FLAGGING THE TOPOGRAPHIC IMPACT ON THE SMOS SIGNAL

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1. INTRODUCTION

The European Space Agency Soil Moisture and Ocean Salinity (SMOS) mission aims at obtaining global maps of soil moisture (SM) and sea surface salinity (SSS) from space for large scales and climatic studies. It consists of a L-band (1400-1427 Mhz) passive sensor to measure the brightness temperatures (TB) of the Earth at horizontal and vertical polarizations, and for different viewing angles. In order to assess the soil moisture retrieval accuracy, it is necessary to identify and quantify the different error sources. The SMOS level 2 retrieval algorithms are based on the use of angular signatures. At SMOS scale (~40km), and for a pixel corresponding to a mountainous area, the surface can present various facets, with varying slopes and azimuth, inducing effects which can make, thereafter, the inversion impossible. The relief effects are twofold: first, the path between the target and the sensor depends on surface altitude, thus leading to a height-dependent atmospheric contribution. The second effect is due to the “macro roughness” which, through the slope distribution, induces the perturbing effects of shadowing or adjacency. Usually, this topographic component is not taken into account in the microwave signal modelling.

The objective of this study is to determine a method to estimate the mountainous area who impacted the SMOS signal. For this purpose, SRTM\(^1\) Digital Elevation Models (DEM) are used to characterise the topography and to simulate the brightness temperature coming from a mountainous area. The product of this study is a map who masks area where the topographic impact is greater that the instrumental precision specification.

\(^1\) Shuttle Radar Topography Mission
2. MATERIAL

The U.S. Geological Survey (USGS) is now distributing elevation data from the Shuttle Radar Topography Mission (SRTM). The SRTM is a joint project between the National Aeronautics and Space Administration (NASA) and the Geospatial-Intelligence Agency (NGA) to map the Earth's land surface in three dimensions. Flown aboard the NASA Space Shuttle Endeavour February 11-22, 2000, the SRTM collected data over 80 percent of the Earth's land surface, for most of the area between 60º N. and 56º S. latitude. The SRTM hardware included the Spaceborne Imaging Radar-C (SIR-C) and X-band Synthetic Aperture Radar (X-SAR) systems. The SRTM data were collected specifically with interferometry that allows image data from dual radar antennas to be processed for the extraction of ground heights. Data available to the data user community include 3-arc-second (approximately 90 m) data over the World. In this study, the used SRTM DEM are on the GeoTiff format\(^2\), in Geographic LAT/LON projection. For the global scale, there are 900 GeoTiff images with a size of 6000x6000 pixels, which corresponds to 5°x5°. For this study, we work only on a zone centred on France and represented on Figure 1.

\(^2\) The used DEM were downloaded on the site of the Consortium for Spatial Information (CGIAR-CSI) http://srtm.csi.cgiar.org/.
3. METHODOLOGY

3.1 CHARACTERISATION OF THE TOPOLOGY

To obtain the masked map, it is necessary to rely the effect of the relief on the brightness temperature to the topography. A way to characterise spatially the topography simply must be found. Previous studies try to cover the point of topography [Kerr04], [Matzler98], [Dozier90], where it is characterised by geomorphologic features, especially the slope distribution. This one depends on the difference of the altitude between each point of the DEM and its spatial resolution. This is illustrated by Figure 2 for three characteristics zones of 36x36 km².

Figure 1: SRTM Digital Elevation Model of France.

The Plain area is characterised by low slope (less than 10°), and mountainous area by high values. Between these two types of distribution, we can distinguish zone of piedmont plain, with more varied values of slope. The representation of its distribution makes it possible to distinguish these types of relief (Figure 2). The difference between the three distributions is illustrated by the mean value. In the Figure 2, the plain area presents a mean value less than 2°, the piedmont plain close to 10° (much value close to 1° but also high values), and a higher value, than 20°, for the mountainous area. The plain is also characterised by a low variance and the piedmont plain by a high variance due to the more important number of type of slope. For mountain, the variance is lower than that of the piedmont, because the slopes are concentrated on high values. So, the variance of the slope distribution doesn't constitute a good parameter for the characterization of the topography.
Figure 2: Slope distribution example for three types of area in the French Alps: (a) Plain (b) Piedmont Plain and (c) Mountain.

For such purpose, we proposed the use of a tool of geomorphologic analysis of landscape, the variogram [Tate98]. McClean [McClean00] showed that the variogram proves to be a simple to use, and relatively easy to interpret, method for considering land surface relief. Semivariance analysis is an effective tool to study the effect of scale on landscape organisation because the variance of landscape properties is treated as a function of the
scale. If semivariance increases with sampling interval, the landscape property is spatially
dependent or spatially autocorrelated. The range of scales where spatial dependence is
present can be identified from a plot of semivariance against the sampling interval \( h \) (Figure
3). The variogram \( \gamma(h) \) of an image is the estimation of the average variance of the pixel
value of two points, separate by a number of \( h \) pixel:

\[
\gamma(h) = \frac{1}{2} E \left[ s(p+h) - s(p) \right]^2
\]

where \( s(p) \) is the value of the pixel \( p=(x,y) \), and \( E \) is an estimation of the mathematical
expectation.

\[ \gamma(h) \]

\[ \text{Sill} \]

\[ \text{Nugget } C_0 \]

\[ \text{Range } a \]

\[ h \]

\[ \text{No correlation} \]

\[ \text{Increasing variability} \]

Figure 3: Variogram and its properties

The variogram of an image has remarkable properties (Figure 3):
1. it varies from zero (or a constant value, the nugget \( C_0 \)) to an asymptote (the sill)
   which is the variance of the image.
2. the tangent at the origin cut the asymptote for a X-coordinate which is the classical
correlation length (the range \( a \)).

For many natural phenomena, the semivariance tends to increase with sampling intervals.
After it reaches a maximum value, the semivariance levels off or the sill. On landscape
analysis, the variogram is used to model scene like forest, urban or agricultural areas, for
example. For each type of texture corresponds a form or class of variogram. For most
geospatial procedures, a mathematical model must be fitted to the variogram. To model
the different type of variogram, analytical models are used [Atkinson00]. Examples of the
more common models expressed mathematically and graphically are presented by Webster
and Oliver [Webster90] and three of them are presented in this study.

### 3.1.1 AFFINE MODELS

It's the most simple model:

\[
\gamma(h) = Ch + b
\]

(2)
This type of model is effective on a short range of $h$ variation, typically a few number of pixels ($h<10$).

### 3.1.2 EXPONENTIAL MODELS

For image with homogeneous texture, the variogram is usually modelled with an exponential function:

$$\gamma(h) = A(1 - e^{-Bh})$$

where $A$ is the image variance and $B$ is a texture parameter. It's an interesting model because it represents, with a good accuracy, scenes with homogeneous texture (for example agricultural area) and only with 2 parameters. But, this model is not sufficient to describe variogram with a significant tangent at the origin, which corresponds to very structured scenes. For these types of landscape, multi-exponential models are used:

$$\gamma(h) = A(1 - e^{-Bh}) + C(1 - e^{-Dh})$$

This model is valid for any type of image but requires the knowledge of four parameters.

The models presented above are too specific to a type of landscape (models (2)) or comprise too many parameters (models (4)). One of our objectives is to find a simple analytical model, representative of a significant number of scenes and with few numbers of parameter to characterise simply the topography. For these reasons, we selected, in a first time, the exponential model (3), which depends only on two parameters. But, as we have noticed, this function is adapted for scenes with homogeneous texture and is thus valid only for a certain number of spatial distribution.

### 3.1.3 FRACTALS AND POWER MODELS

The fractal describes the irregular patterns that possess no clear scale of variation. The degree of irregularity of a fractal form is usually expressed in terms of fractal dimension $D$, which possesses a non-integer value between the more familiar topological dimensions. The magnitude of $D$ is determined by the degree to which the fractal object is more irregular than a simple straight line. For example, a fractal dimension for a surface of $D=2$ should indicate a smooth surface with altitude variance concentrated at long wavelengths, while $D=3$ would represent a surface that is irregular in the extreme. Mandelbrot (1975) stated clearly his original views on fractional Brownian surfaces. They have the property that the differences in $s$ between points on such a surface constitute a zero mean Gaussian random function in two horizontal dimensions ($x$, $y$). This property of fractional Brownian surface has led directly to the use of the variogram method for investigating the fractal properties of land surfaces ([McClean00], [Bian93], [Klinkenberg92]). The power model of variogram is represented by:

$$\gamma(h) = Ch^{2H}$$
If the surface behaves as a fractional Brownian surface, the fractal dimension of the surface, D, is a linear function of H. Because the topography presents a fractal spatial distribution, this model is largely used for the simulation of steeper areas [Tate98]. Its utilisation is adapted for scene with forest or for landscape with fractal structure, e.g. forest, cloud, coastal line, and relief.

3.1.4 PROPOSITION OF VARIOGRAM MODEL FOR SLOPE IMAGE

The power model (5) is interesting because it has a few number of parameters and its utilisation is simple because it corresponds to an affine model on logarithmic representation:

$$\ln(\gamma(h)) = \ln(C) + \alpha \ln(h)$$

(6)

But, in the log-log representation, $\ln(\gamma(h))$ is not a line but is easily fitted by a quadratic polynomial. We propose the use of a quadratic polynomial on the log-log representation, which means in the direct space:

$$\gamma(h) = \exp\left(\alpha \cdot (\ln(h))^2\right) \cdot h^b \cdot e^c$$

(7)

This model is interesting because it easy to use (a simple polynomial fit in log-log representation), with few parameters, and a good accuracy. This model is based on fractal parameterisation of the landscape and it has the same properties:

• the parameters are correlated to the structure of the landscape;
• the structure of the landscape is represented by a point of $\mathbb{R}^3$ (defined by the three parameters);
• the distance between the structures of the landscape is the Euclidean distance of $\mathbb{R}^3$;
• the VarioGram Parameters of the Topography (VPT) $a$, $b$ and $c$ permit the representation of the image in the structures space. the definition of an Euclidean distance between images makes it possible to compare two structures;
• the model is defined for $h \in [0,50]$;
• the parameters are difficult to interpret physically.

This function is promising owing to the fact that it characterizes the image structure with few parameters and it is not specific to the landscape type. Figure 4 shows the comparison between the models (3), (5) and (7) for the three areas of the Figure 2 and the original variogram.

Two conclusions can be drawn from this example:

1. the form of the variogram depends on the structure of the slope image. For example, the variogram of the plain area varies between 0 to 1, but that of the mountain
varies between 0 to 100.

2. the best fit of the variogram is the exponential model. The log-polynomial is better for the piedmont area and close to the exponential model.

![Variogram models applied to slope image of (a) a plain, (b) a piedmont plain and (c) a mountain areas.](image)

To show the correlation between topography and the fit parameters, we can spatialize the VPT. For that, an SRTM DEM of France is used. The size of this DEM is 18,000x18,000 pixels with a 90 m of spatial resolution. In a window of 120x120 pixels (~10.8x10.8 km²), the variogram and the fit parameters (A and B for exponential model, and the VPT) are calculated. A map of 150 x 150 pixels is obtained for each parameter. The value of the pixel is that of a coefficient of a variogram model. These maps are represented on Figure 5 for the exponential and on Figure 6 for the log-polynomial models.

The coefficient B is randomly distributed, except for the water areas, where it’s positive (Figure 5). Over the land, B is negative. The correlation between this parameter and a possible structure of the topography is not clear and difficult to interpret. Then, this coefficient is not adapted to characterise the slope distribution. It is not the case for the A coefficient. Its spatial distribution shows a significant correlation with topography, with a wide range of value. For this area, $A \in [0, 100]$. The higher the slope, the more the value of A is significant. Thus, this coefficient is a good “witness” of the topography, with a significant correlation and wide range of value.

The VPT (Figure 6) present a different spatial distribution. The c coefficient shows a range of homogeneous values: high negatives values over the sea ($c > -0.05$) and low negatives values over land ($c < -0.05$), excepted for certain region: e.g., the Landes forest in the south-west, the region of Paris on the middle North, or the Pô area in the south of Alp mountains ($c \sim 0$). Then, this coefficient seems to present a possible correlation with the slope distribution, but it is not clear, particularly over steeper terrains.
The $a$ and $b$ parameters present an apparent correlation with the topography. The value of $b$ is high ($b > 1$) over the Alp or the Pyrenees, but also over certain less mountainous area. Here again, water areas are clearly distinguished, with $b$ close to 0. The coefficient $a$ is the most correlated with the slope value. Like the $A$ coefficient of the exponential model, the higher the slope, the more the value of $a$ is significant. It is clear that the areas where the coefficient is positive correspond to significant value of slope (Alp, Pyrenees, Massif Central, center of Corse). It appears that the use of these two coefficients, $a$ and $b$, is promising for the characterization of the topography. Generally, the VPT seem to be correlated with topography but in a progressive way, $c$ revealing the areas with low slopes, and $a$, those with relief. The analyse of the correlation between the VPT and the structure of the topography is not our purpose. But, it seems that these coefficients could constitute an interesting mean for the model of the texture of a DEM. For our case, we will retain only the fact that coefficient $a$ is correlated with topography.

![Figure 5: Spatialisation of the parameters of the exponential model (3).](image1)

![Figure 6: Spatialisation of the parameters (VPT) of the log-polynomial model (7).](image2)
To summarize, two coefficients are potentially interesting: the parameter $A$ and the VPT $a$. Now, it is necessary to link these parameters with the impact of topography on the L-band signal. For that, we will use a radiometric model shortly presented below.

### 3.2 Simulation of Brightness Temperature Over Mountainous Area

The model used for the simulation of the brightness temperature is that of Mätzler [Matzler98] generalised by Kerr et al. with a geometric approach [Kerr04]. To characterise the topography impact on the signal, Mätzler propose the simulation of the difference between the signal of a flat horizon (at an altitude $h$) and that of a mountainous area, for the same conditions of observation:

$$TB_{\text{topo}}^i = TB_{\text{flat}}^i + \Delta TB^i$$  

where $i$ is the polarisation (horizontal H or vertical V) and with:

$$\Delta TB^i = \frac{\rho_d}{\pi} \int_0^{\pi} d\theta \int_{\theta_0}^{\theta_{\text{max}}} \left( T_h(x, \theta) \cos \theta \sin \theta \, d\theta - T_{\text{sky}}(\theta) \cos \theta \sin \theta \, d\theta \right)$$  

where $\rho_d$ is the reflectivity of the soil, $\beta$ is the azimuth and $\theta$ is the zenith angles. $T_h$ and $T_{\text{sky}}$ are respectively the brightness temperature of soil and of the sky. This expression is obtain only for areas with simple relief with a V-valley form, $x$ being the position in this valley. But this model is not realistic because it does not take into account the effects of adjacency or mutual influence, the shadowed zones which can be hidden according to the viewing angles. Moreover, the tilted surfaces are considered lambertian, that is to say $\rho_d \neq f(\theta, \beta)$.

If it wants a more realistic model, it should be held account owing to the fact that the surface emissivity depends on the incident angle and the polarization. Even for a relief as simple as a V-valley, the problem becomes too complex and justifies a numerical solution. Kerr et al. generalised the previous model for any type of mountainous area, characterized by a DEM, with a geometrical approach. The geometrical model take into account the shadowing and adjacency effects. It is possible to simulate the case of a plane surface at an altitude $h$, and the case of a mountainous area characterised by a DEM. The emissivities are calculated with the TAUW93 model developed by Wigneron et al. [Wigneron95].

In our case, for each window of 120x120 pixels, we calculated the brightness temperature for a flat surface $TB_{\text{flat}}^i$ and that of the real topography $TB_{\text{topo}}^i$, for an observation configuration $(\theta; \beta)$. The difference $\Delta TB^i$ between these two temperatures represents the impact of topography on the signal. At the France scale, a map of 150 x 150 pixels of $\Delta TB^i$ is obtained and compared with the same map of coefficient $A$ and the VPT.
4. RESULT

4.1 SIMULATION OF TOPOGRAPHIC IMPACT

The topography impact $\Delta T_B$ is simulated for the area showed on Figure 1, for fixed parameterisation of TAU93 and for a viewing angle of $\theta = 55^\circ$ (the limit angle of SMOS configuration). The Figure 7 shows the result of this simulation over France. The impact of topography is clear with high absolute values of $\Delta T_B$ over steeper terrains. The impact is positive for the H polarisation ($TB_{\text{flat}}^H > TB_{\text{topo}}^H$) and negative for the V polarisation ($TB_{\text{flat}}^V < TB_{\text{topo}}^V$). [Kerr04] obtains the same result over Colorado mountains. Over Mountainous area, the value of $\Delta T_B$ is significant ($|\Delta T_B| > 6K$), and is higher than the instrumental precision specification of SMOS (~ 4K).

The angular variation of topographic impact $\Delta T_B(\theta)$ is showed on Figure 8, for the three areas of Figure 2. The topographic impact is computed in a window of 120x120 pixels. The mean, maximum and minimum value over the entire area are also represented.

For plane landscape, the impact is negligible ($\Delta T_B(\theta)$ close to zero). It is not the case for Mountainous area where the impact is larger than 5K at 55$^\circ$ and between 1 and 2K at 0$^\circ$. For this area, the topographic impact is larger than the instrumental precision for angle higher than 40$^\circ$ for H and 50$^\circ$ for V polarisations. This limit angle, which corresponds to the angle $\theta_l$ where $|\Delta T_B(\theta)| = 4K$, varies with the topography. For H polarisation, the limit angle for the maximum value of $\Delta T_B(\theta)$ is close to 30$^\circ$, but $\theta_l$ is close to 50$^\circ$ for the minimum value. For V polarisation, the limit angle for the maximum is close to 40$^\circ$ and to 50$^\circ$ for the minimum. This result implies that it will be necessary to define a flag for each zenith angle when $|\Delta T_B(\theta)| > 4K$. The piedmont is characterised by varied values of slope, this gives a broader range of angular behaviour of $\Delta T_B(\theta)$. In the simulated example, $\Delta T_B(55^\circ)$ varies between 0K and 5.2K and $\Delta T_B(55^\circ)$ between 0K and 4.5K. The topographic impact is more difficult to characterize for this type of distribution. The parameter chosen to characterize topography must be sufficiently explicit for emphasizing well this type of distribution.

Figure 7: Spatial representation of $\Delta T_B^H$ for (a) Horizontal and (b) Vertical polarisation, for a fixed parameterisation of TAU93.
Flagging the topographic impact on the SMOS signal

4.2 COMPARISON BETWEEN VPT AND TOPOGRAPHIC IMPACT

We showed on §3.1.4 that the structural parameters of the landscape are the “witness” of the slope distribution (Figures 4 and 5). To verify a possible correlation between the spatial distribution of the slope and the topographic impact, we compare the coefficient of each selected model (A and a) with the topographic impact $\Delta TB_i(\theta)$. This comparison is represented on the Figure 9. The correlation between topographic impact and the coefficient A of the exponential model is not clear (Figure 9(a)). It appears a linear limit for the low values of $A$, and an density of point for low values of $A$ and $\Delta TB_i(\theta)$. A quasi linear correlation seems to appear, but it is not clear. Moreover, the coefficients corresponding to topographic impacts higher than 4K, take varied values, between 50 and 400. This range of value is significant and correspond to many type of slope distribution. Finally, it appear that the exponential model is not relevant for our purpose.

In comparison, the VPT a present a correlation with the topographic impact (Figure 9(b)). Low values of the VPT a corresponds well with low value of $\Delta TB_i(\theta)$ respectively for the high values. Since the high values of the VPT correspond to the areas where the variation of slopes is significant, it is possible to define a threshold which corresponds to the limit of the instrumental precision specification, $|\Delta TB_i(\theta)| = 4K$.

4.3 DETERMINATION OF A THRESHOLD FOR THE VPT

It seems possible to define a correlation, at least empirical, between the VPT a and the topographic impact. For each polarisation, the variation of $\Delta TB_i(\theta)$ with the VPT is exponential (Figure 10). We decide to approximate the relation between a and $\Delta TB_i(\theta)$ with an exponential function:

$$\Delta TB_i'(\theta,a) = C_i'(\theta) \cdot \exp(C_i'(\theta) \cdot a)$$

(10)

The Figure 10 shows the result obtained for $\theta = 55^\circ$ and for the two polarisations. The threshold is obtain for $|\Delta TB_i(\theta)| = 4K$. The value of the threshold varies with the
polarisation. The evaluated values are \( a_{	ext{int}}^H(55^\circ) = 2.70 \) for the horizontal polarisation, and \( a_{	ext{int}}^V(55^\circ) = 2.94 \) for the vertical one. The threshold values, estimated for France and for various zenith angles (limited by \( \theta_i \)) are summarized in Table 1.

![Figure 9: Comparison between VPT coefficients and the topographic impact \( \Delta TB(55^\circ) \), for (a) the exponential model (3) and (b) the log-polynomial model (7).](image)

![Figure 10: Determination of a threshold of the VPT \( a \). An exponential approximation of its relation with the topographic impact is used to obtain the threshold \( a_{th} \) for (a) the horizontal and (b) the vertical polarisations.](image)

It is necessary to introduce a range of validity of the estimated threshold. Indeed, the geometrical model used to obtain the topographic impact is not exact. Then, it is necessary to introduce a precision of the model. In our case, we have considered that the estimated \( \Delta TB(\theta) \) has a precision of \( \pm 1.5K \). The Figure 11 show the estimated range for the SMOS extreme zenith angle and the H polarisation. The obtained ranges for all configurations are summarized in the Table 1.

Eight values of threshold are obtained, five for the horizontal polarisation, and three for the vertical one. With these values, it is possible to create masks of area where the topographic impact is significant. With the use of these thresholds, it is possible to select pixel with \( a > a_{th} \) but also with \( \Delta TB(\theta) < 4K \). This is the case on Figure 11. Respectively, pixels with \( a > \)}
Flagging the topographic impact on the SMOS signal

$a_{th}$ and $\Delta TB(\theta) > 4K$ are eliminated. To estimate the effect of the use of a threshold for masking mountainous areas, a statistical analysis is presented below.

![Image](image_url)

Figure 11: Estimation of the range of validity of the threshold $a^{H}_{th}(55^{\circ})$ for the horizontal polarisation.

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Table 1: Threshold of the VPT obtained over France, for one zenith angle and its superior and inferior limits

4.4 STATISTICAL ANALYSIS OF ESTIMATED MASK

To determine the goodness of the mask, the map of thresholded pixels are analysed according to the equivalent map of topographic impact (Figure 17). The mask is apply over the map of $\Delta TB(\theta)$ to obtain an image of topographic impact. The Figures 11 and 12 show the histogram analysis of these two images for $\theta$=55$^{\circ}$ and the H polarisation. The number of pixel corresponding to $a > 2.70$ is 638. With a pixel size of 10.8x10.8 km$^2$, the masked area correspond to 74,416.32 km$^2$ (~3% of the study area Figure 1).

Figure 13 shows the histogram of the masked map of $\Delta TB(55^{\circ})$. There are 93 pixels with a $\Delta TB(\theta) < 4K$ and 545 with $\Delta TB(55^{\circ}) > 4K$. In fact, when we apply the mask, there are 85.4% of pixel with significant topographic impact and 14.6% of pixels which do not present impact. This is an acceptable value, according to the validity of the geometrical model and the precision of the exponential approximation.
On the other hand, it is necessary to notice that pixels have values of topographic impact higher than 4K but a corresponding VPT coefficient lower than $a_{th}$. Figure 14 and Figure 15 show the same statistical study for a mask on the topographic impact (just the pixels $\Delta TB(55^\circ) > 4K$ are considered). There is almost as much pixel higher (51.6%) than lower (48.4%) than the threshold. Consequently, nearly 50% of non valid pixels are not eliminated when the estimated threshold $a_{th}$ is used. It is a significant value, even if the problems of model and exponential approximation are considered. To improve the estimate of the threshold and to reduce this problem, we propose to focus the estimation between $a \in [2; \max(a)]$. Within this range, a linear approximation (Figure 16) is used to estimate new values of threshold. These values are summarized on Table 1. With these values, the percentage of non valid and eliminated pixel increase to 35%. It is a reasonable value if we take account the model accuracy and the error of linear approximation. For example, the Figure 16 shows the two ranges of the $a_{th}$ validity obtained with the approximation error (dotted line) and the model accuracy ($\pm 1.5K$) for the H polarisation and $\theta = 55^\circ$. In this case, the obtained values are similar: the limits defined by the approximation error are [2.17; 3.01] and those by the model accuracy are [2.14; 3.04]. If these values are considered, the percentage of non valid
and eliminated pixels varies between 7% and 74%. Finally, the best thresholds are obtained with a linear fit between $a \in [2; \max(a)]$ and are summarized on Table 1.

<table>
<thead>
<tr>
<th>$\theta$ (°)</th>
<th>35</th>
<th>40</th>
<th>45</th>
<th>50</th>
<th>55</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a^H_{\text{th}}$</td>
<td>3.38</td>
<td>3.12</td>
<td>2.91</td>
<td>2.73</td>
<td>2.59</td>
</tr>
<tr>
<td>$a^V_{\text{th}}$</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>3.21</td>
<td>2.93</td>
</tr>
</tbody>
</table>

Table 1: Threshold of the VPT obtained over France with a linear approximation between $a \in [2; \max(a)]$.

Figure 16: Linear approximation of the relation between topographic impact and VPT coefficient, and determination of a threshold (and its range of validity) for the horizontal polarisation and $\theta=55°$.

### 4.5 APPLICATION OF ESTIMATED THRESHOLD OVER THE ANDES REGION

To illustrate the usefulness of the VPT coefficient, the obtained value over France is applied over the mountainous region of the Andes, in South America. The same computation protocol is used to deduce a masked map, using the variogram analysis of DEM sub areas. The size of the analysed DEM is 18,000x12,000 pixels (19,400 km²), with a 90 m of spatial resolution. In a window of 120x120 pixels (~10.8x10.8 km²), the variogram and the VPT coefficient are calculated. A map of 150 x 100 pixels is obtained for the $a$ parameter. The threshold value obtained over France is used to define the mask. To verify the relevance of this mask, it is compared with the map of topographic impact $\Delta TB$ estimated with the geometrical model and the Andes chain DEM. The result is show on the Figure 18 for the two polarisations and $\theta = 55^\circ$. The areas impacted by the topography correspond well with those masked with the threshold. For the horizontal polarisation, there are 1596 pixels masked with the use of the threshold, which represents ~2068 km², and 1421 pixels (~1842 km²) where the topographic impact is higher than the instrumental specification. For the vertical polarisation, there are 590 masked pixels (~764 km²) and 643 pixels (~833 km²).
where $\Delta TB(55^\circ)>4K$. The values obtained for France give similar results on more mountainous zones like the Andes chain, which makes it possible to say that the suggested values are generalizable at over parts of the globe. Then, with the values of Table 1, it is possible to obtain a global mask.
Figure 17: Masked map (pixels where $a > a_0$) obtained for the two polarisations and for $\theta = 55^\circ$ (red). The areas where the topographic impact is higher than the instrumental precision are also drawn (yellow line).
4.6 COMPUTATION TIMES

The objective of this study is to propose a method to estimate, at the global scale, the areas where the impact of topography is too significant to allow the treatment of the SMOS signal. The advantage of using the VPT coefficient is that it is not necessary to calculate several different situations, like the use of a geometrical model. Indeed, it is enough to obtain a map of the $a$ coefficient which is then thresholded to obtain the masks. We developed a non-optimised soft with IDL/ENVI which computes the slope of a DEM and estimates the three VPT coefficients. The duration of the computation depends on the size of the DEM. For the global scale, there are 900 GeoTiff images with a size of 6000x6000 pixels, which corresponds to 5°x5°. The computation time of only one tile is approximately 710 seconds (~11mins) under a Linux PC (1GHz Pentium III and 256Mo RAM). We deduce that the time necessary to calculate the total VPT coefficient map is close to 6 days with this configuration and the IDL/ENVI software. This time is easily improvable with a better configuration, especially more memory, and a translation of the soft in C language. In comparison, the geometrical model is slower since it takes approximately 460 seconds (7mins) to compute $\Delta TB$ for one angle, that is to say 2300 seconds (38mins) for the four zenith angles of the Table 1 and for one 5°x5° tile (the computation time is extended to 23 days for the global scale and the four zenith angles). Moreover, the
geometrical model also depends on the configuration of model TAUW93. Then, the VPT coefficient map and its thresholding are sufficient to characterize the impact of topography.
5. CONCLUSION

In this study, a method to characterise the impact of the topography on the SMOS signal is proposed. It is based on a co-variogram analysis of the slope distribution, modelled by a log-polynomial function. This function appears well adapted to the study of topography because the coefficients of the model are correlated with the spatial structure of the slope. However, as signalled by Kerr et al. [Kerr04], the impact of topography on the L band brightness temperature is an effect of the slope and not of the altitude. Then, we obtain a correlation between the topographic impact and the VPT coefficient. This correlation depends only of the slope spatial distribution and not to other aspects (like the soil characteristics for example).

With the comparison of the topographic impact, we determined threshold value of VPT coefficient for an area centred on France. These values were tested over an area with different slope distribution, particularly more significant value of altitude. This method makes it possible to obtain a global map of VPT coefficient and, by the application of the threshold values, the definition of areas where the topographic impact is too significant and prevents the use of the measured signal.

However, it is noted that a range of validity was also defined. It is necessary to take into account an error on the simulation of the impact of the topography by the geometrical model, as well as an error on the model of its relationship with the VPT coefficient. A study is currently in progress to validate the geometrical model and to verify the results obtained here. It is based on the results obtained with C-band SMMR data by Pellarin et al. [Pellarin06].

The next step is the characterisation of the impact of topography, not on the brightness temperature, but directly on the soil moisture. This part is not easy and requires more effort, especially on the characterization of surfaces of the mountains, on the stratification of the vegetation according to altitude, as well as the effect of the slope on the surface runoff and thus on the soil moisture. So it is to be waited until the surfaces impacted by topography will increase compared to those found along this study.