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Rainfall Rate Prediction for Propagation Applications: Model Performance at Regional Level over Ireland

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Abstract—**Three global rainfall rate prediction methods are evaluated in their ability to estimate local precipitation statistics, which are key to predict the impact of rain on the propagation of electromagnetic waves through the atmosphere. Specifically, the ITU-R P.837-6, MORSE and the ITU-R P.837-7 prediction methods are tested against long-term rainfall data collected in 19 sites in Ireland. The results indicate that the ITU-R P.837-7 prediction method delivers the best performance, and that both the ITU-R P.837-6 prediction method and MORSE exhibit a positive bias, likely due to the overestimation of the yearly rain amount in the maps used as input to such models. The results of the testing activity provide information on the accuracy of rainfall rate prediction methods at regional level, an important factor to consider given the direct link between the magnitude of rain-induced attenuation and the operational frequency of wireless communication links.**

Index Terms— **Rainfall rate modelling, electromagnetic wave propagation, satellite communications**

I. Introduction

The propagation of electromagnetic (EM) waves in the atmosphere at frequencies higher than 10 GHz is severely impaired by the presence of hydrometeors, mainly by rain: raindrops induce high levels of absorption and scattering, which contribute to the decrease in the power density carried by EM waves [1].

The performance of high-frequency communication systems (e.g., satellite systems operating in the Ka, Q and V bands or 5G systems operating beyond the 37 GHz range) is assessed through the application of propagation prediction methods, among which those aimed at estimating rain attenuation play a key role [2],[3]. The accuracy of these prediction methods is tightly linked to their main input, the Complementary Cumulative Distribution Function of the rainfall rate (CCDF, or $P(R)$). For propagation applications, rainfall data must be collected at an integration time of at least 1 minute in order to capture the fast temporal dynamics of the rainfall process [4]. As instruments deployed to monitor rainfall are usually characterized by much longer integration times (e.g., hours or even days), two main types of methodologies have been developed to predict a $P(R)$ suitable for communications system design: the first – which we call conversion methodologies – aims at predicting 1-minute integrated $P(R)$s from local rainfall statistics with a longer integration time (e.g., 60 minutes) [4],[5],[6], while the second relies on analytical formulations for the $P(R)$ whose parameters depend on local long-term meteorological quantities such as monthly/yearly rainfall accumulations and average temperature (see e.g., [7] and [3]). Recommendation ITU-R (International Telecommunication Union – Radiocommunication Sector) P.837-6 (Annex 3) [8] is an example of a conversion methodology, while Recommendation ITU-R P.837-6 (Annex 1) and MORSE (Model for Rainfall Statistics Estimation) [9] are examples of the analytical category. This paper evaluates the performance of three rainfall rate prediction methods: a) Recommendation ITU-R P.837-6 Annex 1 [8], b) MORSE [9], and c) Recommendation ITU-R P.837-7 Annex 1 [12], a recent revision of Recommendation ITU-R P.837-6 Annex 1 based on an improved rainfall rate prediction method developed by ONERA [10]. Reference [11] demonstrated that Recommendation ITU-R P.837-7 Annex 1 provides the best accuracy predicting the rainfall rate exceedance probability on a global scale.

Though analytical prediction methods generally provide good overall accuracy, recent in-depth investigations have shown that, locally, they might deliver quite poor results. See for example [13], where the prediction method in P.837-6 was found to strongly overestimate $P(R)$s collected at several Norwegian sites. Since the effects of rain become more important as the communication system's operational frequency increases, it is critical to investigate the accuracy of rainfall rate prediction methods not only at a global scale, but also at regional level.

Given the weather peculiarity of Ireland, where there is a higher probability of experiencing rain (compared to the mean over Europe), and considering that the ITU-R P.837-6 prediction method is expected to deliver biased predictions due to the overestimation of the rain accumulation in coastal areas (see [13] and [14]), this 19-site dataset offers a unique opportunity to investigate the accuracy of global $P(R)$ prediction methods at a regional level.

The remainder of the paper is organized as follows. Section II gives an overview of the rainfall rate database used to evaluate each prediction method's performance. Section III briefly describes the ITU-R P.837-6 prediction method, MORSE and the new ITU-R P.837-7 prediction method, while Section IV includes the tests against the Irish data. Finally, Section V draws some conclusions.

II. Rainfall rate Database and Data Processing

The data used in this analysis consists of 1-minute integrated rainfall accumulation series, collected over 19 sites that are part of Met Éireann's automated monitoring network (TUCSON). The weather instruments include Casella tipping gauges (with 0.1 mm or 0.2 mm resolution), which provide as output the number of tips per minute.

The availability of the raingauges during the period of observation exceeds 97% in all stations. Table 1 and Fig. 1 provide an overview of station location and measurement

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duration, which ranges from 4 (2012-2015) to 8 (2008-2015) years. This extensive set of data was used to calculate the long-term mean yearly $P(R)$s using the procedure described in detail in [15]. In aggregate, the measured data spans over 135 station-years, making it unique for the purpose of communication system evaluation. For more information on the raingauge network itself, the reader is addressed to [16].

TABLE I
LOCATION OF THE STATIONS USED IN THIS STUDY

#	Station	altitude (m)	Lat (°N)	Lon (°E)	Years
1	Ballyhaise	78	54.051	-7.306	8
2	Oak Park	62	52.857	-6.909	8
3	Moore Park	46	52.158	-8.258	8
4	Roches Point	40	51.789	-8.240	8
5	Sherkin Island	21	51.472	-9.423	8
6	Finner	33	54.490	-8.239	5
7	Malin Head	20	55.370	-7.337	6
8	Phoenix Park	48	53.358	-6.342	8
9	Athenry	40	53.287	-8.785	4
10	Mace Head	21	53.322	-9.901	8
11	Valentia Observatory	24	51.936	-10.238	5
12	Claremorris	68	53.707	-8.989	5
13	Newport	22	53.920	-9.570	8
14	Dunsany	83	53.510	-6.656	8
15	Mt Dillon	39	53.723	-7.975	7
16	Markree	34	54.172	-8.453	8
17	Gurteen	75	53.052	-8.005	8
18	Mullingar	101	53.536	-7.357	8
19	Johnstown II	62	52.292	-6.491	7

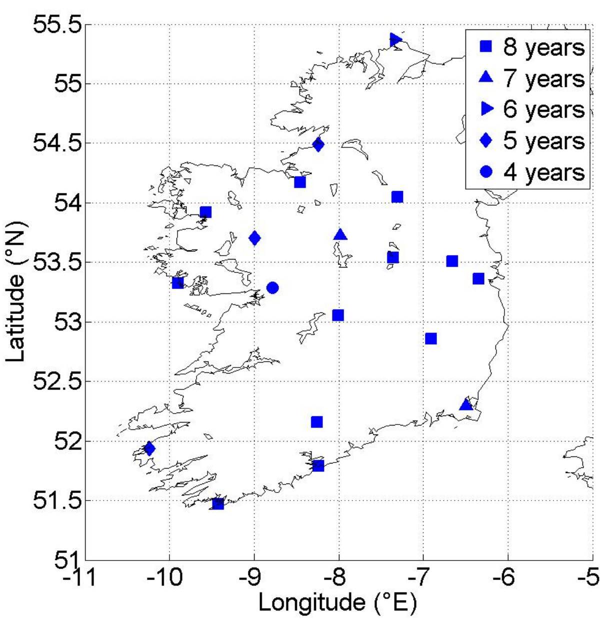

Fig. 1. Location and duration of the measurements for the stations used in this study [16].

III. Rainfall rate Statistics Prediction Methods

A. ITU-R P.837-6

A significant improvement in rainfall rate prediction was achieved with the analytical model for the $P(R)$ proposed by Poiares-Baptista and Salonen [17]. This prediction method was adopted by ITU-R and a slightly modified version of it is included in Annex 1 of Recommendation ITU-R P.837-6 [8]. The prediction method is globally applicable and relies on coarse-resolution meteorological data. Specifically, the probability of exceeding a rainfall rate intensity R in a year is calculated according to [8]:

$$P(R) = P_0 \exp\left(-aR\frac{1+bR}{1+cR}\right) \tag{1}$$

where a = 1.09 and coefficients P_0, b and c are site dependent and related to the meteorological quantities M_t (annual rainfall accumulation), P_{r6} (probability to have rain in 6-hour slots) and β (ratio between convective and total precipitation):

$$\begin{aligned} P_0 &= P_{r6}\left[1-\exp\left(-0.0079\frac{M_t(1-\beta)}{P_{r6}}\right)\right] \\ b &= \frac{M_t}{21797\,P_0} \\ c &= 26.02\,b \end{aligned} \tag{2}$$

The values of M_t, P_{r6} and β for a specific site are extracted through bilinear interpolation from the "calibrated" ERA40, a re-analysis product of ECMWF (European Centre for Medium-range Weather Forecast), which provides a comprehensive set of meteorological quantities mapped on a regular 1.125°×1.125° latitude×longitude grid. The definite overestimation of the M_t value, particularly in the tropical/equatorial areas, led to its recalibration by means of the GPCP (Global Precipitation Climatology Project) database [18] in the framework of an ESA-funded research activity [19]. The resulting "calibrated" M_t map has the same ERA40 spatial resolution and improved accuracy.

B. MORSE

MORSE is a global method for the prediction of 1-minute integrated $P(R)$ at different time scales, ranging from a monthly to a yearly basis. The prediction method requires as input the local convective (M_c) and total (M_t) rain amounts, cumulated over the period of interest, which can be extracted from gridded NWP (Numerical Weather Prediction) [9]. MORSE defines the $P(R)$ as:

$$P(R) = P_0\left[\ln\left(\frac{R_a + R_{low}}{R + R_{low}}\right)\right]^n \tag{3}$$

In (3) R is the rainfall rate (mm/h) exceeded with probability P, P_0 defines the behavior of the curve for R approaching 0 mm/h, R_a is the asymptotical value of $P(R)$, directly related to the maximum measured point rainfall rate, n determines the shape of the curve and R_{low} ensures that the probability assumes a finite value as R approaches 0 mm/h.

The parameters P_0, n, R_{low} and R_a are related to the local

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inputs M_t and β as follows [9]:

$$
\begin{aligned}
n &= -36.1763\bar{\beta}^{0.1242} + 36.9178 \\
R_a &= \left(\frac{n-1.4386}{8.43\cdot 10^{-4}}\right)^{\frac{1}{1.3531}} \\
R_{low} &= \begin{cases} 31.8498\bar{\beta}^{-0.0086} - 31.9399 & \bar{\beta} \le 0.72 \\ 10^{-4} & \bar{\beta} > 0.72 \end{cases}
\end{aligned} \tag{4}
$$

where $\bar{\beta} = \max(0.001, \beta)$ to prevent R_{low} from approaching infinity. The last parameter P_0 is calculated as follows:

$$
P_0 = \frac{\bar{R}_t}{(R_a + R_{low})\gamma\left(n+1, \ln\left(\frac{R_a + R_{low}}{R_{low}}\right)\right)} \tag{5}
$$

with γ the incomplete gamma function.

In (5), $\bar{R}_t$ must be expressed in mm/h by dividing the total rainfall accumulated in the period (mm) by the number of hours in the same period (e.g., 365·24 = 8760 for a non-leap year). The inputs to MORSE, i.e., M_t and β, are extracted from the "calibrated" ERA40 database attached to recommendation ITU-R P.837-6.

C. ITU-R P.837-7 (ONERA)

The P.837-7 prediction method (developed by ONERA) is a global 1-minute integrated $P(R)$ prediction method. It originated from the increasing need to investigate the impact of monthly predictions on system design. The prediction method relies on three assumptions:

- the monthly statistics of rainfall rate, conditioned to the presence of rain, follow a log-normal distribution;
- the monthly scale parameter σ_i of the log-normal distribution is independent of the reference site;
- the monthly mean rainfall rate conditioned to the presence of rain $\bar{r}_i$ only depends on the monthly average temperature collected at 2 meters above the ground[1], T_i.

The first two assumptions have been investigated in the past on a yearly basis [20], but have never been confirmed on a monthly basis.

From a mathematical point of view, the monthly CCDF of rainfall rate for the i-th month, $P_i(R)$, can be written as:

$$
P_i(R) = \frac{P_{0_i}}{2} erfc\left(\frac{\ln(R) + \sigma_i^2/2 - \ln(\bar{r}_i)}{\sqrt{2}\sigma_i}\right) \tag{6}
$$

where P_{0_i} is the monthly probability of rain given by:

$$
P_{0_i} = \frac{M_{T_i}}{24 \cdot N_i \cdot \bar{r}_i} \tag{7}
$$

where N_i corresponds to the number of days in the i-th month (with $N_2 = 28.25$) and M_{T_i} is the monthly total rain amount.

The annual rainfall rate CCDF, $P(R)$, is obtained by combining the monthly distributions:

$$
P(R) = \frac{\sum_{i=1}^{12} N_i P_i(R)}{365.25} \tag{8}
$$

An extensive analysis conducted on a large network of rain gauges deployed across the United States [21] has shown that $\bar{r}_i$ can be calculated as:

$$
\begin{cases} \bar{r}_i = 0.5874 \cdot e^{0.0883 * T_i} & for \quad T_i \ge 0°C \\ \bar{r}_i = 0.5874 & for \quad T_i < 0°C \end{cases} \tag{9}
$$

Further information on the derivation of (9) can be found in [11]. In particular, the use of (9) can sometimes result into unrealistic values of P_{0_i} higher than 70% (and even higher than 100%) mainly in winter and for a very restricted area (west coast of Canada) [11]. In order to obtain more realistic values, P_{0_i} = 70% is set as the maximum reasonable value, which, in turns, results in a slight modification of the value $\bar{r}_i$ (see Step 6b in [12]). In addition, note that the applicability of (9) to areas outside the US has been recently corroborated in [22] using temperature data collected across Spain.

Finally, a fixed value of σ_i is chosen, i.e., the one returning a null bias for the annual rainfall rate exceeded for 0.01% of the time, using the same previous database used to derive (9):

$$
\sigma_i = 1.26 \tag{10}
$$

Monthly maps of M_{T_i} have been generated from a combination of two digital products: GPCC Climatology Version 2015 [23] over land (0.25°×0.25° spatial resolution) and ERA Interim (1979-2014) [24] over water (0.75°×0.75° spatial resolution). Monthly maps of T_i have been generated worldwide from the ERA Interim database (1979-2014).

For the sake of clarity, Table II summarizes the inputs to the three prediction methods considered in this contribution, as well as their temporal and spatial resolutions.

[1] 2 meters is the standard height of any air temperature measurements according to the World Meteorology Organization (WMO) guidelines.

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TABLE II
DETAILED DESCRIPTION OF THE INPUTS TO THE RAINFALL RATE PREDICTION METHODS

Prediction method	Inputs	Temporal resolution of inputs	Spatial resolution of inputs
ITU-R P.837-6	M_t P_{r6} β	Annual	1.125°×1.125° 1.125°×1.125° 1.125°×1.125°
MORSE	M_t β	Annual	1.125°×1.125° 1.125°×1.125°
ITU-R P.837-7	M_t T	Monthly	0.25°×0.25° 0.75°×0.75°

IV. Performance of the Prediction Methods

The accuracy of each method in predicting the rainfall rate statistics is assessed against the measured data presented in Section II. Specifically, the prediction performance is quantified in terms of average value and root mean square value of the following error figure:

$$\varepsilon_i\left(P_j\right)=\frac{R_{E_i}\left(P_j\right)-R_{M_i}\left(P_j\right)}{R_{M_i}\left(P_j\right)} \tag{11}$$

where $R_{E_i}\left(P_j\right)$ and $R_{M_i}\left(P_j\right)$ are the rain rates respectively extracted from the estimated and measured $P(R)$ (for site i), at the same probability level $P_j > 0.001\%$.

Therefore, the single-site average value, E_i, and single-site root mean square value, RMS_i, are defined as:

$$E_i=\frac{1}{n_i}\sum_{j=1}^{n_i}\varepsilon_i\left(P_j\right) \tag{12}$$

$$RMS_i=\sqrt{\frac{1}{n_i}\sum_{j=1}^{n_i}\varepsilon_i^2\left(P_j\right)} \tag{13}$$

where n_i is the number of probability levels taken into account for the $P(R)$ relative to site i. The error figure is limited to samples for which $R > 2$ mm/h in order to avoid taking into account inaccurate low rainfall rate values [11].

Finally, as suggested in [11], the multi-site average value, E, and multi-site root mean square value, RMS, associated to each prediction method is calculated by weighting the error figure in (11) with the number of observation years:

$$E=\frac{\sum_{i=1}^{N_S}\sum_{j=1}^{n_i}\alpha_i\varepsilon_i\left(P_j\right)}{\sum_{i=1}^{N_S}\alpha_i n_i}=\frac{\sum_{i=1}^{N_S}\alpha_i n_i E_i}{\sum_{i=1}^{N_S}\alpha_i n_i} \tag{14}$$

$$RMS=\sqrt{\frac{\sum_{i=1}^{N_S}\sum_{j=1}^{n_i}\alpha_i\varepsilon_i^2\left(P_j\right)}{\sum_{i=1}^{N_S}\alpha_i n_i}}=\sqrt{\frac{\sum_{i=1}^{N_S}\alpha_i n_i RMS_i^2}{\sum_{i=1}^{N_S}\alpha_i n_i}} \tag{15}$$

where α_i is the number of observation years of rainfall accumulation data used to calculated the $P(R)$ relative to site i, and N_S is the number of sites (here $N_S = 19$).

Fig. 2 provides a sample of the measured $P(R)$ (data collected in Phoenix park, over 8 years, between 2008 and 2015), and the rainfall rate statistics obtained from the three prediction methods. As displayed in the figure's legend, the best and worst prediction accuracy is achieved by the ITU-R P.837-7 and P.837-6 prediction methods, respectively.

Fig. 3 and Fig. 4 provide a more comprehensive overview of the prediction performance by showing E_i and RMS_i, respectively, for each site. Overall, the P.837-7 prediction method shows the smallest bias and also provides the lowest RMS_i. Conversely, the ITU-R P837-6 and MORSE prediction methods display a larger RMS. This is mainly ascribable to the positive bias reported in Fig. 3, which, in turn, is likely due to the meteorological inputs to both prediction methods: as reported in [13], M_t tends to overestimate the actual rainfall accumulations, especially in coastal areas. The bias in the ITU-R P.837-7 prediction method is much more limited thanks to a different set of input maps, characterized by better accuracy (GPCC relies on raingauge measurements) and finer spatial resolution (see Table II). Another element contributing to the improved accuracy of the ITU-R P.837-7 prediction method is the calculation of the yearly $P(R)$ as combination of the monthly $P(R)$s: this approach reflects the local peculiarity of the rainfall process much better than methods providing the direct prediction of the yearly $P(R)$.

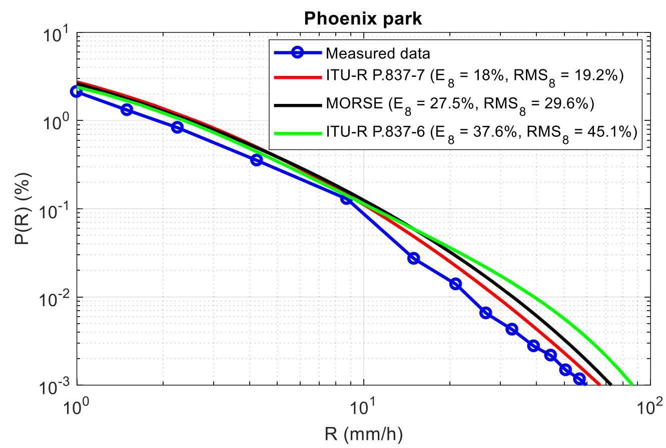

Fig. 2. $P(R)$ prediction example: Phoenix park (2008-2015)

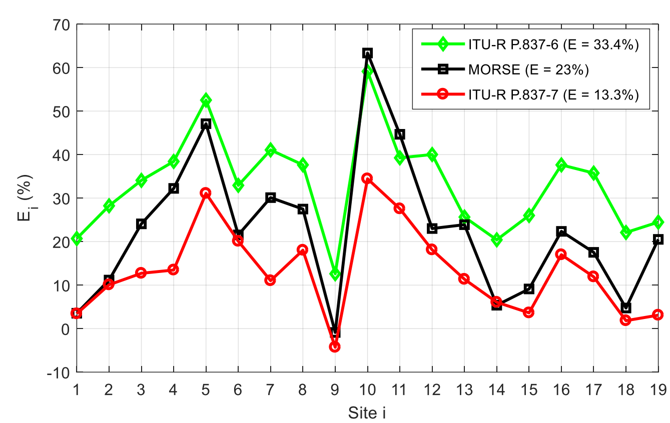

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Fig. 3. Overall accuracy of the prediction methods: average value (E) as a function of the site number in Table I.

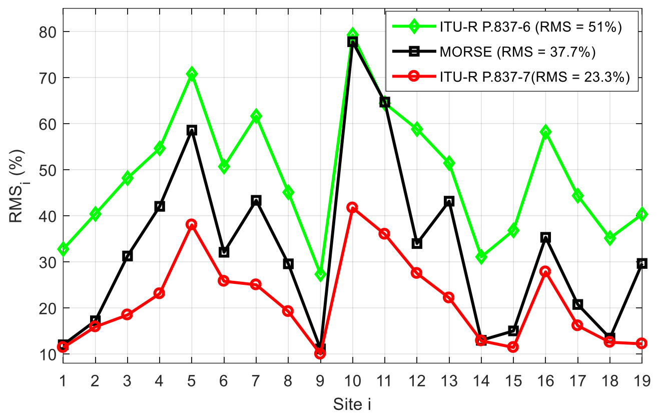

Fig. 4. Overall accuracy of the prediction methods: root mean square value (RMS) as a function of the site number in Table I.

Fig. 5 presents the error ε - as defined in (11) - for a single exceedance probability value: $P = 0.01\%$, significant because it is currently the only $P(R)$ point required to perform rain attenuation predictions using the ITU-R prediction methods (see [25] and [26]). Fig. 6 presents the RMS value calculated for all sites as a function of the exceedance probability P_j; mathematically:

$$RMS\left(P_j\right)=\sqrt{\frac{\sum_{i=1}^{N_S}\alpha_i\varepsilon_i^2\left(P_j\right)}{\sum_{i=1}^{N_S}\alpha_i}} \tag{16}$$

Results in Fig. 5 and Fig. 6 reinforce the results reported in Fig. 3 and Fig. 4: the ITU-R P.837-7 and the ITU-R P.837-6 prediction methods provide the best and worst prediction accuracy, respectively, though a general tendency to overestimate $R_{0.01\%}$ emerges. All prediction methods exhibit similar performance for values of $P \geq 0.1\%$, while for $P < 0.1\%$ the prediction errors increase - expected because of the decrease in the statistical significance of the curves - but more slowly for the ITU-R P.837-7 prediction method.

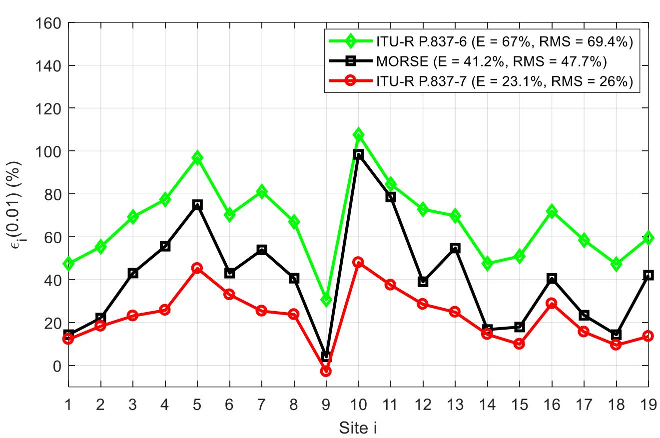

Fig. 5. Prediction accuracy on $R_{0.01}$%.

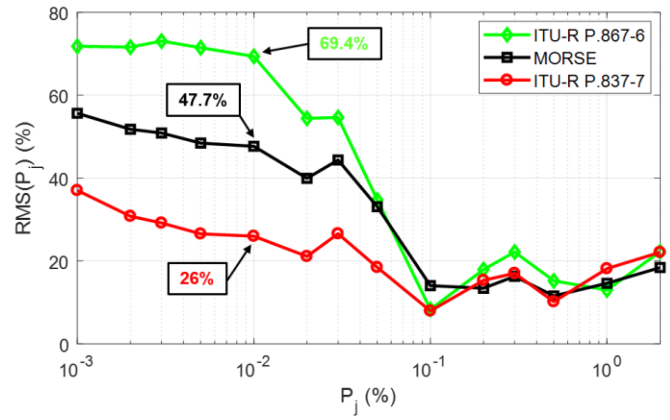

Fig. 6. Prediction accuracy as a function of the exceedance probability.

V. Conclusions

The tests on the performance of the three rainfall rate prediction methods considered in this paper indicate that using the ITU-R P.837-7 method will improve the accuracy in the prediction of a $P(R)$ in Ireland, compared to the results produced by the ITU-R P.837-6 and MORSE prediction methods. Moreover, as presented in [11], the performance improvement brought by the ITU-R P.837-7 prediction method (based on the ONERA approach) over the ITU-R P.837-6 prediction method is corroborated via similar tests conducted over Colombia and Spain. An enhancement in the accuracy of rainfall rate prediction can be directly related to improvements in the attenuation prediction, and will be beneficial for any application involving high frequency wireless links, such as the provision of broadband services via satellite in Ireland (with over seven satellite service providers in the region according to [27]): indeed increasing the accuracy of the input $P(R)$ will translate into more accurate link quality predictions and should also bring improvements to the characteristics of the service delivered.

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