COMPOUND DISTRIBUTIONS FOR RADAR IMAGES

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ABSTRACT

In radar imagery, the statistical modeling is derived from random walk theory because the backscattered field is the sum of the contributions of the different scatterers at the observed surface. In this paper we describe how the dependence of the statistical properties of microwave returns from the ground can be built into a theoretical model in a consistent way. When the number of scatterers varies, the distribution of the resulting field may be non-Gaussian. Here we derive the field distribution based on the assumption of compound Poisson distributions of the number of scatterers. We obtain a new set of backscattered field distributions including well-known K and Rayleigh distributions. These novel classes of probability distributions are found to correlate well with distributions of radar clutter returns. We assess the relevance of the modeling with experimental radar data and we compare the fitting results of the new distributions to the K and Rayleigh ones. We finally point out the explicit dependence between the statistical properties of the number of scatterers and the surface illuminated by the radar.

I. INTRODUCTION

In coherent emission-reception systems such as monochromatic radar and laser, images have a granular appearance which reduces their grey level resolution. Rigden and Gordon as well as Oliver and Goodman [1] initially studied its origin on laser experiments. In the case of very rough surfaces on the wavelength scale, numerous waves are reflected from facets also called scatterers at the observed surface. Each elementary wave has a random phase. At the reception, interference of the monochromatic waves can be constructive or destructive, resulting in the granular texture in the images called speckle. Many fields of physics present similar phenomena, such as synthetic aperture radar, acoustic imagery and narrow band electric noise.

Consequently, the statistical formulation is of interest for designing detection, segmentation, filtering, pattern recognition and performance analysis algorithms. These methods need a statistical model that is usually obtained by one of the following approaches.

The first one consists of parametric models without a priori assumption on the physics of the acquisition system. Frankot and Chellappa [2], Trunk and Georges [3], Maffett and Wackerman [4] have studied the lognormal, Weibull, gamma and the beta of first and second kind distributions for specific data. More recently, the use of the system of Pearson [5] has pointed out the relevance of these two last laws in the case of radar data.

In the second approach, the model is built by considering the clutter scattering mechanism. For coherent monochromatic systems, the mathematical foundations were first established in relation to the random walk theory. Because the number of interfering waves, their amplitudes and their phases depend on the properties of the medium, it is necessary to make assumptions about the backscattering. In the case of homogeneous cells, whose size is large compared to the wavelength, the number of scatterers is a large constant and waves are statistically identical and independent. Using the central limit theorem, the resulting wave is Gaussian and its amplitude obeys a Rayleigh law.

If the size of the structuring elements is of the same order as the spatial resolution, the number of scatterers may vary from one cell to another. The Gaussian model then is not suited to describe the resulting electric field. Since the beginning of the Eighties, the K law has been used for modeling this kind of textures [6-15]. Its genesis results from the modeling of the number of scatterers by a compound Poisson variable with a gamma random expected number of scatterers. This discrete distribution is also known as negative binomial distribution.

In this paper, we extend the family of distributions of the number of scatterers by considering generalized compound Poisson law. This set of distributions, which includes the negative binomial distribution, has been chosen in order to cover a large variety of distributions. As a consequence, we have new parametric distributions for the image intensity, which result from the random walk problem not converging towards the Gaussian law.

The new overall distributions also form a set of intensity distributions of which we assess the modeling and estimating properties.

This article is organized as follows.

In section II, we first discuss the mathematical formulation of the backscattering from the ground surface. We point out the non-Rayleigh behavior of the intensity distribution of amplitude radar images.

Section III is devoted to the statistical modeling of the expected number of scatterers.

In section IV, we calculate the intensity distributions by using the system of distributions and the results section II. The intensity distributions will also be

presented and compared to the classical K distribution.
Section V concerns the automatic selection of a member of the intensity distribution system and the associated parameter estimation.
In section VI, fitting results of the novel classes of distribution are compared to the Rayleigh regime and K law by using the Kolmogorov distance. We show that the predictions of the models are found to be in qualitative agreement with existing experimental data. Moreover, we point out explicit dependence between statistical properties of the number of scatterers and the surface illuminated by the radar.
Our conclusions are given in the seventh section.

II. PRELIMINARIES

Let us consider the propagation in free space of an incident monochromatic wave on a rough surface (surface variation much bigger than the wavelength). The received field at any moderately distant point consists of many coherent components, each arising from a different microscopic element of the surface called scatterer. These components vary in number and geometry according to the nature of the observation. The backscattered field from an illuminated area takes the form:

$$E = \sum_{k=1}^{N} E_k = \sum_{k=1}^{N} A_k e^{iq_k}$$

where N is the number of scatterers, A_k is the amplitude and q_k is the phase of the k^th component.

Hypotheses
The $\{A_k\}$ and $\{q_k\}$, k $Î$ $\{1,\ldots,N\}$ are two sets of independent and identically distributed variables. The distances traveled by these various wavelets may differ by several or many wavelengths if the surface is really rough. In this case, no phase between 0 and 2π is preferred, so that the phases are uniformly distributed between 0 and 2π. Moreover, the amplitudes, phases and number of scatterers are independent.

If N is large and constant, we get a circular Gaussian distribution for the backscattered field. Its components are independent, zero mean and have the same variance Ns^2. Consequently, the amplitude is Rayleigh distributed and the intensity obeys to an exponential law with parameter $1/Ns^2$. This model is usually accepted for fully developed speckle.

There is a number of ways in which the basic assumptions underlying the classical statistics of speckle may be violated, leading to modifications of the model. Assuming that the resolution is large compared to the size of the scatterers, only two cases are described in what follows:

1. The phases of the scatterers are not uniformly distributed. If the distances traveled by the wavelets do not differ by several or many wavelengths, then it may no longer be accurate to assume that the scatterers have uniformly distributed phases on the primary interval. In this case, the resulting field is still well modeled as complex Gaussian variable, but their components no longer have equal means and variances. As a result the statistics of the intensity depart from the classical negative exponential distribution. Barakat has studied this case and modeled the phase by a Von Mise distribution. His results generalizes the K distribution for weak scattering [10,11].
2. The number of scatterers is a random variable. The classical theory of speckle assumes that any fluctuations in the number of scatterers contributing to the field is negligibly small. This hypothesis can be violated particularly if the structuring elements at the earth surface are relatively big. As a result, the backscattered field does not obey a Gaussian law. Modeling of the backscattered field consists first in a statistical estimation of the number of scatterers' distribution. Negative binomial distribution is one possible model [8]. It leads to the K law for the amplitude of the resulting field. In this paper, we propose a method to recognize and estimate the distribution of the number of scatterers, which extends the number of laws of the backscattered electric field.

III. NUMBER OF SCATTERERS

The aim of this section is to show that when the number of scatterers is random according to Poisson distribution defined by the parameter λ, which is thus the "expected number of scatterers", and when λ is large enough, then the field F can be considered as a circular Gaussian field.
Since the components of E are independent and statistically identical, its characteristic function is:

$$f_{E/N}(\boldsymbol{t}) = E\left[e^{i\langle \boldsymbol{t},\boldsymbol{E}\rangle}\right] = E\left[e^{i\langle \boldsymbol{t},\boldsymbol{E_k}\rangle}\right]^N$$

As the phase is uniformly distributed on *[0,2p]*,

$$f_{E/N}(\boldsymbol{t}) = E_{A_k}\left[E_{q_k}\left[e^{i\langle \boldsymbol{t},\boldsymbol{E_k}\rangle}\right]\right]^N = E_{A_k}\left[J_0(A_k t)\right]^N$$

where t is the modulus of $\boldsymbol{t}$ and J_0 is the zero order Bessel function of the first kind [16].
Now suppose N is itself random and is a realization of a random variable N distributed according to a Poisson distribution with expectation equal to λ. The characteristic function of E becomes :

$$f_{E/l}(t)=\sum_n \frac{l^n}{n!}E^n_{A_k}[J_0(A_k t)]e^{-l} = exp\, l\left(E_{A_k}[J_0(A_k t)]-1\right)$$

Given the variance of real and imaginary parts of E is $\lambda\sigma^2$, let us put $E' = E/ l s^2$.

$$f_{E'/l}(t)=f_{E/l}\left(\frac{t}{l s^2}\right)=exp\, l\left(E_{A_k}\left[J_0\left(\frac{A_k t}{\sqrt{l}\, s}\right)\right]-1\right)$$

Using the increasing order development of J_0, we have:

$$f_{E'/l}(t)=exp\left(-\frac{t^2}{4}+\left(\sum_{j=2}^{+\infty}\frac{E\left[A_k^{2j}\right]}{(j!)^2\, l^{j-1} s^{2j}}\left(\frac{-t^2}{4}\right)^j\right)\right)$$

and thus

$$f_{E'/l}(t)=exp\left(-\frac{t^2}{4}(1+o(l))\right) \text{ with } \lim_{l\to\infty} o(l)=0$$

This result means that the normalized backscattered field distribution is zero mean circular Gaussian and E is zero mean circular Gaussian with variance $l s^2/2$. Consequently, if the expected number of scatterers is large and constant, the Poisson law has no influence on the coherent sum of N independent and identically distributed contributions.

Mean number of scatterers

At this stage, we seek to model the l variable. This variable contains information about the nature of the observation. The difficulty of its modeling lies in the incapacity of observing it. In this situation, it is impossible to guide our parametric distribution choice since we do not have the histogram of the expected number of scatterers. Consequently, we do not propose only one parametric law but a set of laws whose shapes are as varied as possible.
We have taken as a starting point the Pearson's system of distributions to model the λ distribution. This system covers a large variety of distribution shapes such as U, J, L and bell-shaped densities. Since the average number of elementary waves is a positive variable, we select the Pearson densities having a positive support. This subset contains a great number of known parametric laws such as gamma, beta of the first kind, beta of the second kind and inverse gamma distributions.
Our statement about the Pearson's subsystem is rather short, and further details can be found in [17].

Compound distribution

In this chapter, we deal with mixture of discrete Poisson distribution. The notion of mixing has often a simple and direct interpretation in terms of the physical situation. For continuous distribution, compounding is commonly used in place of mixing.

If the original distribution of a random variable is $P_{N/l}$, depending on the parameter l, then a compound distribution is constructed by ascribing a probability distribution to l. The so called compound distribution is $E[P_{N/l}]$, the expectation being taken with respect to l.

$$P_N(n)=\int_0^{+\infty}P_{N/l=x}(n)f_l(x).dx$$

with $P_{N/l=x}(n)=e^{-x}x^n/n!$, $n\hat{I}IN$, $l > 0$ the Poisson distribution with parameter $l = x$.
and $f_l\ \hat{I}\ F=\{f_1, f_2, f_3, f_4\}$. The set of distributions of l gives rise to a new discrete distribution system for N: $P = \{P_1, P_2, P_3, P_4\}$.
The moment generating function of a Poisson random variable N is given by

$$E_{N/l}[e^{tN}]=exp(l(e^t-1))$$

Therefore, when the generating functions of the compound distributions are defined, they have the following expression:

$$Y_N(t) = E_l[E_{N/l}[e^{tN}]] = E_l[e^{l(e^t-1)}] = F_l(e^t-1)$$

<u>l obeys the beta law of the first kind</u>

If l obeys a first kind beta law with scale parameters p,q and scale parameter β, the distribution of N is called the degenerate hypergeometric of the first kind distribution because of its expression:

$$P_1(n)=b^k\frac{B(p+n,q)}{B(p,q)}\frac{1}{n!}F(n+p,n+p+q,-b)$$

where Φ is a degenerate hypergeometric function [16]:

$$F(a,g,z)=\frac{1}{B(a,g-a)}z^{1-g}\int_0^z e^t t^{a-1}(z-t)^{g-a-1}dt$$

$$0 < Re(a) < Re(g).$$

The generating function of the degenerate hypergeometric of the first kind is

$$Y_1(t)=M(p,p+q,b(e^t-1))$$

Note that if p and q are close to null, the beta of the first kind density tends to two Dirac masses at 0 and b. In this case, the compound Poisson distribution converges towards a mixture of two Poisson distributions with parameters 0 and b respectively.

<u>l obeys the gamma law</u>

If l is a gamma variable with a as shape parameter and b as scale parameter, the distribution of N is the following

$$P_2(n)=C_{a+n-1}^{a-1}\left(\frac{b}{b+1}\right)^n\left(\frac{1}{b+1}\right)^a$$

The negative binomial generating function is

$$Y_2(t) = \frac{b^a}{\left(1+b-e^t\right)^a}$$

The compound distribution is the negative binomial distribution, which initially has been used by Greenwood and Yule [18] in the accident proneness model.

λ obeys the inverse gamma law

If l is an inverse gamma random variable with shape parameter a and scale parameter b, then the discrete distribution of N is:

$$P_3(n) = \frac{2b^{\frac{a+n}{2}}}{G(a)} \frac{1}{n!} K_{n-a}\left(2\sqrt{b}\right)$$

where K is the modified Bessel function of the second kind [16].
P_3 is the discrete K distribution.

λ obeys the beta law of the second kind

At last, if l is a beta variable of the second kind with p and q as shape parameters and b as scale parameter then N is a degenerate hypergeometric variable of the second kind:

$$P_4(n) = b^{-p+q} \frac{G(p+n)}{B(p,q)} \frac{1}{n!} Y(n+p, n+1-q, b)$$

with Y the degenerate hypergeometric function [16]. (P_4 is called the degenerate hypergeometric distribution of the second kind).

$$Y(a,g,z) = \frac{1}{G(a)} \int_0^{+\infty} e^{-zt} t^{a-1} (1+t)^{g-a-1} dt \quad (Re(a) > 0)$$

The generating function of the degenerate hypergeometric distribution of the second kind is

$$y_4(t) = M\left(p, -q, b\left(e^t - 1\right)\right)$$

IV. PARAMETRIC DISTRIBUTION OF THE INTENSITY.

For each law $\{P_1, P_2, P_3, P_4\}$ of the number of scatterers N, we calculate the distribution of the intensity $\{g_1, g_2, g_3, g_4\}$. The new set of distributions forms a system called KUBW in reference to special functions K, U, B and W.

l obeys the beta law of the first kind

The intensity distribution is expressed by [19]:

$$g_1(x) = \frac{G(p+q)}{G(p)} \frac{1}{s^2 b} \left(\frac{x}{s^2 b}\right)^{\frac{p}{2}-1} e^{-\frac{x}{2.s^2 b}} . W_{\frac{-p-2.q+2}{2}, \frac{p-1}{2}}\left(\frac{x}{s^2 b}\right), \quad x \text{ Î } [0,+ ¥[$$

where $W_{l,m}$ is the Whittaker function, l and m are real numbers.
As the density depends on the Whittaker special function, it is called the W probability density distribution. Note that this law converges towards the well-known K distribution, when q tends to infinity.

l obeys the gamma law

We obtain the K law for the intensity [8]:

$$g_2(x) = \frac{2}{G(a)} \frac{1}{s^2 b} \left(\frac{x}{s^2 b}\right)^{\frac{a-1}{2}} K_{a-1}\left(2\sqrt{\frac{x}{s^2 b}}\right), x \text{ Î } [0,+ ¥[$$

where K is the modified Bessel function of the second kind.
Let us remember that the K distribution tends to the exponential distribution as a tends to infinite.
Concerning this distribution, many studies were first conducted by E. Jakeman and his colleagues [6-8]. Let us also mention Oliver [14] who proposed a correlated K distribution, Jao [9], who used the K law in case of rural illuminated area and Barakat [10,11] who obtained distributions in the case of no weak scattering.

λ obeys the inverse gamma law

We obtain for the intensity the beta law of the second kind. This result is quite interesting because it was already suggested by Maffett and Wackerman [4] and Delignon [20] in another statistical modeling procedure:

$$g_3(x) = \frac{a\left(s^2 b\right)^a}{\left(x+s^2 b\right)^{a+1}}, \quad x \text{ Î } [0,+ ¥[$$

where a and b are parameters of the inverse gamma law.

λ obeys the beta law of the second kind

The intensity distribution is expressed as follows:

$$g_4(x) = \frac{qG(p+q)}{s^2 b G(p)} U_{q+1,2-p}\left(\frac{x}{s^2 b}\right), x \text{ Î } [0,+ ¥[$$

where $U_{l,m}(.)$ is the degenerate hypergeometric function with parameters λ and μ.
The U distribution tends to the K distribution as q tends to infinity, whereas it tends to the beta distribution when p tends to infinity.

V. ESTIMATION

We now proceed to parameter estimation by the method of moments. The statistical moments of the intensity are expressed in terms of the moments of expected number of scatterers:

$$E[\,I^k\,] = G(k+1)s^{2k}E[\,l^k\,]$$

Depending on the distribution of the expected number of scatterers, the moments of the intensity are gathered in the following table 1.

Identification of statistical moments and empirical ones provides estimators of the I-distributions parameters, as showing in table 2 and 3.

Table 1 : Moments of the expected number of scatterers and moments of the intensity ($g = b\,s^2$)

λ law	$E[\,l^k]/b^k$	$E[I^k]\,/g^k$
Beta 1st kind	$\frac{B(p+k,q)}{B(p,q)}$	$\frac{G(k+1).B(p+k,q)}{B(p,q)}$
Gamma	$\frac{G(a+k)}{G(a)}$	$\frac{G(a+k)G(k+1)}{G(a)}$
Inverse gamma	$\frac{G(a-k+1)}{G(a)}$	$\frac{G(k+1)G(a-k+1)}{G(a)}$
Beta 2nd kind	$\frac{B(p+k,q-k)}{B(p,q)}$	$\frac{G(k+1)B(p+k,q-k)}{B(p,q)}$

Table 2 : Estimators of one shape parameter laws with $C_1 = \frac{\hat{m}'_2}{2\hat{m}_1^2}$ and $g = b\,s^2$

I law	$\hat{g}$	$\hat{a}$
K	$\hat{m}'_1(C_1-1)$	$(C_1-1)^{-1}$
B	$\hat{m}'_1$	$\frac{1}{C_1}+1$

Table 3 : Estimators of two shape parameter laws with $C_1 = \frac{\hat{m}'_2}{2\hat{m}'^2_1}$ and $C_2 = \frac{\hat{m}'_3}{3\hat{m}'_1\,\hat{m}'_2}$

I law	$\hat{g}$	$\hat{p}$
U	$\hat{m}_1\frac{C_2(C_1-2)+C_1}{2C_1-C_2-1}$	$2\frac{C_1-C_2}{C_2(2-C_1)-C_1}$
W	$\hat{m}_1\frac{C_2(C_1-2)+C_1}{2C_1-C_2-1}$	$2\frac{C_1-C_2}{C_2(2-C_1)-C_1}$
I law	$\hat{q}$	
U	$\frac{4C_1-3C_2-1}{2C_1-C_2-1}$	
W	$\frac{2(C_1-C_2)(C_1-1)(C_2-1)}{(2C_1-C_2-1)(C_2(2-C_1)-C_1)}$	

VI. RESULTS

We now turn to the experimental evidence supporting our approach. It is not possible to review all of the existing experimental data and we shall confine our attention to a JERS1 image of Rondonie, which contains five classes with various textures (Fig. 2). This image is a 3 looks amplitude radar image with 512 by 512 pixels. Rondonie is a part of Amazonie where cultivation takes the place of the forest.

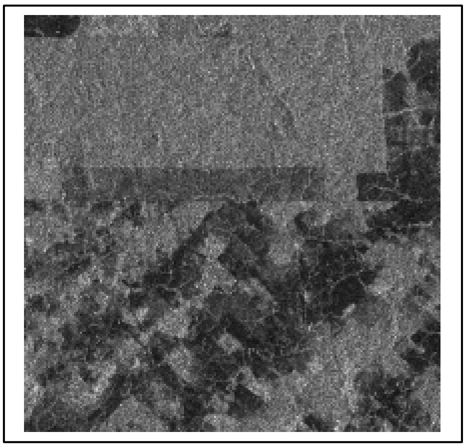


Fig. 2 : Image JERS1 of Rondonie

In Amazonie, the method of cultivation, called 'slash and burn', is made in the following way: first plots of dense forest are cut and burnt. Then, plots of burnt land are put in culture, and convert into meadows after two or three years. Then other plots of forest are cut, burned and transformed into cultivated land.

As the forest of Amazon is very dense, the structuring elements are small compared to the spatial resolution of the imaging system. In that case, the Rayleigh regime is suited. Meadows consist of pasture where various vegetation types cover old burnt plots. Because the cultivation is not yet mechanized, areas are divided in small plots whose size are several tenths of meters. The burnt plots contain homogeneous burnt vegetation.

For each class, the distributions of the intensity are compared to their histogram using the Kolmogorov-Smirnov fitting test. This test is based on the Kolmogorov statistic, which is a distance between the cumulative histogram F_n and the cumulative density function F:

$$d = \sqrt{n}\, \sup_x \left| F_n(x) - F(x) \right|$$

where n is the size of the sample.

For each class, table 4 gives estimates of the parameters for the K, U, B W and rayleigh regime distributions and the Kolmogorov distance between theoretical distributions and grey level histogram of each class.

Rayleigh regime

In table 4, let us note that the smaller the coefficient of variation is, the better is the adjustment to the histogram (Fig. 3). In burnt plots, where the vegetation is reduced to ashes, it is homogeneous and there is no fluctuation of the mean number of scatterers. In this case, the Rayleigh regime is adequate. For other classes, the fitting results are bad, probably because the Rayleigh regime assumptions are not fulfilled.

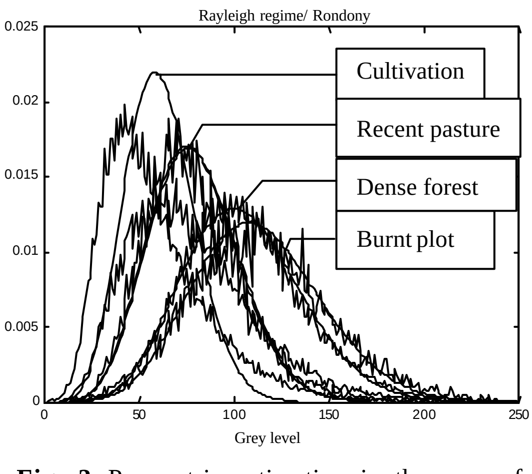
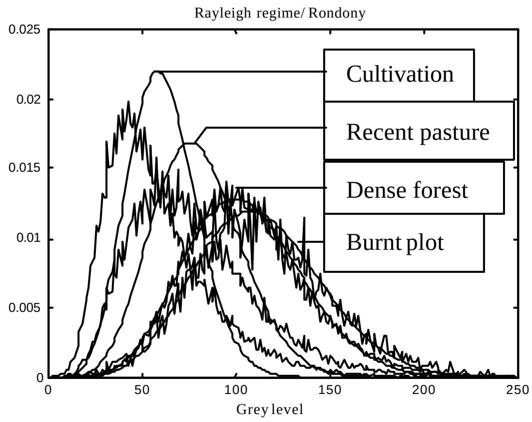


Fig. 3: Parametric estimation in the case of Rayleigh regime



fitting results in case of cultivation and dense forest but the K law is better for burnt plot and pasture.

W and U laws

W and U laws are both two-shape parameter laws. The K law is a limit case of both W and U distributions, and B law is only approximated by the U distribution. Let us note that the scale parameter estimators of U and W distributions have an opposite sign. Accordingly, if one can estimate an histogram by one law, the other cannot estimate the grey level distribution. Because they have two shape parameters, the laws are more flexible than B, K and Rayleigh regime laws (Fig. 6). Consequently, their Kolmogorov distances are the smallest for three classes.

Estimation of the number of scatterers probability density function

The estimation results allow us to predict the distribution of the number of scatterers for the four classes.

We show the best estimation of the distribution of the hidden number of scatterers accordingly to the Kolmogorov distance (Tab. 4).

In Fig. 7, we can see that the distribution of dense forest is a Dirac mass. At the opposite, the distributions of the mean scatterer in the cases of cultivation and pasture have non-zero variance and a long tail. These properties come from the variability of the medium at the ground. In the case of burnt plots, the distribution converges toward the Dirac mass at location 15583. The graphs are thus in accordance with the theory. Indeed, only the pasture and cultivation plots have structural elements with approximately the same size as the spatial resolution of the imaging system.

Table 4: Estimated parameters and fitting results

	Burnt plot	Cultivat.	Dense forest	Recent pasture
Var. coeff.	0.329	0.489	0.311	0.436
		Rayleigh regime		
$l\ s^2$	13895	4095	11943	6915
d_n	**2.17**	**47.63**	**5.164**	**26.30**
		K law		
a	12.45	1.87	26.78	2.71
g	1115,8	2181,6	445.8	2544,9
d_n	**3.05**	**9.65**	**7.02**	**2.70**
		B law		
a	13.4	2.87	27.78	3.71
g	173020	7687	319930	18798
d_n	**3.23**	**8.16**	**6.83**	**6.73**
		W-U law		
	W	U	W	U
p	1.912	2.78	1.99	2.97
q	0.205	6.92	0.132	31.51
g	15385	8718.2	1273	73186
d_n	**1.27**	**6.37**	**7.02**	**2.432**

Table 5: Estimated parameters and fitting results

	Burnt plot	Cultivat.	Dense forest	Recent pasture
l law	Beta 1st kind	Beta 2nde kind	Const.	Beta 2nde kind
N law	Deg. hyp. 1st kind	Deg. hyp. 2nde kind	Poisson	Deg. hyp. 2nde kind
p	1.91	2.78	-	2.97
q	0.20	6.91	-	31.51
g	153	8718.2	-	73186
var	**1.278**	**6.374**	**-**	**2.432**

VII. CONCLUSION

In the course of this paper we have described how the dependency of the statistical properties of microwave returns from the ground can be built into a theoretical model in a consistent way.

The approach is based on the assumption that the illuminated surface can be regarded as a random number of scatterers giving randomly phased contribution to the far field. By modeling the mean number of scatterers by judicious compounding Poisson distributions, we have introduced a discrete distribution system for the number of scatterers and also a new system of distributions for the intensity of radar images. We have presented results for these probability distributions, and shown explicit dependency on the number of scatterers and illuminated area. The new system of intensity distributions, which includes the K law, has been used to fit experimental data. The explicit estimation method is given and fitting results are compared to those obtained for the K law and for the Rayleigh regime. When the size of structural elements at the observed surface is close to the spatial resolution of the radar, the fitting results show the pertinence of the new distributions families. At the opposite, when element are smaller than the spatial resolution, the Rayleigh regime gives better fitting results.

The proposed estimation method allows statistical modeling of the number of scatterers per resolution cell. This information about the ground surface could be helpful in further developments of detection, classification and pattern recognition algorithms.

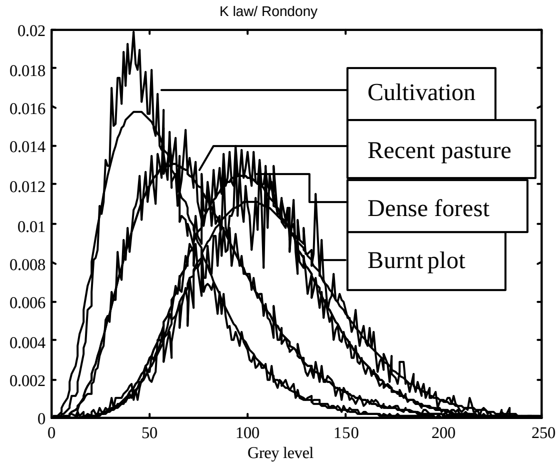


Fig. 4: Parametric estimation with the K law

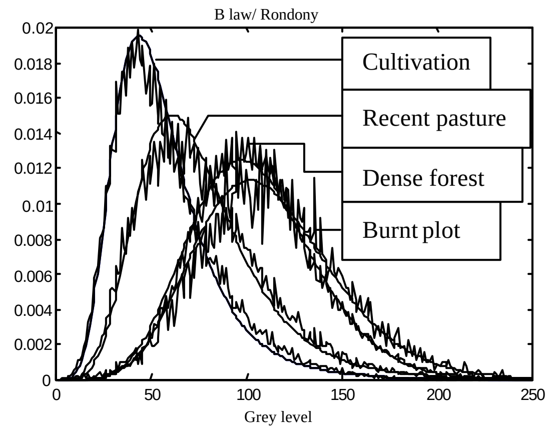


Fig. 5 : Parametric estimation with B law

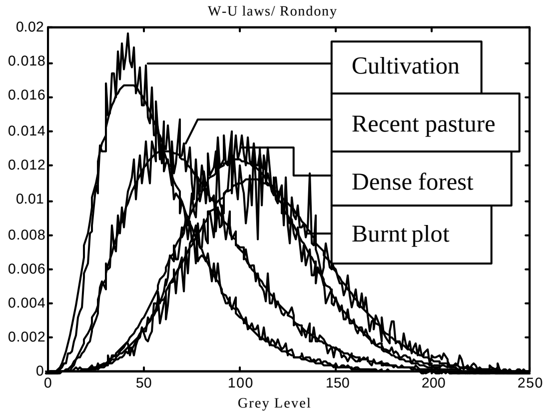


Fig. 6 : Parametric estimation with W and U laws

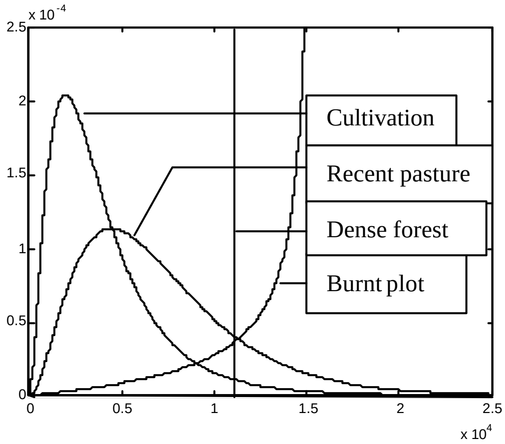


Fig. 7 : Distribution of the mean number of scatterers distributions

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