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Low complexity single-layer neural network for enhanced rainfall estimation using microwave links

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ABSTRACT

A low complexity accurate model for precipitation estimation is crucial for monitoring several hydrological and water resource applications. Based on the *R*-*k* empirical power-law relation described by the P.838-3 ITU recommendation, rainfall rate can be predicted based on specific attenuation of microwave links. The accuracy of this method is impacted by several ambiguities and errors. In order to overcome these limitations, numerous highly complex pre-treatment and post-processing methods should be used. As an alternative method of low complexity, a supervised learning algorithm using a single-layer neural network (the perceptron) is suggested in this paper. Optimal weights parameters were obtained based on the minimization of the mean square error (MSE). A case study was carried out using 40 days of data gathered from two commercial microwave links (CMLs) and one rain gauge. Experimental results showed that this machine learning-supervised approach performed better than the *R*-*k*-based method. The mean square error of the path-averaged rainfall rate was reduced from 0.13 $mm^2\ h^{-1}$ to 0.08 $mm^2\ h^{-1}$ for training data, and from 0.2 $mm^2\ h^{-1}$ to 0.1 $mm^2\ h^{-1}$ for test data. This promising alternative method for rainfall estimation could considerably improve the efficiency of many applications, such as those developed for real-time urban flood risk management.

Key words: artificial neural networks, mean square error, perceptron, precipitation measurements, rain gauges, specific attenuation

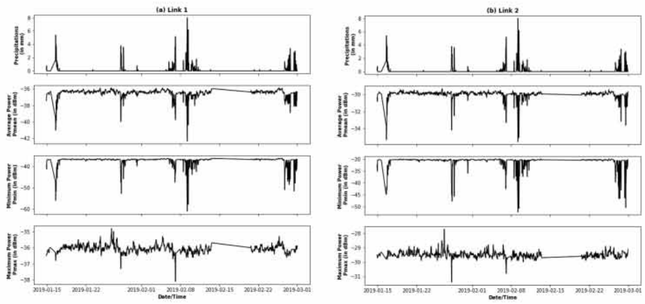
HIGHLIGHTS

- Rainfall can be estimated based on commercial microwave links (CMLs) power attenuations.
- The empirical *R*-*k* power relationship is tested and discussed.
- A single-layer neural network (ANN)-based technique is developed.

GRAPHICAL ABSTRACT

Low Complexity Single-Layer Neural Network for Enhanced Rainfall Estimation Using Microwave Links

Low complexity accurate model for precipitation estimation is crucial for monitoring several hydrological and water resource applications. Based on the $\boldsymbol{R-k}$ empirical power-law relation described by the P.838-3 ITU recommendation, rainfall rate can be predicted based on specific attenuation of microwave links. The accuracy of this method is impacted by several ambiguities and errors. In order to overcome these limitations, numerous highly complex pretreatment and post processing methods can be used. As an alternative method of low complexity, we suggest in this paper a supervised learning algorithm using a single-layer neural network (the perceptron). Optimal weights parameters are obtained based on the minimization of the mean square error (MSE).



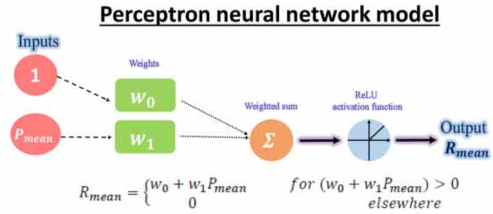
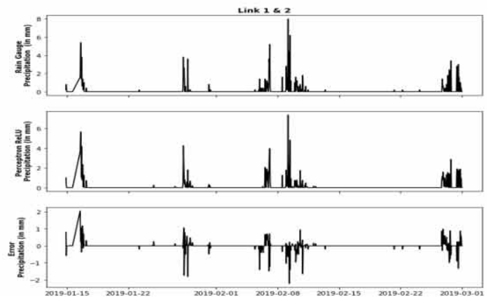


Table 1: Correlations between $Rain$ and RSL data

	P_{mean}		P_{min}		P_{max}	
	Link 1	Link 2	Link 1	Link 2	Link 1	Link 2
Rain Gauge - Link	-0.87	-0.9	-0.89	-0.87	-0.35	-0.23
Link1 - Link2	+0.91		+0.94		+0.62	



1. INTRODUCTION

Real-time accurate rainfall estimation is critical for water management, weather forecasting, flood warnings, agriculture, as well as a range of other applications such as the prediction of river runoff (Tabari 2016). Precipitation is usually estimated directly using ground-based instruments, such as rain gauges and disdrometers, or indirectly using remote sensing techniques, such as satellite sensors and weather radars. These measurements come up against several limits, including poor temporal or spatial resolution of some of them, high cost or difficulty of implementation of others (Allerup & Madsen 1980; Seed *et al.* 1996; Habib *et al.* 2008; Hossain & Huffman 2008). To increase their accuracy and availability, data fusion techniques that combine measurements from many sources can be used.

In order to overcome some limitations of the methods cited above, an innovative opportunistic sensing (OS) approach for rainfall estimation has recently been developed by using received signal levels (RSLs) data of commercial microwave link (CML) networks (Messer 2018; Uijlenhoet *et al.* 2018; Chwala & Kunstmann 2019). This technique was widely investigated and tested in many countries such as the Netherlands (Leijnse *et al.* 2007; Overeem *et al.* 2011, 2016a), the Czech Republic (Fencl *et al.* 2017), Italy (Roversi *et al.* 2020), Germany (Chwala *et al.* 2012, 2016; Smiatek *et al.* 2017; Graf *et al.* 2020), Switzerland (Bianchi *et al.* 2013), and Lebanon (Daher & Al Sakka 2021). This approach does not require any additional installation since RSL data is usually recorded by mobile operators in order to monitor the quality and stability of their networks. Most operators log the minimum and maximum power data over a 15-minute sampling period, while a few others record 15-minute average power data or, in some cases, 15-minute instantaneous power data. Using a large network of CMLs with statistical spatial interpolation methods, high temporal and spatial resolution precipitation estimates can be provided.

Despite its benefits, the $R-k$-based approach for rainfall estimation is affected by various uncertainties. Several experimental studies have been carried out to better understand the underlying uncertainty at various stages of the rainfall retrieval technique (Fenicia *et al.* 2012; Van Leth *et al.* 2018). Using the minimum and maximum RSL data with a constant weighted average approach yields a significant source of uncertainties since the distribution of precipitation or attenuation is rarely consistent. Another common source of inaccuracy is the bias due to the effect of wet antenna attenuation (WAA), fog, and dew formation. In Leijnse *et al.* (2008), a semi-empirical model of WAA, dependent on rainfall intensity, was proposed as a function of the thickness of the water film on the antenna surface. In Overeem *et al.* (2011), a constant WAA value during wet times is considered. In Schleiss *et al.* (2013), compensation of the maximum value of WAA by an exponential model is suggested. The efficiency of direct antenna shielding compared with post-processing approaches in minimizing WAA is examined by Fencl *et al.* (2014). Results showed that shielding did not outperform model-based corrections, as signals from shielded antennas were still attenuated. Rainy and wet weather may affect the scattering and reflection behavior of the surrounding buildings, such as nearby walls, roofs, or impervious surfaces. Indeed, more delicate processing and filtering are necessary to undergo various types of deformations and distortions. Recently, a power relationship between the WAA and rainfall intensity has been described by Valtr *et al.* (2019). Another challenge is the determination of the reference or baseline power, such as in the case of links with variable transmitted power. In Overeem *et al.* (2016a), a method based on the calculation of the median value of past measurements, classified as dry, in a window of 24 h, was used to determine the reference signal level. Reliable classification of wet and dry periods is needed to prevent rainfall overestimation (Overeem *et al.* 2016b). Wet–dry classifiers based on neural network approaches have been explored using communication satellite data by Mishra *et al.* (2018) and RSL CML data by Habi & Messer (2018) and Polz *et al.* (2020). In order to enhance precipitation retrievals based on RSL data, a recurrent neural network (RNN) has been recently developed using disdrometer reference data in Pudashine *et al.* (2020).

Although the RNN-based method and all the studies cited above can provide good accuracy based on the $R-k$-based method, their computational costs are too high. The aim of this research is to develop a low-complexity highly accurate method for rainfall estimation based on RSL data. An optimal single-layer neural network (perceptron) is investigated. Appropriate error indices including correlation coefficient (R), Mean Square Error (MSE), and Mean Absolute Error (MAE) for training and test data were calculated, and the values of the parameters related to the model with the lowest value of the MSE were considered as the optimal model optimal.

Our paper is organized as follows. Section 2 discusses data collection and engineering. Rainfall estimation using the $R-k$ power relationship is described in Section 3. The single-layer neural network-based technique for rainfall estimation using CML RSL data is described in Section 4. Experimental results are presented in Section 5. Finally, the conclusion and perspective are drawn in Section 6.

2. DATA ENGINEERING

This study was conducted over a period of 40 days divided into two periods, the first from January 14, 2019 to February 13, 2019 and the second from February 20, 2019 to February 28, 2019. A typical rain gauge was installed in Tyre, a city of Lebanon located about 80 km (50 mi) south of Beirut. It has a Mediterranean-type climate, characterized by hot and dry summers (June to September) and cool and rainy winters (December to March), with an average annual precipitation of 894 mm and an average annual temperature of 19.2 °C. The geographical position of the rain gauge is given by its WGS84 coordinates: Latitude = $33°15'46.13''$ N and Longitude = $35°12'55.66''$ E (Figure 1). Hourly rainfall precipitation values denoted, by *Rain* (in mm), were gathered by the Lebanese Agricultural Research Institute (LARI). LARI is a governmental organization under the Minister of Agriculture Supervision. It has a network of more than 60 automated agro-weather stations across Lebanon, giving weather forecasts, early alerts on major pests, and pest management advice. The institute also conducts applied and basic scientific research for the development and advancement of the agricultural sector in Lebanon.

On the other hand, RSL data was collected from two active CMLs, vertically polarized and located in Tyre. 15-minute mean, minimum, and maximum received powers were gathered for each link. These measurements were provided in collaboration with Touch, a mobile telecommunication operator in Lebanon. The first link, Link1, has a length of 3.09 km and operates at a frequency of 23.43 GHz while the second link, Link 2, of length 5.54 km operates at 19.15 GHz. Due to some regulations at the mobile operator Touch, we have been informed that these two CMLs are near the rain gauge but we have not been authorized to obtain information on their precise locations.

To evaluate the accuracy, CML-based rainfall estimates were compared with rain gauge measurements considered as reference values. Our optimal estimator is based on the minimization of the *MSE* (Mean Square Error). Other metrics like *MAE* (Mean Absolute Error), *R* (Correlation) and r^2 (*R*-squared) have been defined. The bias (accuracy) and variability (precision) of the estimators have been evaluated.

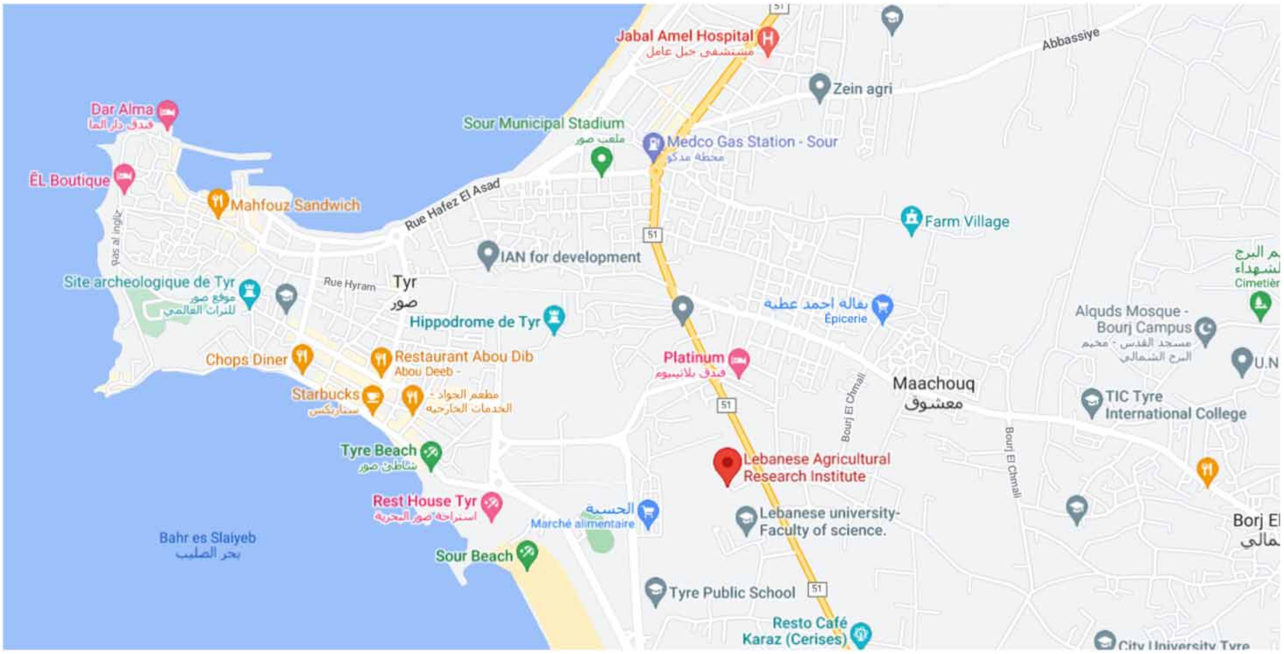


Figure 1 | Rain gauge location.

Rainfall data from the rain gauge was given with a resolution of 1 h. Thus, we have considered an under-sampling procedure that allows hourly RSL data P_{mean}, P_{min}, and P_{max} to be produced, as described below:

$$P_{\text{mean}} = \underset{i\in\{1,2,3,4\}}{\text{Avg}}(P_{\text{mean},i}) = \frac{\sum_{i=1}^{4} P_{\text{mean},i}}{4} \tag{1}$$

$$P_{\text{min}} = \min_{i\in\{1,2,3,4\}}(P_{\text{min},i}) \tag{2}$$

$$P_{\text{max}} = \max_{i\in\{1,2,3,4\}}(P_{\text{max},i}) \tag{3}$$

where Avg(), Min(), and Max() are the functions that return the mean, minimum, and maximum values, respectively. $P_{\text{mean},i}$, $P_{\text{min},i}$, and $P_{\text{max},i}$, $i \in \{1, 2, 3, 4\}$ stand for the mean, minimum, and maximum received powers which correspond to the first, second, third, and fourth quarter of each hour.

3. *R-K* POWER-LAW-BASED METHOD

Raindrops falling on the line-of-sight of the microwave link antennas absorb and scatter a portion of the transmitted signal power, resulting in signal attenuation (loss of power). This attenuation becomes greater as the rain intensity increases. Therefore, an empirical $R - k$ relationship between specific attenuation k (dB km^{-1}) and rainfall rate R (mm h^{-1}) was described by the P.838-3 ITU recommendation (Itu 2005). It is given by:

$$K = \beta R^{\alpha} \tag{4}$$

By reversing Equation (4), the rain rate can be deduced from the specific attenuation as follows:

$$R = aK^{b} \tag{5}$$

where $a = (1/\beta)^{1/\alpha}$ (mm h^{-1} dB^{-b} km^{b}) and $b = 1/\alpha$ (dimensionless) are the coefficient and exponent parameters, respectively. α and β (and thus a and b) are influenced by the rain drop-size distribution, the microwave frequency and the polarization (horizontal, vertical) (Olsen *et al.* 1978; Leijnse *et al.* 2008). For frequencies between 15 and 40 GHz, the exponent parameter b is very close to unity.

Based on Equation (5), the mean path-averaged rainfall intensity R_{mean} can be estimated by:

$$R_{\mathrm{mean}} = \begin{cases} a\left(\dfrac{A_{\mathrm{mean}} - A_a}{L}\right)^b, & \text{for } A_{\mathrm{mean}} - A_a > 0 \\ 0, & \text{elsewhere} \end{cases} \tag{6}$$

where A_a (dB) is a correction term that represents wet antenna attenuation and L is the path length. The average attenuation, A_{mean}, is obtained by:

$$A_{\mathrm{mean}} = P_{\mathrm{ref}} - P_{\mathrm{mean}} \tag{7}$$

where P_{ref} is the reference (baseline) signal power.

Otherwise, if only the minimum and maximum power records are available, R_{mean} can be obtained indirectly, as described in Overeem *et al.* (2016b). Indeed, maximum and minimum attenuations, $A_{\max}$ and $A_{\min}$, are obtained by:

$$\begin{aligned} A_{\max} &= P_{\mathrm{ref}} - P_{\min}, \\ A_{\min} &= P_{\mathrm{ref}} - P_{\max} \end{aligned} \tag{8}$$

The minimum and maximum path-averaged rainfall intensities, $R_{\min}$ and $R_{\max}$, are then obtained by:

$$\begin{aligned} R_{\min} &= \begin{cases} \left(\dfrac{A_{\min} - A_a}{L}\right)^b, & \text{for } A_{\min} > A_a \\ 0, & \text{elsewhere} \end{cases} \\ R_{\max} &= \begin{cases} \left(\dfrac{A_{\max} - A_a}{L}\right)^b, & \text{for } A_{\max} > A_a \\ 0, & \text{elsewhere} \end{cases} \end{aligned} \tag{9}$$

Thus, R_{mean} is obtained by a weighted average as follows:

$$R_{\mathrm{mean}} = \alpha R_{\max} + (1 - \alpha) R_{\min} \tag{10}$$

where α is the weight relative to the maximum path-averaged rainfall intensity ($0 \le \alpha \le 1$).

Optimal values of A_a and α can be obtained by training the model and optimizing CML rainfall estimates compared with the rain gauge measurements.

With a network of CMLs whose positions are known, it is possible to apply statistical spatial interpolation methods in order to estimate the rainfall in each point of the 2D space. Therefore, high temporal and spatial resolution precipitation estimates can be provided by this technique.

4. SINGLE-LAYER NEURAL NETWORK-BASED METHOD

Neural networks provide robust solutions to a wide range of problems in many disciplines, particularly areas involving classification, prediction, filtering, optimization, pattern recognition, and function approximation. An artificial neural network (ANN) is represented by a layered and interconnected group of nodes containing an input layer, one or more hidden layers, and an output layer. A neural network consisting of more than three layers, including the inputs and the output layers, is called a deep neural network. A simple or basic neural network is defined as a network with only two or three layers.

4.1. Perceptron model

In order to develop a low-complexity highly accurate method for rainfall estimation based on RSL data, a single-layer neural network-based model was investigated in this paper.

In this paper, we have only considered the mean received power. Using the hourly average power P_{mean} defined in Equation (1), a 1-input perceptron model was developed as illustrated in Figure 2. We have added the unit vector 1 in order to be able to estimate the constant coefficient w_0 (bias term).

This perceptron model leads to the output R_{mean} given by:

$$R_{\text{mean}} = \begin{cases} w_0 + w_1 P_{\text{mean}}, & \text{for } (w_0 + w_1 P_{\text{mean}}) > 0 \\ 0, & \text{elsewhere} \end{cases} \tag{11}$$

4.2. Optimization and performance

The evaluation and optimization of these models are performed using the adaptive moment (Adam) algorithm and the MSE as a cost (loss) function. Adam is an optimization solver for the neural network algorithm that is computationally efficient, requires little memory, and is well suited for problems that are large in terms of data or parameters. It is a combination of Root Mean Square Propagation (RMSprop) and Stochastic Gradient Descent with Momentum (SGDM) optimization algorithms.

In this study, data were available for only 40 days, which can be considered a small dataset. The two subsets used to train (fit the optimal parameters) and test the model (provide the model evaluation) can be considered as small. Consequently, a simple split cannot reveal the confidence level of the results. Since that, a basic approach called k-fold cross-validation has been used. Indeed, the initial set was split into k smaller sets called folds. The model was trained using $k-1$ folds and tested on the remaining fold. This procedure was repeated such that different training and testing sets were obtained each time. Statistical performance metrics were collected for each repetition and then aggregated in order to provide an estimate of the variability of the model's statistical performance. In this study, k is assumed to be 5. Therefore, at each iteration, 80% of the data were considered in the training subset, while the remaining 20% belongs to the test data.

4.3. *R-k* parameters by the perceptron-based method

For the case where $b = 1$ in the $R-k$ relation, we can conclude that optimal values of the $R-k$ parameters can be obtained by the optimal ANN model weights. Indeed, by comparing Equation (6) to Equation (11), we can write:

$$w_1 = \frac{-a}{L} \leftrightarrow a = -Lw_1 \tag{12}$$

$$w_0 = \frac{a}{L}[P_{\text{ref}} - A_a] \leftrightarrow P_{\text{ref}} - A_a = \frac{Lw_0}{a} = -\frac{w_0}{w_1} \tag{13}$$

5. RESULTS

In our simulation, Python programming language (VanderPlas 2016) was used with several libraries, mainly TensorFlow (Deep Learning Library), pandas (Data Analysis), matplotlib (plotting), scikit-learn (machine learning), NumPy (numerical computing), and seaborn (data visualization). We started pre-processing RSL data by eliminating samples with incomplete data (samples with missing values due to some technical reasons) and samples with erroneous data ($P_{\max,i} < P_{\min,i}$, $P_{\max,i} < P_{\text{mean},i}$, or $P_{\text{mean},i} < P_{\min,i}$).

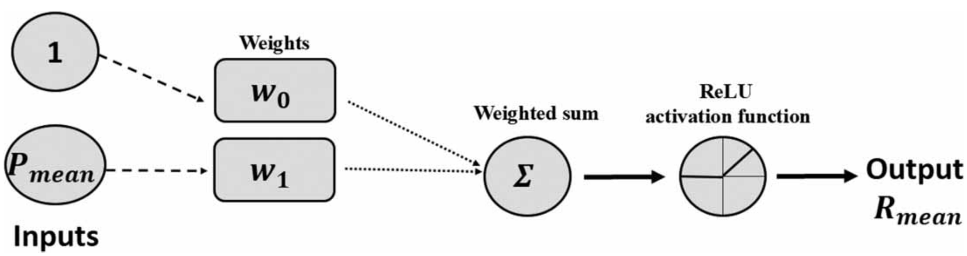


Figure 2 | 1-input perceptron ANN architecture with ReLU activation function.

Figure 3 depicts the temporal variation of rain gauge precipitation and RSL data P_{mean}, P_{min}, and P_{max} collected from CMLs Link 1 (left side) and Link 2 (right side). The rain gauge data reveals a total precipitation of 123.6 mm with the highest hourly rainfall of 8 mm and the highest daily rainfall of 25 mm. Correlation values between the rain gauge and CML RSL data are illustrated in Table 1. They reveal strong correlations, mainly between the rain gauge precipitation data and P_{mean}. Therefore, we can conclude that this CML RSLs data has the potential to estimate rainfall. In addition, correlation values between the

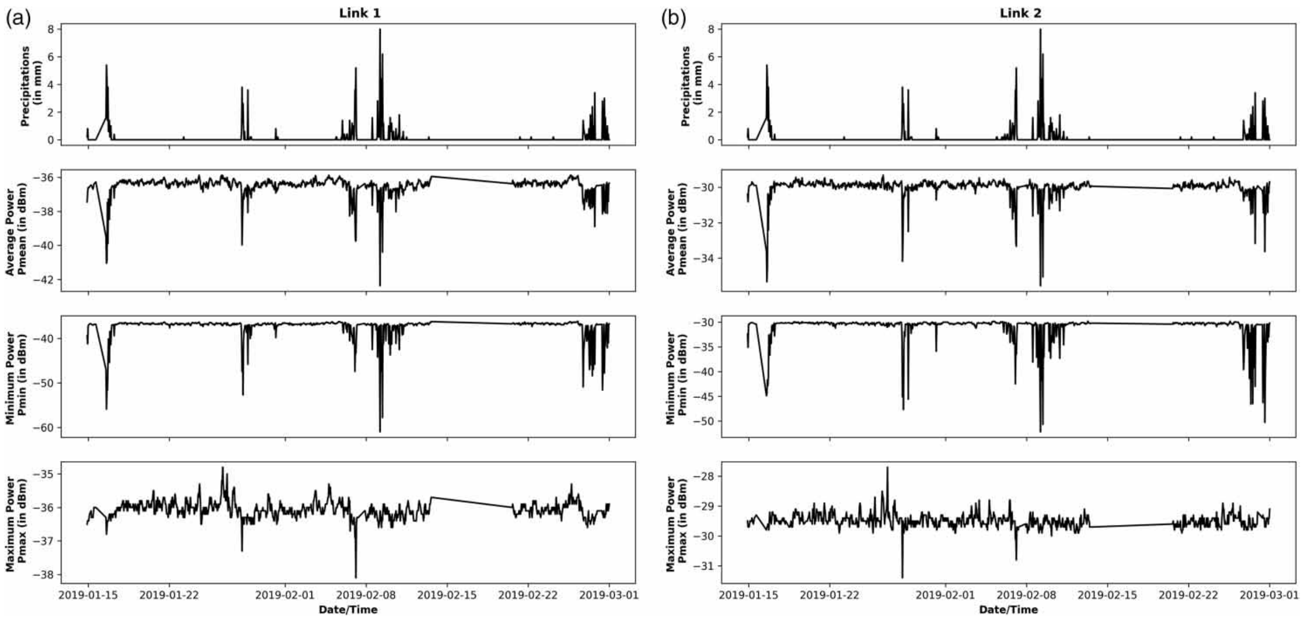


Figure 3 | Temporal variation of *Rain*, P_{mean}, P_{min}, and P_{max} for (a) Link 1 and (b) Link 2.

Table 1 | Correlations between *Rain* and RSL data

	P_{mean}		P_{min}		P_{max}	
	Link 1	**Link 2**	**Link 1**	**Link 2**	**Link 1**	**Link 2**
Rain gauge – Link	−0.87	−0.9	−0.89	−0.87	−0.35	−0.23
Link 1 – Link 2	+0.91		+0.94		+0.62	

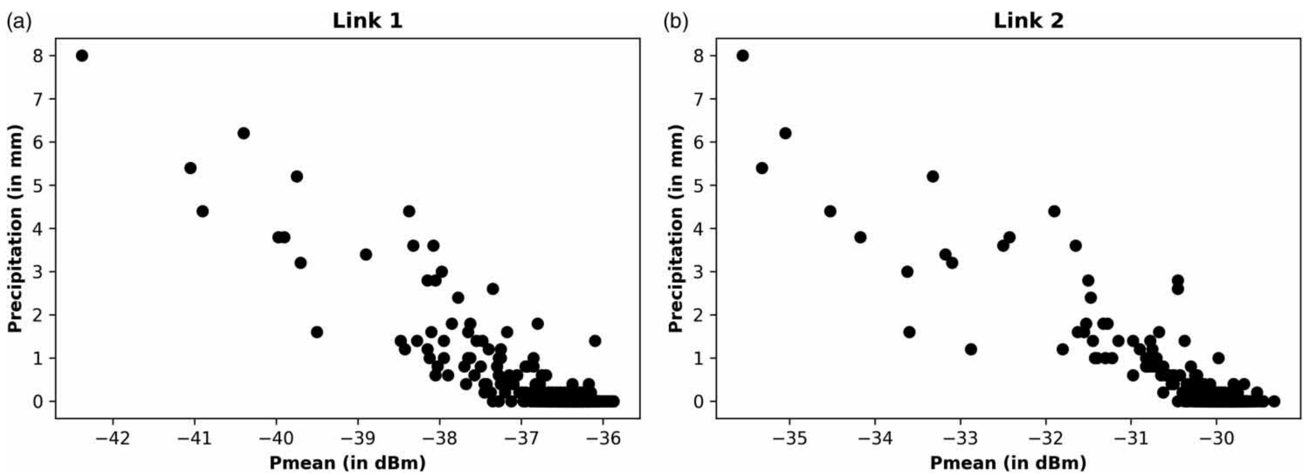


Figure 4 | Precipitation *Rain* in terms of mean received power P_{mean} for (a) Link 1 and (b) Link 2.

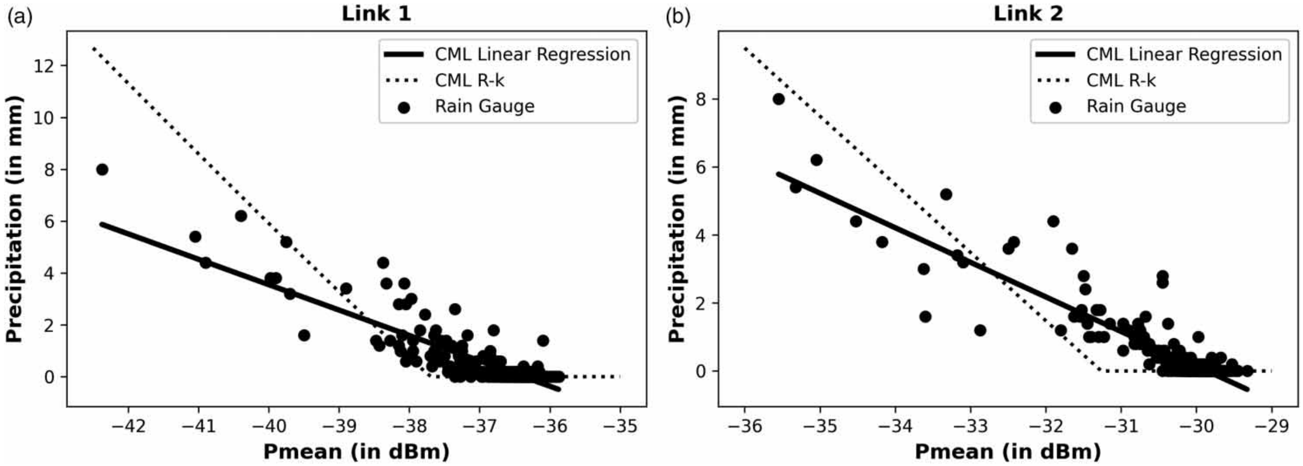


Figure 5 | CML linear regression: (a) Link 1 and (b) Link 2.

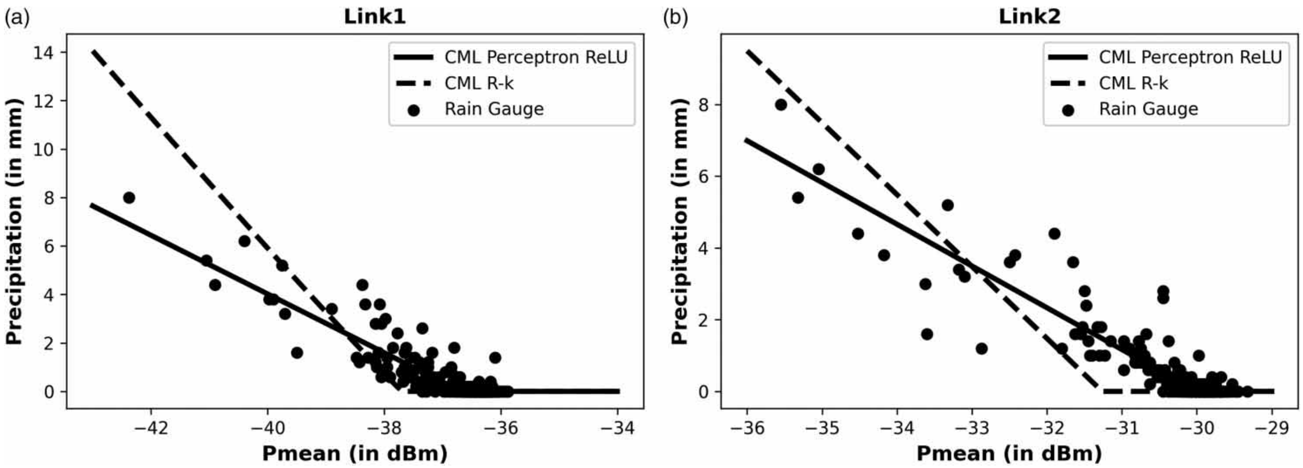


Figure 6 | CML linear regression with ReLU: (a) Link 1 and (b) Link 2.

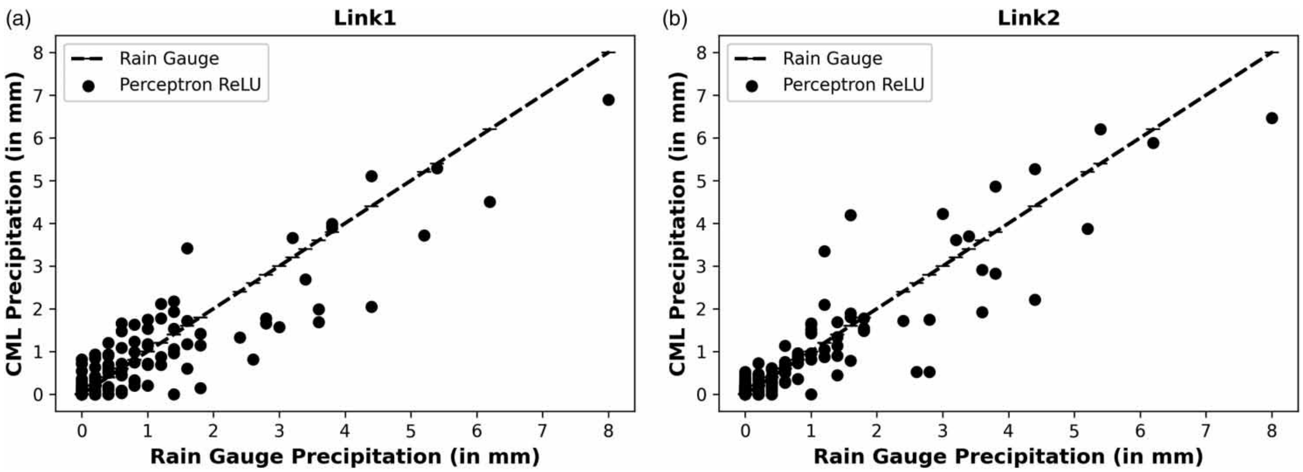


Figure 7 | CML linear regression with ReLU, CML estimates versus rain gauge precipitations: (a) Link 1 and (b) Link 2.

Table 2 | Overall results of rainfall estimation Link 1 and Link 2

	MSE		MAE		*R*		r^2	
Dataset	**Training**	**Test**	**Training**	**Test**	**Training**	**Test**	**Training**	**Test**
R-k method	0.135 $\pm$ 0.015	0.19 $\pm$ 0.072	0.09 $\pm$ 0.006	0.1 $\pm$ 0.026	0.84 $\pm$ 0.02	0.81 $\pm$ 0.006	0.6 $\pm$ 0.04	0.53 $\pm$ 0.1
Linear regression	0.09 $\pm$ 0.01	0.09 $\pm$ 0.04	0.17 $\pm$ 0.015	0.18 $\pm$ 0.013	0.88 $\pm$ 0.019	0.87 $\pm$ 0.04	0.77 $\pm$ 0.035	0.73 $\pm$ 0.078
Perceptron with ReLU	0.06 $\pm$ 0.01	0.065 $\pm$ 0.05	0.07 $\pm$ 0.007	0.071 $\pm$ 0.04	0.92 $\pm$ 0.006	0.88 $\pm$ 0.04	0.85 $\pm$ 0.026	0.68 $\pm$ 0.23

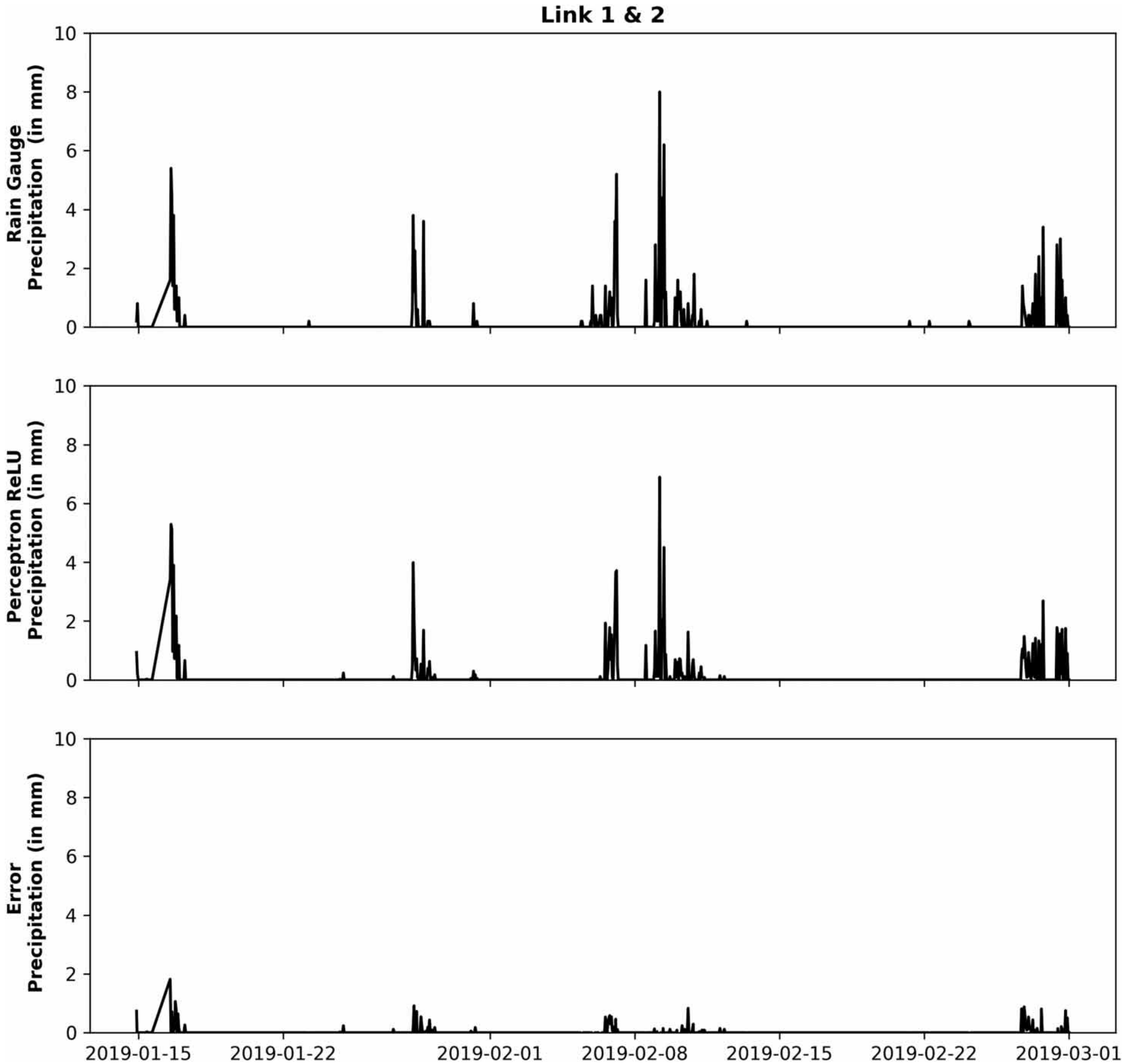


Figure 8 | Temporal variation of precipitations obtained by rain gauge (Top), CML perceptron ReLU (Middle) and error (Bottom).

RSL data of the two CMLs are shown. They admit strong relationships, mainly between the mean powers, P_{mean}, and between the minimum powers, P_{min}. These correlation values allow us to conclude that these two links are located in the same region of the rain gauge under almost the same precipitation conditions.

The variation of rain gauge precipitations, *Rain*, as a function of hourly average powers, P_{mean}, is shown in Figure 4. We can notice that, for Link 1, an almost linear relationship exists for values of P_{mean} below -36.8 dBm, while precipitation is mostly zero for $P_{mean} > -36.8$ dBm. Similar results are obtained for Link 2 with a threshold of -30.5 dBm.

Based on Itu (2005), a and b values described in Equation (5) have been determined. For Link 1, we have obtained $a = 8$ and $b = 1.04$ while they are $a = 11.1$ and $b = 1.01$ for Link 2. Theoretical values of a and b coefficients have been determined as a function of the frequency and polarization only, while in reality, they also depend on the raindrop size distribution. Figure 5 illustrates the difference in precipitation estimates between the CML $R - k$ power-law-based method and the rain gauge measurements, considered as the reference measurement. The linear regression model will result in an optimal estimation of *Rain*. However, negative outcomes may occasionally be produced as shown.

To improve our estimation and avoid negative numbers, 1-input perceptron model is investigated by using the ReLU (Rectified Linear Units) activation function. Figures 6 and 7 illustrate the results.

The different CML-based methods are evaluated based on the estimation of different parameters (MSE, MAE, R, and r^2). Their corresponding mean and standard deviation are summarized in Table 2. In these calculations, we have considered that the two CMLs are equally weighted. These results showed that our perceptron-based methods with the ReLU activation function lead to better accuracy estimates.

Finally, the temporal variation of precipitations as estimated by the perceptron ReLU model, reference values as given by the rain gauges and the resulting error are shown in Figure 8. We can conclude that this single-layer neural network model incurs a small error with a mean very close to zero.

6. CONCLUSION AND PERSPECTIVES

In this study, we have tested and analyzed the simple use of the empirical $R - k$ power relationship that derives rainfall estimates based on CMLs power attenuations. In order to overcome its limitations and enhance its accuracy, we have proposed a single-layer neural network-based method. Experimental results have proven the high accuracy of this new technique. This may help to develop real-time applications for rainfall monitoring, forecasting, flood warnings, and many other hydrological domains. More precise and consistent estimates of precipitation can be reached by exploiting more evolved ANN architectures with deeper network topology and longer-term CML data, at the cost of higher complexity. This can be useful mainly for cases where the coefficient b of the $R - k$ relation is somewhat far from unity.

We hope that this work inspires the Lebanese Ministry of Telecoms, as well as Lebanon's mobile telecommunications and data operators, to continue and strengthen their grateful cooperation with us in the near future. By delivering data from all the microwave links covering Lebanon, with their precise geographical locations, we will be able to draw an accurate series of rainfall maps of the country.

ACKNOWLEDGEMENTS

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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