A rain estimation model based on microwave signal attenuation measurements in the city of Ioannina, Greece

Vasilis Christofilakis\textsuperscript{1} | Giorgos Tatsis\textsuperscript{1} | Christos J. Lolis\textsuperscript{2} | Spyridon K. Chronopoulos\textsuperscript{1} | Panos Kostarakis\textsuperscript{1} | Aristides Bartzokas\textsuperscript{2} | Hector E. Nistazakis\textsuperscript{3}

\textsuperscript{1}Department of Physics, Electronics–Telecommunications and Applications Laboratory, University of Ioannina, Ioannina, Greece
\textsuperscript{2}Department of Physics, Laboratory of Meteorology, University of Ioannina, Ioannina, Greece
\textsuperscript{3}Department of Electronics, Computers, Telecommunications and Control, Faculty of Physics, National and Kapodistrian University of Athens, Athens, Greece

Correspondence
Vasilis Christofilakis and Spyridon K. Chronopoulos, Department of Physics, Electronics–Telecommunications and Applications Laboratory, University of Ioannina, Ioannina GR-45110, Greece. Email: vachrist@uoi.gr (V.C.) and schrono@cc.uoi.gr (S.K.C.)

Abstract
Rain monitoring through signal attenuation has been a significant concern for the scientific community over the last decade. The lowest L-, S- and C-bands in the microwave spectrum are full of potential for environmental monitoring devices. It has not been extensively proven whether signal attenuation can be used for rain estimation throughout the microwave spectrum in the region of 1–6 GHz. The study derives a power-law rain estimation model by validating the one year data for the amount of rain and signal attenuation at the lowest limit of the S-band. This is achieved by a prototype accurate experimental set-up in a laboratory environment at the campus of the University of Ioannina, northwest Greece. A comparison with global rain attenuation models as well as measurements near this frequency band are also presented and discussed.

KEYWORDS
measurements, microwave, rain estimation, S-band, signal attenuation

1 | INTRODUCTION

Rain is one of the essential meteorological parameters because it affects transportation, agriculture and, in general, every daily social activity. Specifically, high rainfall intensities may be responsible for floods, which are associated with significant disasters and can even be dangerous to human life. Rainfall presents very high spatial and temporal variability, especially over areas with complex relief (Fotiadi et al., 1999; Bartzokas et al., 2003a). Rain is measured or estimated using various in-situ and remote techniques, including pluviometers, rain gauge recorders, weather radars, meteorological satellites, and so on. High-resolution measurement techniques must be employed due to the corresponding demands associated with the existence of high spatial and temporal variability of rainfall. These techniques can sometimes be considered very important for floods’ estimation (Creutin et al., 2009). Conventional meteorological rain gauge recorders provide accurate rain measurements with very high temporal resolution, but these recordings are usually valid only for a specific geographical location near the rain gauge (Kidd and Huffman, 2011). The spatial extent of the validity of the measurements strongly depends on the geographical and morphological characteristics of the region. Thus, the density of the rain gauges over a region is very crucial for accurate monitoring of the spatial distribution of rainfall. Several studies concerning rain gauge density and rain accuracy over a region have been published. Mishra (2013) showed that...
the absolute error increased from 15% to 64% as the number of gauges decreased from seven to one over a region. In areas where low rain gauge densities are combined with high precipitation intensities, the efficiency of the rain data collected decreases significantly (Girons et al., 2015). Even so, a large density of rain gauges over an area could lead to unprecedented errors during extreme precipitation events (Griffiths et al., 2009). Methods of monitoring rainfall based on weather radars or satellites, which involve sensors being far from the area of rainfall, use specific rain estimation algorithms (Russell et al., 2010; Thies and Bendix, 2011). Although these algorithms have been significantly improved over the last decades, they still introduce uncertainties in the estimation of rain, primarily when this estimation is carried out at a very high resolution (Jeon et al., 2019; Reddy et al., 2019). Radar measurements data are burdened with a wide spectrum of errors from different sources which cannot be neglected (Jurczyk et al., 2019). Concerning satellite measurements, the most significant limitation is the indirect character of the retrieval that correlates microphysical and dynamical cloud characteristics with rain amounts at ground level (Levizzani et al., 2001).

The idea behind rainfall measurement, as well as the first measurements, using the power loss estimation over a wireless microwave link (MWL), dates back almost 15 years (Marzano et al., 2002; Upton et al., 2005; Messer, 2006; Leijnse et al., 2007; Zinevich et al., 2008). Until then, several mainly theoretical models had been developed relating the signal attenuation to rainfall intensity. The latter is a dominant attenuation parameter specifically for frequencies > 10 GHz. Since then, a part of the scientific community has worked extensively on rain estimation using commercial MWL networks, an issue remaining rather challenging. Several research groups around the world have contributed significantly to this topic. Specifically, two research teams in the Netherlands have estimated rainfall in the Rotterdam region by using 17 day data sets and 57 MWLs (Overeem et al., 2011). The same teams (Overeem et al., 2013) keep on contributing to the study of space–time dynamics of rainfall for the Netherlands with the use of nearly 2,400 MWLs. The first quantitative evaluation of rain estimation based on a commercial link in West Africa is presented by Doumounia et al. (2014). Moreover, in a case study in the Czech Republic, a research team collected a unique data set of 14 MWL signals with a temporal resolution of a few seconds and compared it with the rainfall reference data sets from multiple rain gauges (Fencl et al., 2015). Recently, rain evaluation for three months against data from nearby gauges was found to be possible for 116 links Commercial Microwave Links (CMLs) located in the city of São Paulo, Brazil (Rios Gaona et al., 2018). Also, 35 MWLs in Faisalaba, Pakistan, were used for observing near-surface rainfall at the 20 temporal resolutions of 15 min (Sohail Afzal et al., 2018). In Korea, eight MWLs operating at frequencies between 6 and 8 GHz and with path lengths of 5.7–37.4 km, traversing the city of Seoul, were used to detect rainfall and estimate path-averaged rainfall rates. Significant differences from frequency-dependent co-efficients for estimating specific rain attenuation of the International Telecommunication Union (ITU)-R P.838-8 model have been observed (Kim and Kwon, 2018). Several issues—including wet antenna effects, baseline estimation (water–dry classification), the limited precision of the received signal of 1 dB, the data latency of 1 day, and coarse resolution times of 15 min, 1 hr and 24 hr—were investigated and should be further addressed (Schleiss et al., 2013; Messer and Sendik, 2015; Overeem et al., 2016a; Habib and Messer, 2018; Ostrometzky et al., 2018). Although the commercial MWLs have been structured for successful communication and not for precipitation-monitoring, the great advantage lies in the fact that no additional implementation costs are required when using the existing infrastructure.

Regarding the Earth-to-Earth rainfall microwave attenuation measurements at frequencies < 6 GHz, to the best of the authors’ knowledge, there are only a few studies in the academic literature. These studies are mainly based on the measurements of the received signal strength indicator (RSSI) on mobile terminals in global system for mobile communications (GSM) band as well as works of RSSI measurement for wi-fi links in frequency bands 2.4 and 5 GHz. Beritelli et al. (2018) presented a rain estimation method based on four rainfall intensity classes (no rain, weak rain, moderate rain and heavy rain) in an long-term evolution (LTE)/4G Mobile Terminal by using a probabilistic neural network. The rainfall classification method was based on three received signal level (RSL) local features of the 4G/LTE. A research group from Taiwan (Fang and Yang, 2016) performed experiments on the 1.8 GHz band of GSM networks at Yuan-Ze University (YZU), sensing actual radio power signals by using mobile phones and, in turn, recording the transmission conditions during various weather events. Karagianni et al. (2016) determined the attenuation level for MWLs based on local rain data. Additionally, a measurement of rain attenuation for a link in the S-band was carried out. In a proposed disaster alarm system (Libatique et al., 2009), the 5 GHz link was deployed over 400 m and monitoring was performed during rainy and clear days. A nationwide experiment in the Philippines used a 5 GHz fixed wireless network as a rain alarm system for monitoring changes in the RSLs. Rainfall mapping was presented with an intensity
classification scheme of 1–10, with subscribers of strong attenuation obtaining redder colours (Labuguen et al., 2015). Finally, Gustilo (2018) monitored a 400 m transmitter and receiver SmartBro link performance with 5.8 GHz operating frequency during different types of rain conditions.

The primary purpose of the present paper is to present a rain estimation model involving signal attenuation in the S-band region of the microwave spectrum. The reason for choosing the S-band to measure rainfall signal attenuation is threefold. (1) This research effort aims to contribute to the filling of the existing research gaps referring to the almost absence of the measured attenuation data over this region. (2) Measuring over this spectrum region for distances < 100 m provides the advantages of fewer errors and supports the assumption of spatially uniform rainfall which can be adopted for such small distances by introducing the bottleneck of more precise measurements which is also an additional research challenge. (3) This region of the spectrum is ruled by abundant devices operating under specific wireless communications standards, for example, Institute of Electrical and Electronics Engineers (IEEE) 802.11, GSM, Code-Division Multiple Access (CDMA), Universal Mobile Telecommunications System (UMTS) and LTE. These devices could potentially adopt scientific as well as technical aspects in future, in terms of precision and accuracy, to measure rainfall due to signal attenuation. Combining rain data from several sources—including ground sensors, radar, microwave estimations, devices operating in S-band and several other bands (C, L, X)—should deliver more reliable information (Craciun and Catrina, 2016; Raich et al., 2018). In this way, the present study does not intend to replace existing rain measurement methods, but on the contrary it contributes innovatively towards the improvement of the monitoring of spatial rainfall variability, which is significant mainly for convective rainfall regimes. In order to correlate signal attenuation data with rainfall rate, a customized experimental set-up that can frequently and precisely measures signal attenuation was implemented. The whole experimental set-up and tuning required almost one year of preliminary test procedures in order to produce the first reliable prototype model. Both antennas, the transmitter and the receiver, were designed and implemented in the Physics Department of the University of Ioannina (UOI) (Christofilakis et al., 2018; Tatsis et al., 2018). Ioannina is mainly a result of the west to east movement of Mediterranean depressions causing southwesterly flow in the lower troposphere and remarkable precipitation amounts over the windward areas of northwestern Greece. In the warm period, precipitation is mainly convective and it is usually a result of high static instability conditions over the mainland associated with the prevalence of upper air disturbances and the intense daytime radiative heating of the land surface (Bartzokas et al., 2003b; Lolis, 2007, 2012). The recorded data for the present study for nearly one year, including received signal power at 2 GHz as well as rain (mm), are exploited by the methodology described in Section 2. The measurement set-up is presented in Section 3 while the results and a discussion are presented in Section 4. Finally, the conclusions are drawn in Section 5.

2 | METHODOLOGY

The primary objective of the study is the determination of a rainfall estimation model for the S-band under temperate weather conditions. The proposed method for calculating signal attenuation due to rain intensity, and vice versa, is based on the measurements recorded in a laboratory-like environment by a customized and accurate experimental set-up. Based on the methodology described below and for N rainfall events that took place between March 2015 and April 2016, a database of \( \{R(t), A\} \), pairs, where \( R(t) \) is rainfall for \( t \) min’ integration time (mm·hr\(^{-1}\)); and \( A \) the signal attenuation (dB·km\(^{-1}\)), was successfully exported. Following the 1 min recommendation of P.837-6 by ITU (Recommendation ITU-R P.837-6, 2012) and for four empirical models rainfall intensity with a 1 min integration time \( R(1) \) was acquired. For simplicity reasons, \( R \) is used instead of \( R(1) \) in the rest of the paper. Finally, the signal attenuation parameters are estimated and the new rainfall estimation model \( R = f(A) \) is determined for the four 1 min empirical models.

2.1 | Radio Frequency signal parameters

Along a short distance \( d = 21.5 \) m where the rainfall can be considered uniform, a transmit and receive system was placed in two adjacent buildings near the meteorological station of the UOI. The transmit system transmits an unmodulated carrier with constant output power at \( f_c \) and the receiving system recorded the received power in array \{date, time, \( P_{r}(t) \)\} with a time resolution of 0.2 min. The received \( P_{r}(t) \) power (for either Earth to Space links or Earth to Earth links or even if there is no rainfall) is not constant but changes over time and fluctuates. These
variations are mainly due to temperature and water vapour concentration changes, interference, multipath fading, thermal noise in the emitter and receiver system as well as due to the water droplets on the surface of the two buildings. Having both the transmitter and receiver system inside the buildings, jitter effects due to wind and the wet antenna effect were eliminated. Additionally, a moving average filter is used to reduce random noise while retaining a sharp step response. Determination of the received power for dry and rainy seasons was defined as the baseline reference power, which is a complicated and challenging issue and has been discussed for both Earth to Space links (Barthès and Mallet, 2013) as well as Earth to Earth links (Zinevich et al., 2010; Overeem et al., 2016b; Ostrometzky and Messer, 2018). In the present study, the following cases for the determination of $P_{\text{ref}}$ are used. Suppose the conventional rain gauge measures the amount of rain $(RA; \text{mm})$ for the period of $t$ to $t + \tau$, where $\tau$ is defined as the integration time.

### 2.1.1 | Case 1: Dry periods

If for time $t_c$ before the first rain event the received power $P_r(t)$ has a co-efficient of variation (CV) $< 0.2\%$, then the reference power is given by:

$$P_{\text{ref}} = \frac{1}{t_c} \int_{t-t_c}^{t} P_r(t)\,dt$$

where $t_c$ is the time interval.

Taking into account the condition of the CV $< 0.2\%$, it is ensured that there is not a strong fluctuation of the signal. The time $t_c$ has a minimum value $(t_c|_{\text{min}})$ of 2 hr. The minimum value of 2 hr was empirically selected by analysing the $P_r(t)$ data as the optimum time interval, without rain, where there were very small fluctuations and an adequate number of $P_r$ values.

2.2.2. Case 2: Rainy season

Rainy intervals are defined for time $t_c|_{\text{rain}} < t_c|_{\text{min}}$. If the co-efficient of the received signal’s variation is $< 0.2\%$ for this rainy interval, then $P_{\text{ref}}$ is defined as:

$$P_{\text{ref}} = \frac{1}{(t_c)_{\text{rain}}} \int_{t-t_c}^{t} P_r(t)\,dt$$

In the case of a CV $\geq 0.2\%$, then $P_{\text{ref}}$ is defined as the received maximum power value of the past 5 min. This subcase concerns instances where there are strong rain-fall events following weak rainfall events.

Signal attenuation due to rain, along the actual path length $(d)$, is defined by:

$$A_r = P_{\text{ref}} - \bar{P}_r$$

where:

$$\bar{P}_r = \frac{1}{\tau} \int_{t-\tau}^{t} P_r(t)\,dt$$

and $\tau$ is the integration time.

It is the mean of the $P_r$ during the time the rain gauge measures RA. The equivalent mean of the $P_r$, at the discrete-time domain with time resolution 0.2 min, is given by:

$$\bar{P}_r = \frac{1}{25} \sum_{i=1}^{25} P_r(t)$$

Since the rainfall is uniformly distributed along the actual path length, the specific rain attenuation $A$ (dB-km$^{-1}$) is derived by:

$$A_r = Ad$$

With the signal to quantization error of 145 dB, it was made possible to eliminate as much uncertainty as possible between small rain events and noise.

### 2.2 | Rainfall parameters

#### 2.2.1 | Rainfall intensity

The raw rainfall data of the conventional meteorological gauge of the UOI was stored in a database using the following format {date, time, RA}. For the first days of measurements, the integration time of the rain gauge was 30 min. It is known that high rain amounts are likely to be lost when this period is too large (Tamosiunaitė et al., 2011). For this reason, integration time of the rainfall was set to a minimum of $\tau = 5$ min. The rainfall intensity measured (mm-hr$^{-1}$) is given by:

$$R(\tau) = \frac{60RA}{\tau}$$

#### 2.2.2 | “1 min” rainfall intensity

According to P.837-6-Annex 1 recommendation, rainfall rate statistics with a 1 min integration time are required for the prediction of rain attenuation in terrestrial and satellite links (Recommendation ITU-R P.837-6, 2012). In
order to convert rainfall intensity measured data from 5 to 1 min, four global (parameters of these models, however, are based on local measurements are defined as global) “1 min” rainfall intensity empirical models were used:

- **ITU-837-5 model** is based on Segal method 1986 (Segal, 1986) and belongs to power-law models. The rainfall rate for a 1 min integration time can be obtained by:
  \[
  R = a R(\tau)^b \text{ (mm-hr}^{-1}\text{)}
  \]  
  where \( R \) and \( R(\tau) \) are the rainfall rates with 1 and \( \tau \) min integration times, respectively; and \( a \) and \( b \) are regression co-efficients which are 0.986 and 1.038, respectively, for a 5 min integration time (Recommendation ITU-R P.837-5, 2007). These values are obtained from long-term measurements of point rainfall rate at 14 sites in Korea, China and Brazil.

- **Joo et al. model** based on two year rain-rate measurements conducted by the Electronics and Telecommunications Research Institute (Joo-Hwan Lee et al., 2000). This method proposed that a 1–\( \tau \) min rainfall rate is given by the probability to 1 min rainfalls from \( \tau \) min rainfalls expressed by:
  \[
  P_1 = 1.71 P_\tau 10^{(-0.242e^{-\frac{\tau}{24}})}
  \]  
  where \( \tau \) = 5 min.

- **Moupfouma and Martin (MM):** Another empirical model used is that of Moupfouma and Martin (1995), which is based on England’s rainfall data, whose accuracy is confirmed, and for temperate localities. According to this model:
  \[
  R = R(\tau)^{0.987e^{0.061}} \text{ (mm-h)}
  \]  
  where \( \tau = 5 \) min.

- **Emiliani et al. (PL) is also a power-law model where derived co-efficients are obtained using a comprehensive database (Emiliani et al., 2008). The derived co-efficients are shown to improve the performance of the conversions using the ITU method. For temperate climate and conversions from 5 to 1 min, \( a \) and \( b \) regression co-efficients are \( (a, b) = (0.953, 1.041) \) (Emiliani et al., 2009).

### 3 | MEASUREMENT SET-UP

This section depicts the experimental set-up and the operating parameters of the system. The complete measurement set-up is shown in Figure 1 and consists of (1) the transmitter module, (2) the receiver and data-logging module, (3) the rainfall recording subsystem of the conventional meteorological station’s gauge at the UOI, and (4) the data-acquisition and processing module. As shown, there are two identical waveguide antennas. The elevation angle as 0° and the two antennas are placed at the height of 2 m above the ground surface. The antennas are within the buildings and, in this way, additional errors are eliminated from the acquired measurements. These errors would come from influences such as ice and moisture in the antenna’s surface and a jitter phenomenon due to the wind. The transmitter module consisted of a signal generator that emitted an unmodulated carrier in the antenna’s resonant frequency. The antenna was designed and implement in the Electronics–Telecommunications and Applications Laboratory so that it is directional, occupies a small volume, is lightweight and has a resonant frequency of 2 GHz. Within 21.5 m from the Tx antenna, there is an identical Rx antenna waveguide and the receiving/recording module. The receiving/recording module includes, apart from the antenna, the band-pass filter with cut-off frequencies of 1,960 and 2,310 MHz, the power detector unit, the analogue to digital converter, and the Arduino-based microprocessor. The \( P_r \)’s are stored on an SD card and finally fed to the computer. Rainfall and power measurement data are transferred to a computer for offline analysis and processing. In the direction of reducing the probability of error in the measurement data, except for the appropriate actions performed for the limitation of noise effects due to wind and antenna, the random nature of \( P_r(t) \) was also eliminated even during dry seasons since it is related to the link’s length. The probability of error was further reduced by measuring with 0.0001 dB precision (in terms of power resolution) and a signal-to-noise ratio of 145 dB. All the above actions give an advantage to measuring even low rainfall events which are reflected in the time series of the figures in the next section.

### 4 | RESULTS AND DISCUSSION

#### 4.1 | Received signal and rain data

The received signal power is recorded five times per min, as shown in column 2 of Table 1 for a dry period during January 28, 2016. A timestamp with a date and time resolution of 12 s is shown in column 1. The rainfall amounts are recorded with an integration time of 5 min (Table 2).

Figures 2–6 show time variation of the measured \( P_r \) (dBm) (left-hand axes) and RA (mm) (right-hand axes). Specifically, Figure 2 shows four rain events (on January 4, 2016) with equal amounts of 0.2 mm. Two occurred
between 0035 and 0045 hr and two between 0340 and 0350 hr. Although similar signal attenuation due to the same four rainfall events is observed, the data useful for exploitation are the first and third, which were recorded after a dry season. Figure 3 presents four rain events on September 24, 2015. Two consecutive events can be seen with rain amounts of 0.4 mm between 1555 and 1605 hr. The third rain event with rain of 0.2 mm is not exploitable because it comes immediately after two double-rain events. The fourth rain event is also 0.2 mm and it is exploitable as the baseline is determined by Equation (2).

### Table 1

| Date and time              | $P_r$ (dBm) |
|----------------------------|-------------|
| January 28, 2016, 0430:15  | -49.3939    |
| January 28, 2016, 0430:27  | -49.3937    |
| January 28, 2016, 0430:39  | -49.3937    |
| January 28, 2016, 0430:51  | -49.3935    |
| January 28, 2016, 0431:03  | -49.3933    |

Note: Time is shown as hour:seconds.

### Table 2

| Date               | Rain (mm) |
|--------------------|-----------|
| January 3, 2016, 1440 hr | 0         |
| January 3, 2016, 1445 hr | 0         |
| January 3, 2016, 1450 hr | 0.4       |
| January 3, 2016, 1455 hr | 0.4       |
| January 3, 2016, 1400 hr | 0.6       |

September 24, 2015. Two consecutive events can be seen with rain amounts of 0.4 mm between 1555 and 1605 hr. The third rain event with rain of 0.2 mm is not exploitable because it comes immediately after two double-rain events. The fourth rain event is also 0.2 mm and it is exploitable as the baseline is determined by Equation (2).

Figure 4 shows the time variation of the measured $P_r$ on February 9–10, 2016, at 0600 hr. From 0150 to 0500 hr there are eleven 0.2 mm rain amount events. The first occurred at 0150 hr after a long dry season > 2 hr, so $P_{ref}$ is defined by Equation (1). From 0240 to 0320 hr there is a rainfall gap where the increase of the $P_r$ is apparent.
Figure 4 (inset) shows two exploitable events from 0320 to 0325 hr and from 0340 to 0345 hr. From 0345 to 0505 hr, there is no rainfall event, so the baseline is again increased. At 0505 hr there is one rainfall event followed by one more, starting at 0515 hr. From Figure 4, it is also clear that there is a distinct detection capability even for minimal rainfall events. Also, after cumulative rain amounts, the baseline changes the reference, as shown in Figure 4. The change of the base signal level before and after the precipitation events is attributed to the corresponding change in atmospheric humidity and the concentration of small water droplets in the atmosphere. Figure 5 shows the time variation of the measured \( P_r \) from 1530 to 2030 hr. Several rainfall events exhibit power decreases, first with two small 0.2 mm and one at 0.6 mm, followed by three equivalent events at 2.2, 2.4 and 2.6 mm of rain. After a small pause of 40 min, smaller rainfall events follow with a maximum at 0.8 mm and another exploitable event at 0.6 mm. After the end of the events, the baseline still remains low. Figure 6 shows the time variation of the measured \( P_r \) and rainfall amount, but with an integration time of 30 min. In fact, this was the first measurement after one year of design, implementation and tuning up of the customized experimental set-up. The 0.4 mm rainfall event follows a stronger one event with rain of 1.2 mm, which corresponds to 0.5 dBm signal attenuation. Between 1430 and 1500 hr there is no rain, followed by rain of 0.2 mm, which also becomes distinct in the \( P_r \).

4.2 | Rain estimation

From the rainfall intensities \( R(\tau) \) of the recording period, the study evaluated, according to Yang et al.’s (2011) classification of rain events, two very high rain events of > 60 mm-hr\(^{-1}\), seven high rain events of 30–60 mm-hr\(^{-1}\), 42 medium rain events of 10–30 mm-hr\(^{-1}\), and 84 low rain events of < 10 mm-hr\(^{-1}\). A significant number of events could not be evaluated due to power outages during the events, strong signal fluctuations, interference and mainly because they did not meet the criteria set out in the methodology section. The final four sets of \( N = 135 \) exploitable measurements \{A, R\} are shown in the scatter diagrams of Figure 7 and derived by the \{A, R (\tau)\} set and the 1 min recommendation models as
described in the Section 2.2.2. The best possible curves based on power law:

\[ R = \alpha A^\beta \]  

(11)

are estimated using the non-linear regression method based on the Levenberg–Marquard algorithm, where \( R \) is rain intensity (mm hr\(^{-1}\)) for a 1 min integration time and the (1) ITU-837-5, (2) Joo et al., (3) MM and (4) PL models; and \( A \) is rain attenuation (dB km\(^{-1}\)). The co-efficients \( \alpha \) (mm hr\(^{-1}\)), (km dB\(^{-1}\)) \( \beta \), and the co-efficients bounds \( c_{\alpha} \) and \( c_{\beta} \) for the multiplier and exponent, respectively, are listed in Table 3. The estimated exponents vary from 2.5 to 3.0, while multipliers vary from 2.2 \( \times \) \( 10^{-3} \) to 8.4 \( \times \) \( 10^{-3} \) mm hr\(^{-1}\) (km/dB)\(^{-1}\) with an \( R^2 \) goodness-of-fit > 93%.

Concerning subplots i (ITU-R P.837-5) and iv (PL) 94.8% of measurements are within the prediction bounds, while 94% are within prediction bounds for subplot iii (MM). Concerning measurements in subplot ii (Joo et al.), 96.3% are within prediction bounds. For the four estimated curves, there are no major variations for moderate rain events. For higher rainfall intensities, there is a difference between the four estimated curves according to the 1 min model used. Specifically, measurement of 20 dB km\(^{-1}\) corresponds to a rain intensity of 2 mm hr\(^{-1}\), which is higher for the \( R_{\text{iii}} \) curve compared with the \( R_{\text{ii}} \). Signal attenuation of 35 dB km\(^{-1}\) corresponds to 55 mm hr\(^{-1}\) rain intensity for \( R_{\text{ii}} \) and 80 mm hr\(^{-1}\) for \( R_{\text{iii}} \). As for the estimated curves using the ITU and PL 1 min models, it is obvious that these curves are almost identical. Even for violent rain events with rainfall intensities of 90 mm hr\(^{-1}\), this is only a 0.3 dB km\(^{-1}\) increment for the PL 1 min model.

The sensitivity for rainfall intensity classes: low \( (R_i \leq 10 \text{ mm hr}^{-1}) \), medium \( (10 < R_i \leq 30 \text{ mm hr}^{-1}) \), high \( (30 < R_i \leq 60 \text{ mm hr}^{-1}) \) and very high \( (R_i > 60 \text{ mm hr}^{-1}) \) is shown in Figure 8. From the four classes, the separation of the boundaries of the boxes is clear. There is no overlap for the width of the boxes, defined as the separation between the 25th and 75th percentiles for each rainfall intensity class. Specifically, 50% of values lie between 5.3 and 12.1, between 18.6 and 23.0, between 27.1 and 30.2, and between 32.2 and 40.1 dB km\(^{-1}\) for rainfall intensity classes low, medium, high and very high, respectively.

### 4.3 Verification of the proposed model

#### 4.3.1 Specific attenuation models for rain

The most common relation between the specific rain attenuation and rain rate was presented in both tabular and graphical forms by Olsen et al. (1978) for several drop size distributions. According to Olsen’s power-law approach:

\[ A = c R^d \]  

(12)

where the multiplier: \(c = \left( \frac{1}{\alpha} \right) \left( \frac{1}{\beta} \right) \left( \frac{\text{dB}}{\text{km}} \right) \left( \frac{\text{mm}}{\text{hr}} \right)^{-d} \) and the exponent \( d = \frac{1}{\beta} \) in accordance with Equation (11).

**FIGURE 7** Scatter plots between rain rates \( R \) (mm hr\(^{-1}\)) and specific attenuations \( A \) (dB km\(^{-1}\)) and nonlinear estimated lines for models ITU-837-5, Joo et al., Moupfouma and Martin (MM), and Emiliani et al. (PL)
In this case, the co-efficients $c$, $d$ for the estimated data curves and the four “1 min” rain models are listed in Table 4.

Estimated specific rain attenuation $A$ versus rain rate $R$ curves are shown in Figure 9 for the four “1 min” models. Figure 9 (inset) shows the specific attenuation versus rain rate for the Crane (1980) and ITU-R P.838-3 (Recommendation ITU-R P.838-3, 2005) specific attenuation models at a frequency of 2 GHz. From these figures, it is obvious that specific rain attenuation is negligible at this frequency range according to the Crane and ITU-R models. For a very high rain event at 80 mm $\text{hr}^{-1}$ according to the proposed estimated model and for the MM 1 min rain model, the specific rain attenuation is approximately higher by three orders of magnitude compared with the specific attenuation of the Crane model. The Crane Global attenuation model was developed for use on either Earth to Space or terrestrial paths. It is based entirely on geophysical observations of rain rate, rain structure and the vertical variation of atmospheric temperature (Crane, 1980). The global Crane model was validated for terrestrial paths operating at frequencies $> 11 \text{ GHz}$. For measurements of acceptable quality, the measurements and predictions agree within the predicted 1 SD (standard deviation) bounds (Crane, 1980). The ITU database includes rainfall rate and rain attenuation cumulative probability distributions derived from concurrent measurements in 89 links situated, mainly, in temperate climates (Livieratos and Cottis, 2019). The operation frequencies range from 7 to 137 GHz, and the path lengths from 0.5 and 58 km, while the model attenuation calculation is based on the Laws–Parsons size distribution (Maitra, 2004).

In general, the spatial variability of precipitation is very high, even in small areas (500 × 500 m) (e.g. Jensen and Pedersen, 2005). For example, for the case of the destructive Flash Flood Event of November 15, 2017, in Greece, a huge spatial variation of precipitation was estimated over small areas of a few hundred square metres (Varlas et al., 2019). Thus, the precipitation estimation models that use distances $> 500 \text{ m}$ actually estimate spatially averaged precipitation amounts over the effective path length, while in the present approach, which is based on a relatively short distance of $< 100 \text{ m}$, it can be considered that actual in-situ precipitation amounts that are very close to the values recorded by a typical rain gauge are estimated. The above means that the change of correspondence of the signal attenuation due to rain, along the experimental path to the path of 1 km, according to Equation (6), is necessary since the actual physical path link and the effective path link are the same in the present case, but it cannot support the assumption that the local actual precipitation rates can be extrapolated at longer paths where precipitation is characterized by significant variability. Such extrapolation may lead to very high, not realistic precipitation rates and amounts. In other words, the extrapolation of uniform rain over a kilometre should definitely yield a significant amount of water between the transmitter and the receiver. It is noted that locally high precipitation rates are mainly a result of convective clouds usually characterized by a small spatial extent. Thus, the extrapolation of such rates over large geographical areas leads to the overestimation of spatially averaged precipitation rates. Such extrapolation can lead to the estimation of realistic spatial precipitation averages only in the case of stratiform clouds, which are generally associated with spatially uniform but considerably lower precipitation rates.

Finally, it is well known that physical processes are adopted to extend predictions to conditions (e.g. 

### Table 3 Estimated co-efficients

| Co-efficients | Model I | Model II | Model III | Model IV |
|---------------|---------|----------|-----------|----------|
| $\alpha \pm cb$ (mm $\text{hr}^{-1}$ (km $\text{dB}^{-1}$)$^2$) | 0.0032 $\pm$ 0.0013 | 0.0084 $\pm$ 0.0004 | 0.0022 $\pm$ 0.0009 | 0.0030 $\pm$ 0.0012 |
| $\beta \pm cb$ (s) | 2.8 $\pm$ 0.1 | 2.5 $\pm$ 0.1 | 3.0 $\pm$ 1 | 2.8 $\pm$ 0.1 |

*Note: 95% co-efficient bounds.*

**FIGURE 8** Sensitivities for rainfall intensity classes low, medium, high and very high.
frequency, location, temperature, Drop Size Distribution) where adequate measurements are not available (Crane, 2003). However, empirical models do not perform satisfactorily in all conditions, and it is not possible to apply a prediction model to any condition (Crane and Diasanayake, 1997; Livieratos and Cottis, 2019). The differences between the experimental data and the theoretical or empirical models are something that has been identified in the present work and it is something that needs further investigation in future. However, the study does not aim to validate or dispute any of the global models. It refers to experimental research work in a specific location, which can be considered representative of a broad area inside the Mediterranean region. The specific measurements can be used in future for the improvement of the existent models or the construction of new models, is suitable for the specific geographical and area and relief.

4.3.2 | Measurements near this frequency band

Signal attenuation due to rain for frequencies < 6 GHz has not been studied extensively. Only a few studies are mainly based on the measurements of the RSSI on terminals in the GSM or wi-fi bands. For this reason, it is difficult to make a direct comparison with the present measurements and the proposed estimation model, although the repeatability of the present measurements for events up to 0.8 mm is confirmed (Christofilakis et al., 2018). Fang and Yang (2016), among others, present 23 measurements for the RSSI attenuation versus rain rate for the 1.8 GHz band of the GSM at YZU. For these measurements depicted in Figure 10 and the 135 measurements at 2 GHz at UOI, the direct correlation of the two sets is clear. Applying the nonlinear regression method based on the Levenberg–Marquard algorithm to the set of 23 measurements with a maximum rain rate of around 30 mm/hr means an estimated curve with an exponent of 2.7, a multiplier of $6.64 \times 10^{-3}$ and an $R^2$ goodness-of-fit > 85% (Figure 10). Figure 10 also shows the estimated curve for UOI measurement and the MM 1 min model. For low rain events between 2 and 10 mm/hr, it is clear that the two curves almost coincide. In Figure 10, a 25 dB-km$^{-1}$ attenuation corresponds to a rainfall intensity of 30 mm/hr, while the YZU$_{RSS}$ is 40 mm/hr. For very high rain events, and specifically for 100 mm/hr, the attenuation is 35 dB-km$^{-1}$ for the YZU$_{RSS}$, while the same attenuation is related to 20 mm/hr less rain for the UOI$_{MM}$. As expected, rain intensities correspond to higher signal attenuations in the proposed UOI model relative to the YZU, since the measurements have resulted from

### TABLE 4  Specific rain attenuation co-efficients

| Co-efficients | UOI$_{MM}$ | UOI$_{ITU-R P.837.5}$ | UOI$_{300 et al.}$ | UOI$_{PL}$ |
|---------------|------------|-----------------------|-------------------|-----------|
| $c$ (dB-km$^{-1}$)(mm-hr$^{-1}$)$^{-d}$ | 7.929 | 7.854 | 6.889 | 7.957 |
| $d$ | 0.338 | 0.359 | 0.404 | 0.358 |

*Note: UOI, University of Ioannina.*

![Figure 9](image9.png)  
**FIGURE 9** Estimated specific rain attenuation $A$ (dB-km$^{-1}$) as a function of rain rate $R$ (mm-hr$^{-1}$) for the four 1 min models. The inset shows Crane and ITU-R P.838-3 specific attenuation models.

![Figure 10](image10.png)  
**FIGURE 10** Estimate rain rate (mm-hr$^{-1}$) versus attenuation (dB) for University of Ioannina (UOI) measurements and Yuan-Ze University (YZU) received signal strength (RSS) measurements (Fang and Yang, 2016).
uniform rainfall over a very short distance, and because the operating frequency is somewhat higher than 1.8 GHz. Although the material and the methodology used by Fang and Yang (2016) are different from those used in the present work (as it is based on the RSSI mobile terminals, with different accuracy, at various distances, with omnidirectional antennas and with different levels of transmitted and received power), it cannot be ignored that the two systems’ frequencies, which are the basic parameters on which the co-efficients \( \alpha \) and \( \beta \) depend, are very close.

The RSSI values for the three LTE/4G mobile terminals, operating at 2.6 GHz, located at 200 m with visibility to the base station, are collected for the cases of: (1) no rain conditions, (2) rainfall intensity \( < 2.5 \text{ mm·hr}^{-1} \), (3) \( 2.5–5.0 \text{ mm·hr}^{-1} \), and (4) \( 6–10 \text{ mm·hr}^{-1} \). The probability density function of the RSLs has a different mean and variance for the four cases. For the case of rainfall intensities, \( 6–10 \text{ mm·hr}^{-1} \), RSL varies from 4 to 14 dBm at 200 m (Beritelli et al., 2018). These values are too close to that presented in the present study as well as to the measurements for rain amounts \( < 1 \text{ mm} \) presented by Christofilakis et al. (2018). With a commercial terminal with 1 dBm accuracy (Gustilo, 2018), the present authors correlated rain with signal attenuation at 5.8 GHz, and the estimated co-efficients were \( d = 0.2045 \) and \( c = 1.35 \). Experimental values, in general, have a large deviation from those given by the theoretical and empirical models. Few other works present the RSSI measurements for wi-fi links such as Libatique et al. (2009) showed for a 3 dB signal attenuation at 5 GHz for a transmitter–receiver distance of 0.4 km and a 12 mm·hr\(^{-1} \) rainfall intensity, which yields a specific signal attenuation of 7.5 dB·km\(^{-1} \). Karagianni et al.’s (2016) measurements for moderate rainfall events around 12 mm·hr\(^{-1} \) showed a power loss around 12 dBm at 2.4 GHz; supposing that a maximum path loss of 1.6 km was used, this yields specific path attenuation from 7.5 (for the case of maximum wi-fi distance) to 15 dB·km\(^{-1} \).

### 4.4 Restrictions

The proposed method for calculating the signal attenuation correlated to the rain intensity, and \textit{vice versa}, is based on the measurements acquired in a laboratory-like environment. Along a short distance of \( d = 21.5 \text{ m} \) (rainfall can be considered uniform), a telecommunication system (transmitter and receiver working at the lowest limit of the S-band) was placed in two adjacent buildings. This location was near the meteorological station of UOI. The restrictions that should be mentioned along with their solutions are as follows:

- The recorded data of nearly one year could be considered as adequate because they were acquired during all the seasons of the year and near the meteorological station of UOI for comparison purposes. Nevertheless, more measurement time would be appropriate in order to be more sure that the acquired measurements correspond better to various seasons and not to a potential rain peculiarity of a certain year. This could be well implemented through systematic rainfall measurements of a period of many years.
- Alternative data sets in nearby regions for comparison will be acquired in the near future, as the dedicated telecommunication systems which will be placed at those regions will soon be ready. Albeit the use of only one system that really showed significant results (such as the one proposed herein), more validity will be added due to the aforementioned additional measurement systems by confronting the fact that both radio and rain are highly location/distance dependent (Fang et al., 2018).

### 5 CONCLUSIONS

The paper presented a rain attenuation model in the lowest region of the microwave S-band from measurements that took place in the campus of the University of Ioannina, in northwest Greece, by a customized and accurate experimental set-up. From the results, it is clear that there is non-negligible attenuation due to rain at frequencies \( < 6 \text{ GHz} \). Moreover, the derived estimation model showed very good agreement with measurements near this frequency band. Significant differences from frequency-dependent co-efficients for estimating the specific rain attenuation of the empirical models were observed. Further improvement of the proposed model requires additional signal attenuation measurements as a function of rainfall intensity, especially for higher intensities, and also measurement in a variety of different climatic conditions. The great advantage of this new model is that signal attenuation measurements were correlated with uniform rainfall, as the link distance is relatively small. Also, having a protected environment for both the transmitter and the receiver, jitter due to wind, and water on the antenna were eliminated. Signal level variation due to humidity in the interspace between the transmitter and the receiver as well as fading due to reflections from the ground and nearby objects and because of thermal noise are very challenging issues for consultation in future work.

### ACKNOWLEDGEMENTS

The authors declare that there is no conflict of interest.
REFERENCES

Barthès, L. and Mallet, C. (2013) Rainfall measurement from opportunistic use of Earth–Space link in Ku band. *Atmospheric Measurement Techniques Discussions*, 6, 2113–2150. https://doi.org/10.5194amtmd-6-2113-2013.

Bartzokas, A., Lolis, C.J. and Metaxas, D.A. (2009a) The 850 hPa relative vorticity centres of action for winter precipitation in the Greek area. *International Journal of Climatology*, 29(7), 813–828. https://doi.org/10.1002/joc.909.

Bertelli, F., Capitzi, G., Lo Sciuto, G., Napoli, C. and Scaglione, F. (2018) Rainfall estimation based on the intensity of the received signal in a LTE/4G mobile terminal by using a probabilistic neural network. *IEEE Access*, 6, 30865–30873. https://doi.org/10.1109/ACCESS.2018.2839699.

Christofilakis, V., Tatsis, G., Votis, T., Chronopoulos, S.K., Kostarakis, P., Lolis, J.C. and Bartzokas, A. (2018) Rainfall measurements due to radio frequency signal attenuation at 2 GHz. *Journal of Signal and Information Processing*, 9(3), 192–201. https://doi.org/10.4236/jsip.2018.93011.

Craciun, C. and Catrina, O. (2016) An objective approach for comparing radar estimated and rain gauge measured precipitation. *Meteorological Applications*, 23(4), 683–690. https://doi.org/10.1002/met.1591.

Crane, R. (1980) Prediction of attenuation by rain. *IEEE Transactions on Communications*, 28, 1717–1733. https://doi.org/10.1109/TCOM.1980.1094844.

Crane, R. (2003) *Propagation Handbook for Wireless Communication System Design*, Electrical Engineering & Applied Signal Processing Series. Boca Raton: CRC Press.

Crane, R.K. and Dissanayake, A.W. (1997) ACTS propagation experiment: attenuation distribution observations and prediction model comparisons. *Proceedings of the IEEE*, 85, 879–892. https://doi.org/10.1109/5.598411.

Creutin, J., Borga, M., Lutoff, C., Scolobig, A., Ruin, I. and Créton-Cazanave, L. (2009) Catchment dynamics and social response during flash floods: the potential of radar rainfall monitoring for warning procedures. *Meteorological Applications*, 16(1), 115–125. https://doi.org/10.1002/met.128.

Doumounia, A., Gosset, M., Cazenave, F., Kacou, M. and Zougmore, F. (2014) Rainfall monitoring based on microwave links from cellular telecommunication networks: first results from a West African test bed. *Geophysical Research Letters*, 41, 6016–6022. https://doi.org/10.1002/2014GL060724.

Emiliani, L.D., Luini, L. and Capsoni, C. (2008) Extension of ITU-R method for conversion of rain rate statistics from various integration times to one minute. *Electronics Letters*, 44, 557. https://doi.org/10.1049/el:20080490.

Emiliani, L.D., Luini, L. and Capsoni, C. (2009) 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*, 51, 70–84. https://doi.org/10.1109/MAP.2009.5251195.

Fang, S., Cheng, Y. and Chien, Y. (2018) Exploiting sensed radio strength and precipitation for improved distance estimation. *IEEE Sensors Journal*, 18(16), 6863–6873. https://doi.org/10.1109/jsns.2018.2851149.

Fang, S.-H. and Yang, Y.-H.S. (2016) The impact of weather condition on radio-based distance estimation: a case study in GSM networks with mobile measurements. *IEEE Transactions on Vehicular Technology*, 65, 6444–6453. https://doi.org/10.1109/TVT.2015.2479591.

Fenc, M., Rickermann, J., Sýkora, P., Stránský, D. and Barev, V. (2015) Commercial microwave links instead of rain gauges: fiction or reality? *Water Science and Technology*, 71, 31–37. https://doi.org/10.2166/wst.2014.466.

Potiadi, A.K., Metaxas, D.A. and Bartzokas, A. (1999) A statistical study of precipitation in northwest Greece. *International Journal of Climatology*, 12, 1221–1232. https://doi.org/10.1002/(SICI)1097-0088(199909)19:11%3C1221::AID-JOC436%3E3.0.CO;2-H.

Girons, L.M., Wennerström, H., Nordén, L. and Seibert, J. (2015) Location and density of rain gauges for the estimation of spatially varying precipitation. *Geografiska Annaler: Series A, Physical Geography*, 97, 167–179. https://doi.org/10.1111/geoa.12094.

Griffiths, P.G., Magis, C.S., Webb, R.H., Pytlak, E., Troch, P.A. and Lyon, S.W. (2009) Spatial distribution and frequency of precipitation during an extreme event: July 2006 mesoscale convective complexes and floods in southeastern Arizona. *Water Resources Research*, 45(7), 1–14. https://doi.org/10.1029/2008WR007380.

Gustilo, R. (2018) Design of wireless disaster alarm system using microwave links. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, [online], 10(1–6), 103–108. Available at: http://journal.utem.edu.my/index.php/jtec/index.

Habi, H.V., Messer, H., 2018. Wet–dry classification using LSTM and commercial microwave links. In: *2018 IEEE 10th Sensor Array and Multichannel Signal Processing Workshop (SAM).* Presented at the 2018 IEEE 10th Sensor Array and Multichannel Signal Processing Workshop (SAM). Sheffield: IEEE, pp. 149–153.

Jensen, N.E. and Pedersen, L. (2005) Spatial variability of rainfall: variations within a single radar pixel. *Atmospheric Research*, 77, 269–277. https://doi.org/10.1016/j.atmosres.2004.10.029.

Jeon, D., Pachepsky, Y., Kim, B. and Kim, J. (2019) New methodology to develop high-resolution rainfall data using weather radar for watershed-scale water quality model. *Desalination and Water Treatment*, 138, 248–256. https://doi.org/10.1002/dwt.2019.23344.

Jurczyk, A., Sztorc, J. and Ośrođka, K. (2019) Quality-based compositing of weather radar-derived precipitation. *Meteorological Applications*, 27(1), e1812. https://doi.org/10.1002/met.1812.

Karagianni, E., Vazouras, C.N., Papageorgiou, E.H., Sarantopoulos, A.D. and Nistazakis, H.E. (2016) Maximum rain-rate evaluations in Aegean Archipelagos Hellas for rain attenuation modeling at microwave frequencies. *TransNav: International Journal on Marine Navigation and Safety of Sea
Recommendation ITU-R P.838-3. (2005) Specific Attenuation Model for Rain for Use in Prediction Methods, Question ITU-R 201/3. Geneva, Switzerland: ITU-R.

Reddy, M., Mitra, A., Momin, I., Mitra, A. and Pai, D. (2019) Evaluation and inter-comparison of high-resolution multi-satellite rainfall products over India for the southwest monsoon period. *International Journal of Remote Sensing*, 40(12), 4577–4603. https://doi.org/10.1080/01431161.2019.1569786.

Rios Gaona, M.F., Overeem, A., Raupach, T.H., Leijnse, H. and Uijlenhoet, R. (2018) Rainfall retrieval with commercial microwave links in São Paulo, Brazil. *Atmospheric Measurement Techniques*, 11, 4465–4476. https://doi.org/10.5194/amt-11-4465-2018.

Russell, B., Williams, E.R., Gosset, M., Cazenave, F., Descroix, L., Guy, N., Lebel, T., Ali, A., Metayer, F. and Quantin, G. (2010) Radar/rain-gauge comparisons on squall lines in Niamey, Niger for the AMMA. *Quarterly Journal of the Royal Meteorological Society*, 136, 289–303. https://doi.org/10.1002/qj.548.

Schleiss, M., Rieckermann, J. and Berne, A. (2013) Quantification and modeling of wet-antenna attenuation for commercial microwave links. *IEEE Geoscience and Remote Sensing Letters*, 10, 1195–1199. https://doi.org/10.1109/LGRS.2012.2236074.

Segal, B. (1986) The influence of rain gauge integration time on measured rainfall intensity and distribution functions. *Journal of Atmospheric and Oceanic Technology*, 3(4), 662–671.

Sohail Afzal, M., Shah, S.H.H., Cheema, M.J.M. and Ahmad, R. (2018) Real time rainfall estimation using microwave signals of cellular communication networks: a case study of Faisalabad, Pakistan. *Hydrology and Earth System Sciences Discussions*, 1–20. https://doi.org/10.5194/hess-2017-740.

Tamošiuniene, M., Tamošiunas, S., Žilinskas, M. and Tamošiuniene, M. ed. (2011). Atmospheric attenuation due to humidity. In: *Electromagnetic Waves*. [online] IntechOpen. Available at: https://www.intechopen.com/books/electromagnetic-waves/ [Accessed 5 June 2019].

Tatsis, G., Votis, C.I., Christofilakis, V., Chronopoulos, S.K., Kostarakis, P., Lolis, C.J., Bartzokas, A., Nistazakis, H.E., 2018. Rainfall events’ correlation with S-band signal attenuation. In: 2018 7th International Conference on Modern Circuits and Systems Technologies (MOCAST). Presented at the 2018 7th International Conference on Modern Circuits and Systems Technologies (MOCAST). Thessaloniki: IEEE, pp. 1–4.

Thies, B. and Bendix, J. (2011) Satellite based remote sensing of weather and climate: recent achievements and future perspectives: satellite based remote sensing of weather and climate. *Meteorological Applications*, 18, 262–295. https://doi.org/10.1002/met.288.

Upton, G.I.G., Holt, A.R., Cummings, R.J., Rahimi, A.R. and Goddard, J.W.F. (2005) Microwave links: the future for urban rainfall measurement? *Atmospheric Research*, 77, 300–312. https://doi.org/10.1016/j.atmosres.2004.10.009.

Varlas, G., Anagnostou, M.N., Spyrou, C., Papadopoulos, A., Kalogiros, J., Mentzafou, A., Michaelides, S., Baltas, E., Karymbalis, E. and Katsafados, P. (2019) A multi-platform hydrometeorological analysis of the flash flood event of 15 November 2017 in Attica, Greece. *Remote Sensing*, 11, 45. https://doi.org/10.3390/rs11010045.

Yang, H.H., et al. (2011) Analysis of hydrological processes of Langat River sub basins at Lui and Dengkil. *International Journal of the Physical Sciences*, 6(32), 7390–7409. https://doi.org/10.5897/IJPS11.1036.

Zinevich, A., Alpert, P. and Messer, H. (2008) Estimation of rainfall fields using commercial microwave communication networks of variable density. *Advances in Water Resources*, 31, 1470–1480. https://doi.org/10.1016/j.advwatres.2008.03.003.

Zinevich, A., Messer, H. and Alpert, P. (2010) Prediction of rainfall intensity measurement errors using commercial microwave communication links. *Atmospheric Measurement Techniques*, 3, 1385–1402. https://doi.org/10.5194/amt-3-1385-2010.

How to cite this article: Christofilakis V, Tatsis G, Lolis CJ, et al. A rain estimation model based on microwave signal attenuation measurements in the city of Ioannina, Greece. *Meteorol Appl*. 2020;27:e1932. https://doi.org/10.1002/met.1932