On the Power of Microwave Communication Data to Monitor Rain for Agricultural Needs in Africa

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Abstract: Over the last two decades, prevalent technologies and Internet of Things (IoT) systems have been found to have potential for carrying out environmental monitoring. The data generated from these infrastructures are readily available and have the potential to provide massive spatial coverage. The costs involved in using these data are minimal since the records are already generated for the original uses of these systems. Commercial microwave links, which provide the underlying framework for data transfer between cellular network base stations, are one example of such a system and have been found useful for monitoring rainfall. Wireless infrastructure of this kind is deployed widely by communication providers across Africa and can thus be used as a rainfall monitoring device to complement the sparse proprietary resources that currently exist or to substitute for them where alternatives do not exist. Here we focus this approach’s potential to acquire valuable information required for agricultural needs across Africa using Kenya as an example.

Keywords: Africa; agriculture; rainfall; commercial microwave links; IoT

1. Introduction

1.1. On the Scarcity of Rain Measurement Resources in Africa

As the poorest continent in the world, Africa suffers from disease outbreaks, droughts, floods, a prevailing lack of water supply, and a generally degraded health environment [1–4]. African countries’ economies are primarily based on agriculture, and the continent is rich in natural resources. However, a lack of infrastructure, among other obstacles, constrains the landmass’s potential [5,6]. To date, the ability to acquire extensive and precise quantitative precipitation estimates (QPEs) in Africa has been limited due to technical and practical constraints. State-of-the-art rainfall monitoring tools predominantly comprise rain gauges, radar systems, and satellites. Rain gauges, however, provide only local observations that are not representative of the larger space, and their deployment across Africa is extremely low [7]. As a result, the chance that a rainstorm cloud will entirely miss the point rain gauge in a certain domain is particularly high. Even where rain has already been measured by this instrument, the probability is very low that the recorded rainfall intensity represents the entire area. Satellites can provide good spatial coverage, but their retrievals may contain large uncertainties and mean biases, depending on factors such as target region, elevation, atmospheric conditions, and season [8]. Additionally, the spatial resolution of these observations is too coarse to analyze rainfall distributions at local scale [9]. Advanced weather radars can acquire extensive information about precipitation and the dynamics of rainstorms [10]. However, these instruments may face issues such as...
clutter effects, beam blockage caused by terrain obstacles, or errors and uncertainty in the derived surface QPEs [11–13]. Because of their high costs, radar systems are not widely deployed in Africa.

The last two decades witnessed an acceleration in the use of data streams created by prevalent technology and Internet of Things (IoT) systems. The volume of data generated is massive, the spatial coverage large, and the costs minimal, since the data are created during routine operations [14]. At times, the information contained in the generated data is of great environmental value [15]. For example, sensors embedded in smartphones have been found to be effective in retrieving atmospheric temperature information [16], barometric pressure [17,18], and the atmospheric tide [19]. Other work has shown that surveillance cameras have the potential to provide information on air pollution [20], while social networks can be used to improve the observations of automatic weather stations [21]. The example of focus in this paper is the use of commercial microwave links (CMLs) for monitoring rainfall.

1.2. Rain Monitoring Using CMLs

Monitoring rain in general and particularly in Africa should ideally combine the positive elements of each of three conventional monitoring instruments (rain gauges, satellites, radars) with minimal costs. CMLs constitute the infrastructure for data transmission in cellular communication networks and combine many of the characteristics required: measurements are taken over large areas (similar to satellites and radars) and at ground level (as with rain gauges). Since these systems are already deployed in the field by cellular providers, the costs are minimal. Indeed, dozens of works carried out around the world indicate the ability of CMLs to monitor rain [22–27].

Cellular communication networks operate on the principle that every mobile phone located in a particular area (a “cell”) communicates with the closest base station. This base station transmits the signal to a second base station situated farther away, and so on, until the signal is received at the last station located in the vicinity of the other end user. A cost-effective way to transfer the data between these base stations is through commercial microwave links. The density of these link networks is typically higher in urban areas, where the population is more dense, and lower in rural regions. Accordingly, the link lengths range on a scale of tens of meters (more common in urban areas) to a few tens of kilometers (more common in rural areas), where the typical representative link length is several kilometers long.

These links operate at frequencies of tens of GHz and are affected by various weather conditions, including fog [28], atmospheric moisture [29,30], temperature inversions [31], and areal evaporation [32]. Rain in particular is the atmospheric parameter that causes a dominant attenuation of signals vs. other phenomena in the frequency range in which CMLs operate. As a result, microwave communication systems can be used as wireless sensor networks for monitoring rainfall, particularly across Africa. Figure 1 shows a microwave base station located in the city of Njabini (western Kenya).

In 2015, the “Rain Cell Africa” workshop in Ouagadougou, Burkina Faso, promoted this emerging method in an area where its future implementation has great potential [33]. However, some difficulties remain in collaborating with and obtaining the microwave data required from cellular providers in Africa. As a result, only a handful of papers have focused on applying the method in this continent using real data measurements [34]. To the best of our knowledge, despite the large number of scientific articles written about this technology in the last 15 years, no paper has focused directly on this method’s capacity to improve agricultural needs particularly in Africa. The goal of this paper, which is an extension of a previous study [35], is to demonstrate CMLs’ potential to provide direct QPEs for an agricultural field in Africa, using standard measurements that are produced during routine operation of the microwave network. Additionally, the goal is to test the spatial potential of the method in detecting rainfall against rain gauges in a real target area, using the experiment site in the vicinity of the town of Kericho, in Kenya, as an example.
Figure 2 suggests the observational capabilities of CMLs already deployed in the field. It presents their deployment in Kenya, where each line represents the propagation path of at least one link. The network comprises some 3000 CMLs operating over distances ranging from a few kilometers and less to approximately 80 km.

Figure 1. A microwave communication mast situated in the city of Njabini (in Nyandarua County, Kenya). (a) The white round apparatuses installed on the mast are the microwave communication antennas used for rainfall monitoring; (b) a closer look at the microwave antenna. (Photo credit: K. K. Kumah.).

Figure 2. Deployment of commercial microwave links in Kenya (by a single cellular network provider). The mapped links (indicated by straight lines) operate in the frequency range of 7–26 GHz, with a magnitude resolution of 0.1 dB. The location of the test site near the town of Kericho is noted by a red dot on the map. (Data source: Safaricom.).
2. On Added-Value of Harnessing CMLs for Agricultural Needs

CMLs were originally designed for communication needs. Consequently, monitoring rainfall using CMLs is suboptimal and influenced by limitations deriving from, for example, geometric deployment in the field and operating frequencies that are less than ideal [36] and the coarse magnitude resolution of the microwave system [37]. Therefore, the method should be considered as complementary to the specialized tools associated with rainfall monitoring. Nonetheless, in many cases where no dedicated resources exist, as is common in many developing countries, and in Africa in particular, valuable information can be derived from this technique. For example, using CMLs to acquire QPEs across an agricultural field can help prevent overirrigation, leading to water savings and more efficient use of fertilizers. Likewise, timely information about inadequate rainfall in a certain area is important to ensure production of healthy crops.

The ability to contend with limited information on rainfall should improve markedly given the vast number of CMLs compared to the low number of sparsely deployed rain gauges, which only exist on some smallholder farms in Africa, if at all. Furthermore, under some circumstances, CMLs can be more effectively used to monitor rainfall than proprietary instruments. For example, in mountainous regions, remote sensing systems such as radars are limited by topographic conditions. A link network deployed along the various inclines could more reliably acquire QPEs [37]. Notably, a potential application of rainfall data from CMLs is in the design of rainfall-based index insurance, often considered an important risk mitigation tool for local farmers [38]. Existing rainfall insurance products rely on rainfall measured by nearby weather stations or satellites to calculate the indemnity. However, insured farmers often experience local rainfall remarkably different from the rainfall measures used in insurance contracts, resulting in the presence of a large basis risk—the probability that an index insurance contract will not accurately reflect the agricultural losses of insured farmers. Harnessing CML measurements of rainfall can thus provide a solution to reduce such basis risks.

The proposed method may not only acquire vital information regarding rainfall for agricultural uses but may also provide the infrastructure for additional relevant needs. For example, previous research has indicated CMLs’ ability to detect dew [39,40], a parameter linked with the spread of fungal and bacterial diseases [41]. Another example is the use of CML data for locust damage mitigation. Locust swarms pose a real danger to food security around the world, and especially in Africa. In an outbreak, swarms of the insects cover huge areas and consume massive amounts of agricultural crops trapped in their path. Weather conditions, including rainfall in particular, are directly related to the eruption of locust swarms and their trajectory over space. Therefore, CMLs can be harnessed as an effective sensor network to monitor weather and hence mitigate the damage from locust swarm infestations by taking proactive measures.

3. Method

The following formula [42] describes the relationship between rain-induced attenuation, \( A_{\text{RAIN}} \) (in dB/km), and rainfall intensity, \( R \) (in mm/h):

\[
A_{\text{RAIN}} = aR^b
\]

where the parameters \( a \) and \( b \) are known from the literature [43] and are dependent on the frequency/polarization of the signals and the rain drop size distribution.

3.1. Estimating the Rainfall Intensity

Each CML in the microwave network used in this study produces a set of \( N \) average received signal level (RSL) measurements, \( RSL_1, RSL_2, \ldots, RSL_N \), with an interval of 15 min between each of the records. Take \( RSL_M \) to be the RSL value measured at a certain time. For each link, the RSL value to be used as the reference, \( RSL_{\text{REF}} \), until the condition described in Equation (2) is first met, is the median value of the measurements of that link.
in the hour prior to the moment when $RSL_M$ was measured. Since the RSL may fluctuate even at times when no rain is present [44], a value of $\gamma = 0.8$ dBm was chosen, which has been experimentally found to be a threshold value in prior research [45] conducted at the test site.

When the condition described in Equation (2) occurred simultaneously for at least two links in the test area, the time interval where the condition was met was considered a “wet period”, that is, a period of time when it rained.

$$A_M = |RSL_M| - |RSL_{REF}| - \gamma > 0$$

where $A_M$ is the attenuation measured during that time interval.

When the condition (Equation (2)) was not met (or was only met for a single CML), the time interval was defined to be a “dry period”, that is, a period of time where there was no rainfall.

In this study we assumed a constant $RSL_{REF}$ value for each link for the entire period of the rain event demonstrated. This value was set to the $RSL_{REF}$ calculated (using the median, as described) for the moment when the condition (Equation (2)) was first met.

During rain, microwave antennas get wet, causing increased attenuation that may lead to overestimation of rainfall intensity. Wet antenna corrections were made according to the following known procedure while $A_P$, which is the path-integrated rain-induced attenuation, was calculated as follows [46]:

$$A_P = A_M - \min \left\{ a \left(1 - e^{-\beta \cdot A_M / L}\right) / A_M \right\}$$

where $L$ is the CML length (km), and the values of the parameters $a$ and $\beta$ were taken from prior research [46]. Finally, given $A_P$, and based on Equation (1), rainfall intensity, $R$, along the propagation path of the CML was estimated:

$$R = \left( \frac{A_{RAIN}}{a} \right)^{\frac{1}{b}} = \left( \frac{A_P}{La} \right)^{\frac{1}{b}}$$

3.2. Performance Evaluation

In order to assess the QPEs derived from the CMLs measurements against the observations recorded by the rain gauges, we used Pearson’s correlation test and the root mean square difference (RMSD) [30,47,48]. The RMSD (in mm/h), which is a measure for calculating the differences between values predicted by a model or an estimator (in this case, Equation (4)) and the observed values (in this case, by the rain gauge records), was calculated using Equation (5):

$$\text{RMSD} = \sqrt{\frac{\sum_{i=1}^{N} (R_{mi} - R_{gi})^2}{N}}$$

$R_{mi}$—the $i$th rainfall intensity as measured using the CML.

$R_{gi}$—the $i$th rainfall intensity as measured using the rain gauge.

$N$—number of samples.

Further information regarding the methods for rain monitoring using CMLs, error values of the measurements, and additional quantitative comparisons can be found in the literature [24,26,27,29,44].

4. Real Data Demonstration

Figure 3 shows the test site and the microwave link deployment over an agricultural area (a tea farm) near the town of Kericho, Kenya. Four microwave links operating at a 15 GHz frequency over three propagation paths (indicated as straight lines) are deployed
in the test area of focus (while CML1 and CML2 operate over the same propagation path at two slightly different frequencies around 15 GHz). The rain gauges deployed in the experimental area for research needs are indicated by triangles. It is worth noting that additional CMLs were deployed in the broader area (not indicated here), but to carry out the comparison we concentrated on the links deployed over the agricultural field or in greatest proximity to it, as well as those closest to the rain gauges.

Figure 3. The test site, showing the location of the commercial microwave links (indicated by straight lines with the term CML beside them) and the adjacent rain gauges (indicated by triangles). An additional rain gauge (not indicated here) is located near the town of Kericho, but its measurements were not available during the event discussed here. (Image source: Esri, Maxar, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community).

Figure 4 demonstrates CMLs’ spatial advantage to detect rain as compared to the point rain gauge method. The observations shown were taken by the four CMLs (3.7 to 4.8 km long) and the four rain gauges during a precipitation event that took place on 10 May 2013.

Figure 4a presents the measurements of the four rain gauges, and Figure 4b the measurements of the CMLs, where the dashed line in Figure 4b indicates the measurements of rain gauge 1 (G1). A convincing correlation between the gauges and the CMLs is observed ($R = 0.56–0.90$), where the range of RMSDs between the rain gauge and link measurements is between 0.86 and 3.18 mm/h.

Note that although the first rain gauge (G1) is situated in close vicinity to the CMLs/other gauges, it missed complete rain episodes between 17:45 to 18:15 and around 19:30 UTC (marked by the arrows in Figure 4b) due to the spatially unrepresentative nature of its measurement.

Additionally, note that along the path of CML4 (4.8 km), which is located farther away than the other links/gauges (though on the border of the same agricultural area), rain only began to fall from 18:45 during the second wet period. This reflects the high spatial variability of rain over a given area, and how vital the indication of no rainfall over a certain segment of terrain can be, especially if the cumulative effect over several weeks and months is taken into account. A difference is also discernible between the rain intensities measured by the CMLs, which represent averages over a few kilometers, and those from the point rain gauges.

This example demonstrates that if the observations for a given area, even when it is of limited size, are solely based on rain gauge measurements, the ability to gather reliable spatial information is limited. This is even more true when only a single rain...
gauge is deployed in an area. Using CMLs that are already deployed in the area can thus complement existing rain monitoring tools when they exist or can provide an alternative when proprietary measurements are not available at all.

Figure 4. Commercial microwave links vs. rain gauge measurements (rain event of 10 May 2013). (a) The measurements of the four rain gauges; (b) the measurements of the CMLs, where the dashed line indicates the measurements of rain gauge 1 (G1). The arrows indicate periods when the spot rain gauge did not measure rainfall, while the links in its close vicinity did.

5. Summary

Different technical and environmental factors may lead to disparities between CML and rain gauge measurements, including variability of rain across space and the different ways through which the observations are taken (point measurement vs. an average over several kilometers) [27,44].

Calculating rainfall estimates from measurements derived from a system originally designed for communication is challenging. For example, an RSL value may change as a result of many factors, including variations in atmospheric conditions [39], white noise, or the system’s built-in quantizing error [44]. The attenuation of the microwave signal due to wetting of the transmission and reception antennas during rainfall can cause uncertainty when estimating rainfall intensity, and at times, this effect can be meaningful [49]. Obviously, a rain gauge provides the most reliable measurement for a specific location. However, due to their widespread deployment, newly available CML “sensors” provide a good alternative that can outperform conventional gauges, which are sparsely deployed in Africa (if at all). Specifically, CMLs have the advantage in terms of spatial resolution compared to rain gauges, while their deployment near ground level favors them over remote radars or satellites, which provide measurements from space. Indeed, the results demonstrated here indicate CMLs’ spatial advantage over rain gauges to detect rain over a given agricultural area. This advantage is enhanced given CMLs’ existing presence in the field and the fact that the proposed method uses standard data, recorded regularly during routine network operation, and used without the need for any further adjustment. Of course, whenever measurements from different means (radar, satellite, rain gauge, CMLs) are available, it is desirable to combine them to produce the most reliable QPE.

The proposed approach already has great potential for different applications, including warning against flash floods [50], nowcasting hazardous storms, and more. In particular,
its contribution to the agriculture sector, a major source of income for many poor farmers in Africa, may be invaluable.

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