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Rainfall Retrieval from Challenging 7 GHz Commercial Microwave Links in Burkina Faso Using a Deep Learning Wet-Dry Classification Framework

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Abstract

Commercial Microwave Links (CML) have demonstrated their potential for opportunistic rainfall estimation. They offer a promising solution for improving the spatial and temporal coverage of precipitation observations in poorly instrumented regions. However, the exploitation of CML operating in the 6 - 7 GHz frequency range remains a major challenge. At these frequencies, rain-induced attenuation is relatively weak and can be strongly affected by non-rain-related fluctuations, making the extraction of rainfall information particularly difficult. This study proposes a dedicated processing framework for 7 GHz CML in Burkina Faso. The approach relies on a deep learning-based wet-dry classification model developed using MSG-SEVIRI satellite observations and rain gauge measurements. The model outputs are projected along the microwave link paths using intersection weights and are subsequently used to identify rainy periods, estimate rainfall rates, and reconstruct spatial rainfall fields. The results demonstrate that the proposed framework can extract meaningful rainfall information despite the strong non-rain-related attenuation affecting this frequency band. The wet-dry classification framework achieved consistent performance across the analyzed links, with a median Matthews Correlation Coefficient (MCC) of approximately 0.30. Comparisons with rain gauge observations show encouraging temporal agreement for the main rainfall events, although quantitative uncertainties remain due to the point-scale nature of rain gauge measurements and the path-integrated nature of CML observations. In addition, daily and cumulative rainfall maps demonstrate the capability of 7 GHz CML networks to capture both the spatial variability and temporal evolution of precipitation. These findings represent an important step toward the use of low-frequency commercial microwave links as opportunistic rainfall sensors in regions where weather radar coverage is unavailable and conventional observation networks remain sparse.

Keywords

Commercial Microwave Links (CML), Rainfall Retrieval, 7 GHz Frequency Band, Deep Learning, Opportunistic Sensing

1. Introduction

Accurate precipitation monitoring is essential for hydrological studies, water resource management, agriculture, and flood risk mitigation. However, obtaining reliable rainfall observations remains challenging in many regions of the world, particularly in developing countries where meteorological infrastructures are sparse and weather radar coverage is unavailable [1]-[3]. In such environments, alternative observation systems are needed to complement conventional rain gauges and satellite products.

Over the last two decades, Commercial Microwave Links (CMLs) have emerged as a promising source of opportunistic rainfall observations [4] [5]. These links, which are widely deployed by mobile network operators for data transmission, experience signal attenuation during rainfall events. This attenuation can be related to rain intensity through well-established electromagnetic relationships, allowing rainfall rates to be estimated along the propagation path [3] [6] [7]. Because telecommunication networks are already operational in many countries, CMLs provide a cost-effective opportunity to improve the spatial and temporal monitoring of precipitation.

Numerous studies have demonstrated the potential of CMLs for rainfall estimation in different climatic regions and network configurations [6] [8]-[10]. Country-scale rainfall mapping using dense telecommunication networks has been successfully achieved, and several processing techniques have been developed for rain event detection, wet antenna correction, and rainfall retrieval [8] [11]-[16]. These studies have confirmed that CMLs can significantly complement conventional precipitation monitoring systems.

However, most previous investigations have focused on microwave links operating at frequencies above 10 GHz, where rainfall attenuation is sufficiently strong to be clearly distinguishable from other attenuation sources [17]-[19]. In contrast, the use of CMLs operating in the 6 - 7 GHz frequency range remains challenging.

At these frequencies, rain-induced attenuation is weaker and can be masked by several non-rain-related effects, including multipath propagation, temperature variations, vegetation influences, antenna oscillations, and instrumental instabilities [9] [17]-[19]. As a result, extracting reliable rainfall information from 7 GHz CML observations remains largely unexplored.

This challenge is particularly important for Sub-Saharan Africa, where many operational telecommunication networks rely on microwave links within the 6 - 7 GHz band. Unlocking the rainfall information contained in these networks could substantially increase the availability of opportunistic rainfall sensors in regions where conventional meteorological observations are limited.

In this study, we investigate the potential of 7 GHz commercial microwave links for rainfall retrieval in Burkina Faso. We propose a processing framework based on a deep learning wet-dry classification model combining MSG-SEVIRI satellite observations and rain gauge measurements. The framework is used to identify rainfall periods, improve attenuation processing, and derive rainfall rates from challenging 7 GHz microwave links. The obtained results show encouraging agreement with reference observations and demonstrate the feasibility of rainfall retrieval from this particularly challenging frequency range. These findings represent an important step toward the operational use of 7 GHz CMLs for rainfall monitoring in data-scarce regions.

Beyond rainfall retrieval, the study also investigates the capability of the retrieved CML observations to reconstruct spatial rainfall patterns through interpolation-based rainfall mapping.

2. Study Area and Data

2.1. A. Study Area

The study was conducted along the Ouagadougou-Bobo-Dioulasso corridor in Burkina Faso. This corridor connects the country's two largest cities and represents one of the most important telecommunication routes in the national network. A dense set of commercial microwave links (CMLs) is deployed along this axis, making it a suitable area for investigating rainfall retrieval from telecommunication infrastructure.

Burkina Faso is located in the Sudano-Sahelian region of West Africa and experiences a marked seasonal rainfall regime controlled by the West African monsoon. The climate is characterized by a dry season extending from approximately October to May and a rainy season occurring from June to September. Rainfall events are often highly variable in space and time, highlighting the need for observation systems with high spatial and temporal coverage.

The study period extends from 14 June to 10 October 2020, covering most of the monsoon season. During this period, numerous rainfall events were recorded across the study area, providing suitable conditions for evaluating the performance of rainfall retrieval from 7 GHz commercial microwave links.

Figure 1 shows the study area and the distribution of the CML network along the Ouagadougou-Bobo-Dioulasso corridor. The highlighted section in Figure 1(a) corresponds to the zoomed view presented in Figure 1(b).

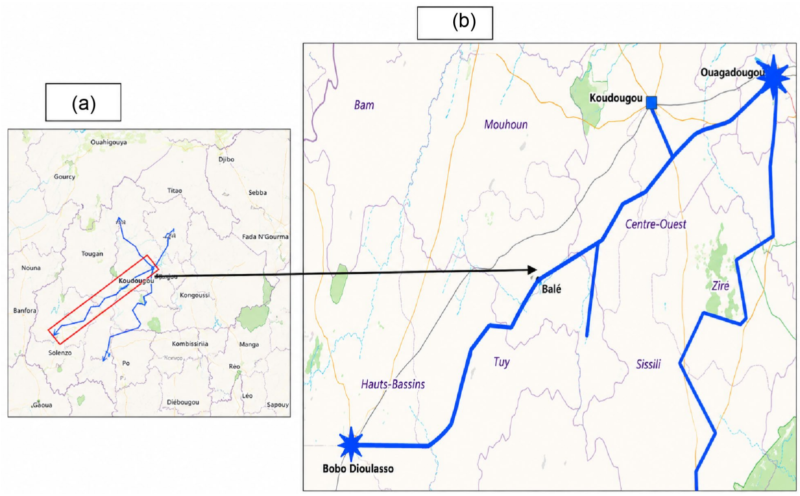

Figure 1. CML map of the Ouagadougou Bobo-Dioulasso axis illustrating the study area. The blue line corresponds to the CML link of the axis.

2.2. CML Data

The Commercial Microwave Link (CML) data used in this study were collected through a real-time acquisition system deployed on the telecommunication network of Burkina Faso. The system currently covers several regions of the country and continuously records signal level information from operational microwave backhaul links [20].

The collected data consist of the Transmitted Signal Level (TL) and the Received Signal Level (RL), sampled at a temporal resolution of one minute. From these measurements, the Total Received Loss (TRL) can be derived and subsequently processed to estimate rainfall-induced attenuation.

This study focuses on the microwave links deployed along the Ouagadougou-Bobo-Dioulasso corridor. A total of 84 CMLs are available in the study area, including 19 single-link configurations. The links operate at frequencies ranging from 5 GHz to 7 GHz and have path lengths between approximately 10 km and 40 km. Both horizontal and vertical polarizations are represented within the dataset, as illustrated in Figure 2.

This study uses all 84 Commercial Microwave Links (CMLs) available along the Ouagadougou-Bobo-Dioulasso corridor. The links operate in the 5 - 7 GHz frequency range, with both horizontal and vertical polarizations, and have path lengths ranging from approximately 10 km to 40 km. No subset selection was performed, as the objective of this study was to evaluate the proposed rainfall retrieval framework using the complete operational CML network available in the study area. These characteristics provide a representative dataset for assessing the performance of rainfall retrieval from low-frequency commercial microwave links under operational conditions.

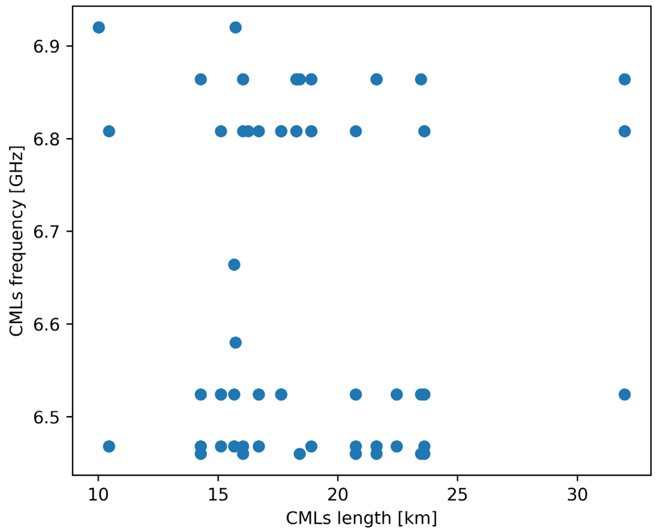

Figure 2. Characteristics of CMLs.

2.3. MSG SEVIRI Data and Rain Gauge Data

Two reference datasets were used in this study: MSG-SEVIRI satellite observations and rain gauge measurements. The MSG-SEVIRI wet-dry information was obtained from the pre-trained deep learning classifier developed by Wiegels *et al.* [21], which combines MSG-SEVIRI satellite observations with rain gauge data to produce wet-dry predictions. In the present study, this classifier was used directly as an input product, and no retraining or fine-tuning was performed.

Rain gauge observations from the Kokologo station, operated by the Agence Nationale de la Météorologie (ANAM), were used as the reference dataset for evaluating the rainfall estimates derived from the Commercial Microwave Links (CMLs). The Kokologo rain gauge is located approximately 5 km from the CML crossing Kokologo, ensuring reasonable spatial consistency between the path-integrated CML observations and the point-scale rain gauge measurements. The rain gauge data are available at a temporal resolution of 15 minutes. Therefore, all rainfall estimates derived from the CMLs were aggregated to the same temporal resolution before quantitative evaluation. This temporal matching ensures a consistent comparison between the CML-derived rainfall estimates and the ground-based observations.

3. Method

3.1. Overview of the Processing Framework

Rainfall retrieval from 7 GHz commercial microwave links is particularly challenging because rain-induced attenuation is often masked by strong non-rain-related signal fluctuations. To address this issue, a multi-step processing framework was developed.

The workflow starts with the preprocessing of raw CML measurements to remove anomalous signal behavior. A deep learning-based wet-dry classification model is then used to identify rainfall periods. The resulting wet-dry information is combined with spatial intersection weights along the microwave link paths to generate rainfall occurrence time series for each CML. During detected rainfall periods, baseline estimation and wet antenna correction are applied to isolate the rainfall-induced attenuation. Finally, rainfall rates are derived using the standard k-R relationship recommended by the ITU-R.

The performance of the retrieved rainfall rates is evaluated against independent rain gauge observations using both detection and quantitative precipitation metrics.

3.2. CML Data Preprocessing

Raw CML measurements may contain various anomalies that are unrelated to rainfall and can lead to erroneous precipitation estimates. These anomalies include sudden baseline shifts (jumps), isolated outliers (spikes), and periods with missing observations. Such effects are commonly observed in operational telecommunication networks and may result from multipath propagation, antenna oscillations, environmental conditions, or instrumental instabilities.

To improve data quality, a preprocessing step was applied before rainfall retrieval. The filtering procedure relies on the methodology developed for CML networks in Burkina Faso by Djibo *et al.* [19]. Three dedicated filters were used to detect and remove jumps, eliminate spikes, and discard periods containing an excessive number of short data gaps.

The resulting filtered attenuation time series provides a more reliable basis for the subsequent wet-dry classification and rainfall retrieval steps.

3.3. Deep Learning Wet-Dry Classification

3.3.1. Wet-Dry Classification Model

Accurate identification of rainy periods is a prerequisite for rainfall retrieval from commercial microwave links. This task is particularly challenging for 7 GHz CMLs because rainfall-induced attenuation is often masked by strong non-rain-related signal fluctuations.

To address this issue, a binary wet-dry classification model based on Deep Learning (DL) was employed. The model was developed using MSG-SEVIRI satellite observations and rain gauge measurements following the methodology described in [21]. For each time step, the model provides a binary prediction indicating the occurrence or absence of rainfall, together with the corresponding spatial coordinates.

The resulting wet-dry information is used to identify potential rainfall periods and to support the subsequent rainfall retrieval procedure.

3.3.2. Spatial Projection along CML Paths

The wet-dry classification used in this study was obtained from the pre-trained convolutional neural network (CNN) developed by Wiegels *et al.* [21]. The model was trained independently by these authors using MSG-SEVIRI satellite observations and reference precipitation data to estimate rainfall occurrence at a 15-minute temporal resolution. The CNN architecture combines visible, infrared, and water-vapour channels from MSG-SEVIRI and contains approximately 233,000 trainable parameters. Detailed information regarding the network architecture, training strategy, and validation procedure is provided in [21]. In the present study, only the resulting wet-dry prediction product over Burkina Faso was used as input for the rainfall retrieval framework, and the classifier was neither retrained nor modified.

The intersection weight matrices are stored as sparse arrays to reduce memory requirements and facilitate efficient processing of large CML networks. **Figure 3** illustrates the intersection weights associated with a representative microwave link and shows good spatial consistency between the satellite pixels and the CML path.

Using these weights, a wet-dry time series is generated for each microwave link. The computation is performed efficiently using sparse matrix operations. Rainfall periods are identified when the projected wet-dry probability exceeds a threshold of 0.5, corresponding to the standard probability threshold adopted in the original deep-learning wet-dry classification framework of [21]. **Figure 4** presents an example of a wet-dry time series derived along a 6.47 GHz microwave link and demonstrates the temporal consistency of the proposed approach.

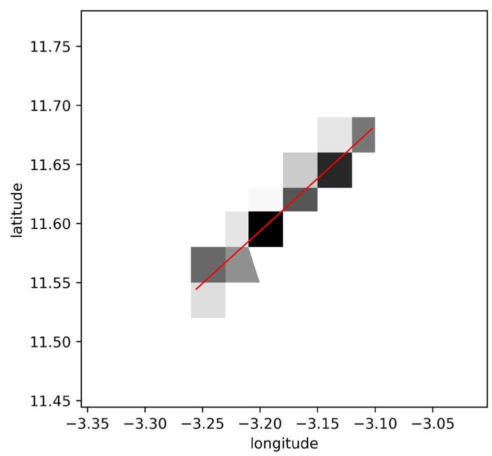

Figure 3. Intersection weights and CML path.

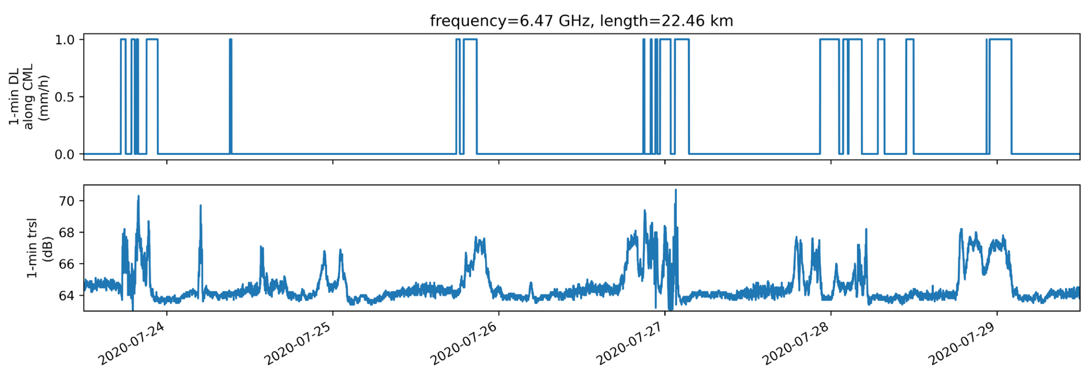

Figure 4. Time series of the DL model with a CML of 6.47 GHz and a length of 22.46 km.

3.4. Rainfall Retrieval from CML Data

Rainfall retrieval from Commercial Microwave Link (CML) data is based on the temporal variations of the Total Received Loss (TRL), which is computed from the measured received signal level (RL) and transmitted signal level (TL) as TRL = RL − TL. Since the transmitted signal level is incorporated into the TRL computation at each time step, any temporal variations in the transmitted power are inherently accounted for before the subsequent baseline estimation and wet antenna correction. The rainfall retrieval procedure then consists of separating the rainfall-induced attenuation from other attenuation sources before converting it into rainfall intensity.

3.4.1. Baseline and Wet Antenna Correction

Once rainy periods have been identified, the rainfall-induced attenuation must be separated from other attenuation sources present in the microwave link signal. During rainfall events, the signal baseline is assumed to remain at its pre-event level because information about baseline variations during precipitation is generally unavailable.

In addition, attenuation caused by water droplets accumulating on the antenna radome, commonly referred to as wet antenna attenuation, may lead to an overestimation of rainfall intensity. To mitigate this effect, the correction approach proposed by [16] was applied. Following the correction method proposed by Schleiss *et al*. [16], a maximum wet antenna attenuation of 2.5 dB was assumed. This value was adopted as recommended in the original method to ensure consistency with the established wet antenna correction approach.

After baseline removal and wet antenna correction, the remaining attenuation is considered to be primarily associated with rainfall and is subsequently used for rainfall retrieval.

3.4.2. Rainfall Rate Estimation

Rainfall rates were derived from the corrected attenuation using the well-established relationship between specific attenuation K (dB·km^{-1}) and rainfall intensity R (mm·h^{-1}) [22].

$$K = aR^b \tag{1}$$

where the coefficients a and b depend on the microwave frequency, polarization, and propagation characteristics. In this study, the values recommended by [23] were adopted.

The corrected path-integrated attenuation was first converted into specific attenuation by considering the microwave link length. The corresponding rainfall rate was then estimated using the k-R relationship. This procedure was applied to all selected microwave links to generate rainfall time series throughout the study period.

3.5. Performance Metrics

The performance of the proposed rainfall retrieval framework was evaluated by comparing the CML-derived rainfall estimates with rain gauge observations. Both rainfall detection and rainfall quantification performances were assessed.

For the wet-dry classification, a confusion matrix was constructed using rainy and non-rainy periods identified from the reference data. From this matrix, the Matthews Correlation Coefficient (MCC) (formula 2) and the Mean Detection Error (MDE) (formula 3) were computed according to **Table 1**. MCC provides a balanced measure of classification performance, while MDE quantifies the average rate of missed and falsely detected rainfall events.

Table 1. Confusion matrix of CML and reference data.

CML		Reference	
		Wet	Dry
	Wet	True wet (TP)	False wet (FP)
	Dry	Missed wet (FN)	True wet (TN)

$$\mathrm{MCC} = \frac{\mathrm{TP} \times \mathrm{TN} - \mathrm{FP} \times \mathrm{FN}}{\sqrt{(\mathrm{TP}+\mathrm{FP})(\mathrm{TP}+\mathrm{FN})(\mathrm{TN}+\mathrm{FP})(\mathrm{TN}+\mathrm{FN})}} \tag{2}$$

$$\mathrm{MDE} = \frac{\frac{\mathrm{FN}}{\mathrm{n}(\mathrm{wet})} + \frac{\mathrm{FP}}{\mathrm{n}(\mathrm{dry})}}{2} \tag{3}$$

For quantitative rainfall evaluation, several commonly used statistical metrics were calculated. The Pearson Correlation Coefficient (PCC) (formula 4) was used to assess the linear agreement between CML-derived rainfall and rain gauge observations. In addition, the Root Mean Square Error (RMSE) (formula 5) and the relative Bias (formula 6) were computed to quantify estimation accuracy and systematic deviations.

All metrics were calculated using rainfall data aggregated to a 15-minute temporal resolution to ensure consistency with the rain gauge observations.

$$\mathrm{PCC} = \frac{\mathrm{cov}(\mathrm{R}_{\mathrm{CML}}, \mathrm{R}_{\mathrm{reference}})}{\mathrm{SD}(\mathrm{R}_{\mathrm{CML}}) \times \mathrm{SD}(\mathrm{R}_{\mathrm{reference}})} \tag{4}$$

$\mathrm{R}_{\mathrm{CML}}$ is the 15-minute aggregation derived from the microwave link (CML). $\mathrm{R}_{\mathrm{reference}}$ is the 15-minute rain rate from the rain gauge. cov(.) is the covariance function, and SD(.) is the standard deviation function.

$$\mathrm{RMSE} = \sqrt{\mathrm{AM}\left((\mathrm{R}_{\mathrm{CML}} - \mathrm{R}_{\mathrm{reference}})^2\right)} \tag{5}$$

AM(.) is the arithmetic mean function.

$$\mathrm{BIAIS} = \frac{\overline{(\mathrm{R}_{\mathrm{reference}} - \mathrm{R}_{\mathrm{CML}})}}{\overline{\mathrm{R}_{\mathrm{reference}}}} \tag{6}$$

3.6. Spatial Rainfall Mapping

To investigate the spatial distribution of rainfall derived from the 7 GHz commercial microwave links (CMLs), daily rainfall maps were generated using an inverse distance weighting (IDW) interpolation approach. This method was selected because of its simplicity, computational efficiency, and successful application in previous CML rainfall studies [19] [24].

Each rainfall estimate retrieved from a CML was represented by a synthetic observation located at the midpoint of the microwave link path. Spatial rainfall fields were then reconstructed by interpolating these observations onto a regular grid using distance-dependent weights proportional to the inverse square of the distance between each grid cell and the surrounding CML midpoints. The resulting rainfall maps were used to visualize the spatial organization and temporal evolution of precipitation events across the study area.

4. Results and Discussion

4.1. Signal Behavior and Rainfall Retrieval

The transmitted signal level (TL) and received signal level (RL) were recorded at a temporal resolution of one minute. Figure 5 presents an example of the raw measurements together with the corresponding attenuation and retrieved rainfall rates for a representative 7 GHz microwave link.

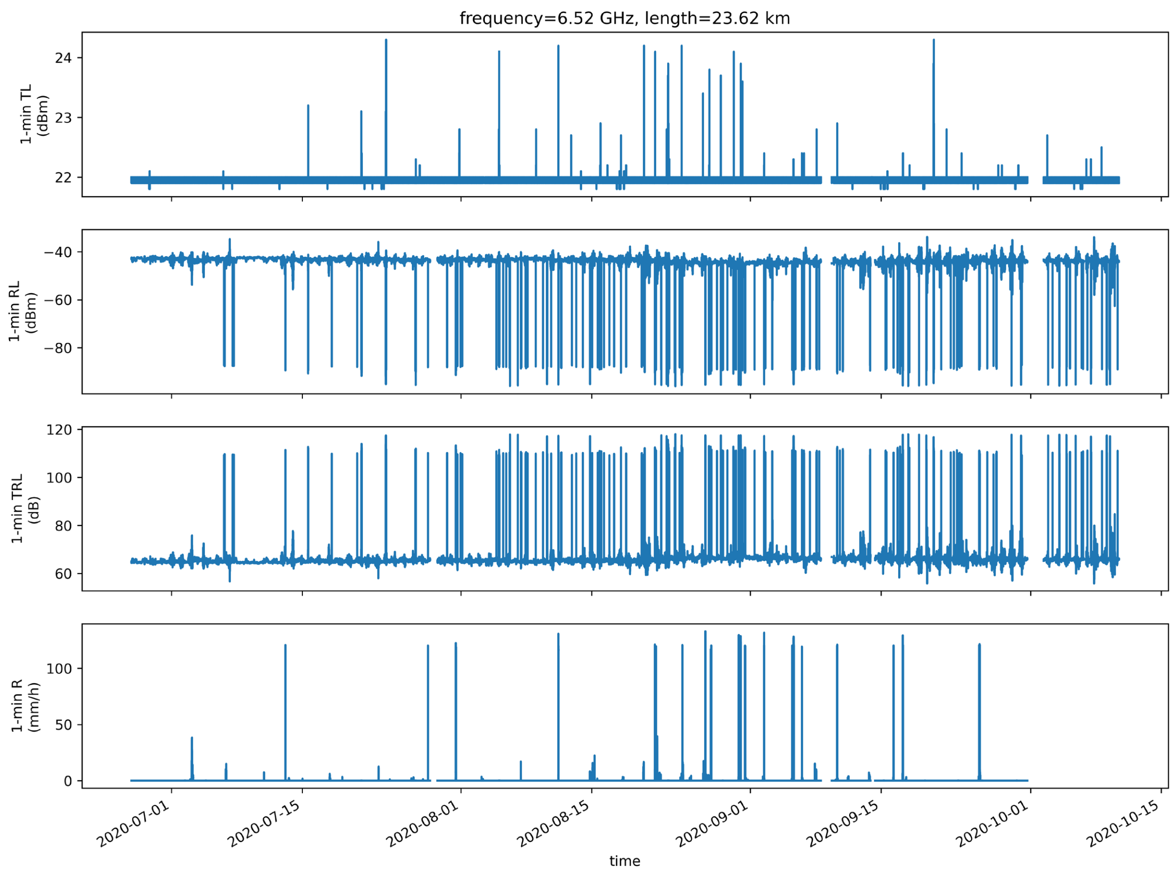

Figure 5. Raw data for TL [dBm] and RL [dBm]. Illustration of TRL [dB] (RL-TL) and R [mm/h] for a CML link with a frequency of 6.52 GHz and a length of 23.62 km.

The TL and RL time series exhibit noticeable fluctuations throughout the observation period. Several attenuation peaks can be identified in the resulting attenuation signal. After applying the proposed processing framework, these attenuation peaks are translated into rainfall events. The retrieved rainfall rates show temporal behavior that is consistent with the occurrence of significant attenuation events.

This result demonstrates that reliable rainfall estimates information can be extracted from 7 GHz microwave links despite the presence of substantial non-rain-related attenuation. It also confirms the ability of the wet-dry classification framework to support rainfall retrieval under challenging signal conditions.

4.2. Comparison with Rain Gauge Observations

The limited number of rain gauges remains a source of uncertainty in the validation process. A qualitative comparison was performed between the rainfall rates derived from the CMLs and the measurements provided by the ANAM rain gauge located in Kokologo.

Figure 6 shows that the main rainfall events detected by the rain gauge are also captured by the CML-derived rainfall estimates. Although differences remain in the timing and magnitude of some events, the overall agreement is encouraging, given the challenging nature of the 7 GHz links and the spatial separation between the observation systems.

These results suggest that the proposed framework is capable of extracting relevant rainfall information from attenuation signals that are strongly affected by non-rain-related fluctuations.

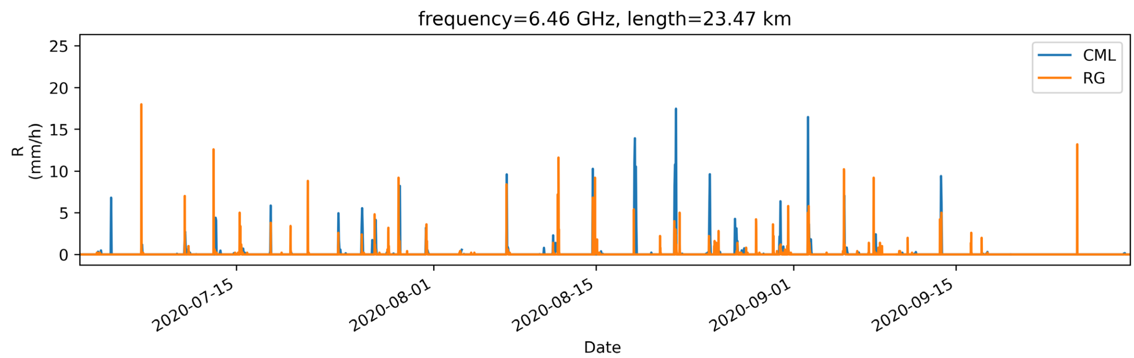

Figure 6. Comparison of rain rate derived from CML and rain gauge. Case of CML 6.46 GHz and 23.47 km.

4.3. Event-Scale Comparison between CML and Rain Gauge Observations

To further investigate the capability of the proposed framework to capture rainfall dynamics, a detailed comparison was performed over a selected period characterized by several rainfall events. Figure 7 presents the rainfall rates derived from a representative 6.46 GHz commercial microwave link, together with the corresponding measurements from the Kokologo rain gauge.

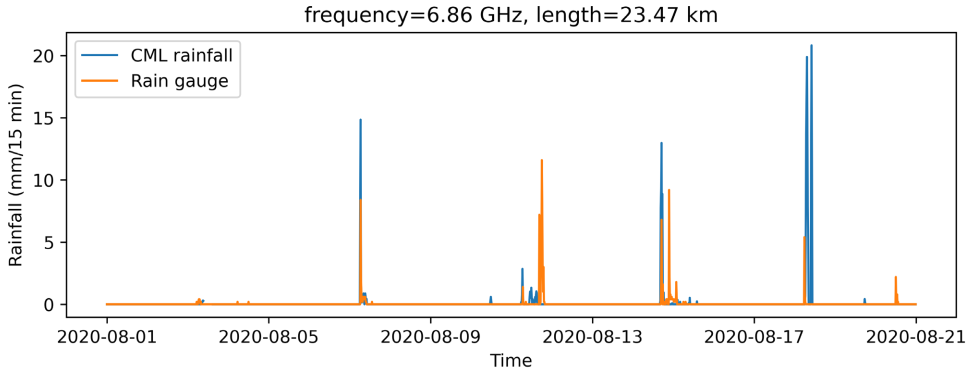

Figure 7. Zoomed comparison between CML-derived rainfall and Kokologo rain gauge observations for selected rainfall events. The figure highlights the temporal consistency between the two observation systems during several rain events.

The results show that the main rainfall events detected by the rain gauge are generally identified by the CML-derived rainfall estimates. Several rainfall peaks occur simultaneously in both datasets, indicating good temporal consistency between the two observation systems. This agreement confirms that the proposed wet-dry classification framework is capable of identifying rainfall occurrences despite the strong non-rain-related attenuation affecting the 7 GHz frequency range.

Differences can nevertheless be observed in the magnitude of some rainfall events. In particular, certain peaks are overestimated by the CML, while others are more pronounced in the rain gauge observations. These discrepancies are expected because rain gauges provide point measurements, whereas commercial microwave links integrate rainfall information over propagation paths exceeding 20 km. Consequently, localized convective cells may affect only part of the microwave link path or the rain gauge location, leading to differences in the observed rainfall intensity.

Overall, the event-scale analysis demonstrates that useful rainfall information can be extracted from challenging 7 GHz commercial microwave links. Although quantitative differences remain, the temporal agreement observed during several rainfall events highlights the potential of the proposed framework for rainfall monitoring in data-scarce regions.

4.4. Rainfall Retrieval Performance

The performance assessment presented in Figure 8 was carried out using the complete set of 84 Commercial Microwave Links (CMLs), and no exclusion criteria were applied. For the quantitative evaluation, the rainfall retrieval time series obtained from all CMLs were concatenated into a single continuous time series and compared with the Kokologo rain gauge, which served as the reference dataset. This strategy was adopted to evaluate the overall performance of the proposed rainfall retrieval framework over the complete operational CML network and to derive statistically robust performance metrics from a large number of rainfall observations. Therefore, the reported metrics represent the overall performance of the proposed rainfall retrieval framework rather than the performance of individual microwave links.

The overall performance of the proposed rainfall retrieval framework is summarized in **Figure 8**. The figure presents the distributions of the wet-dry classification metrics (MCC and MDE) and the rainfall quantification metrics (PCC, RMSE, and Bias) computed using the complete set of 84 Commercial Microwave Links (CMLs).

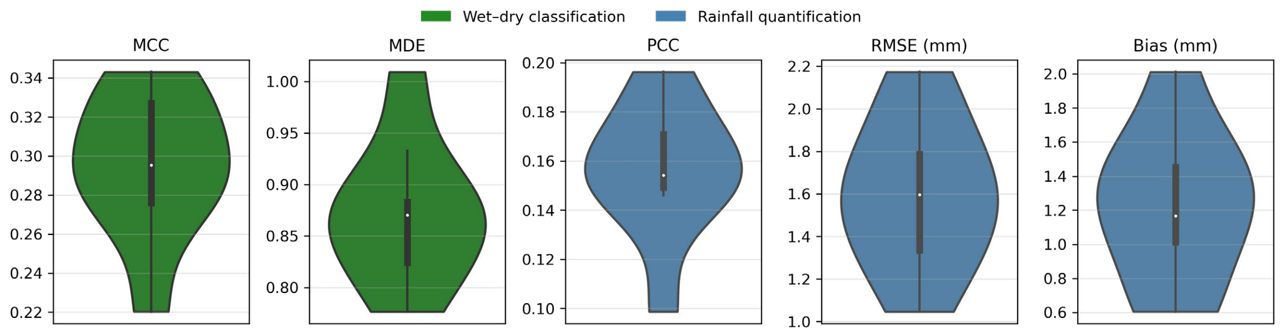

Figure 8. Distribution of wet-dry classification and rainfall retrieval performance metrics obtained from the complete set of 84 Commercial Microwave Links (CMLs).

The wet-dry classification results indicate a consistent ability of the proposed deep learning framework to distinguish rainy from non-rainy periods. The MCC values are generally centered around 0.30, while the MDE values remain relatively stable across the analyzed links. These results demonstrate that the integration of MSG-SEVIRI observations and rain gauge information provides reliable rainfall occurrence detection, despite the strong non-rain-related fluctuations commonly observed at 7 GHz.

For rainfall quantification, the PCC values show a moderate agreement between the CML-derived rainfall estimates and the rain gauge observations. Although the correlations remain lower than those typically reported for higher-frequency microwave links, they are noteworthy given the limited rain-induced attenuation expected at frequencies around 7 GHz. Although lower than the PCC values reported for CMLs operating above 15 GHz, which typically range between 0.7 and 0.9 [4] [11] [20] [25], the obtained results remain encouraging considering the challenging 7 GHz operating range. The relatively narrow distribution of PCC values further suggests a consistent behavior among the analyzed microwave links.

The RMSE distributions indicate that the retrieval errors remain within a limited range across the network, while the positive Bias values reveal a tendency of the CML retrievals to slightly overestimate rainfall intensity. Such behavior is expected when using long path-averaged observations to represent rainfall measured at a single point. In addition, residual wet antenna effects, uncertainties in baseline estimation, and spatial rainfall variability may contribute to these discrepancies.

Overall, the results demonstrate that meaningful rainfall information can be extracted from challenging 7 GHz commercial microwave links. While the quantitative performance remains below that commonly achieved with higher-frequency CML networks, the proposed deep learning wet-dry classification framework substantially improves the exploitation of low-frequency microwave links and highlights their potential for rainfall monitoring in regions with sparse ground-based observations.

4.5. Spatial Rainfall Patterns Reconstructed from 7 GHz Commercial Microwave Links

Figure 9 presents the cumulative rainfall field reconstructed from the 7 GHz CML network over the study period. The resulting map reveals clear spatial gradients in rainfall accumulation across the monitored area, with higher rainfall totals observed in the central and northeastern sectors and lower accumulations toward the southwestern part of the domain.

Despite the limited number of available links, the reconstructed rainfall field exhibits a coherent spatial organization that is consistent with the heterogeneous nature of rainfall during the West African monsoon season. This result demonstrates that the proposed framework is capable of extracting meaningful rainfall information from low-frequency microwave links and transforming these observations into spatially distributed rainfall estimates. The cumulative map provides an integrated view of rainfall variability over the study period and highlights the potential of 7 GHz CML networks for rainfall monitoring in data-scarce regions.

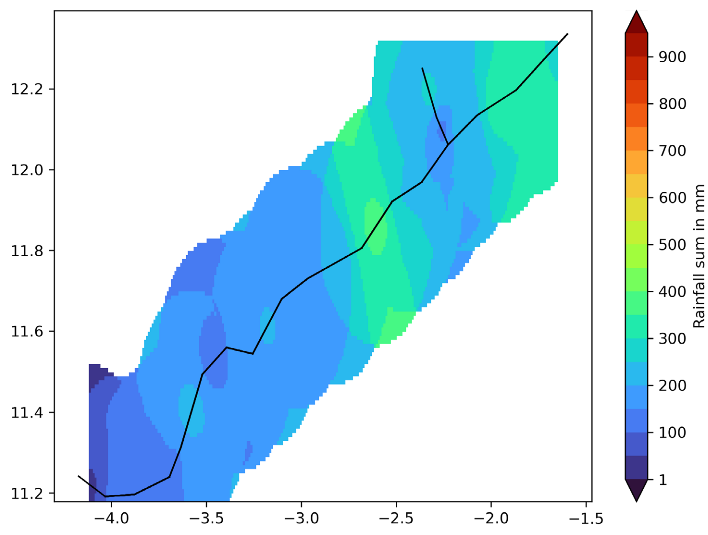

Figure 9. Cumulative rainfall field.

Figure 10 illustrates the daily rainfall fields reconstructed between 18 and 26 August 2020. The sequence highlights pronounced spatio-temporal variability in rainfall distribution across the study area, ranging from widespread precipitation events to more localized rainfall patterns, as well as days with little or no rainfall.

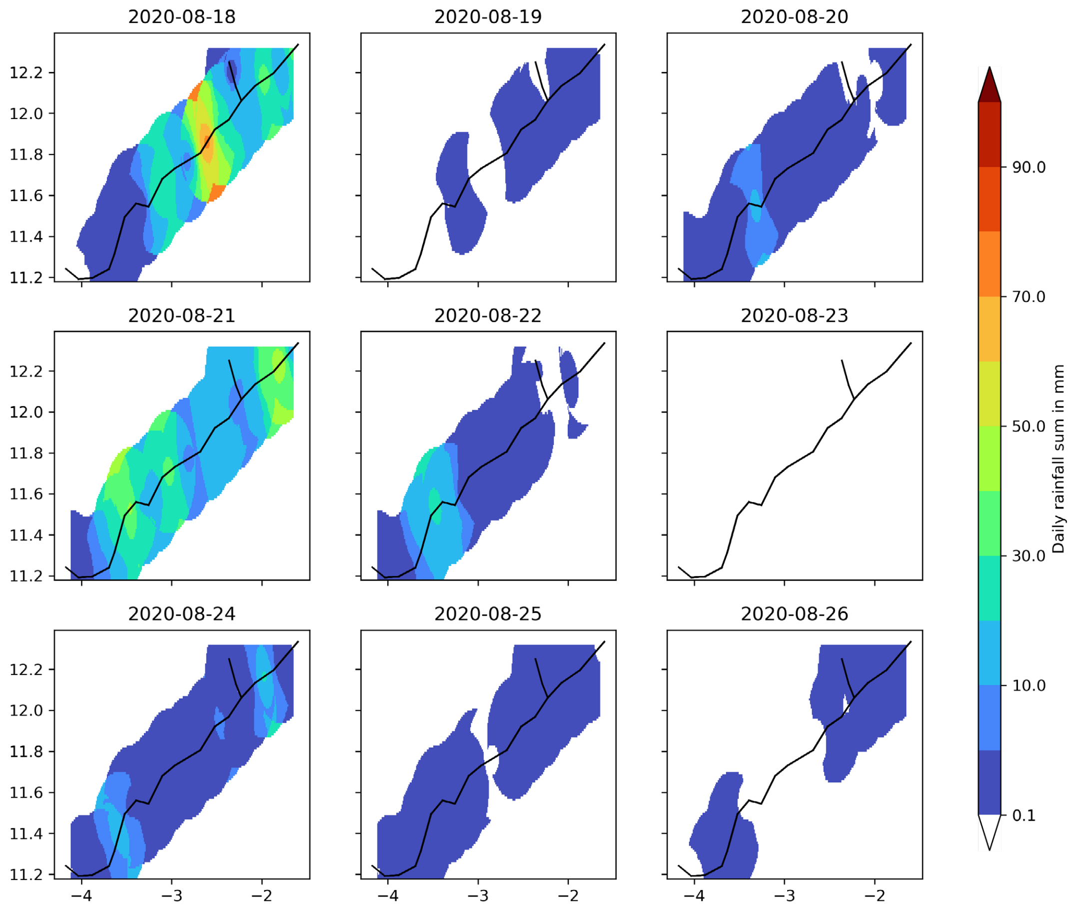

Figure 10. Daily rainfall fields.

Significant rainfall events are observed on 18 and 21 August, affecting large portions of the monitored region, while weaker and more localized precipitation structures characterize other days. In contrast, some days exhibit very limited rainfall or dry conditions, reflecting the intermittent nature of precipitation during the study period. Overall, the reconstructed maps demonstrate that 7 GHz commercial microwave links are capable of capturing the spatial organization and temporal evolution of rainfall systems. These results highlight the potential of low-frequency CML networks to provide meaningful information on rainfall dynamics, despite the challenges associated with non-rain-related signal fluctuations.

5. Conclusions

This study investigated the potential of challenging 7 GHz commercial microwave links for rainfall monitoring in Burkina Faso. Unlike higher-frequency links, microwave links operating around 7 GHz are characterized by relatively weak rain-induced attenuation and are strongly affected by non-rain-related signal fluctuations, making rainfall retrieval particularly difficult.

To address this challenge, a rainfall retrieval framework combining CML observations with a deep learning-based wet-dry classification model was developed.

The proposed approach integrates MSG-SEVIRI satellite observations and rain gauge measurements to improve the identification of rainfall periods before rainfall estimation from microwave link attenuation.

The results demonstrate that meaningful rainfall information can be extracted from 7 GHz commercial microwave links despite the presence of significant non-rain-related attenuation. The wet-dry classification framework achieved consistent detection performances across the analyzed links, while the retrieved rainfall estimates showed encouraging agreement with independent rain gauge observations. Event-scale analyses further confirmed the capability of the proposed framework to capture the timing and occurrence of major rainfall events.

Beyond rainfall retrieval, the reconstructed rainfall maps demonstrated that 7 GHz CML networks can also provide valuable information on the spatial organization and temporal evolution of precipitation systems. Both cumulative and daily rainfall fields revealed coherent rainfall patterns across the study area, highlighting the potential of low-frequency microwave links as opportunistic sensors for spatial rainfall monitoring in data-scarce regions.

Overall, the study confirms that operational telecommunication networks operating at 7 GHz can contribute not only to rainfall detection and quantification but also to rainfall mapping. These findings represent an important step toward the operational use of low-frequency commercial microwave links for hydrometeorological applications in regions where conventional observation networks remain sparse.

Future work will focus on extending the analysis to larger CML networks, integrating additional reference observations, and improving rainfall retrieval and mapping accuracy through advanced machine learning and spatial interpolation approaches.

The proposed methodology opens new opportunities for exploiting low-frequency telecommunication infrastructures as dense hydrometeorological observation networks across sub-Saharan Africa.

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Author Contributions

Conceptualization, M.D., A.D., F.Z. and B.W.Y.S.O.; methodology, M.D. and A.D.; software, M.D. and R.S.S.; validation, M.D., A.D, and B.W.Y.S.O.; formal analysis, F.Z., Z.K. and M.S.; investigation, F.Z., Z.K., A.D., M.D., B.W.Y.S.O. and R.S.S.; resources, M.D., J.R.B., D.V.O.; data curation, F.Z., Z.K., A.D., M.D., B.W.Y.S.O. and R.S.S.; writing—original draft preparation, M.D., A.D., B.W.Y.S.O., J.R.B., and D.V.O; writing—review and editing, M.D., A.D., F.Z. and B.W.Y.S.O.; visualization, M.D., A.D., F.Z. and B.W.Y.S.O.; supervision, F.Z. and Z.K.; project administration, A.D. B.W.Y.S.O., F.Z. and Z.K.; All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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