A Unified Model for the Prediction of Spatial and Temporal Rainfall Rate Statistics

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***Abstract*— This paper presents MORSE (MOdel for Rainfall Statistics Estimation), a unified model for the prediction of spatial ($P_S(R)$) and temporal ($P_T(R)$) high-resolution rainfall rate statistics. Inputs to MORSE are the convective (M_c) and total (M_t) rain amounts cumulated in different time intervals, ranging from a few hours for the prediction of $P_S(R)$ to much longer intervals for the estimation of $P_T(R)$. Tests performed against $P_T(R)$s on yearly (curves included in the DBSG3 database) and monthly (distributions derived from rain rate time series) basis provide very satisfactory results, which makes MORSE a reliable global model for the prediction of $P_S(R)$ on hourly basis and of $P_T(R)$ at any time scale (e.g. monthly, seasonal, yearly).**

***Index Terms*—Radiowave propagation, rainfall modeling, tropospheric effects**

I. Introduction

Rainfall attenuation represents the most severe impairment to the propagation of electromagnetic waves in the atmosphere at frequencies higher than 10 GHz, because hydrometeors scatter and absorb part of the transmitted power [1]. As a result, the design of wireless communication systems requires the knowledge of the local rainfall statistics, $P(R)$, input to all the models predicting the impairments due to rain at one station [2], [3], as well as to synthesizers of realistic rain fields used for the simulation of distributed systems [4], [5]. Due to the lack of global long-term statistics, collected by raingauges with 1-minute integration time, as required for propagation applications to adequately sample the fast dynamics of the rainfall process, remarkable research efforts, dating back to the seventies (e.g. see [6] and [7]), have been devoted to developing methodologies for the estimation of local yearly rainfall statistics on a global basis from poor resolution or even cumulated (hourly, monthly or yearly) rainfall data.

Conversion methods aimed at predicting 1-minute integrated $P(R)$s from rainfall statistics with longer integration time T (e.g. T = 1 hour [8]), although providing the best prediction accuracy among all the methodologies proposed so far [9], require input data that are not always readily available. Less accurate, but worldwide applicable, are meteorologically based methods, which rely on an analytical formulation of the $P(R)$ whose parameters depend on local long-term meteorological information [6], [7], [10]. The most acknowledged methodology of this kind, currently adopted by the International Telecommunication Union – Radio communication sector (ITU-R) [11] (hereinafter 'ITU-R model'), requires as input the convective (M_c) and the total (M_t) rain amounts cumulated in an average year, and the mean yearly probability to have rain in a 6-hour time interval, P_{6h}. This information originates from the global ERA40 database [12], made available by the European Centre For Medium-range Weather Forecast (ECMWF) on a regular latitude/longitude grid with 1.125°×1.125° resolution.

Yearly rainfall statistics does not always provide the most appropriate information for the design of wireless communication systems. Indeed, some specific services take advantage of the knowledge of the $P(R)$ on a seasonal or monthly basis, because they can be accordingly adapted in order to increase the system availability or the Quality of Service (QoS) [13].

Other applications require statistical information on the spatial distribution of rainfall. This is the case, for instance, of advanced satellite communication systems operating at Ka-band and above for high data rate applications (e.g. broadcast of high-definition contents and internet connectivity via satellite). These systems counteract deep atmospheric fades [14] by implementing smart solutions, known as Fade Mitigation Techniques (FMTs), such as the dynamic resource allocation achievable with a reconfigurable on-board antenna [15]. By knowing the spatial distribution of rainfall over the whole satellite coverage area, the system distributes the limited onboard extra power so as to maximize the number of served users.

This contribution presents MORSE (MOdel for Rainfall Statistics Estimation), a global methodology for the prediction of long-term point rain rate statistics on yearly ($P_T(R)$) and monthly ($P_T(R)^m$) basis, as well as of spatial rainfall statistics ($P_S(R)$). MORSE relies on the general methodology introduced in [16] and the parameters regulating the shape of the predicted rainfall statistics depend on the local values of M_t and $\beta = M_c / M_t$ (e.g. extracted from the ERA40 database). The model's coefficients for $P_T(R)$ and $P_T(R)^m$ predictions have been tuned to reflect the use of rain accumulations collected on yearly (or monthly) instead of on hourly basis [16], thus making the application of MORSE very

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effective to estimate temporal rain rate statistics.

The remainder of the paper is organized as follows: section II presents the database of yearly and monthly point rainfall statistics employed in this study. Section III discusses the calibration of MORSE based on a subset of the available $P_T(R)$s (reference data) and on the "calibrated" ERA40 database (input data). In section IV, the prediction performance of MORSE is evaluated against an extensive dataset of $P_T(R)$s collected worldwide and against monthly rainfall statistics derived from rain rate time series available to the authors. Afterwards, after final considerations on the model's consistency in section V, section VI draws some conclusions.

II. Databases of Point Rainfall Rate Statistics

Several yearly $P_T(R)$s with 1-minute integration time have been gathered in the DBSG3 database of ITU-R [17]. Their number is, anyway, quite limited with respect to the needs because most of the instruments deployed for rainfall measurement produce outputs with long integration time (hour, day or even month). Since prediction models inherently estimate long-term distributions because they are devised to represent the average characteristics of the rain process, in this work, multiple single-year $P_T(R)$s available for the same site have been aggregated to produce 104 long-term rainfall statistics. Fig. 1 shows the position of the sites which the 104 $P_T(R)$s refer to: they have been collected in 22 different Countries, with minimum and maximum site latitude equal to 30.03° S and 64.86° N, respectively.

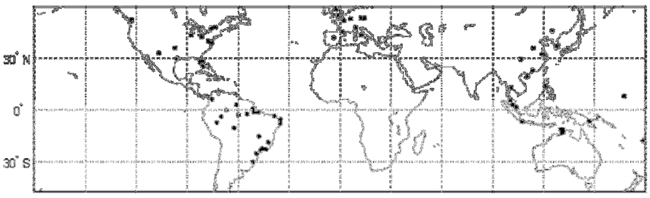

Fig. 1. Sites where $P(R)$s included in the DBSG3 have been collected.

In order to assess the ability of MORSE in predicting rainfall statistics at time scales shorter than the year, the limited set of raingauge-derived rain rate time series available to the authors (no global catalogue is at disposal) have been worked out to produce monthly rain rate distributions ($P_T(R)^m$s). Table I lists some details on the rain rate time series: the 7 datasets refer to sites characterized by different climates (roughly defined as cold for Prague and Montreal, temperate for Spino d'Adda and Rome and tropical/equatorial for Florida, Houston and Kwajalein) and have been collected for at least five years. This is a key point because the statistical significance of the available data obviously becomes more and more critical as the time scale, which the statistics refer to, gets shorter. Indeed, while a calendar year can be considered a meteorological repetition period, the same month in different years may be characterized by very different precipitations, both in terms of occurrence and of type. As a result, the year-to-year variability of rainfall statistics is far more pronounced on monthly than on yearly basis. In this respect, Fig. 2 gives an idea of the variability occurred in May in a temperate site like Spino d'Adda.

TABLE I
Details on the Rain Rate Time Series Used in This Work (Geographical Coordinates of the Raingauge and Duration of the Experiments)

Site	Latitude (°N)	Longitude (°E)	Duration (years)
Spino d'Adda	45.46	9.56	9
Rome	41.87	12.48	8
Prague	50.10	14.44	5
Montreal	45.52	-73.57	10
Florida	28.34	-80.93	8
Kwajalein	8.79	167.62	8
Houston	29.77	-95.73	8

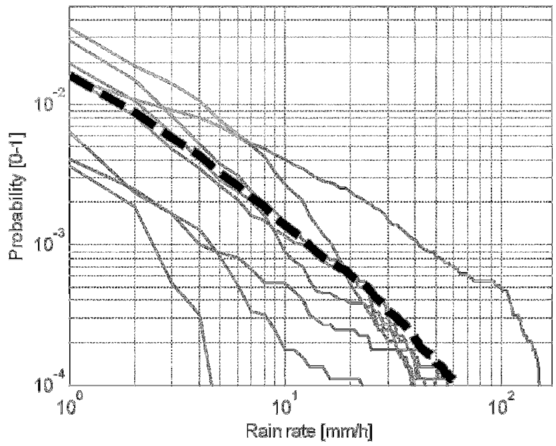

Fig. 2. Year-to-year variability of $P(R)^m$s for Spino d'Adda, May. The bold dashed line refers to the whole measurement period (9 years).

III. The Model

The prediction method presented in this contribution is founded on the analytical expression already introduced in [18], [2] and [4], and subsequently employed in [16] to estimate the small-scale spatial cumulative distribution of the rain rate. In this work, we re-propose the analytical form in (1) for the definition of a unified model for spatial and temporal rainfall rate statistics, $P(R)$.

$$P(R) = P_0\left[\ln\left(\frac{R_a + R_{low}}{R + R_{low}}\right)\right]^n \quad (1)$$

Here R is the rain rate (mm/h) exceeded with probability P, P_0 defines the behavior of the curve for $R \to 0$ mm/h, R_a is the asymptotical value of $P(R)$, directly related to the maximum measured point rain rate, n mainly determines the shape of the curve and R_{low} allows the probability to assume a finite value when $R \to 0$ mm/h, as it is physically the case.

Besides permitting a very good analytical fit of any measured $P(R)$, equation (1) also allows a simple computation of its third order derivative, as it is requested by well-established propagation prediction models relying on the cellular representation of rain fields [2], [4].

The parameters P_0, n, R_{low} and R_a are related to M_t (mm) and $\beta = M_c/M_t$ as follows:

$$\begin{aligned} n &= a\beta^{b} + c \\ n &= d\,R_a^{e} + f \\ R_{low} &= g\beta^{h} + k \\ P_0 &= \frac{M_t}{(R_a + R_{low})\gamma\left(n+1, \ln\left(\frac{R_a + R_{low}}{R_{low}}\right)\right)} \end{aligned} \quad (2)$$

The above relationships indicate that the shape of the curve in (1) is tightly related to both R_a and R_{low}, and, as a consequence, they depend on the M_c/M_t ratio. Similarly to what is shown in [16], the coefficients in the first three expressions of (2) are obtained by comparison with a set of reference rainfall statistics, whilst the last relationship has been introduced so as to preserve the input M_t value. Indeed, any analytical model of rainfall statistics should fulfill this requirement to maintain its physical soundness.

The relationships in (2) are likely to be defined by different a, b, c, d, e, f, g, h coefficients when used for the prediction of $P_T(R)$ and of $P_S(R)$ because they receive as input M_t and β values calculated respectively on yearly (monthly) and on hourly basis. In fact, the coefficients of (2) reported in [16] are devised to properly react to combinations of M_t and β values typical of 3-/6-hour time intervals (β between 0 and 1) and, as such, are not suitable for input values averaged over long periods, whose β value never exceeds 0.78.

Based on the discussion above, the coefficients relating n, R_{low} and R_a to the input parameters have been tuned by taking as reference a subset of 23 out of the 104 $P_T(R)$s mentioned in section II. Inputs are the mean yearly values of M_t and β extracted from the "calibrated" ERA40 database (hereinafter referred to as M_t^{ITU} and β^{ITU}). Such a database, also used as input to the ITU-R model, was elaborated in the framework of an ESA (European Space Agency) study [19] to mitigate the significant bias shown by the original ERA40 mean yearly rainfall amount (M_t^{ERA}). In particular, M_t^{ITU} is the result of the calibration procedure described in detail in [19] and [20].

As recommended by the ECMWF, for a site j with given geographical coordinates, $M_t^{ITU}(j)$ and $\beta^{ITU}(j)$ are calculated by bilinear interpolation of the M_t^{ITU} and β^{ITU} values associated to the four ERA40 pixels surrounding site j.

The calibration of MORSE for $P_T(R)$ estimation was achieved by reducing the prediction error quantified as:

$$\varepsilon(P) = 100\,\frac{R_{est}(P) - R_{meas}(P)}{R_{meas}(P)} \quad (3)$$

where $R_{est}(P)$ and $R_{meas}(P)$ are the rain rates respectively extracted from the estimated and measured $P_T(R)$, at the same probability level P. For each curve, the root mean square value of $\varepsilon(P)$, RMS_ε, was calculated (values of P higher than 0.01% have been taken into account) and its average value over the 23 reference $P_T(R)$s was minimized. The result of this global optimization procedure, based on Genetic Algorithms [21], provided the following expressions:

$$\begin{aligned} n &= -36.18\overline{\beta}^{0.1242} + 36.92 \\ n &= 8.43\cdot 10^{-4}\, R_a^{1.3531} + 1.44 \\ R_{low} &= \begin{cases} 31.85\overline{\beta}^{-0.0086} - 31.94 & \overline{\beta} \le 0.72 \\ 10^{-4} & \overline{\beta} > 0.72 \end{cases} \end{aligned} \quad (4)$$

In (4), it is necessary to set $\overline{\beta} = \beta$ for $\beta \ge 0.001$ and $\overline{\beta} = 0.001$ for $\beta < 0.001$ to prevent R_{low} from tending to infinity.

The equations in (4), together with the last expression in (2), completely define the parameters of MORSE for the prediction of temporal rainfall statistics, while the spatial ones are estimated by resorting to the relationships proposed in [16], which, for convenience, are also reported below in (5).

$$\begin{aligned} n &= -113.75\overline{\beta}^{0.0383} + 115.36 \\ n &= 2.75\cdot 10^{-4}\, R_a^{1.9848} - 8.12 \\ R_{low} &= 6.31\overline{\beta}^{-0.0366} - 5.5158 \end{aligned} \quad (5)$$

In this way, MORSE turns out to be a unified model although with different coefficients for the prediction of spatial and temporal rainfall rate statistics.

IV. Assessment of the Model

A. Tests on yearly basis

The performance of MORSE has been assessed against the full DBSG3 dataset of 104 single- or multiple-year $P_T(R)$s. For each curve we have calculated the average (E_ε) and root mean square value (RMS_ε) of $\varepsilon(P)$ in (3) by including probability values associated to rain rates higher than or equal to R^* = 1 mm/h. The lowest probability value P_{min} was chosen so as to consider at least 20 samples (minutes) and thus guarantee an acceptable degree of statistical significance to the reference $P_T(R)$ (e.g. for a one-year $P_T(R)$, this condition is met for P_{min} = 0.004%).

The prediction performance of MORSE is shown in Fig. 3 and Fig. 4 for each input measurement (the numbering of the experiments is arbitrary). In addition, the figures' legend reports M_E and M_{RMS}, the average value of E_ε and RMS_ε, respectively. As a reference, Fig. 3 and Fig. 4 also depict the

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prediction performance of the ITU-R model. Overall, with respect to the latter, MORSE shows a higher positive bias, but approximately the same M_{RMS}.

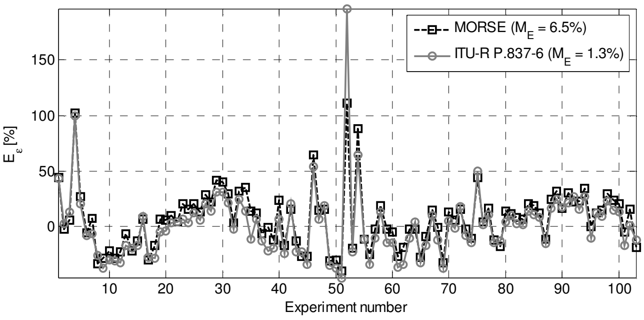

Fig. 3. Average value of the error for each of the 104 $P_T(R)$s extracted from the DBSG3 database and used for model assessment. Comparison between MORSE (black dashed line with squares) and the ITU-R model (gray solid line with circles).

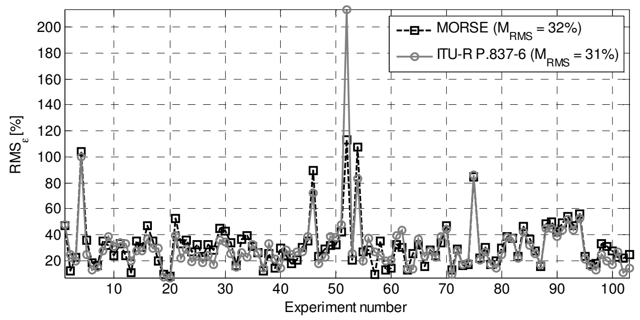

Fig. 4. Root mean square value of the error for each of the 104 $P_T(R)$s extracted from the DBSG3 database and used for model assessment. Comparison between MORSE (black dashed line with squares) and the ITU-R model (gray solid line with circles).

Results in Fig. 3 and Fig. 4 indicate that MORSE yields a slightly lower prediction accuracy with respect to the ITU-R model (the difference in M_{RMS} is 1%). This finding is due to the key physical characteristic of MORSE which, in contrast with the ITU-R model, preserves the input M_t value. As a result, the $P_T(R)$s predicted by the ITU-R model tend to underestimate the mean yearly rain accumulation provided as input [22]. This additional constraint makes MORSE more physically sound at the expenses of a slightly lower performance. Finally, Fig. 5 shows the effectiveness of the models in predicting the exceedance probability associated to R_{min}, the lowest rain rate value for each curve available in the DBSG3 database. We have considered only R_{min} values between 0.2 and 1 mm/h because higher ones have been already included in the performance indicators depicted in Fig. 3 and Fig. 4. In addition, R_{min} values lower than 0.2 mm/h have been discarded to avoid extremely low values, whose accuracy and reliability is typically limited by the instrument resolution. This selection reduces the dataset to 32 experiments.

The figure's legend reports the average (E) and root mean square value (RMS) of the estimation error, in this case defined as the difference between the percentage of the yearly time for which R_{min} is exceeded, as estimated by each model and as extracted from measured data: the two models show quite similar RMS values, while MORSE offers a lower bias.

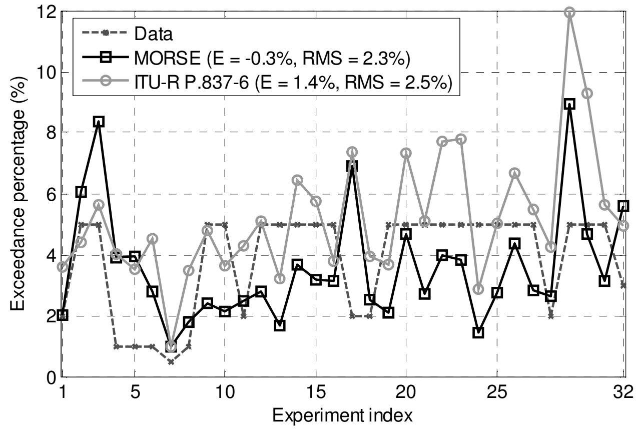

Fig. 5. Exceedance probability (expressed in percentage values) associated to 0.2 mm/h < R_{min} < 1 mm/h, the lowest rain rate value for each curve available in the DBSG3 database. Comparison between measured data (solid gray line with squares), MORSE (dashed black line with squares) and the ITU-R model (solid gray line with circles).

B. Tests on monthly basis

To assess the accuracy of MORSE in predicting $P_T(R)^m$s we have derived from the original ERA40 data the mean monthly values of the convectivity ratio, β^m, to be coupled with $M^m_{t,RG}$, the mean monthly rainfall accumulation derived from the rain rate time series collected by the raingauge (7 sites listed in Table I) and used to produce $P_T(R)^m$s. The choice of $M^m_{t,RG}$ instead of the one provided by a general database allows to partially mitigate the problems associated to the high year-to-year variability of $P_T(R)^m$s and points out that MORSE is not indissolubly linked to the total cumulated rain provided by the ERA40 database, but it can benefit from any other dataset with better accuracy (on the other side, β^m cannot be directly calculated from raingauge data); indeed, this advantage comes from the last expression in (2), which defines the preservation of M_t: the more precise is this input to the model, the more accurate will be MORSE predictions. This is in contrast with the ITU-R model, in which the dependence of the model's parameters on M_t is not so straightforward and, thus, it is not easy to draw any a-priori conclusion on the effects of using M_t values extracted from different datasets other than the ERA40 database.

Fig. 6 depicts the prediction accuracy of MORSE. The best performance is achieved in the months from May to November ($M_{RMS} \approx 20\%$), when convective precipitation prevalently occurs; on the contrary, the prediction error is higher in the remaining months ($M_{RMS} \approx 30\%$) which are typically affected by mixed rain types (e.g. September/October in Spino d'Adda): this, in fact, yields more irregular $P_T(R)^m$s which can be more hardly reproduced by any analytical expression, including the one proposed in (1).

As a matter of fact, $M^m_{t,RG}$ values are quite easily retrievable from global meteorological databases such as GPCC [23] and GHCN [24]. In fact, both datasets combine high accuracy (they originate from thousands of raingauges deployed worldwide), statistical stability (many years of measurement) and global coverage (regular 0.25°×0.25° latitude/longitude grid for the former, point measurements for the latter).

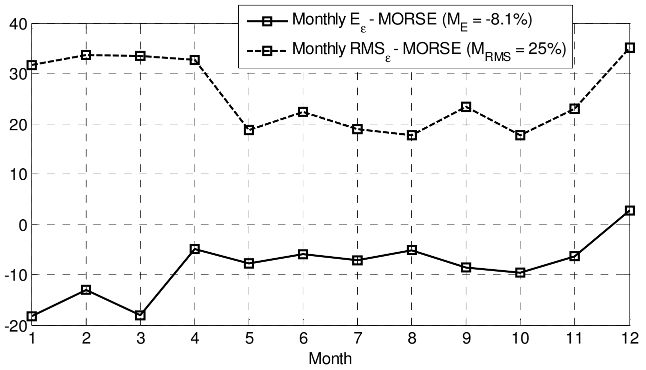

Fig. 6. Monthly average (solid line) and root mean square (dashed line) values of the error for the $P_T(R)^m$ available in this work. Predictions calculated using $M^m_{t,RG}$ and β^m used as input to MORSE.

V. Model Consistency

MORSE is a unified model able to predict both spatial and temporal rain rate statistics and, as such, the results should be consistent each to the others regardless of the time/space basis which the input data refer to. This characteristic relies on the quasi-ergodicity property of the rainfall process, which implies that the temporal rain rate statistics collected by a rainguage at a given site, $P_T(R)$, is equivalent to the one obtained by cumulating the information on the precipitation affecting, at a given time, very many sites in the area surrounding the raingauge location, $P_S(R)$ [25]. It must follow that $P_S(R)$s can be considered as $P_T(R)$ on hourly basis, i.e. $P_T(R)^h$, and that, as a consequence, despite the different set of model coefficients (see (4) and (5)), by aggregating the $P_S(R)$s of the whole year, one must obtain the expected $P_T(R)$. This concept already tested in [16] on a limited set of data has been verified for all the sites included in the DBSG3 database, providing very good results: as an example, refer to Fig. 7, which depicts the $P_T(R)$ predictions for Jacksonville (Florida, USA, 8-year experiment) obtained by aggregating $P_S(R)$s (gray dashed line, E_ε = -0.3% and RMS_ε = 15.6%) and by directly applying MORSE as described in section IV.A (gray solid line, E_ε = 3.7% and RMS_ε = 6.5%). Although both the use of the expressions in (4) and the procedure defined in [16] provide very satisfactory results in estimating $P_T(R)$, the former has the obvious advantage of being much simpler (it requires only one couple of M_t^{ITU} and β^{ITU} as input instead of all the M_t^{6h} and β^{6h} values).

Although not shown here for brevity's sake, the model's consistency was verified to hold also at time scales different from 6 hours. For example, the distribution obtained by aggregating the predicted $P_T(R)^m$s ($M^m_{t,RG}$ and β^m as input to the set of relationships in (4)) correctly reproduces the yearly $P_T(R)$.

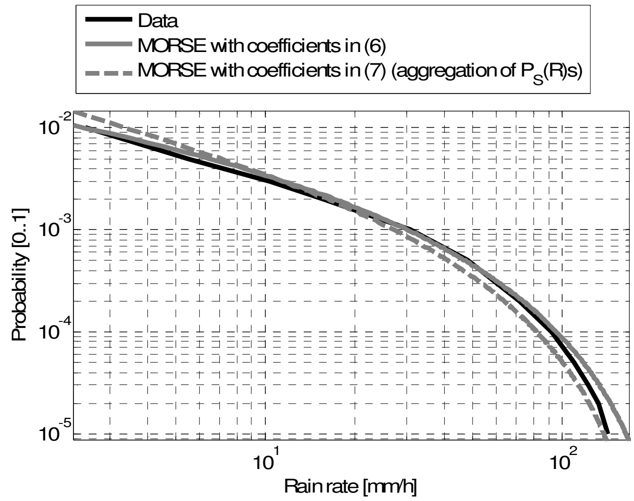

Fig. 7. MORSE prediction accuracy on $P_T(R)$: Jacksonville, Florida, USA. Data extracted from the DBSG3 database (black solid line) are compared with the predictions obtained by applying MORSE with the coefficients in (4) (direct estimation using M_t^{ITU} and β^{ITU} as input) and with the coefficients in (5) (aggregation of several $P_S(R)$s using M_t^{6h} and β^{6h} as input).

VI. Conclusion

MORSE (MOdel for Rainfall Statistics Estimation), a unified model for the prediction of spatial ($P_S(R)$) and temporal ($P_T(R)$) rainfall rate statistics at high resolution is presented and tested here. MORSE relies on an analytical formulation of the $P(R)$ whose main tuning parameters are linked, through simple expressions, to the local convective (M_c) and total (M_t) rain amounts cumulated in different time intervals (e.g. extracted from the ERA40 database), ranging from a few hours for the prediction of $P_S(R)$, to much longer intervals, such as one month or one year, for the estimation of $P_T(R)$ at different time scales. Starting from the formulation presented in [16] for $P_S(R)$ prediction, the model's parameter have been first re-tuned on a subset of yearly $P_T(R)$s made available by the ITU-R in its DBSG3 database, in order to reflect the use of M_t and $\beta = M_c/M_t$ values averaged on yearly (monthly) basis, rather than on hourly basis. Tests performed on the whole set of yearly $P_T(R)$s included in the DBSG3 database indicate that, when compared against the model currently recommended by the ITU-R for the global prediction of yearly $P_T(R)$s, MORSE shows comparable results, but with the definite advantages of requiring two instead of three input meteorological parameters and of preserving M_t given in input. Indeed in force of this latter feature, MORSE is not indissolubly linked to the total cumulated rain extracted from the ERA40 database, but it can benefit from any other dataset with better accuracy. In addition, MORSE turns out to provide a better performance in estimating the exceedance probability associated to R_{min}, the lowest rain rate value in the $P(R)$. Finally, the tests performed against raingauge-derived monthly

$P_T(R)$s in the seven available sites show that MORSE provides a very satisfactory prediction accuracy also at time scales shorter than the year. As a matter of fact, although requested for the design of some satellite communication systems, predicted monthly $P_T(R)$s should be handled with great care due to the very high month-to-month variability that greatly exceeds the already significant year-to-year variability.

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