Scattering Properties of Electromagnetic Waves in Stratified air/vegetation/soil and air/snow/ice media : Modeling and Sensitivity Analysis

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Outline

- ***Motivation : Modeling and sensitivity analysis for radar data interpretation***

- ***Sensitivity analysis by means of Design of Experiment***

- ***Applications***

  Radiative transfer modeling for a forested medium and sensitivity analysis : example of the french project ERABLE

  M. Dechambre, A. Bosisio, et al.

  Radar altimetry over the antarctic ice sheet Modeling and Sensitivity analysis.

  M. Dechambre, P. Lacroix et al.

- ***Conclusion and perspectives***

Motivation

Mathematical representation of a physical phenomenon

Radiative transfer

Many input geophysical parameters,

Field approach

Electrical, geometrical input parameters

Prediction knowledge

Output

Radar cross section, emissivity, Attenuation in the medium, altimetric waveform parameter..

inversion

Some Input parameters

Problem : Wave-medium interaction modeling

Several physical scattering models have been obviously developed with the double objective of:

- Increasing the knowledge of waves and natural medium interaction processes
- Predicting σ_0 (radar cross section) and A (attenuation), e (emissivity)

Some complex problems make these models difficult to validate and to use as predicting tools.

- Description of a stratified medium, vegetation canopies, snow and ice, soils, …
- Measurements of the geophysical parameters with a sufficient accuracy allowing to get representative values
- Large number of input parameters → reduction depending on their relevance

Parameter reduction : Sensitivity analysis (SA)

Sensitivity analysis of a model output (SA) is a valuable tool in building of models:

- ***Help in verifying that the response of a model to its inputs conforms the theory***
- ***Assist in the model calibration process, by optimizing the experimental conditions most suited to the determination of a given unknown factor***
- ***Help to decide to what extend the existing uncertainties allow a given mechanism to be unambiguously identified when testing different mechanisms against available evidence***
- ***Make statements about the relative importance of input factors. Build a statistical model***

Sensitivity analysis (SA)
Choice of an experimental design method

Often the full potentiel of SA is not exploited and that, in some instances, SA is used improperly, especially when making statements about the relative importance of input factors.

First choice

Changing one factor at a time (OAT) and the factors are not dependent on each other
The baseline value is kept constant, the factors are moved away from the baseline only once or twice and the baseline is not changed throughout the analysis.
While this approach is easy to implement, not time consuming, and useful to provide a glance at the model behaviour, it is limited

OAT

essai		A	B	C	D	E	F	G	H	I	Résultat de l'essai
		Facteurs essayés									
1		1	1	1	1	1	1	1	1	1	R1
2		2	1	1	1	1	1	1	1	1	R2
3		1	2	1	1	1	1	1	1	1	R3
4		1	1	2	1	1	1	1	1	1	R4
5		1	1	1	2	1	1	1	1	1	R5
6		1	1	1	1	2	1	1	1	1	R6
7		1	1	1	1	1	2	1	1	1	R7
8		1	1	1	1	1	1	2	1	1	R8
9		1	1	1	1	1	1	1	2	1	R9
10		1	1	1	1	1	1	1	1	2	R10

Tab.III.1 - plan d'expérience ne faisant varier qu'un facteur à la fois

Each level (value) of each factor is only tested one time versus a single configuration of the different levels (values) of the other factors

Sensitivity analysis (SA)
The experimental design method

New choice

***An experimental design** is a series of tests completely organized in advance in order to determine with the least possible amount of tests and the highest precision, the influence of the different input parameters possible in order to optimize the results of the system itself*

It is not necessary to understand anymore before acting; a methodical observation is sufficient. The physical model can be understood as being a BLACK BOX on which the inputs or factors act.

Tables of experiment are built, they are conceived for an experimental use in order to conduct test and quality control at a least cost

Sensitivity analysis (SA)
Choice of the experimental table (1)

The insufficiencies of the OAT method, can be eliminated using a full factorial table or a fractional table.

Full factorial tables : these tables study all the possible combinations of the factor levels.

They are theoretically perfect but time consuming, particularly when the model is time consuming by itself.

For instance, if a model has 19 input parameters and each one has 2 levels (2 values) the number of tests is 2^{19}.

Sensitivity analysis (SA)
Choice of the experimental table (2)

Fractional orthogonal tables ***: it was observed that some tests contribute more efficiently than others. These tables unable the analysis of a subset of the complete model. The quality of the model is conditioned by the structure of predict combinations not realized. The construction of the fraction table is based on the notion of orthogonality, i.e., each level of each parameter is combined with each level of the other factors and this, an equal number of times.***

There is not only one self sufficient algebraic process for building an orthogonal table but only a subset of known tables represented in test matrix form. This matrix is made up to the list of the factor levels, defined in advance, that are necessary in order to obtain test results that can be analyzed.

In such a way, the contribution of each term can be isolated

Fractional orthogonal table

essai		A	B	C	D	E	F	G	Résultat de l'essai
		Facteurs essayés							
1		1	1	1	1	1	1	1	R1
2		1	1	1	2	2	2	2	R2
3		1	2	2	1	1	2	2	R3
4		1	2	2	2	2	1	1	R4
5		2	1	2	1	2	1	2	R5
6		2	1	2	2	1	2	1	R6
7		2	2	1	1	2	2	1	R7
8		2	2	1	2	1	1	2	R8

Tab.III.2 - Plan factoriel fractionnaire de 7 facteurs à 2 niveaux

Example of 7 factors (input parameters) each of them with 2 levels (values)

Each level of each factor is combined with each level of the others factors in an equal number of test

Sensitivity analysis (SA)
How to build the experimental fractional table ?

The tuning of a fractional table is a matter of specialist

Taguchi approach and tools : a subset of known standard tables computed in advance and other useful tools are proposed. The complex statistical aspect of the experimental design construction is simplified or discarded.

- Interesting and method easy to implement for non specialists
- Limited but interesting results and used as a preparation to a more elaborated method of design of experiment.

••Interaction between factors are not taken into account

••Impossible to build a statistical model

Tagushi tools : example

Position of the problem, an example:
we want to improve the quality of roof tiles produced in an imperfect oven without changing this oven.
Solution :
Change the composition, the size, etc.. of the tiles, i. e. acting on them
How to make the best choice?

Make a lot of tests by changing the values of the input parameters in an organized way defined in advance

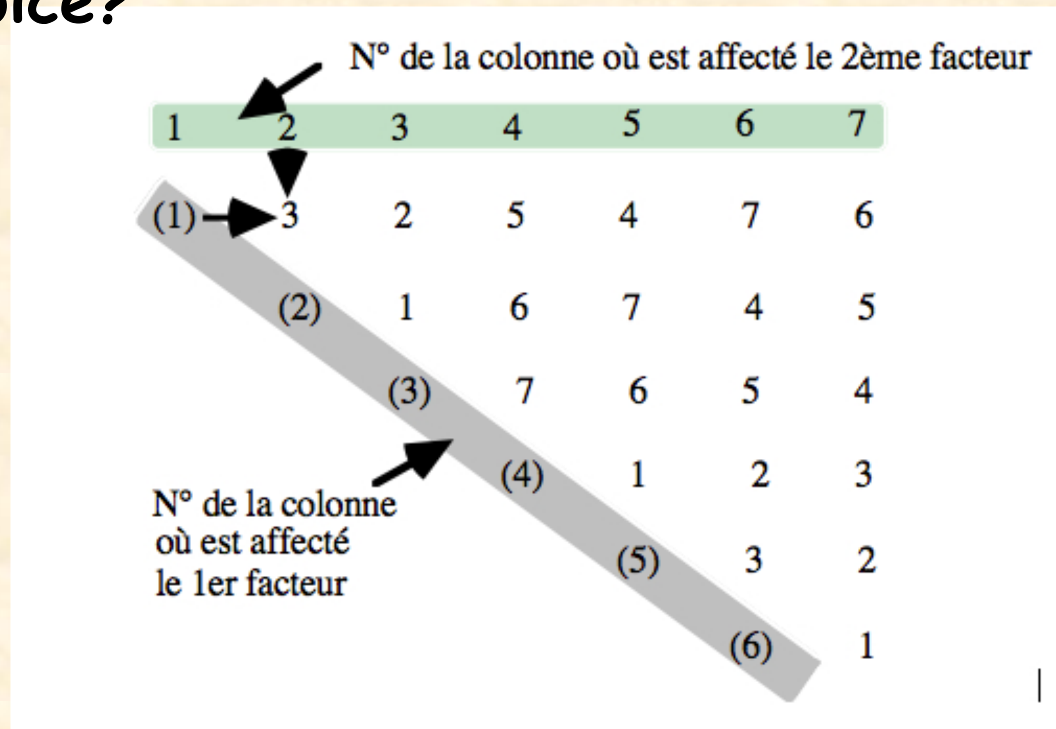


Fig.III.2 - Table triangulaire pour la matrice L_8

Implementation of the Experimental Design Method

The implementation is split into 3 parts :

- Choosing the input factors, they coincide with the model input parameters or the experimental design inputs
  → number of factors

- Defining the number of values of each input parameter
→ number of levels of each factor

- Choosing the experimental table
→ given by a specialist or taken in the Tagushi package

Processing and interpreting the results: 2 applications

- Scattering and attenuation measurements of electromagnetic waves over a forested area
- Modeling and validation of the radar altimetric echo over the Antarctica ice sheet

First application

Measurement and modeling of the attenuation of waves in a forested controlled area

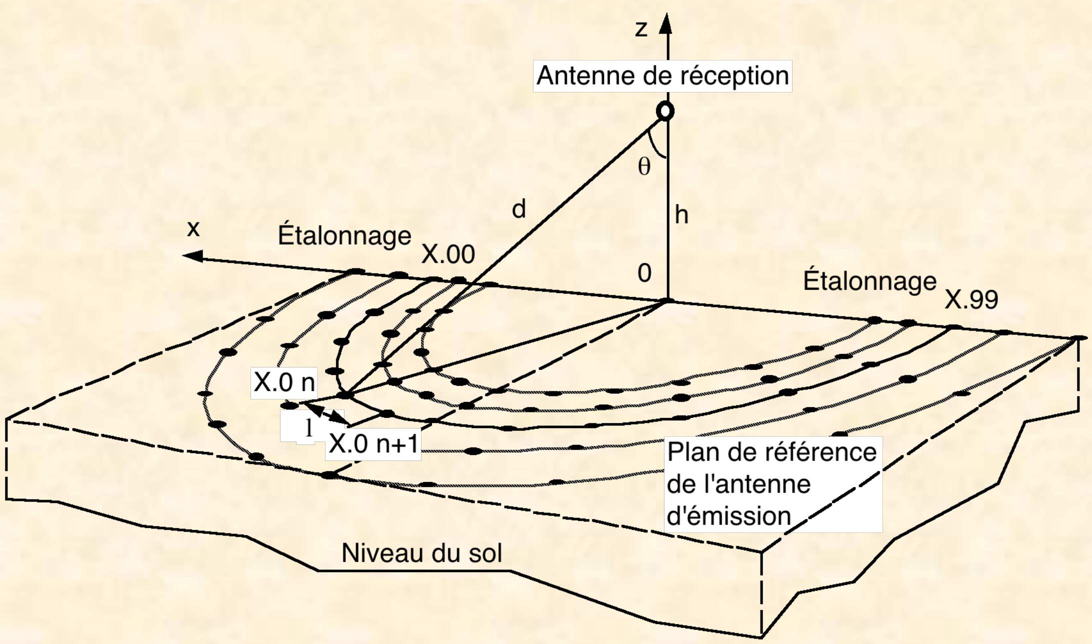
M. Dechambre, A. Bosisio, et al

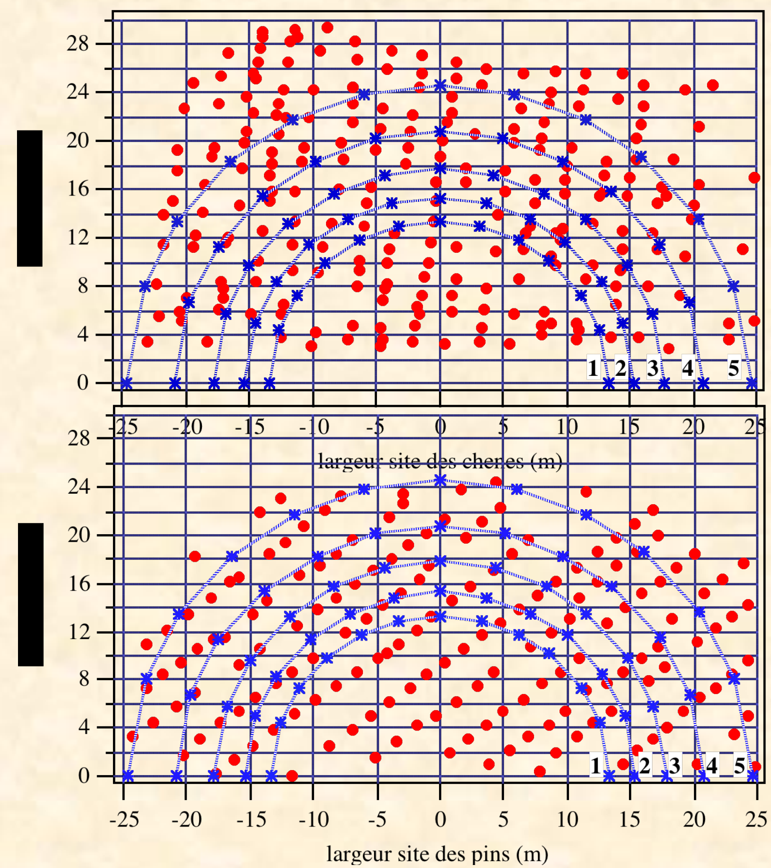
The inputs were measured during French the ERABLE experiment.

The values of the parameters tested in the SA method are within the variance interval of each factor

The experimental project : ERABLE

- *Small scale radar experiments over controlled oak and pine stands during summer and winter*
- *Ground measurements of the vegetation characteristics*
- *Radar cross section and attenuation measurements*
- *2.2 GHz (S) and 5.8 GHz (C)*
- *HH and VV polarization*
- *5 incidence angles*





The experimental setup

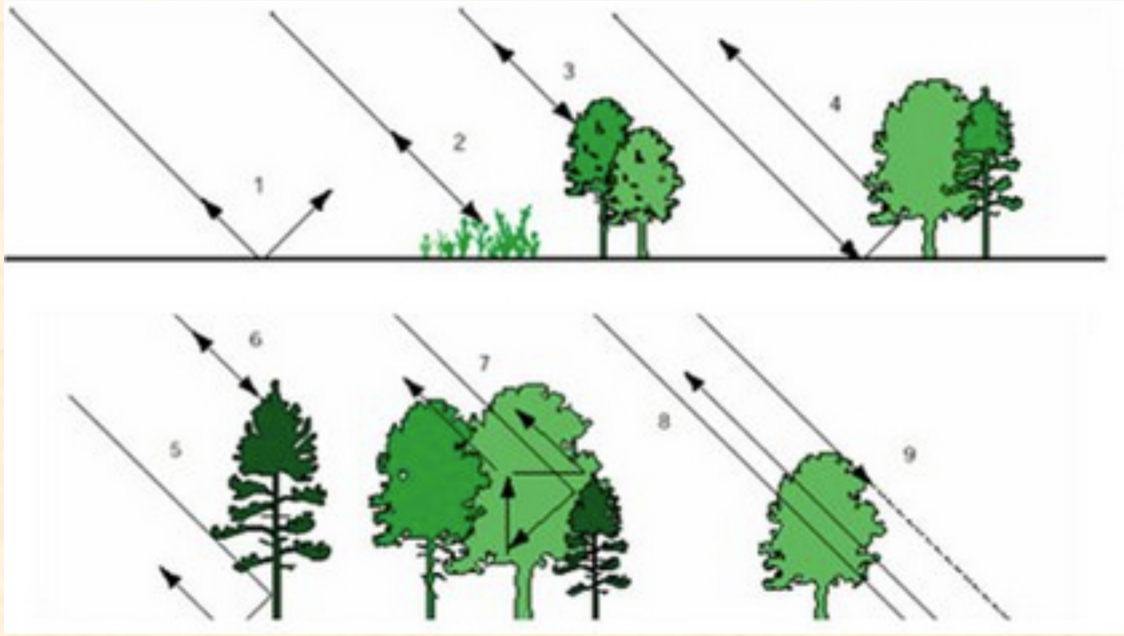
Ground measurements
Antenna pointing

The scattering Model : MIMICS (Ulaby and al.)

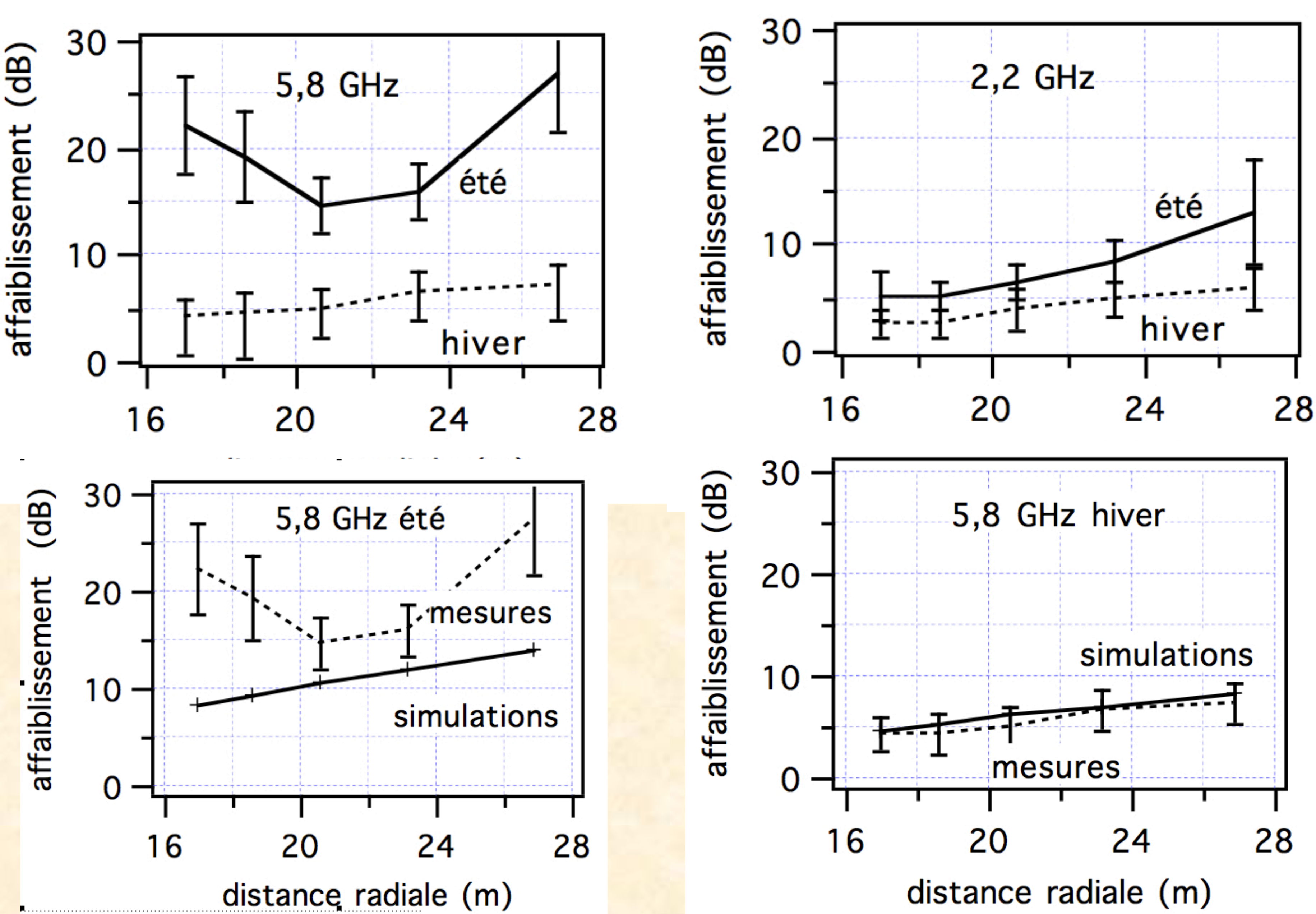
Main characteristics of MIMICS

•First order backscattering model based on a radiative transfer approach. The vegetation (forest) is modeled as a 2 layers random medium composed of small discrete scatterers and limited by a random rough surface

• 19 input parameters
geometrical parameters
dielectric parameters
• 2 output parameters
radar cross section
Attenuation



Measurement results – oak trees
Model validation



Application of the Experimental Design Method

The inputs were measured during the ERABLE experiment. The levels are within the variance interval of each factor

MIMICS input parameters and their levels

factors	winter		summer	
Tree density #/m^2	A	0.168 / 0.173	A	0.168 / 0.173
Trunk diameter cm	C	7.73 / 8.73	C	7.73 / 8.73
sture %	D	0.35 / 0.37	D	Id branches
Crown thickness m	B	4.8 / 4.85 / 4.9 / 4.95	B	4.8 / 4.9
Branch length m	G	2 / 2.1	G	2 / 2.1
Branch diameter cm	H	2/ 2.02/ 2.04/ 2.06	H	2 / 2.2
Branch density #/m^3	I	1.5/ 1.53/ 1.55/ 1.57	I	1.5 / 1.6
Branch orientation °	F	60° / 65 °	F	60° / 65°
Branch moisture %	E	0.35 / 0.37	E	0.42 / 0.44
Leaf thickness mm			J	0.215 / 0.230
Leaf diameter cm			K	6.18 / 6.38
Leaf density #/m^3			M	422 / 425 / 435 / 445
Leaf orientation			N	sin(i)
Leaf moisture %			L	0.42 / 0.44

Application of the Experimental Design Method

The inputs were measured during the ERABLE experiment. The levels of are within the variance interval of each factor : Experiment matrix from Tagushi

$L_{16}(6^2 \times 3^4)$ $L_{16}(12^2 \times 1^4)$

Trials	WIN	A	B	C	D	E	F	G	H	I	SU.	A	B	C	D	E	F	G	H	I	J	K	L	M
1		1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1	1	1	1	1
2		1	1	1	1	2	2	2	2	2		1	1	1	1	1	1	2	2	2	2	2	2	2
3		1	1	1	2	1	2	3	3	3		1	1	1	2	2	2	1	1	1	2	2	2	3
4		1	1	1	2	2	1	4	4	4		1	1	1	2	2	2	2	2	2	1	1	1	4
5		1	2	2	1	1	1	1	3	4		1	2	2	1	1	2	1	1	2	1	2	2	4
6		1	2	2	1	2	2	2	4	3		1	2	2	1	1	2	2	2	1	2	1	1	3
7		1	2	2	2	1	2	3	1	2		1	2	2	2	2	1	1	1	2	2	1	1	2
8		1	2	2	2	2	1	4	2	1		1	2	2	2	2	1	2	2	1	1	2	2	1
9		2	1	2	1	1	1	1	4	2		2	1	2	1	2	2	1	2	1	1	1	2	2
10		2	1	2	1	2	2	2	3	1		2	1	2	1	2	2	2	1	2	2	2	1	1
11		2	1	2	2	1	2	3	2	4		2	1	2	2	1	1	1	2	1	2	2	1	4
12		2	1	2	2	2	1	4	1	3		2	1	2	2	1	1	2	1	2	1	1	2	3
13		2	2	1	1	1	1	1	2	3		2	2	1	1	2	1	1	2	2	1	2	1	3
14		2	2	1	1	2	2	2	1	4		2	2	1	1	2	1	2	1	1	2	1	2	4
15		2	2	1	2	1	2	3	4	1		2	2	1	2	1	2	1	2	2	2	1	2	1
16		2	2	1	2	2	1	4	3	2		2	2	1	2	1	2	2	1	1	1	2	1	2

Data processing

The average response for each factor level corresponds to the average result of all the tests where the factor is at this level

$$\overline{A_1} = \sum_{i=1}^{8} E_i \qquad \overline{A_2} = \sum_{i=9}^{16} E_i$$

Averages are calculated for each controlled factor and for each of their respective levels.
The general average T for the set of tests corresponds to the central point of the average responses for each factor level,

$$\overline{T} = \overline{A}_1 + \overline{A}_2 / 2$$

and the average effect of each factor level is calculated against the general average.
For instance, the average effect of A to the level 1 and 2 are

$$E_{A_1} = \overline{A}_1 - \overline{T} \qquad E_{A_2} = \overline{A}_2 - \overline{T}$$

with obviously

$$\overline{E}_{A_1} = -\overline{E}_{A_2}$$

Sensitivity analysis results

Effects of the different parameters and interaction between them

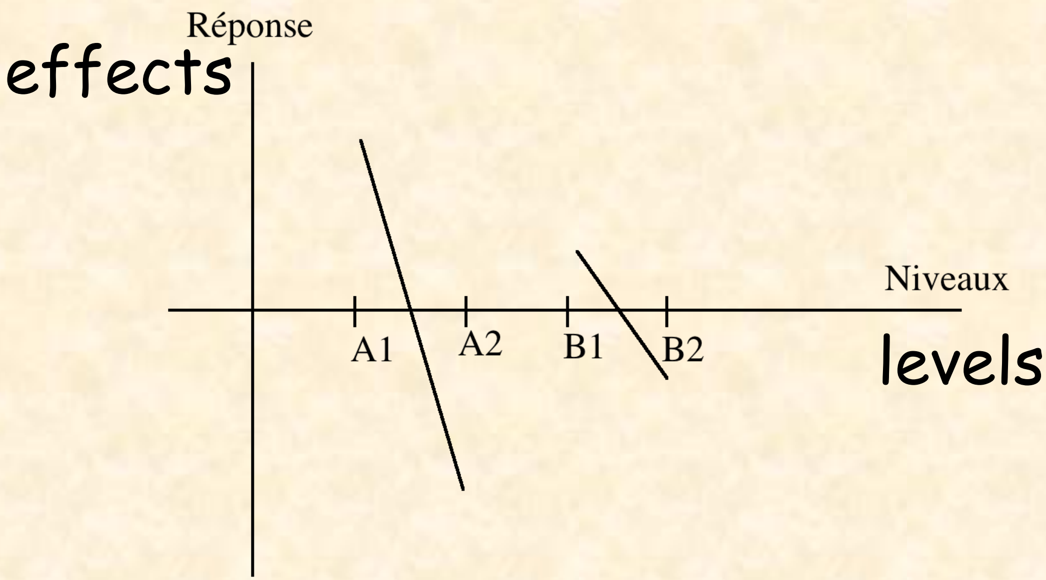


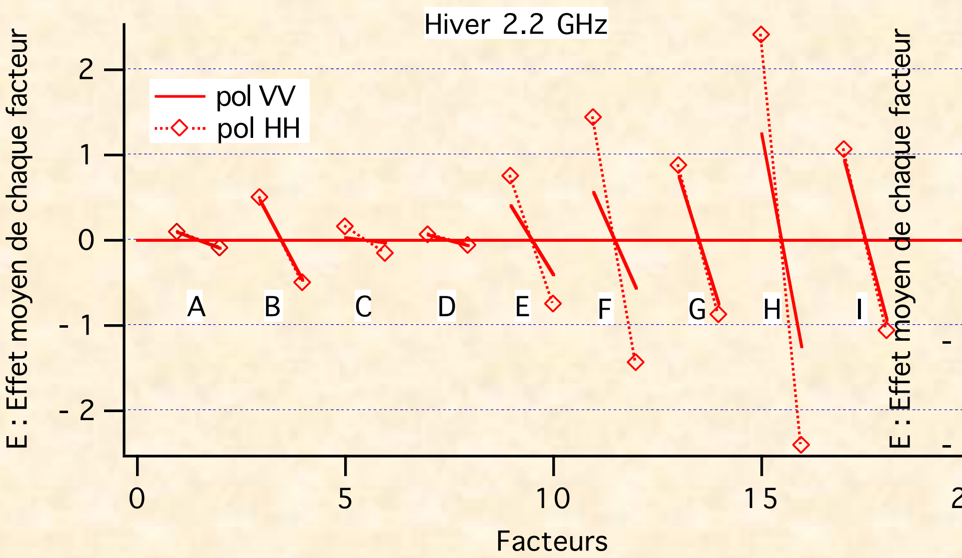
Fig.III.1 - Interaction entre les facteurs A et B

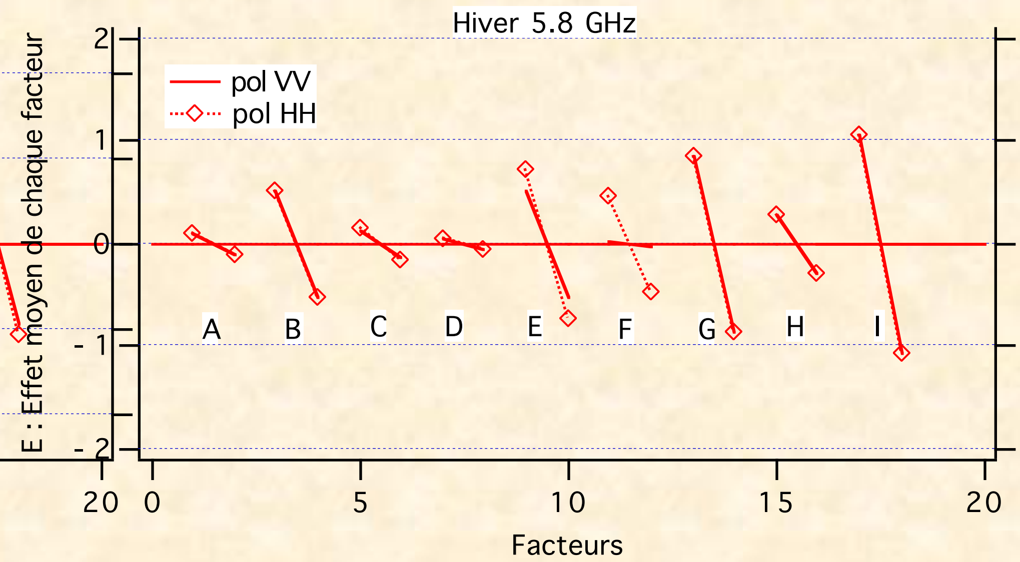
The interaction is the difference between the slopes representing the factor sensitivities.

Difference = 0 → no interaction

Difference ≠ 0 → interaction between A and B, ….

Results in winter





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Branch diameter cm	H	2/ 2.02/ 2.04/ 2.06	H	2 / 2.2
Branch density #/m³	I	1.5/ 1.53/ 1.55/ 1.57	I	1.5 / 1.6
Branch orientation °	F	60° / 65 °	F	60° / 65°
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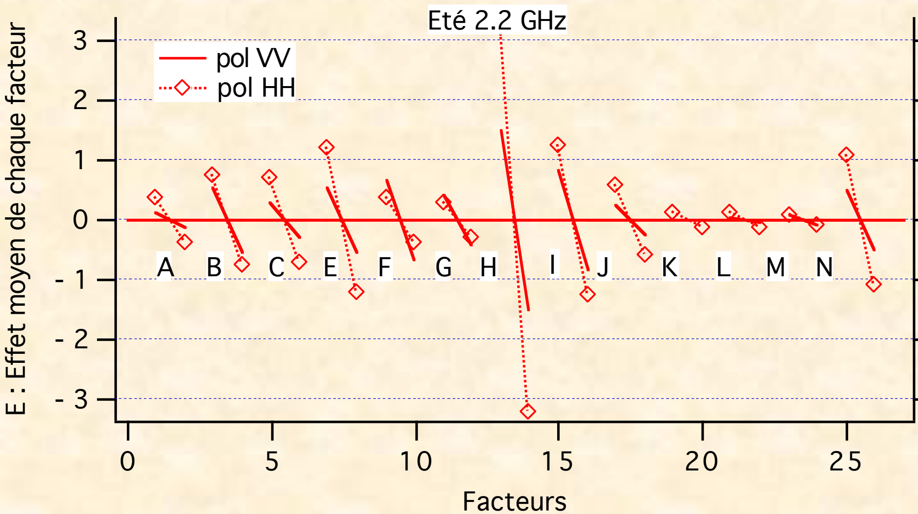
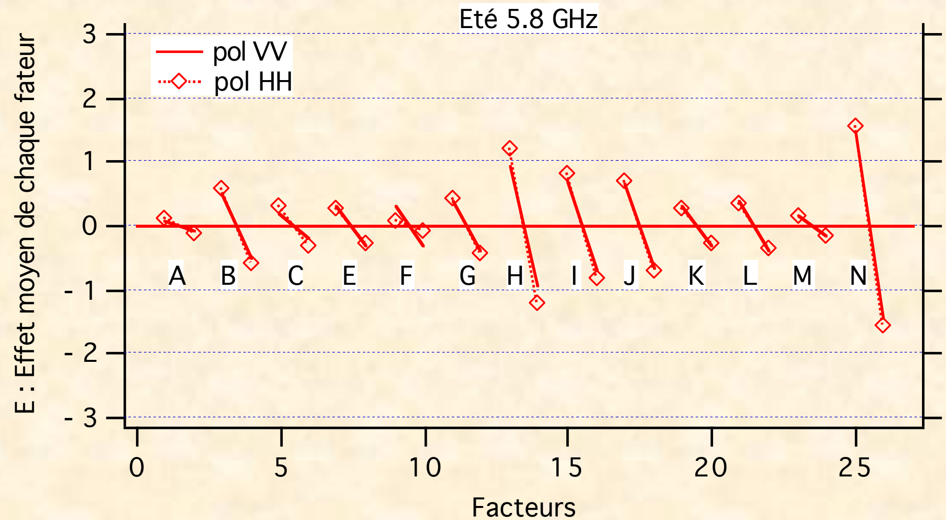
Leaf diameter cm			K	6.18 / 6.38
Leaf density #/m³			M	422 / 425 / 435 / 445
Leaf orientation			N	sin(i)
Leaf moisture %			L	0.42 / 0.44

9 parameters

Results in summer





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Leaf density #/m³			M	422 / 425 / 435 / 445
Leaf orientation			N	sin(i)
Leaf moisture %			L	0.42 / 0.44

13 parameters

Summary of results (1)

Winter:

- The importance of the parameters linked to the branch characteristics, mostly at 2.2 GHz confirms experimental results. Therefore, it is not surprising that the effect of branches orientation is notably more perceptible at this frequency.
- The chosen distribution of leave orientation leads to orientations ranging from 20° to 50° off the vertical; this corresponds quite well to the oak structure in the stand and can explain more sensitivity to horizontal polarization.
- The study of parameter "trees' density" leads us to think that it is not essential. Nevertheless, observed saturation on biomass retrieval at those frequencies confirm this point.

Summer :

- The contribution of leaves is more important at 5.8 than at 2.2GHz. This results confirm the experimental ones.
- The most pertinent parameter seems to be the orientation of leaves.

Summary of results (2)

This study leads us to point out that globally, polarization does not seem to have an effect on most of the parameters whatever the frequency and season. The branches orientation only seems to depend on polarization.

The SA, also, underscores a more important influence of the geometrical parameters whose measurements and analysis are unfortunately more complex to restitute.

In addition, the influence of water content seems weak, a more surprising result, to be confirmed.

At the end, this study confirms mostly experimental results and the weak contribution of trunks, a result well described by MIMICS.

Second application

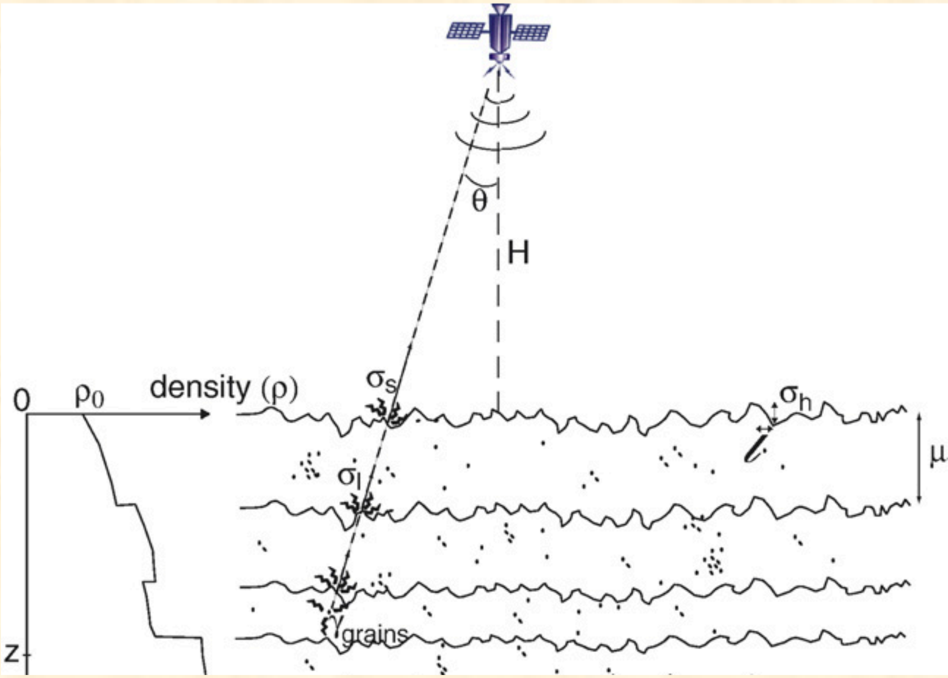
Measurement and modeling of the altimetric waveform in Antarctica

M. Dechambre, P. Lacroix et al.

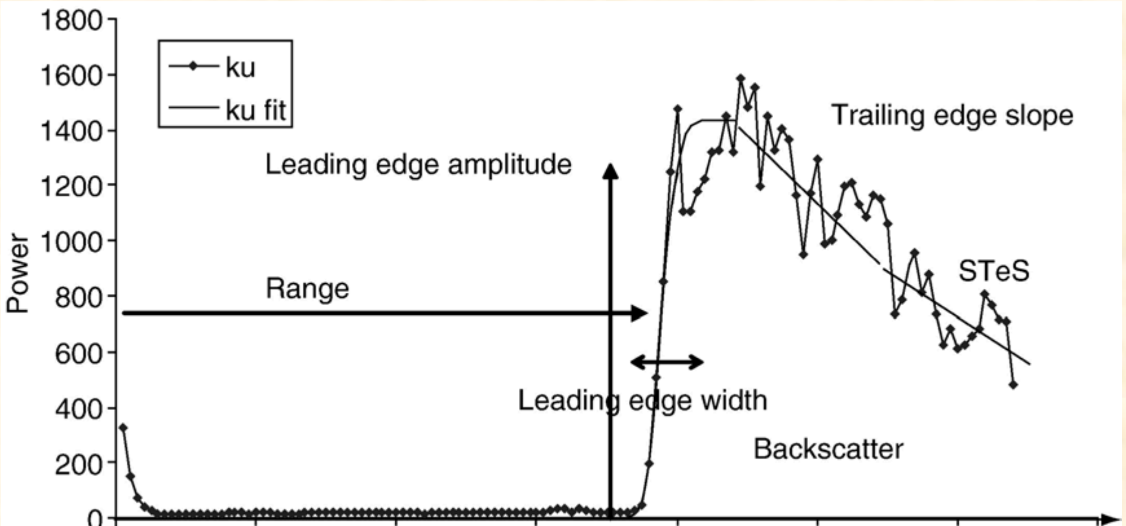
The measurement setup

ENVISAT RA-2 dual frequency Radar altimeter
S (3.2 GHz) Ku (13.6 GHz)

Stratified snow medium with a density and temperature gradient and rough interfaces



The altimetric waveform : 3 output parameters



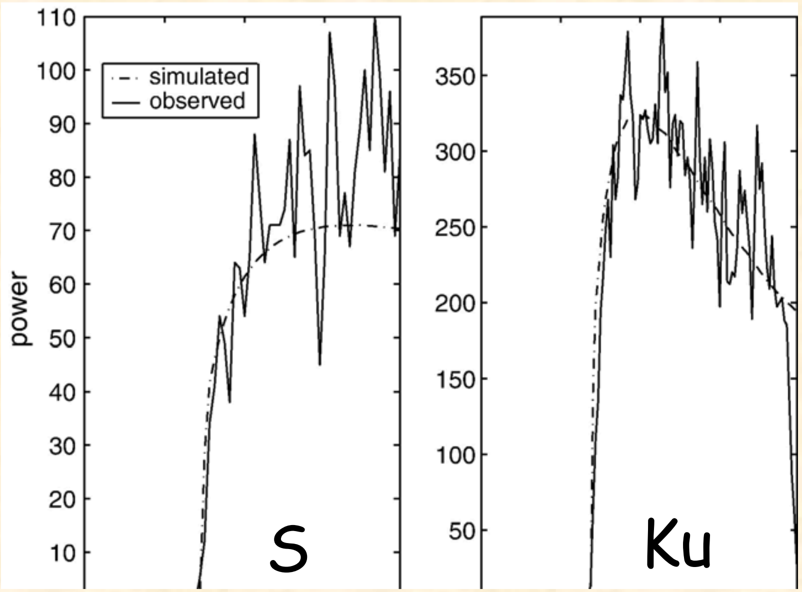
Sensitivity analysis (SA)
Altimetric waveform modeling (P. Lacroix et al.)

The model combines a surface model with a sub-surface one, for both the S (3.2 GHz) and Ku 13.6 GHz) bands.

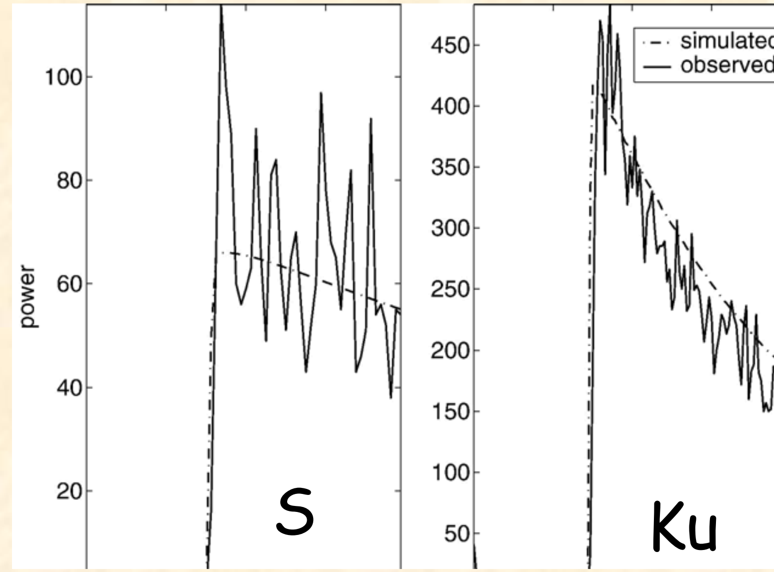
- The Brown's model is used to describe the interaction of the radar wave with the snow surface.
- The backscatter coefficient of the rough surface is derived using the IEM method.
- The sub-surface signal takes into account both the layering effects and the scattering caused by the homogeneous media which is composed of small snow grains.

Model validation

Vostok lake



Dronning Maud

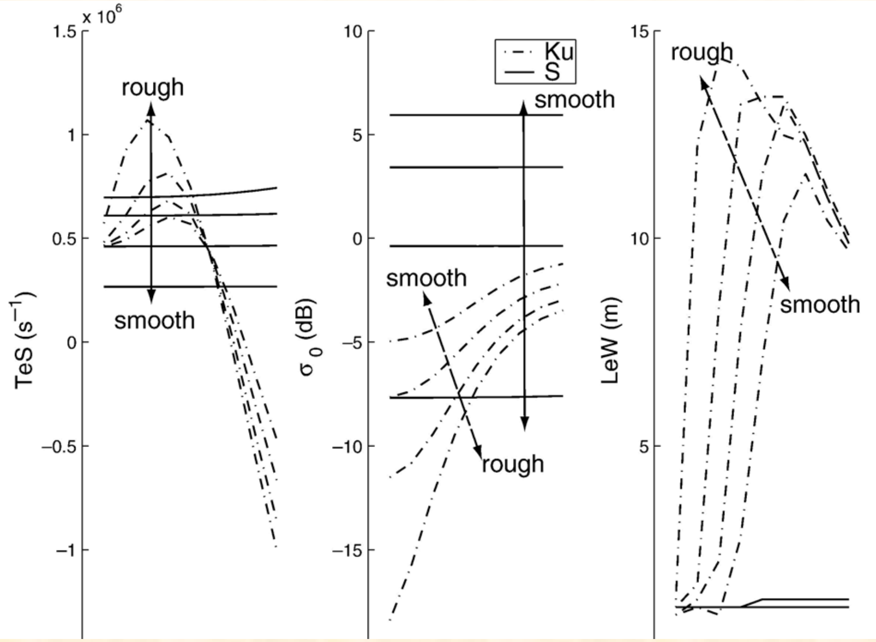


Waveforms observed (solid) and modelled (dashed)

The model is tested in 2 areas of the Antarctic plateau which present very different waveform parameters

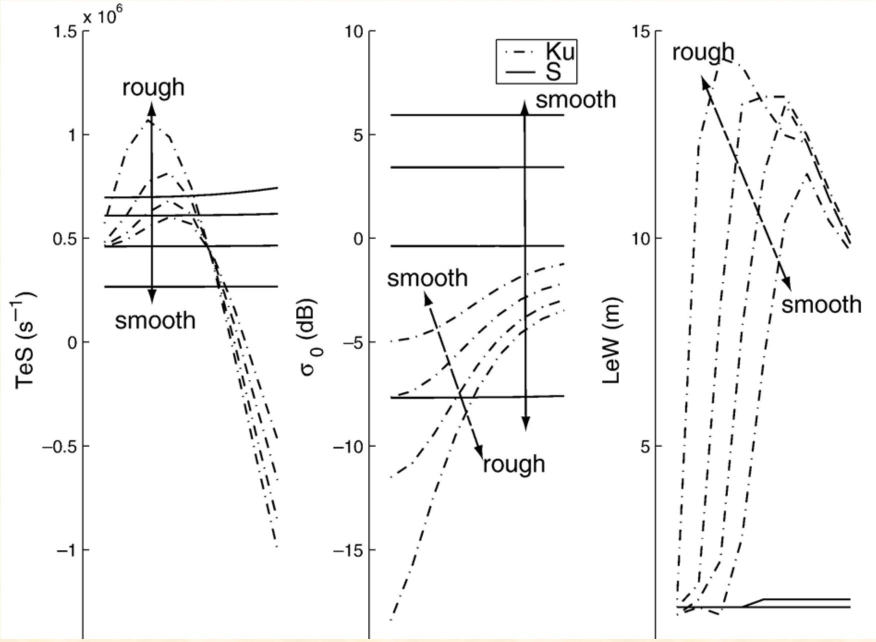
Sensitivity analysis (OAT)

Grain size



Trailing *backscatter* *leading*

Surface density



Trailing *backscatter* *leading*

The sensitivity of the radar signal to the different snowpack properties is investigated.

Sensitivity analysis (SA) with an experiment design method

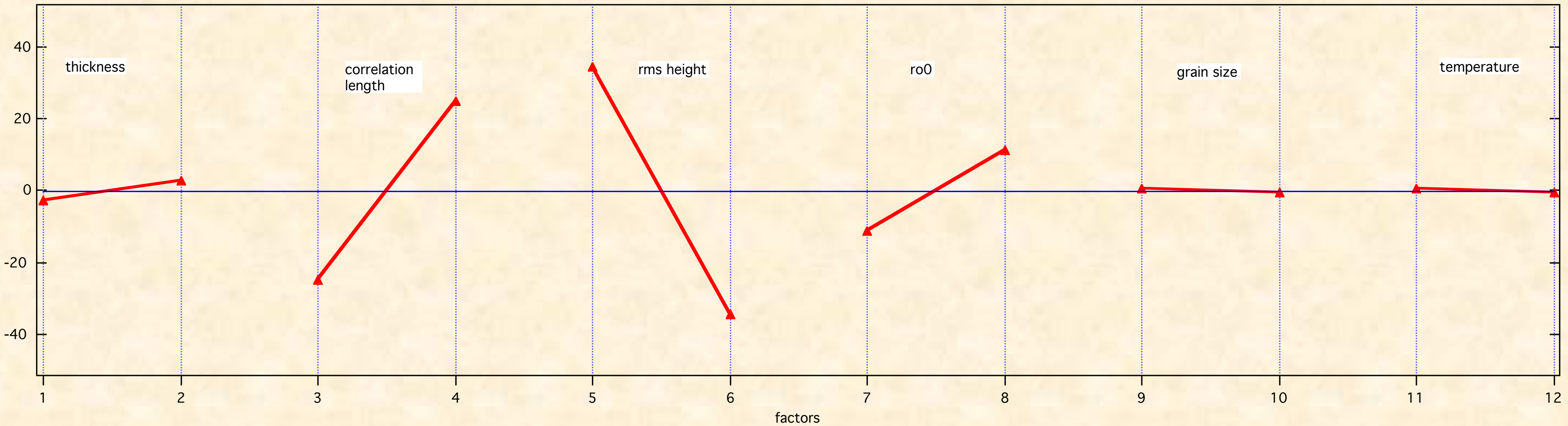
Input parameters

band	1=Ku, 2=S
mode	mode=1 grain size depends on z,
	mode=2 grain size profile is constant
$\rho 01$ $\rho 02$	snow density
a b c d	$\rho(z)=a.z+b.z\hat{}2+c\hat{}3+d\hat{}4+\rho 0$
$\sigma h1$ $\sigma h2$	rms height (roughness)
l1 l2	correlation length
T1 T2 pasT	temperature
$\Phi g01$ $\Phi g02$ pasΦg	
$\mu 1$ $\mu 2$ nbμ	nbμ défini le nombre de valeurs à prendre entre les 2 bornes
layers	0 no heterogeneities 1 layering
D	layer thickness
topo	surface slope in degrees

Sensitivity analysis 6 parameters for the 3 waveform parameters

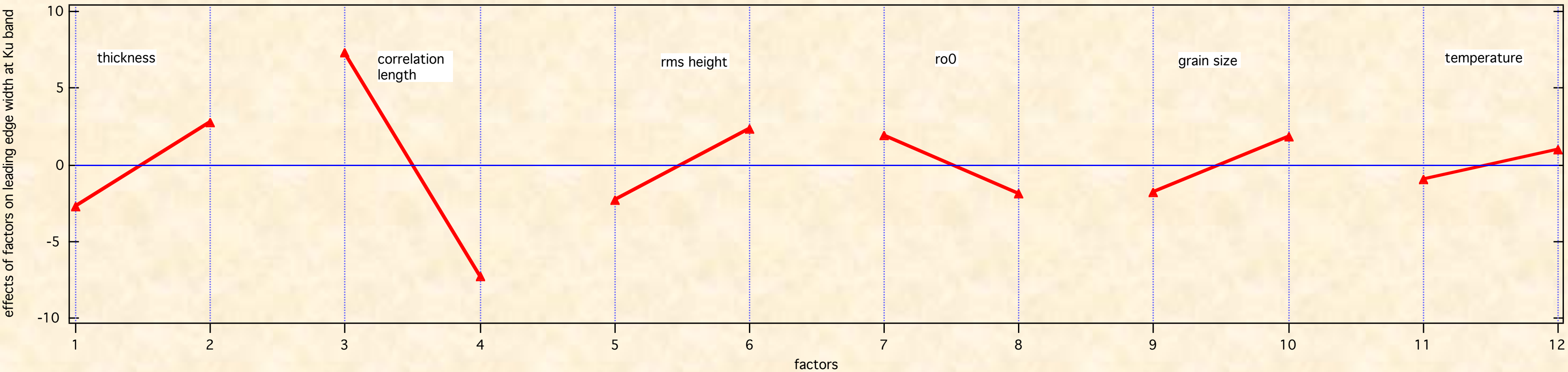
Sensitivity analysis (SA)
Backscattering : Radar cross section (linear)

effects of factors on the backscattering coefficient S-Band (linear)



effects of factors on the backscattering coefficient Ku-Band (linear)

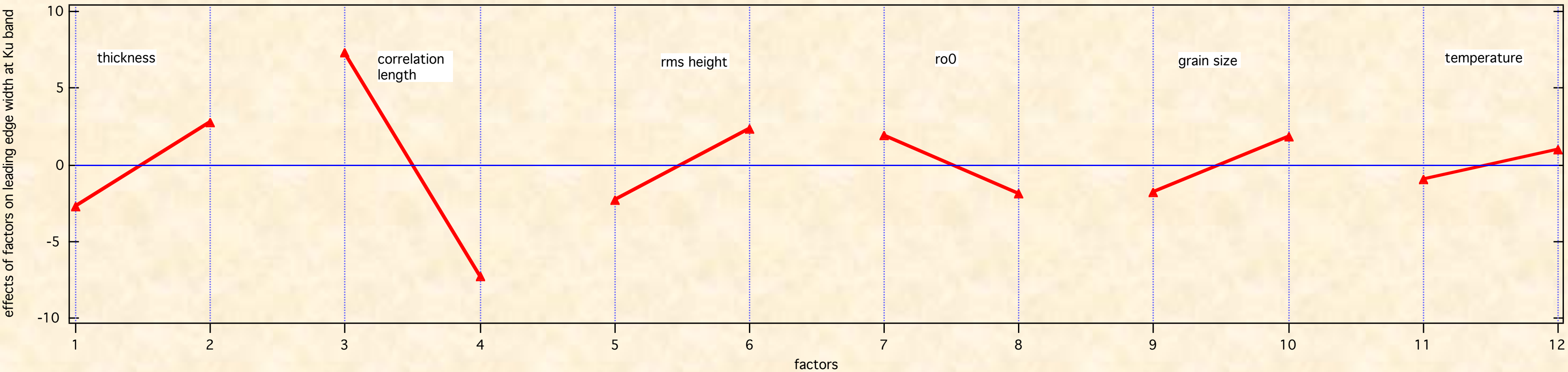
Sensitivity analysis (SA)
Trailing edge



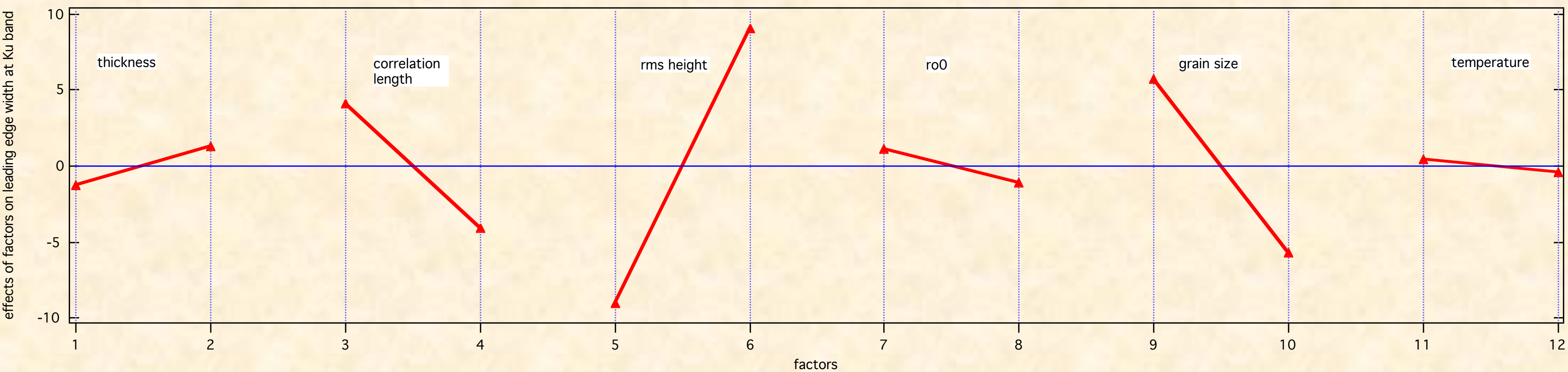
effects of factors on the Trailing Edge Slope at S-Band

effects of factors on the Trailing Edge Slope at Ku-Band

Sensitivity analysis (SA)
Leading edge



effects of factors on the Leading Edge Slope at S-Band



effects of factors on the Leading Edge Slope at Ku-Band

Summary of results

The roughness parameters are dominant whatever the parameter backscatter, leading and trailing edge

The grain size has no impact on the backscatter

The temperature has no influence

…

The method of the design of experiment must be applied with more accuracy before robust conclusions

Conclusion

Taguchi method has been used as a first approach to sensitivity analysis studies. It is a qualitative study

- *Easy to implement*
- *Limited*
- *Model validation*

Experimental design seems a good tool for numerical sensitivity analysis and validation

- *More complex experiment tables*
- *Interaction between input parameters*

- *Statistical modeling of the "black box" by multiple linear regression*

- *Model performance comparison*