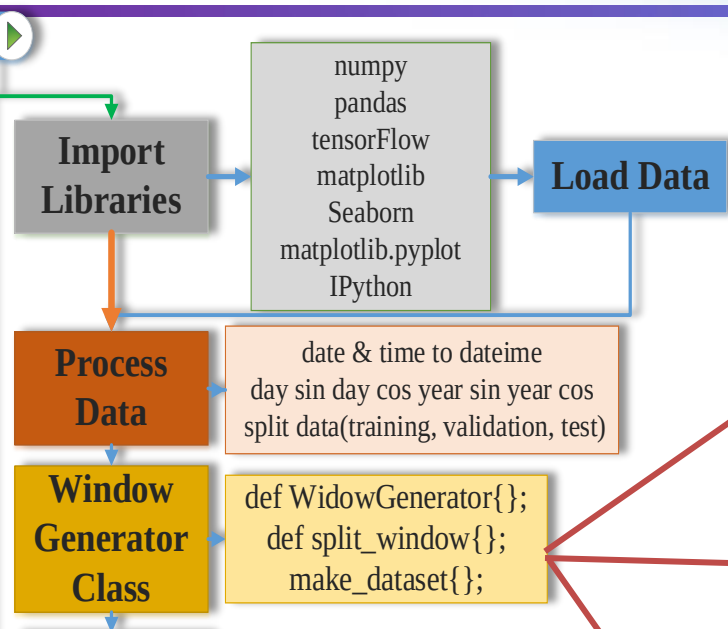


- Sequential Data Format:** Essential for LSTM to capture time-related patterns.
- Unix Timestamp Conversion:** `pd.Timestamp.timestamp` transforms datetime to seconds since Unix Epoch.
- Uniform Numeric Sequence:** `.map()` function standardizes `date_time` column for LSTM processing.
- Normalization Post-Conversion:** Scales data, enhancing LSTM training efficiency.
- Cyclical Features:** `day-sin`, `day-cos`, `year-sin`, `year-cos` functions to encode cyclic nature of day and year, helping the model to understand data.

- Data Splitting:** Sequential split of data into 70% training, 20% validation, and 10% testing.
- Order Preservation:** No random shuffling to maintain time series integrity.
- Consecutive Sampling:** Enables windowing for LSTM models.
- Model Assessment:** Validation and testing on unseen, subsequent data for accurate performance evaluation.



LSTM Based Rain Attenuation Prediction



```
[25]: class WindowGenerator():
    def __init__(self, input_width, label_width, shift,
                 train_df=train_df, val_df=val_df, test_df=test_df,
                 label_columns=None):
        # Store the raw data.
        self.train_df = train_df
        self.val_df = val_df
        self.test_df = test_df

        # Work out the label column indices.
        self.label_columns = label_columns
        if label_columns is not None:
            self.label_columns_indices = {name: i for i, name in
                                           enumerate(label_columns)}
        self.column_indices = {name: i for i, name in
                               enumerate(train_df.columns)}

        # Work out the window parameters.
        self.input_width = input_width
        self.label_width = label_width
        self.shift = shift

        self.total_window_size = input_width + shift

        self.input_slice = slice(0, input_width)
        self.input_indices = np.arange(self.total_window_size)[self.input_slice]

        self.label_start = self.total_window_size - self.label_width
        self.labels_slice = slice(self.label_start, None)
        self.label_indices = np.arange(self.total_window_size)[self.labels_slice]

    def __repr__(self):
        return '\n'.join([
            f'Total window size: {self.total_window_size}',
            f'Input indices: {self.input_indices}',
            f'Label indices: {self.label_indices}',
            f'Label column name(s): {self.label_columns}'])
```

- **Data Windowing:** Prepares sequential data for LSTM models by creating input and label windows.
- **WindowGenerator:** A class that defines window sizes, offsets, and indices for slicing data.
- **Parameters:** Includes window dimensions (input_width, label_width) and DataFrame inputs (train_df, val_df, test_df).
- **Functionality:** Calculates indices for inputs and labels, allowing for single or multi-step predictions. It's a foundational component for structuring time series data for LSTM training and prediction.

LSTM Based Rain Attenuation Prediction

```
lstm_model = tf.keras.models.Sequential([  
    # Shape [batch, time, features] => [batch, time, lstm_units]  
    tf.keras.layers.LSTM(32, return_sequences=True),  
    # Shape => [batch, time, features]  
    tf.keras.layers.Dense(units=1)  
])
```

```
history = compile_and_fit(lstm_model, wide_window)  
  
IPython.display.clear_output()  
val_performance['LSTM'] = lstm_model.evaluate(wide_window.val, return_dict=True)  
performance['LSTM'] = lstm_model.evaluate(wide_window.test, verbose=0, return_dict=True)  
  
272/272 — 1s 2ms/step - loss: 1.0768 - mean_absolute_error: 0.2280
```

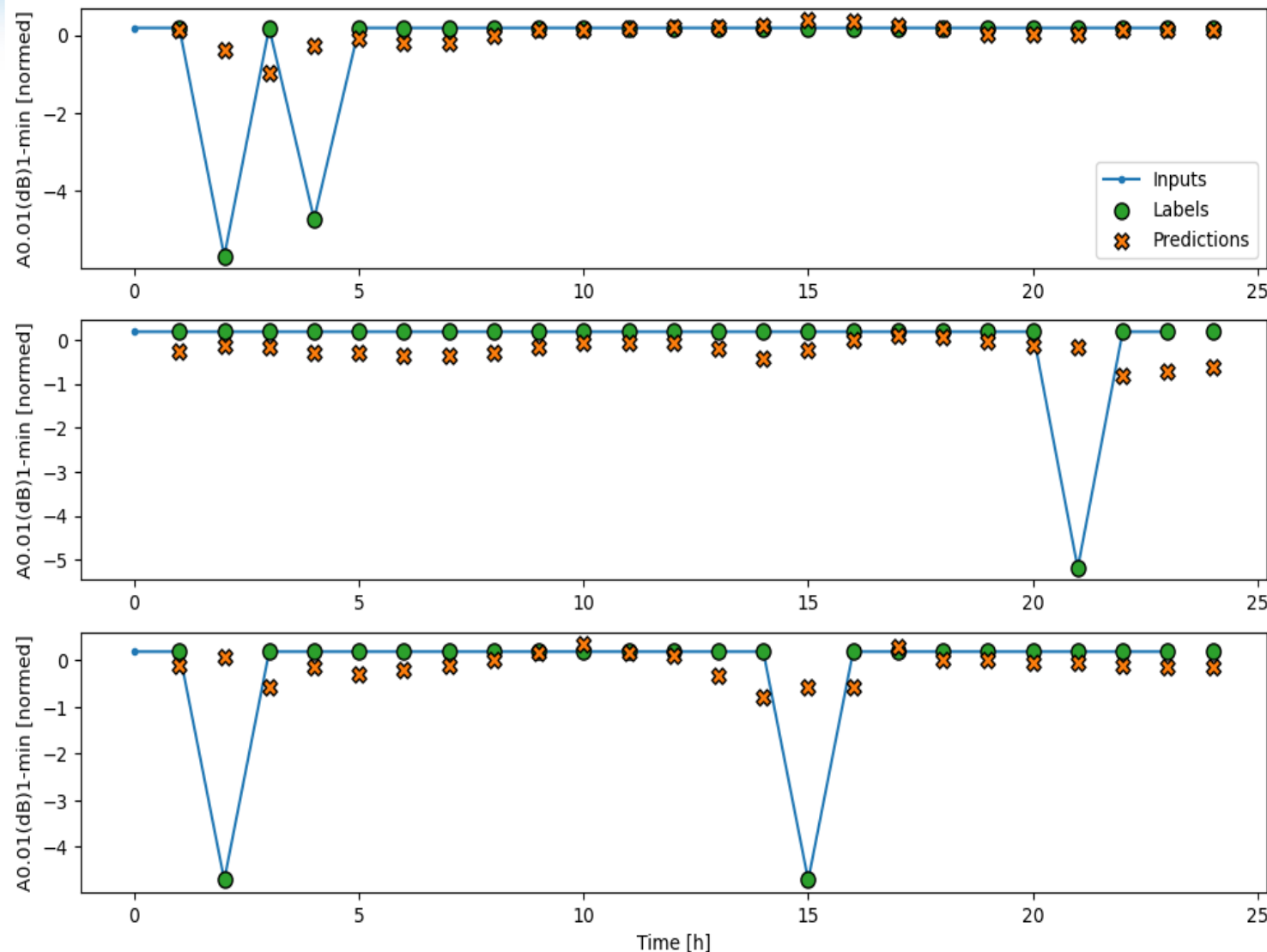
Create
LSTM
Model

```
lstm_model =  
tf.keras.models.Sequential({};
```

Compile
and Fit
Model

```
history =  
compile_and_fit(lstm_model,  
wide_window)
```

- **LSTM Model Creation:** Sequential model with an LSTM layer (32 units) and a Dense output layer.
- **Compilation & Fitting:** Model compiled and fitted using a custom function on training data within a specified window.



LSTM Based Rain Attenuation Prediction

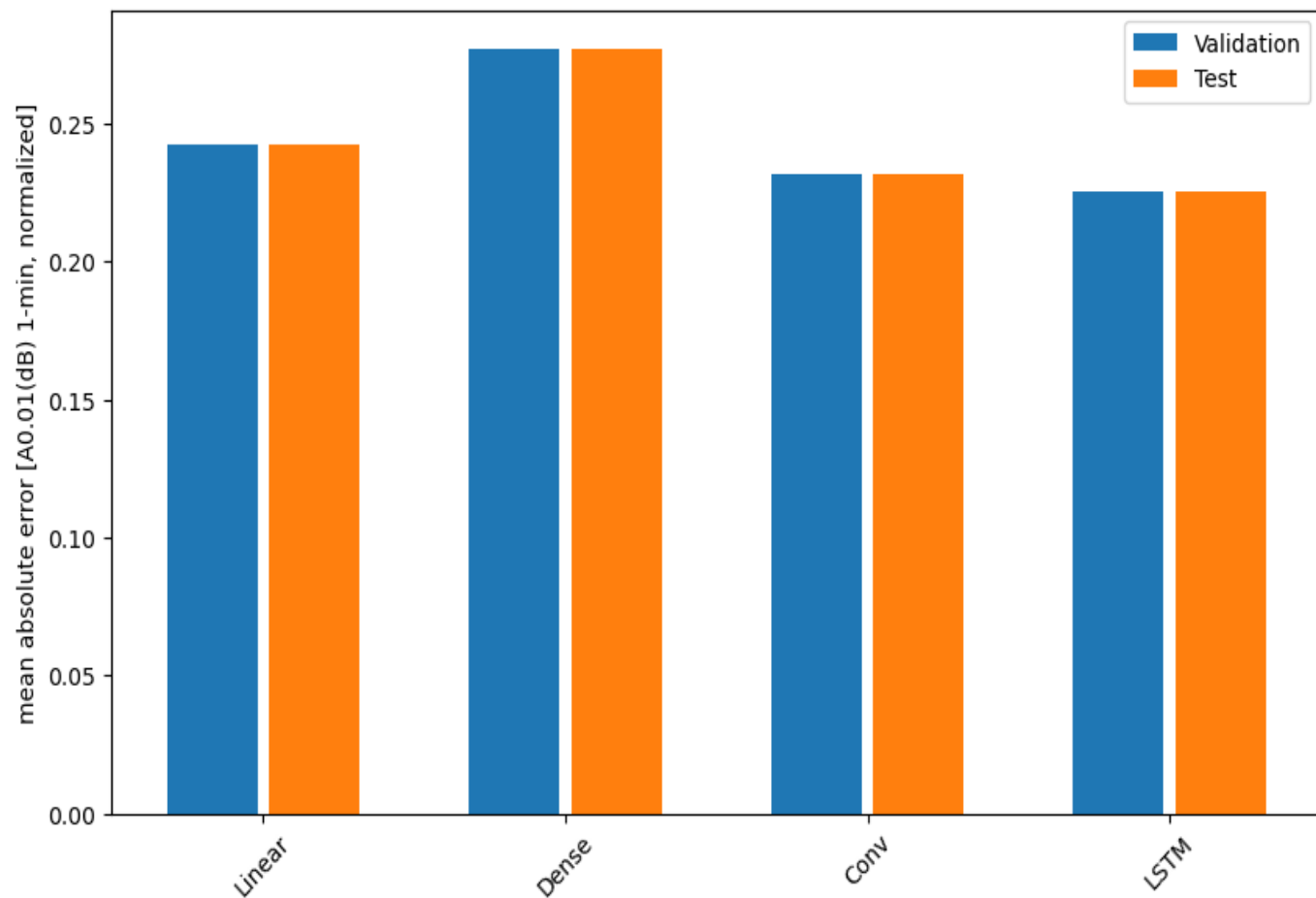
•**Evaluation:** Model performance evaluated on validation and test sets, with results stored for comparison.

performance

```
{'Linear': {'loss': 1.1159884929656982,  
  'mean absolute error': 0.24249599874019623},  
 'Dense': {'loss': 1.1064506769180298,  
  'mean absolute error': 0.27746206521987915},  
 'Conv': {'loss': 1.117496371269226,  
  'mean absolute error': 0.2314935326576233},  
 'LSTM': {'loss': 1.107550859451294,  
  'mean absolute error': 0.22566133737564087}}
```

Evaluate
Model

```
x = np.arange(len(performance))  
metric_name =  
'mean_absolute_error'
```





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Conclusion

- 1) Advanced knowledge of radio link characteristics is crucial for designers to optimize communication systems effectively, specially for higher frequency bands such as microwave, mmWave and beyond.
- 2) One-minute rain rate modeling is necessary to precisely prediction rain attenuation(ITU-R P.837) and conversion of higher integration time rain rate such as 15-minutes to 1-minute can be performed using statistical methods and rain attenuation can be computed based on the 1-minute data.
Specific Attenuation: $1.55 \times 10^{-2} \text{ dB/km}$ **Total Path Attenuation:** $6.77 \times 10^{-2} \text{ dB}$
- 3) An LSTM model was developed and validated with 8 years of historical data, predicting rain attenuation with a mean absolute error of 0.226.

Contributions

- 1) AI-based models show high accuracy when trained with adequate historical data.
- 2) The deep learning model promises superior accuracy in predicting rain-induced attenuation with flexibility to integrate with ITU-R models for enhanced predictions.
- 3) The research findings are vital for microwave link design, offering data to optimize network performance in specific locations with its rapid prediction capabilities making it ideal for real-time applications scenarios.
- 4) This thesis is a valuable resource for the microwave and millimeter wave communications community, encouraging further research and development.

Prospect

- 1) Employing LSTM and other AI-based models extensively for predicting stochastic events like rainfall to enhance precision and accuracy should be done more using local data.
- 2) Expand research efforts to locations like Ethiopia, where measured rain attenuation data is not readily available, to improve the robustness of communication systems

相关成果

已投稿期刊论文

H.Endale Legesse, D.JingJing, L. Xiong “Deep Learning Based Rain Attenuation Prediction Modeling for Microwave and Millimeter Wave Band ” 2024 【一作】

H.Endale Legesse, Y. Liu, L. Xiong, D. Fei, R. Liu, “Characteristics analysis and modeling of train-to-train wireless channel in station scenario, 【二作】

WILEY

DASHBOARD / ARTICLE DETAILS

ID 9497970

Characteristics analysis and modeling of train-to-train wireless channel in station scenario

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Academic Editor: Giulio Maria Bianco

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Updated on 08 May 2024

Version 3

PENDING APPROVAL

参与科研项目

1. B5G典型场景无线信道建模，广东省重点研发计划项目

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ICCC 24	Deep Learning Based Rain Attenuation prediction modeling for Microwave and Millimeter Wave Band	Active (has manuscript)				

Deep Learning Based Rain Attenuation Prediction Modeling for Microwave and Millimeter Wave Band

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Abstract—This paper presents a deep learning model for predicting rain attenuation in tropical climates, where weather-related interference is significant due to prolonged rainy seasons. Utilizing local rainfall data and an 11GHz microwave link profile from Addis Ababa, Ethiopia, historical attenuation data in dB is obtained by the International Telecommunication Union-Radiocommunication (ITU-R) and Crane models, which shows rain attenuation up to 31.61dB and 28.65dB, respectively. The proposed model utilizes this data as input and it demonstrates high accuracy prediction with a mean absolute error of 0.0485, indicating its effectiveness in forecasting rain-induced signal degradation.

Keywords— Deep Learning, Rain Attenuation Prediction, Microwave and Millimeter wave, Long Short-Term Memory (LSTM) network.

I. INTRODUCTION

The microwave and mmWave frequency bands are essential for data transmission, but are sensitive to environmental factors like rain, which can scatter, absorb, or diffract the waves, leading to signal power loss known as rain attenuation. This affects the clarity and reliability of terrestrial line-of-sight link[1] and satellite communication link[2]. While in temperate regions, frequencies up to 10 GHz are viable, in tropical areas, rain interference can occur at frequencies as low as 7 GHz due to larger raindrops.

following ITU-R guidelines. The LSTM model trained on this data achieved an accuracy of 91.88%, surpassing the best external model's accuracy of 87.99%. This approach holds potential for improving satellite network performance through rain attenuation prediction. Due to the variable and stochastic nature of rain, finding one model is a big challenge. However, by considering the gaps a limitations of previous research work, a better approach can be made.

The rest of this paper is organized as follows. Section II describes materials and methods with graphical illustrations, Section III, presents existing rain attenuation models, Section IV explains the proposed prediction model, and finally Section V concludes the paper.

II. MATERIALS AND METHODS

This study focuses on developing a deep learning method of predicting rain attenuation using local data to accurately predict the attenuation of a microwave link due to rain. Rainfall rate data were obtained for Addis Ababa city from the National Metrology Agency of Ethiopia (NMAE) recorded in 15-minute interval for 8 years. This data is visualized in Fig.1. Although, the conventional rain attenuation prediction models such as the ITU-R models provide a solid foundation for understanding of rain attenuation, they are quite complex and have some limitation

Characteristics Analysis and Modeling of Train-to-Train Wireless Channel in Station Scenario

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ABSTRACT In this paper, ray tracing (RT) is used to analyze the characteristics of Train-to-Train (T2T) wireless channel in 2.1 GHz frequency band, including path loss, multipath clustering, delay spread, Rice factor, angular spread and channel non-stationarity. It is found that the change of environment has a great influence on the characteristics of wireless channel, which not only causes the birth and death of multipath clusters, but also makes the channel appear non-stationary characteristics. In order to characterize the non-stationarity of T2T wireless channel, we introduce the time correlation coefficient (TPCC) of power delay profile (PDP), analyze the non-stationarity of T2T wireless channel, and give the quasi-stationarity definition. The results are basically consistent with the measured data.

INDEX TERMS High-speed rail, T2T, Ray-tracing, Multipath clustering and tracking, Non-stationary channel modeling

I. INTRODUCTION

With the development of the next generation train control system, T2T communication has gradually become the focus of academic research in order to ensure the real-time and accuracy of high-speed railway mobile communication system. T2T can assist train operation control system based on Train-to-Ground (T2G) wireless communication, reduce communication delay, strengthen collision danger detection and broadcast warning, and improve train operation efficiency and safety. At the same time, T2T is also a key technology for virtual coupling and autonomous driving. So far, the international academic research on radio wave propagation and wireless channel characteristics in railway scenarios has basically focused on the T2G wireless channel. For example, the channel models of tunnel scene [1–3], plain scene [4], viaduct scene [5–7], cutting scene [8, 9], bridge crossing scene [10] and so on are established. However, the research on T2T wireless channel is relatively few. Compared with T2I communication, T2T communication presents high dynamic characteristics of both receiver and transmitter. The rapid change of environment and scatterers is easy to install the MIMO antenna system, it is possible to combine the MIMO technology with the channel spatial characterization study of T2T. A large-scale MIMO channel measurement campaign was conducted in an indoor metro environment at 3.5 GHz carrier frequency and 160 MHz bandwidth by Asad Saleem et al. The channel parameters were investigated for both co-polarization and cross-polarization. The results show that the antenna configuration and polarization type have a large impact on the channel characteristics. The angular extension changes significantly when different antenna polarizations are used on the transmit and receive antenna sides [11]. Asad Saleem et al. investigated the statistical properties of a novel geometry-based three-dimensional (3D) stochastic model for next-generation vehicle-to-vehicle (V2V) multiple-input-multiple-output (MIMO) communications in a non-isotropic scattering environment [12].

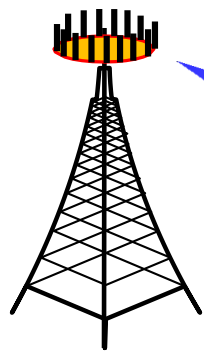
The Roll2Rail project established by the European Union in Shift2Rail is already conducting T2T wireless channel research. Paul Unterhuber et al. conducted a measurement campaign on an T2T channel traveling on two



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感谢各位老师指导!



Thanks

Thank you for taking the time to engage
with my Thesis Defense.
I am open to any questions or feedback you
may have.