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Evaluación de modelos para conversión de distribuciones de precipitación de período *T* a distribuciones equivalentes integradas cada minuto para uso en Colombia.

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Abstract

The design of microwave communication systems requires knowledge of the one-minute cumulative distribution of rainfall. However, since time series of rainfall fulfilling this constrain are not common, the conversion of a distribution obtained from time series with a longer integration time *T* (such as 30 or 60 minutes) into equivalent one-minute distribution has been proposed as an alternative. This paper reviews existing models for the conversion of cumulative distributions of rainfall and compares their predictions against a database of measured distributions from the Aburrá Valley in the department of Antioquia, with a view towards recommending a model suitable for the Colombian climate. Based on the results of the evaluation, the EXCELL RSC model represents a suitable alternative for rainfall rate predictions in the valley, and the best alternative for predictions in other regions in Colombia. This model would be useful for fade margin calculations for microwave systems, terrestrial or earth-to-space.

----- *Keywords:* Rain, millimeter wave propagation, microwave, satellite, integration time, statistical distribution, propagation in tropical zones

Resumen

El diseño de un sistema de comunicaciones que opera en frecuencias de microondas requiere el conocimiento de la distribución acumulada de

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probabilidad de la intensidad de lluvias, integrada cada minuto. Dado que este tipo de información es muy escasa, se ha propuesto como alternativa la conversión de distribuciones obtenidas usando series temporales con otros períodos de integración (como 30 o 60 minutos) a una distribución equivalente integrada cada minuto. En este artículo se presenta una revisión de varias metodologías para efectuar dicha conversión y una comparación de sus predicciones contra una base de datos de distribuciones medidas en el Valle de Aburrá (departamento de Antioquia) con miras a recomendar un modelo útil para las condiciones climáticas colombianas. Con base en los resultados de la evaluación, se ha determinado que el modelo Excell RSC representa una buena alternativa para uso en el valle de Aburrá y es además aplicable a otras regiones en Colombia.

----- *Palabras clave:* Lluvia, período de integración, microondas, satélite, propagación, redes de comunicaciones, zonas tropicales

Introduction

When designing a microwave communications system in frequencies above around 8 GHz, knowledge of the rain attenuation cumulative distribution function (henceforth $P(A)$) is fundamental, as rain attenuation is the main cause of propagation-related outages. Depending on the frequency of operation of the system, the path's length and the system's availability objective, rain fades can be as much as two orders of magnitude deeper than fades caused by other tropospheric phenomena. To adequately estimate $P(A)$, the International Telecommunications Union (ITU) recommends the use of rainfall distributions (henceforth $P(R)$) obtained from rainfall time series with a one-minute integration time T [1]. This integration time ensures that the peaks of a rain event are adequately sampled and registered: the use of longer integration times would result in an averaging effect (as the rain rate would be the average of the accumulation over a longer time interval), causing high intensity rain rate values to appear lower. Since the relationship between rainfall rates and the associated fade is directly proportional (although not linear), fade estimations using long integration time data yield lower values than estimations using 1-minute rainfall data. This is shown in figure 1, which presents two attenuation distributions obtained from $P(R)$ with 60 and 1-minute integration times. As can be seen, the difference at the 0.01% point is over 3 dB.

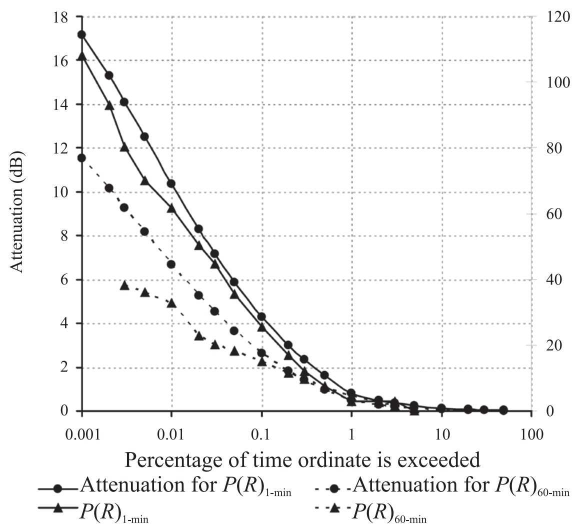

Figure 1 Impact of integration time on the estimation of attenuation. Calculations using the ITU-R model P.618-9 [2]. Frequency: 12.457 GHz, Polarization: Circ., Elev. angle: 47 deg

The main obstacle that a telecommunications engineer faces when estimating rain fades is the lack of local one-minute integrated data. In order to overcome this limitation, models such as Annex 1 of ITU-R recommendation P.837 [1] have been developed. Other approaches have been proposed, with the objective of taking advantage of the increased availability of long-integration time data (such as 30-minute or 60-minute time series), measured for the purposes of water sewage management systems or for hydrology and agronomy applications.

Such models take as input a rainfall distribution with a given integration time, $P(R)_T$, and use it to predict an equivalent one-minute distribution, $P(R)_1$, useful for attenuation calculations. Recent results [3] have shown that the RMS of the errors obtained using the current ITU-R model for integration time conversion [1] is 19.57%, a value lower than the RMS obtained from a direct prediction of the one-minute $P(R)$ using the ITU model for $P(R)$ prediction. It seems interesting then to explore the use of these “integration time conversion” approaches as they appear to provide better results, and in the case of Colombia, could prove a valuable alternative in the face of very limited one-minute data availability. This paper will focus on an evaluation of four integration time conversion models for Colombia. To this end, comparisons using a database of 10 sites in the Aburrá Valley in the department of Antioquia will be carried out and based on those results a recommendation for use on other regions in Colombia will be attempted. The results are useful in the light of access network developments in the EHF frequency range and for the design of Ku and Ka band satellite payloads (such as the ones in the planned Colombian telecommunications satellite).

Description of the available data and overview of the climatology of the Aburrá Valley

The data at our disposal consist of four years (2000-2003) of one-minute integrated rain accumulation time series, collected on 10 stations in the Aburrá Valley, which have been processed to obtain empirical $P(R)$s for integration times of 1, 5, 10, 20, 30 and 60 minutes. The Valley is a landlocked region in northwest Colombia (6.24S, 76.24W) characterized by moderate temperature and humidity: the maxima and minima of both variables, according to the local meteorological agency IDEAM, are 33.6°C and 10°C and 63% and 73% respectively. The annual cycle of precipitation on the valley follows a seasonal pattern in line with the passages of the Inter-Tropical Convergence Zone, peaking in May and September. Other climatic phenomena affecting precipitation in the Valley are the south-eastern trade winds, which bring humidity from the Amazon basin to the Andean Cordillera, and the Chocó Jet, which brings humidity from the Pacific Ocean [4]. The average annual rain accumulation measured over a 20-year period (1981-2001) is 1711.9 mm with a maximum daily accumulation of 124.6 mm. The rain gauge network consists of ten tipping bucket gauges equipped with data-logging devices, set up to process and record rainfall accumulation every minute, and spread in an uneven fashion along the Valley with an average separation of 12.9 kilometres. A particular characteristic of this network is the fact that the gauges are installed inside the valley with mountains bounding the network on the east and west. This is important since in general, as an air mass climbs the slope of a mountain, it discharges its humidity reducing the amount of rain it holds. The result is that most of the rainfall will tend to be deposited on the windward side of the mountain and probably not inside the valley. This is a common occurrence in the Andes, where the presence of mountains favours the creation of microclimates. The average altitude of the stations in the network is 1.76 Km, with maximum and minimum of 2.3 and 1.3 Km. The average direction of the surface wind in the valley, measured by a station at ground level over a period of 97 months, is north during 23% of the time and south during 14% with average speed between 13.9 and 17.1 m/s, which, according to [5], causes an underestimation of rain measured by rain gauges in the order of 20 to 40%.

Description of models selected for testing and validation

Among the various methodologies available for the solution of the *T-min* conversion problem, we have selected four methods which have proven to be applicable, with different degrees of success, on a global scale [3]. The selected methods will be briefly described below. For a detailed description of each, the reader is directed to the references given in the appropriate section in this text.

Empirical methods

Empirical methods consist of relatively simple laws that reflect a trend in a process but that do not necessarily account for the physical mechanisms behind the observations. They represent useful tools as oftentimes the underlying mechanisms are not known or the number of required parameters to model them would be unmanageable. However, as empirical models reflect a tendency specific of a given dataset, its applicability outside the observation domain is not recommended [6].

For the purposes of this paper, two empirical methods have been selected: Direct conversions with a power law and conversions via the use of a conversion factor. The models will be briefly reviewed below.

1) Direct conversions using a power law (PL)

Conversions using this method are achieved by means of equation 1:

$$R_1(P) = a(T)R_T(P)^{b(T)} \tag{1}$$

where $R_1(P)$ and $R_T(P)$ represent the rain rate values, exceeded with the same probability P, and $a(T)$ and $b(T)$ are integration time dependant coefficients.

As this approach is very simple to parameterize and use, ($a(T)$ and $b(T)$ can be determined by means of linear regressions to the logarithm of a $P(R)$), it has been studied by other authors such as [7]. The PL model is currently recommended by the ITU-R in Recommendation P.837 [1]. In this paper, both the coefficients of [3] and those in [1] will be tested. For simplicity, the coefficients are reproduced in table 1.

2) Conversion by means of a conversion factor modeled with a power law (CF-PL)

Another common empirical approach for the conversion of distributions is to use a conversion or scaling factor, defined as the ratio of equiprobable rain rates obtained from each distribution (equation 2). The conversion factor is then modelled as a function of P, the percentage of time the rain rate is exceeded (P is also referred in the literature as *the percentage of exceedance*), using a power law.

$$CF(P) = \frac{R_1(P)}{R_T(P)}, \tag{2}$$

$$CF(P) = a(T)\, P^{b(T)}$$

As with equation 1, $R_1(P)$ and $R_T(P)$ are rain rate values, exceeded with a probability P, and $a(T)$ and $b(T)$ are integration-time dependant coefficients, obtained through linear regression. This methodology was originally studied in [8] and later adopted by the CCIR (ITU-R today). For the evaluation in this paper, the parameters estimated in [3] using a database of 18 locations over the world will be used. These coefficients are shown in table 1.

Physical methods

A physical method involves the combination of analytical approaches with a set of inputs that correspond to meaningful physical variables for the phenomenon of interest. Physical methods are not widespread as in some cases the phenomenon cannot be either fully modelled or understood due to its inherent complexity (for example, models for global climate) or, even if the phenomenon is understood, its implementation would result in long computation times (as in ray tracing or the estimation of multipath fade in a dense urban environment using diffraction theory). Nevertheless, whenever available, physical approaches are preferred because results are more reliable than those obtained from simple empirical or analytical formulations [6]. Fully physical methods are not available for the prediction of a $P(R)_1$ for telecommunication purposes but methods with climatological inputs and a physical formulation (semi-physical) have been proposed. In the case of this study, we will focus on two semi-physical methods for $P(R)_1$ predictions:

1. A model for the conversion of rainfall statistics that relies on the concept of a virtual rain gauge, over which a set of

rain cells move according to the wind speed measured at the 600 hPa isobar [9, 10].

2. A particular case of a model for the prediction of the inter-arrival time rain drops described in [11].

Table 1 Coefficients for the PL, CF-PL and LG conversion methods

	ITU P837-5		***PL***		***CF-PL***		***LG***
Conversions from	***a(T)***	***b(T)***	***a(T)***	***b(T)***	***a(T)***	***b(T)***	***α***
5 min to 1 min	0.986	1.038	0.924	1.044	0.910	-0.021	
10 min to 1 min	0.919	1.088	0.829	1.097	0.813	-0.044	
20 min to 1 min	0.68	1.189	0.736	1.169	0.716	-0.073	0.1634
30 min to 1 min	0.564	1.288	0.583	1.265	0.588	-0.108	
60 min to 1 min	N.A.	N.A.	0.509	1.394	0.521	-0.155	

1) EXCELL Rainfall Statistics Conversion

The EXCELL Rainfall Statistics Conversion model (henceforth EXCELL RSC) [9, 10] was developed using a physical foundation based on the simulated movement of rain cells over a virtual raingauge, with given integration time *T*, whose translation velocity depends on the type of precipitation, on the yearly mean wind speed and on the observation period.

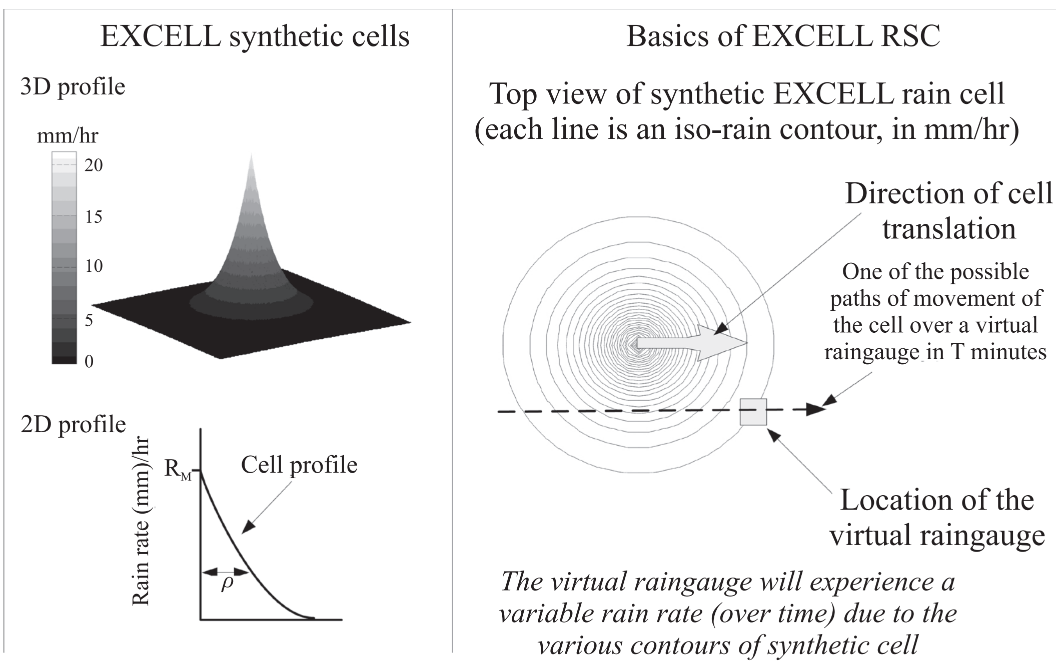

Figure 2 Schematical representation of the principles of the EXCELL RSC conversion model. A virtual raingauge experiences a variable rain rate *R* over time due to the movement of a rain cell above it, at a speed *V*

As sketched in figure 2, EXCELL RSC relies on the description of the local meteorological environment by means of an ensemble of synthetic cells with rotational symmetry and exponential spatial distribution of rain intensity R inside (dependent only on the cell equivalent radius ρ_0 and on the peak rain rate value R_M) of the form shown in equation 3:

$$R(\rho) = R_M\ e^{-\frac{\rho}{\rho_0}} \qquad (3)$$

where ρ is the distance from the cell center (in kilometres). These synthetic cells, whose probability of occurrence is adapted such that their ensemble correctly reproduces the local $P(R)_1$, move over a virtual raingauge, with given integration time T, with translation velocity derived from the global database of wind speed provided by the European Centre for Medium-range Weather Forecasts (ECMWF): as a result, EXCELL RSC is inherently applicable on a global basis. The simulated movement of the synthetic rain cells allows to calculate the total rainfall accumulated by the raingauge over a T minute period, and, therefore, to calculate $P(R)_T$ starting from $P(R)_1$. Finally, an iterative inversion procedure aims at identifying the local $P(R)_1$, which, when used as input to the raingauge simulation described above, provides the best possible estimate of the measured $P(R)_T$. A comprehensive description and validation of the EXCELL RSC model and its essential parameters and assumptions can be found in [9] and [10].

2) *Lavergnat-Gole Rainfall Statistics Conversion method*

The Lavergnat-Golé model [11] (henceforth LG) was developed starting from a physical basis: by modeling the time interval separating two consecutive rain drops as a renewal process. The conversion of distributions from an integration time T to the target integration time of one minute is a specific case of the general model and is achieved by means of an integration time independent conversion factor defined as the ratio between the two integration times (in this case one minute and T minutes), as shown in equation 4:

$$CF = \frac{1}{T} \Rightarrow R_1 = \frac{R_T}{CF^{\alpha}} \text{ and} \qquad (4)$$

$$P_1(R_1) = CF^{\alpha} P_T(R_T)$$

Another important difference with respect to the empirical models described above is the use of a single empirical conversion parameter (a) (as opposed to one per each source integration time) that affects both the rain rate and the probability values. As can be seen, the model's weakness lies in its reliance on an empirical parameter a for which no global maps are available. For the purposes of our test and validation exercise, the empirical parameter a is set to the global average value reported in [3], and reproduced in table 1. For more information on the general law governing the renewal process, the reader is referred to [11].

Model testing and validation

As the main objective of this paper is to evaluate the performance of various existing conversion models, a test procedure has to be defined. The process of testing and comparison involves calculating, using all the selected models, an equivalent $P(R)_1$ using all the available $P(R)_T$ distributions per site. The performance metric selected for the evaluation is the relative error, defined in equation (5) below.

$$\varepsilon^T(P) = 100\frac{\left(R_e^T(P) - R_m^1(P)\right)}{R_m^1(P)}\ [\%] \qquad (5)$$

In (5) the superscript T refers to the source integration time, P refers to the percentage of time the rain rate was exceeded and the e and m subscripts represent, respectively, the predicted and measured one minute rain rate values. It is necessary to note that the error variable in (5) yields higher errors in the low rain rate portions of the $P(R)$. Notwithstanding its sensitiveness to the lower rain rates, this error figure is a common metric for model evaluation.

In order to select the model that performs best, the mean, standard deviation and root mean square (RMS) values of the error variable in equation (5) need to be calculated. The expressions used are shown in equations (6) to (8):

$$\hat{\mu} = \frac{1}{N}\sum_{i=1}^{N}\varepsilon^{T}(P_i) \qquad (6)$$

$$\hat{\sigma} = \frac{1}{N}\sum_{i=1}^{N}\left(\varepsilon^{T}(P_i) - \hat{\mu}\right) \qquad (7)$$

$$RMS = \sqrt{\hat{\mu}^2 + \hat{\sigma}^2} \qquad (8)$$

where N denotes the number of error samples available.

The optimum prediction method is selected on the basis of the magnitude of the three parameters: the best method would ideally deliver the smallest values of the statistical metrics [6].

Establishing a lower and upper bound on the RMS of the prediction error

To study the performance of models and draw meaningful conclusions regarding the benefits and disadvantages of each approach, it is useful to establish boundaries on the value of the RMS of the relative error variable. The best performing model should be close to the lower bound, and any model performing worse than the upper bound should be rejected.

A proposal for the lower bound on error performance is to use the RMS of error obtained from empirical models when parameterized using the $P(R)$s available on the database. It must be remembered that even though empirical models can be easily adapted to the database compiled for this test, the parameters obtained would not be applicable or representative of other climatic regions in Colombia. Figures 3 and 4 present an example of the linear regressions that need to be performed to the logarithm of the equiprobable rain rates ($R(P)_T$, $R(P)_1$), in the case of the PL method, and to the logarithm of the ($CF(P)$,P) ordinate pairs in the case of the CF-PL model, to obtain the parameters of each model. As far as the fitting process is concerned, it can be seen how outside the [0.001%, 1%] range the linear fit is no longer adequate (an attempt to extend the range of validity of the fit resulted in an increase of the RMS values as high as 180%). The departure from linearity could be due in part to stability of the distributions in the low rain rate (limited by the instrument's resolution) and in the high rain rate (limited by the number of extreme events captured during the measurement interval) sections.

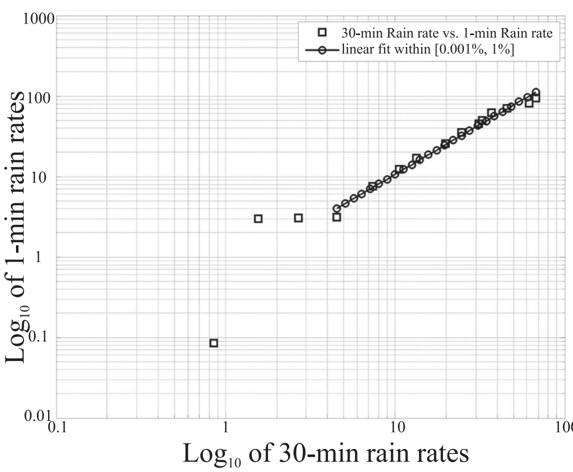

Figure 3 Sample linear fit to the ratio of T-min and 1-min rain rates. For probability values below 0.001%, the ratio's behaviour departs from linearity

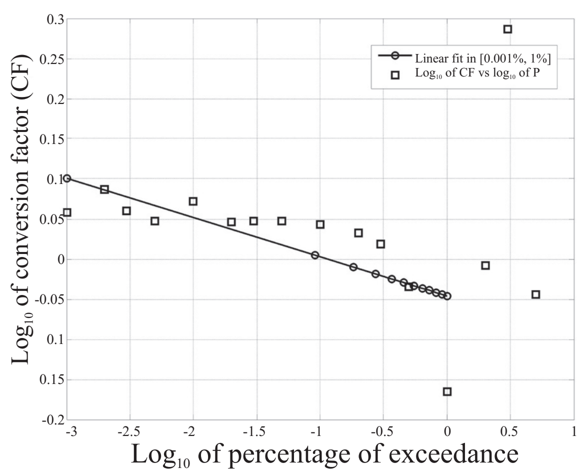

Figure 4 Sample linear fit to the conversion factor (CF). For probability values above 1% (greater than 0 in the figure), the ratio's behaviour departs from linearity

The error performance figures which will serve as the lower bound are given in table 2. As the EXCELL RSC model does not need to be parameterized to each $P(R)$, it is not included in table 2. The RMS value of the PL model applies also to the model in Annex 3 of ITU P.837-5.

Table 2 Lower bounds for error evaluation: RMS of the relative error variable, for three models, in the interval [0.001%, 1%]

Model	*RMS*	*Mean*
PL	11.58	2.13
CF-PL	11.15	0.79
LG	14.09	5.75

Continuing, an upper bound to the RMS of the error can be set by considering the model in Annex 1 of ITU-R P837-5, for direct $P(R)_1$ prediction: as this model represents (based on international consensus) the best choice available in the absence of local data and is regularly used for system dimensioning, if any of the models studied in this paper is to be considered a viable alternative then the resulting RMS and mean of the relative error must be lower than that of the ITU recommendation. The results of the performance evaluation (RMS and mean of the error variable) are shown in table 3, for two sets of data: the ITU-R SG3 global measurement database for tropical regions [12] and the Aburrá Valley database.

Table 3 Upper bound to error evaluation: performance of Annex 1 of ITU P.837-5 model in tropical localities and in the Aburrá Valley. The test included only the range of probabilities flagged as "stable" on each experiment in the database

	DBSG3-Tropical		*Aburrá Valley DB*	
	RMS	*Mean*	*RMS*	*Mean*
ITU Annex 1 (full P(R))	65.35	10.36	349.7	89.8
ITU Annex 1 [0.001%,1%]	30.5	5.8	25.6	20.2
ITU Annex 1 with P=0.01%	17.95	0.03	24.5	21.6

Referring to table 3, the behaviour observed in the Valley's dataset regarding deviations in the extremes of the distributions (the very low and very high probabilities) applies also to other sites in the ITU database, and this behaviour translates into high prediction errors from the ITU model. Such high RMS value could be due to various factors, but particularly to the mentioned problems in the tails of the distributions: in the more stable reduced range, the model performs rather well. Figures 5 and 6 respectively illustrate the relative differences between predictions and measurements using data from one station in the Aburrá Valley network and one station in the ITU database. In the case of the Aburrá Valley, the figure highlights the increase of said difference in the tail of the distribution (low percentages).

The good performance of the ITU model in the Valley (within the reduced range) could be partially explained by the fact that the four parameters in this version of the ITU model were optimized over a database that includes a rain gauge from the valley, representative of the highest rain rates recorded. It is necessary to stress that this result does not mean that the performance of the ITU model in other regions in Colombia would be as good (particularly in other mountainous regions), but we expect the results to be close to the RMS values obtained when evaluating the model over the whole of the DBSG3 data for annual rainfall statistics. For the purposes of the analysis at hand, the performance of the ITU model over the tropical stations in DBSG3 will serve as the upper bound to the error performance of models.

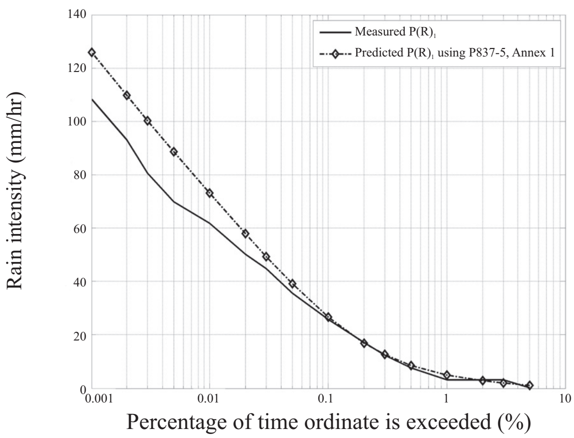

Figure 5 Deviations between a predicted P(R) and a measured one. Predictions using the current ITU model, measurements from a station in the Aburrá Valley network

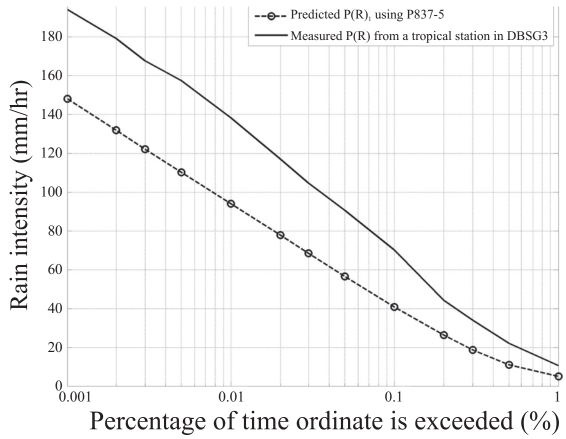

Figure 6 Differences between a predicted P(R) using ITU P.837-5 and a sample tropical distribution in DBSG3

Another key point to highlight here is the results obtained when predicting $R_{0.01\%}$, the main input required for attenuation prediction using ITU-R P.618 [2]. The RMS obtained (17.95% over tropical regions and 24.5% in the valley) indicates that the model performs within the bounds of the year to year variability (close to 30%).

Prediction model evaluation

The performance of the models, both over the entire *P*(*R*) and within the [0.001%, 1%] range, is shown in tables 4 and 5 respectively. The fact that empirical models are applicable only in a reduced range does not disqualify them, as the range of interest for system design lies usually within this interval: for example, ITU-R recommendation F-1703 [13] for links in the access portion (last mile solutions) of a network gives an unavailability objective of 0.05% of the time for each direction in the link, while for links of the national long-haul and international portion, the objective lies between 0.014%, for a path 50 km in length, to 0.3% for a 2500-km link. Moreover, the performance of models in the very high probability ranges (5% and above) has to be put in the context of the absolute probability of having rain (denoted P_0). For example, for the network in the Aburrá Valley, the average value of the estimate of P_0 is 2.7%. This means that predictions above 3% are not meaningful.

Table 4 Final performance of prediction models

	Full P(R)		*Within [0.001%,1%]*		*For P=0.01%*	
Model	***RMS***	***Mean***	***RMS***	***Mean***	***RMS***	***Mean***
ITU P837-5 Annex 3	137.21	18.74	16.33	7.93	15.84	9.99
PL	126.96	13.2	13.85	2.1	12.73	3.85
CF-PL	164.1	25.57	15.24	6.5	12.96	7.82
LG	68.27	7.47	14.22	5.02	15.81	3.05
EXCELL RSC	20.66	-7.43	15.76	-4.45	14.09	-1.15

Table 5 Performance with respect to integration time, within the reduced probability range

	5 to 1 min		10 to 1 min		20 to 1 min		30 to 1 min		60 to 1 min	
	RMS	Mean	RMS	Mean	RMS	Mean	RMS	Mean	RMS	Mean
ITU Annex 3	15.78	13.86	16.68	12.89	15.33	2.42	17.65	2.03	NaN	NaN
PL	11.58	8.96	11.37	4.99	14.55	3.75	15.70	-1.87	16.07	-7.01
CF-PL	17.03	14.73	12.37	6.06	15.38	4.97	15.34	2.35	16.00	3.62
LG	18.21	17.01	14.26	11.71	9.82	5.26	8.58	-0.12	17.76	-12.01
EXCELL RSC	16.59	7.31	13.30	2.38	13.80	-5.52	14.14	10.41	20.62	-18.69

1) Evaluation of model performance in the Valley

Based on the results in table 5, and using the bounds established in previous sections, the best performing model in the [0.001%, 1%] range, over all integration times and over all sites in the valley, is the PL approach, followed closely by the LG, CF-PL and EXCELL RSC methods. However, noting that the difference among models is not significant (less than 3% between the best and worst performing models), no model shows a clear advantage. The RMS values of the PL prediction error using 30 and 60-minute integrated data (of great importance due to the likelihood of availability of data for other regions in Colombia) are also acceptable, as they are below the upper bound set by the ITU model. An alternative for long term predictions is the use of the LG approach, simpler and preferable as it has physical foundations: the LG model displays the lowest RMS for predictions using 30-minute data and comparable RMS for predictions using 60-minute data. This is an important result considering the type of data available in Colombia. Finally, for system design in the Aburrá valley or in the city of Medellin using the full *P(R)*, the Excell RSC model results in the lowest RMS.

As noted before, the current ITU recommendation for attenuation prediction (terrestrial or earth-to-space) requires as input not the full $P(R)$ but the rain rate exceeded for 0.01% of the time. After evaluating the performance of each model for the prediction of the rain rate exceeded for 0.01% of the time, we found that all models are able to deliver an improvement over the existing ITU recommendation. As shown in table 6 the results follow the same trend discussed in the previous section, with the lowest RMS corresponding to predictions using the CF-PL model.

2) Recommendations for using of models in other regions of Colombia

It is worth remembering that, as shown in [3], empirical models are very susceptible to changes in their parameters. This means that a slight error in the selection of the parameters of the conversion (or the use of a parameter determined on a different climatic region) will result in a large error in the predicted $P(R)$. Therefore, when extending the discussion of the results to other regions in Colombia, we must consider the impact that using the empirical coefficients obtained for the Valley will have on predictions for other zones with different climatic characteristics. As the impact is likely to be high, this leaves only two candidates for further discussion: the LG approach, and the EXCELL RSC model. The main disadvantage of the LG approach is that, even though it has physical foundations, its dependence on an empirically determined coefficient (**a**) will always shed uncertainty regarding its application outside the original parameterization domain. On the other hand, the main advantage of said method is that it is robust in the presence of changes on this empirical parameter, which means that the RMS will not grow excessively with small changes in the value of **a** [3].

The second option, EXCELL RSC, has no dependence on empirical parameters and receives as input global climatic maps, which facilitate its use in various regions. The performance over the Aburrá Valley database, although not the best, is still better than the results of the ITU conversion model in [1] (both when used to predict the full $P(R)$ and when using the $P(R)$ within the useful range: 15.76% against 25.6% of the ITU model in the valley) and only 2 points away from the best performing model. Therefore, based on the results observed, the EXCELL RSC model provides the best alternative to Annex 1 of ITU P.837-5, as it can:

1. Be used over the entire probability range of a $P(R)$ distribution, therefore allowing the calculations of low fade margins using attenuation prediction models such as [14]. These models are under discussion in the ITU with a view towards a recommendation change;
2. Provide a lower RMS of the prediction error than that obtained using the ITU P.837-5 model,
3. As it is based on a physical approach, it is not prone to the same errors that are inherent to empirical models: there is no uncertainty in the use of the model in tropical zones, as its performance is similar in temperate and tropical regions.

Therefore, it is our view that the most suitable model for use in other regions in Colombia is EXCELL RSC.

Table 6 Results corresponding to the prediction of $R_{0.01\%}$ from different integration times

	5 to 1 min		*10 to 1 min*		*20 to 1 min*		*30 to 1 min*		*60 to 1 min*	
	RMS	***Mean***	***RMS***	***Mean***	***RMS***	***Mean***	***RMS***	***Mean***	***RMS***	***Mean***
ITU Annex 3	15.48	15.46	16.09	14.92	8.22	0.64	21.74	8.95	NaN	NaN
PL	10.93	10.90	9.38	7.45	8.06	0.97	18.77	3.40	15.39	-3.48
CF-PL	16.97	16.96	8.80	7.33	6.42	1.10	16.03	5.79	14.49	7.94
LG	20.25	20.21	14.98	14.61	6.32	4.05	7.05	-3.17	22.80	-20.44
EXCELL RSC	18.16	17.11	10.19	7.93	10.33	-3.54	11.07	-9.79	18.26	-17.44

Summary and conclusions

This paper highlighted the importance of using proper rainfall information when designing microwave systems, and in particular, when estimating rain-induced attenuation using ITU-R Recommendations P.530 or P.618. Through a focused study, we have reviewed the concept of the conversion of long integration time statistics into an equivalent one-minute $P(R)$, useful for rain fade calculations, and using data from a rain gauge network in the Aburrá Valley, showed how empirical approaches do provide a simple means to calculate the required distributions. Nevertheless, based on the good results obtained using physical methods as shown here, and in [3,10], we discourage the use of empirical methods in other regions in Colombia, particularly in those recognized by having extremes in precipitation (such as the pacific coast or the Amazon basin) and orography (such as cities on the Andes). For these regions, physical models are a better option and among the two studied the EXCELL RSC provides the most suitable alternative to the ITU-R recommended models for the prediction of a one-minute $P(R)$. Our conclusion is based on the global nature of EXCELL RSC, which renders it effectively immune to the errors that characterize empirical methods when they are extended to predict a $P(R)_1$ outside their initial parameterization domain.

In the Colombian context, one-minute integrated time series are scarce but the availability of 10, 15 and 60-minute data has increased (from agencies like the Dirección de Prevención y Atención de Emergencias in Bogotá, or the Water Company of Manizales). Therefore, an application of EXCELL RSC will enable the use of such data for microwave system design: based on the results in this paper, the $P(R)_1$ obtained using the model approximates better the measurements available (an RMS of.14% vs. 25% of ITU-R P.837).

The results reported here are very relevant to the Colombian telecommunications industry: they contribute to reduce the uncertainty in the application of precipitation prediction models in the country. The recommendations put forth in this paper can be applied to the design of microwave systems such as fixed point-to-point and point-to-multipoint links in the 15 to 38 GHz bands, and are also very relevant in the context of the proposed Colombian communications satellite as they provide a suitable alternative for the development of the attenuation contour maps required for the design of the communications payload.

Other studies on rainfall rates in the valley for the purposes of telecommunication system design can be conducted, such as evaluating other $P(R)_1$ prediction models, studies of duration and intensity of rainfall events, spatial correlation of rainfall intensity, etc. These are part of currently ongoing work.

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