Hydrological network detection for SWOT data

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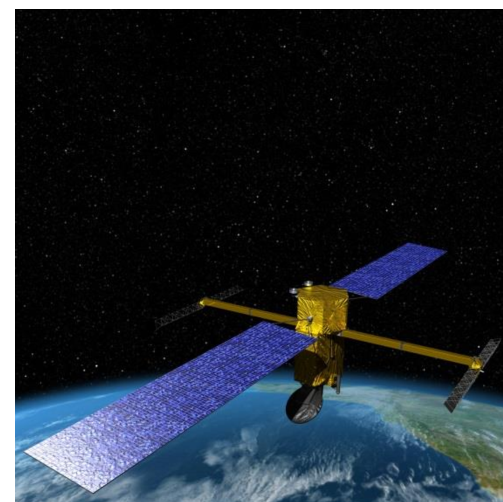
- SWOT mission
- Large water bodies detection
- Fine network detection
- Further works

SWOT mission

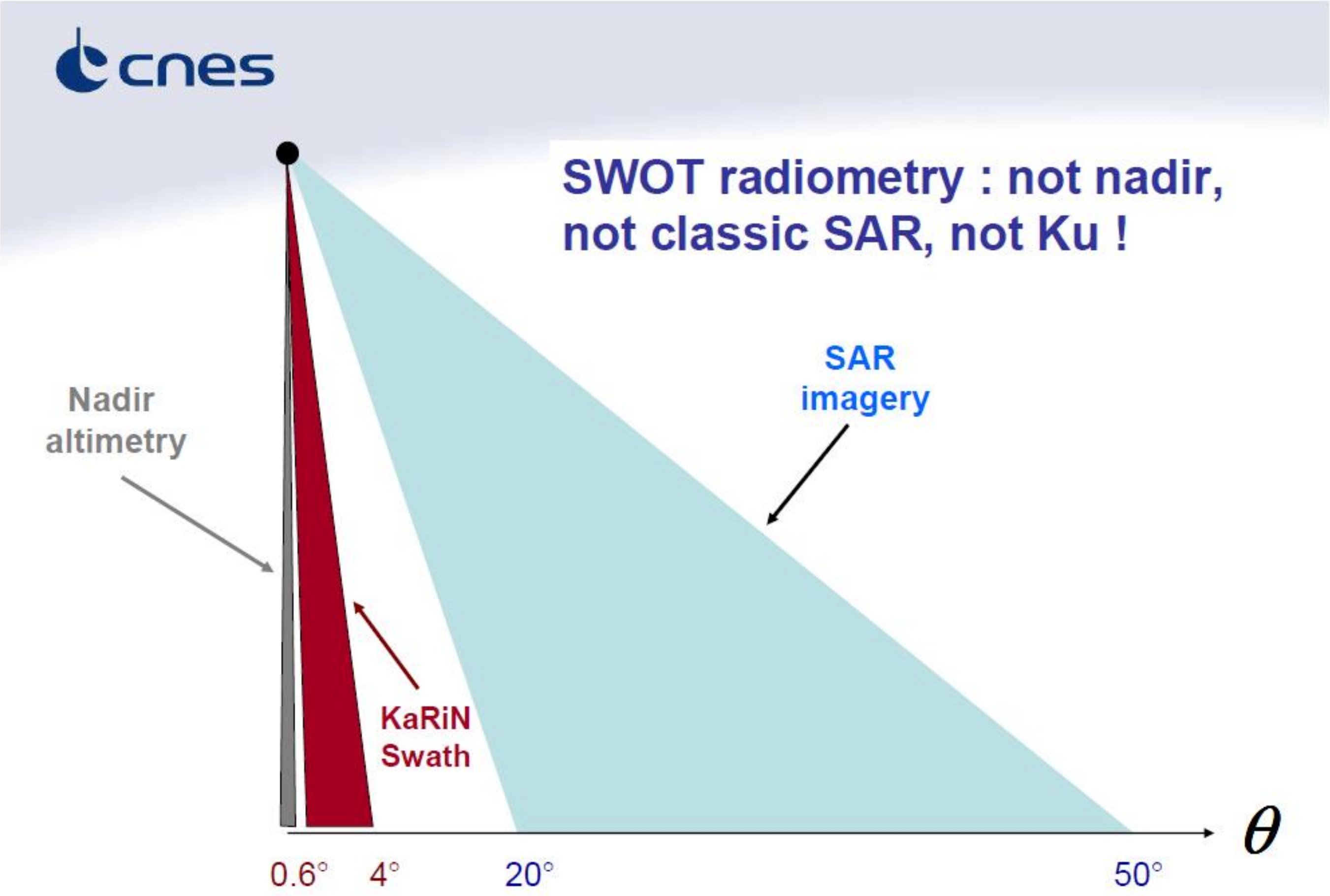
- **SWOT**
  - Surface Water and Ocean Topography
  - **Hydrology**: estimation of the river and lake volumes, reservoirs, wetlands for a better understanding of the global water cycle
  - **Oceanography**: global measurements of ocean surface topography with high spatial resolution to improve ocean circulation models (weather prediction, climate, navigation,…)
  - NASA / CNES mission
  - Launch planned in 2020

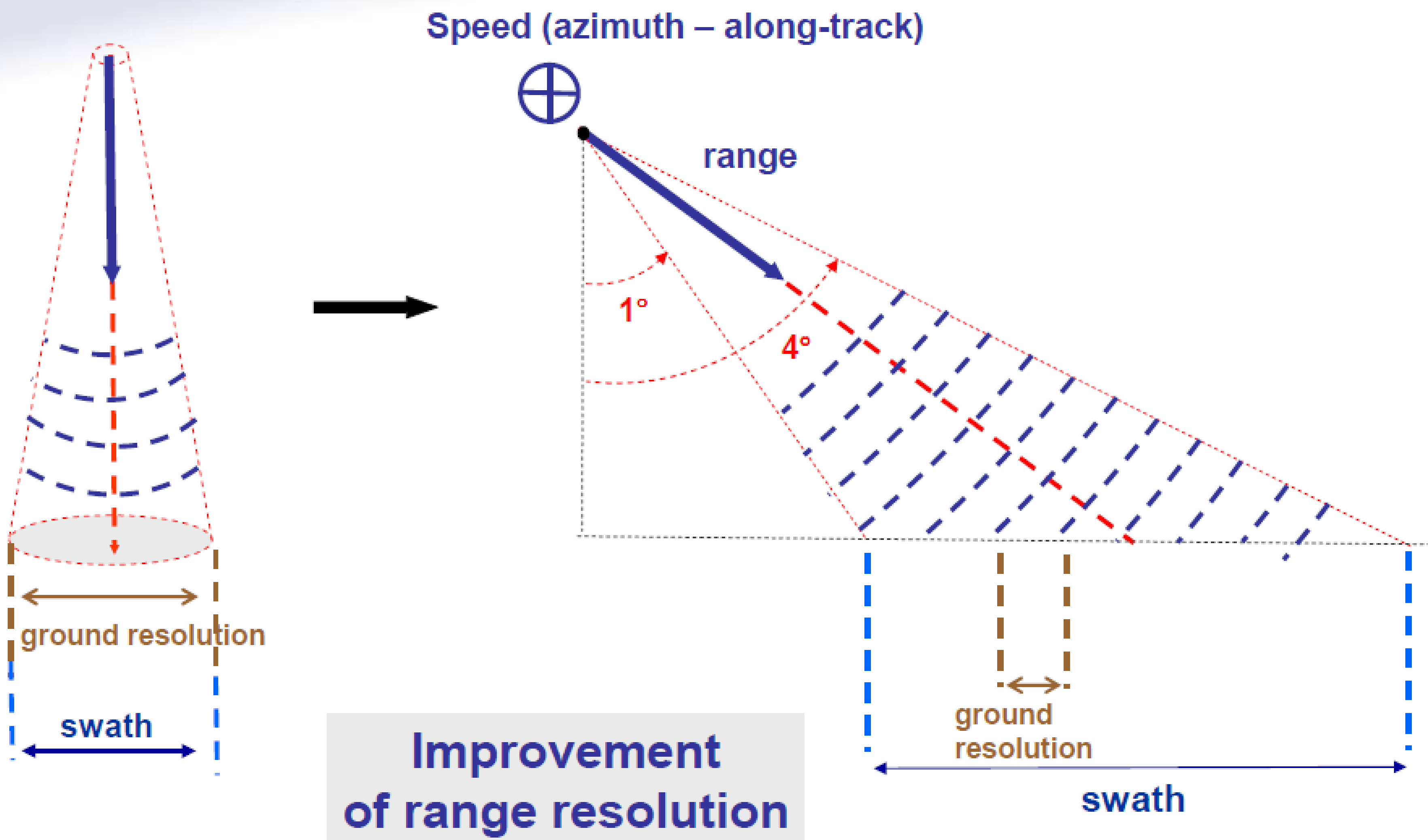
SWOT mission

- **Specifications (images)**
  - Altimetry with interferometric SAR
  - KaRIn instrument (Ka band radar interferometer): single pass interferometry
  - Angles : 1° to 4°
  - Ka band : 8.6mm
  - Temporal cycle : every point on the earth measured twice every 21 days



http://swot.jpl.nasa.gov/

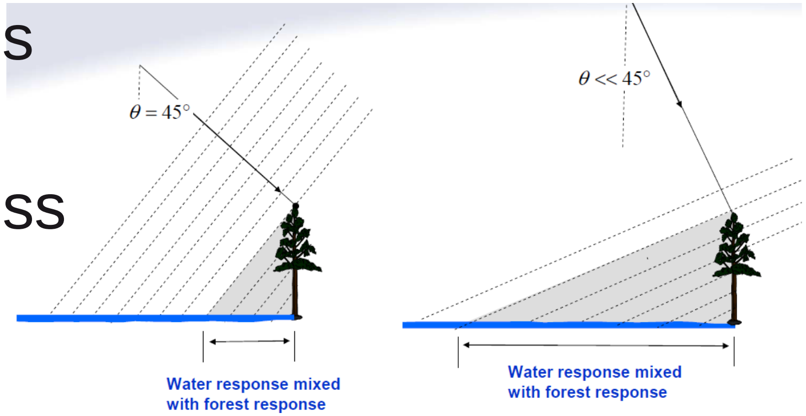

SWOT radiometry : not nadir,
not classic SAR, not Ku !
SAR
imagery
Nadir
altimetry
KaRiN
Swath
θ
0.6°
4°
20°
50°



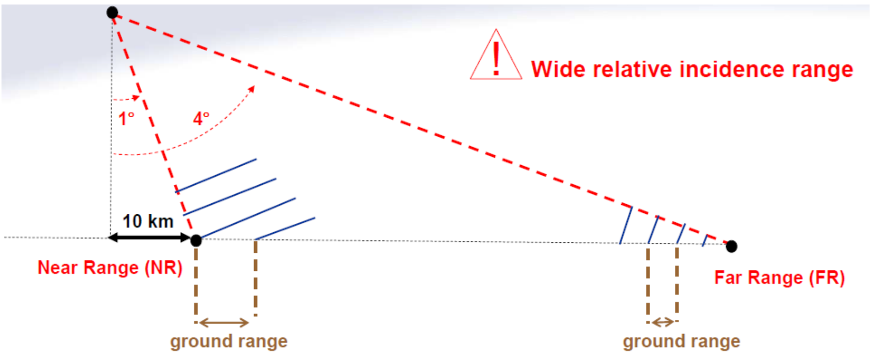
Improvement of range resolution

SWOT – specifications

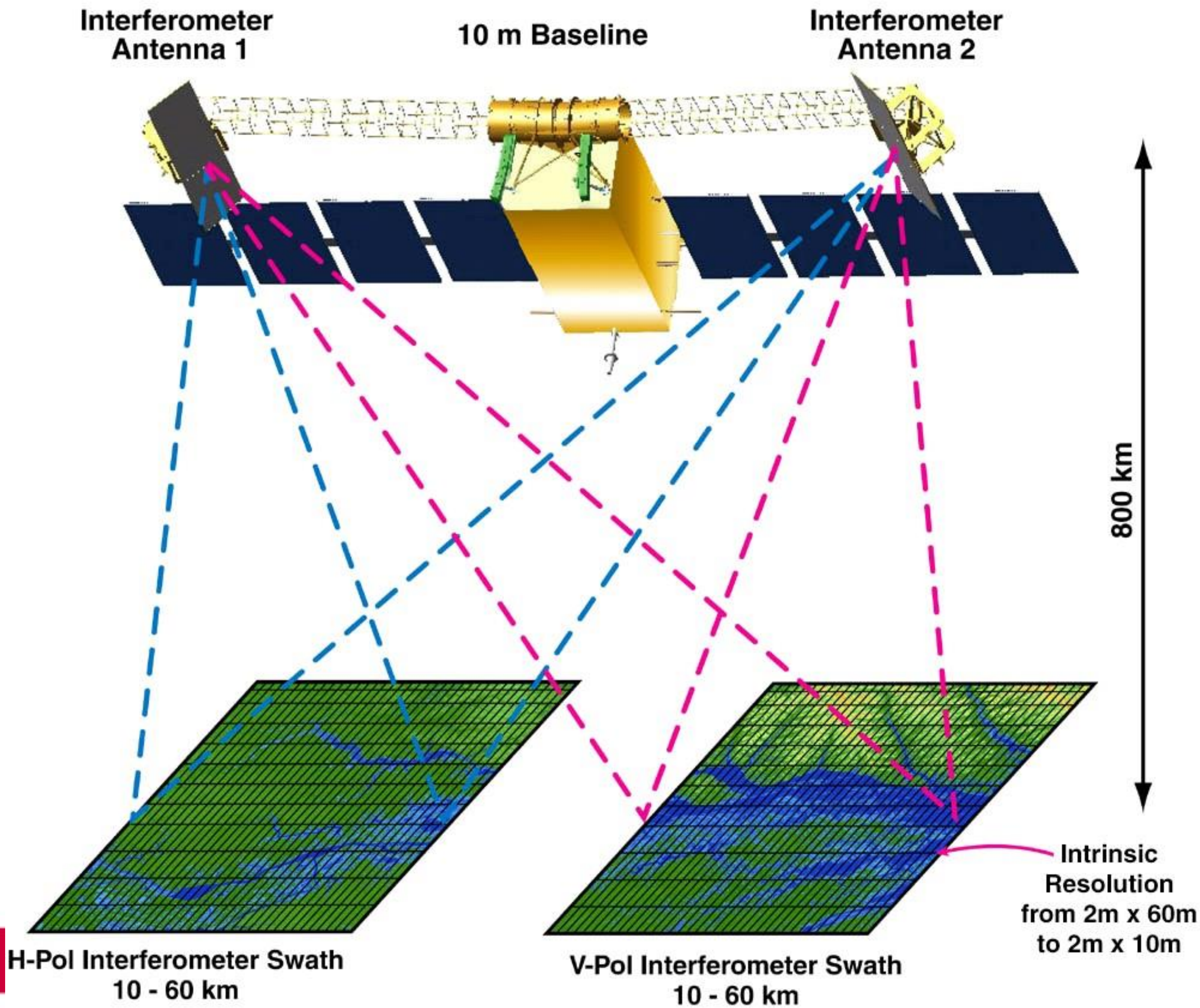
- **Use of Ka band (8.6mm)**
  - Interferometric sensitivity depends on basis / λ
  - High sensitivity to object roughness
  - Sensitivity to tropospheric conditions



- **Very small incidence angle ([0.6°,4°])**
  - Lay-over effects
  - Range resolution variation
  - Strong land / water contrast



Mission SWOT



KaRIn / SWOT requirements for water detection

- **Water bodies**
  - Whose surface area /width exceeds 250x250 m² / 100m
  - In region of moderate topographic relief

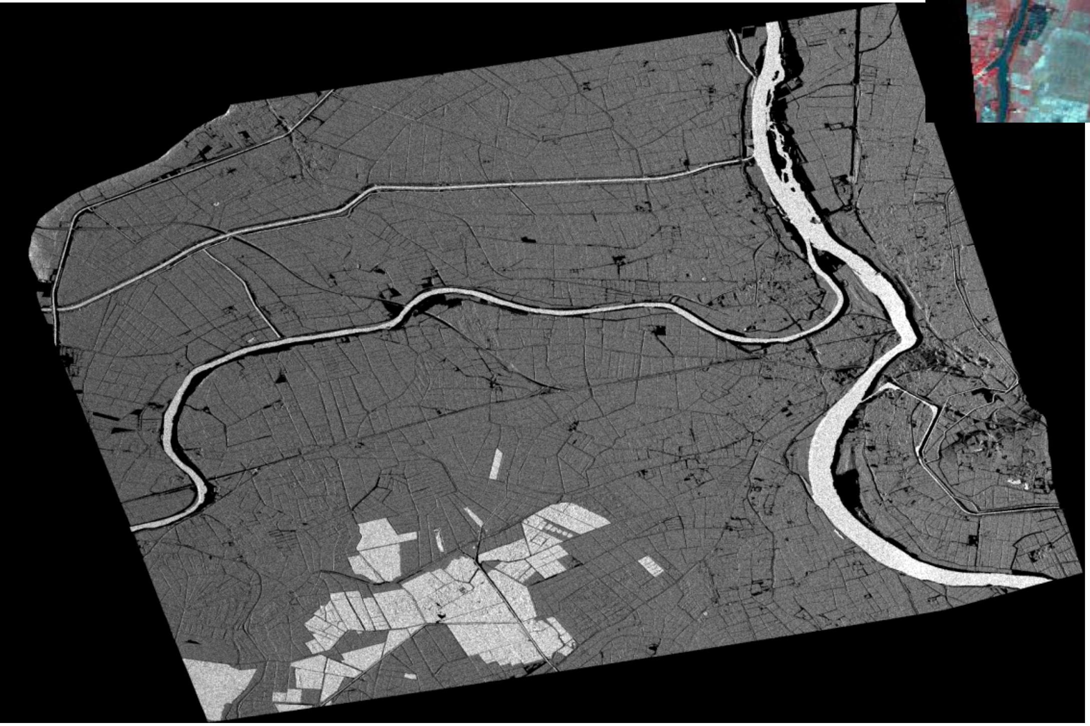
- **Issues**
  - Variable water / land contrast, speckle impact
  - Position and orientation of the river in the swath
  - Pollution by other features ? (roads ?)

SWOT mission – ADT

- **Challenges for the Algorithm Definition Team**
  - Fast and reliable processing methods for
    - River and water bodies detection
    - Height estimation (interferometric phase)
  - Difficulties :
    - Fine networks
    - Speckle
    - Geometric deformations
    - Simulated data

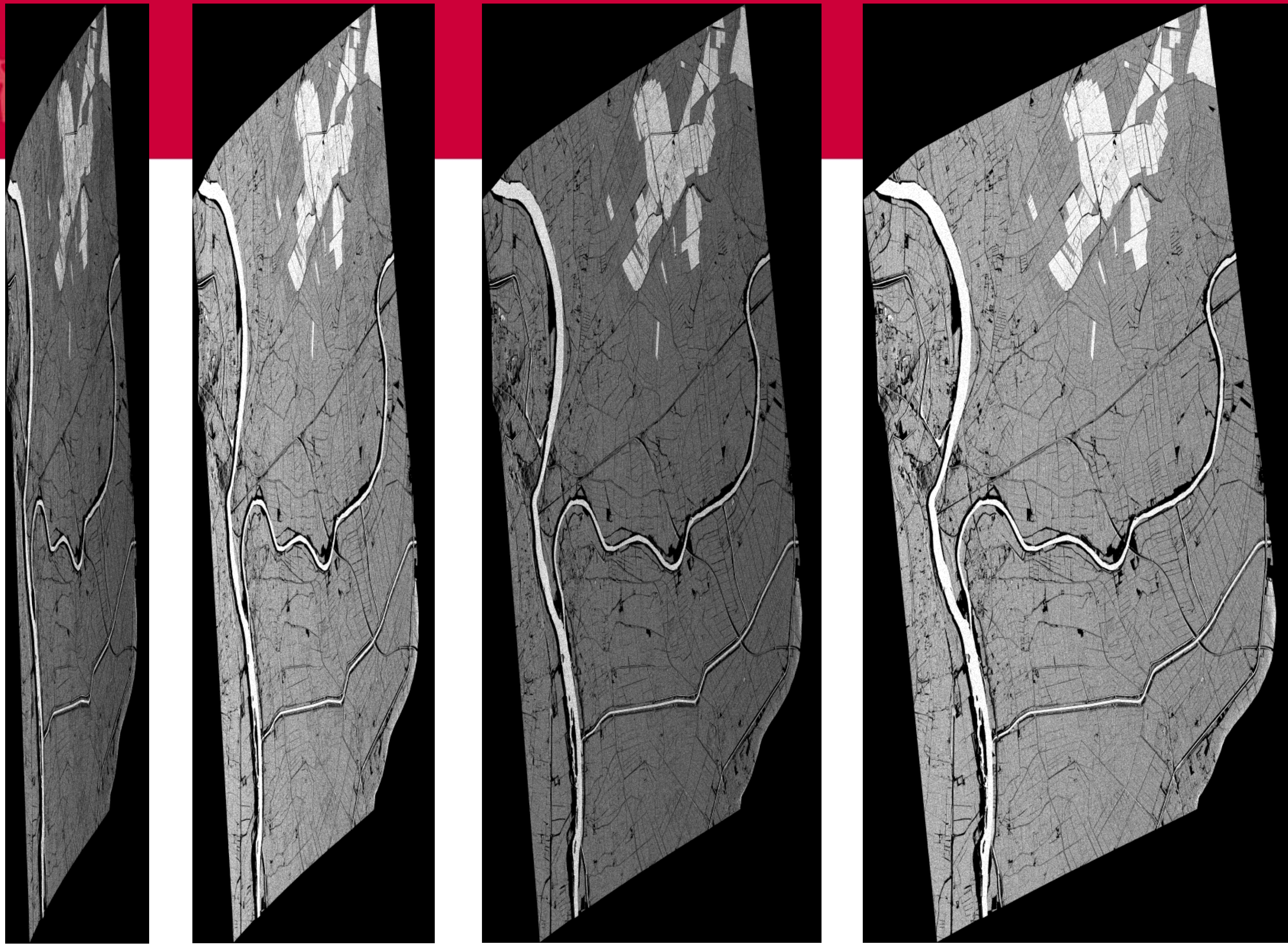
SWOT SAR data

Spot image



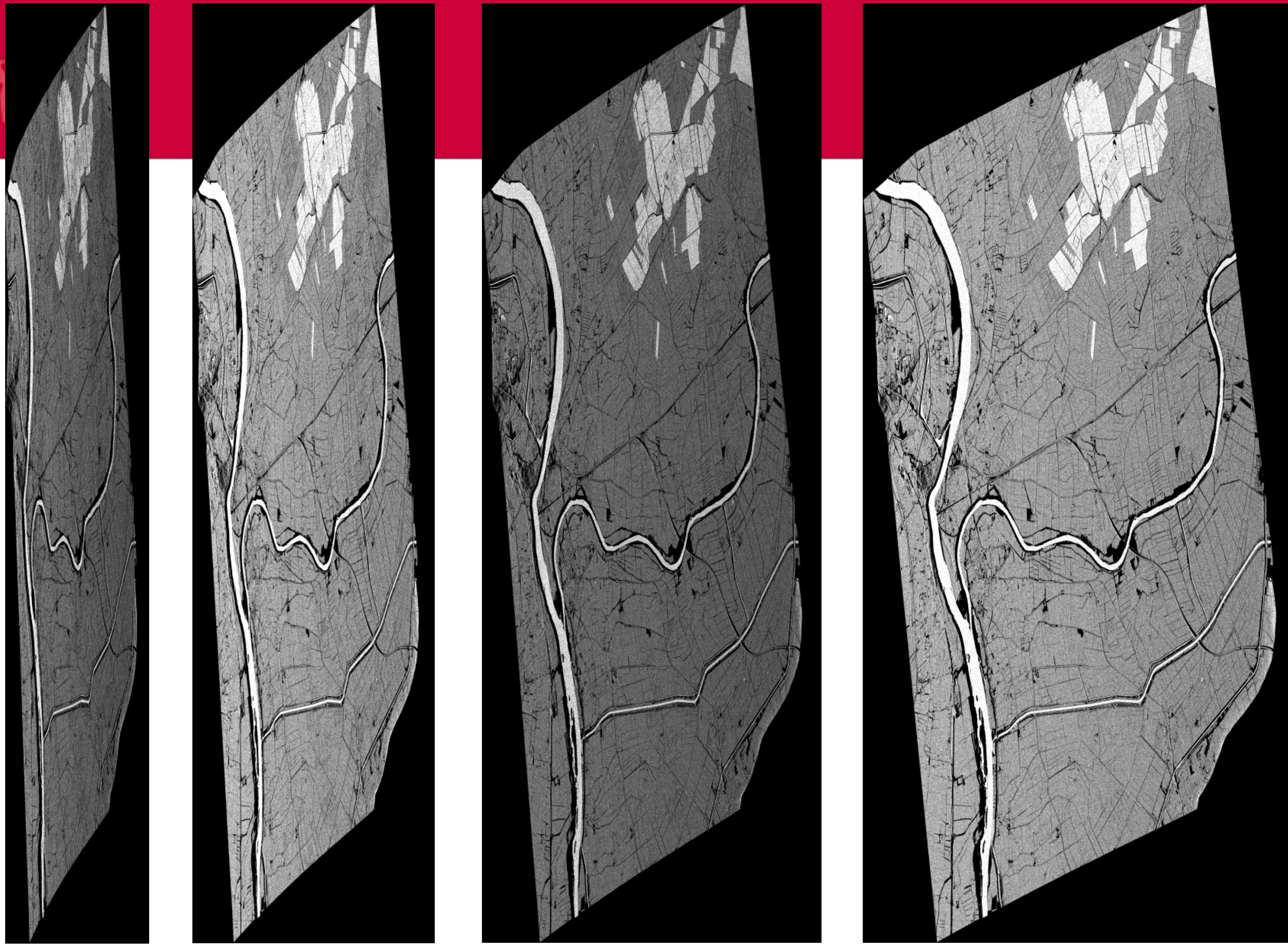
SWOT SAR image [pt4,c1]

- **Simulated SWOT data**
  - North Camargue test site
  - 4 incidence angles
  - 3 simulation cases



Incidence angle 1 ° 2 ° 3° 4°

[pt1] [pt2] [pt3] [pt4]



Incidence angle 1 ° [pt1] 2 ° [pt2] 3° [pt3] 4° [pt4]

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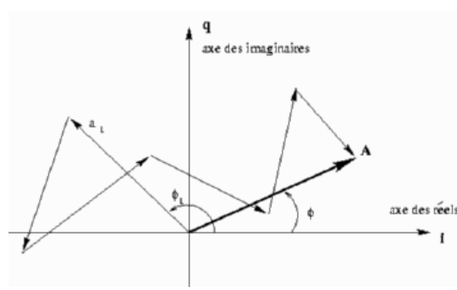
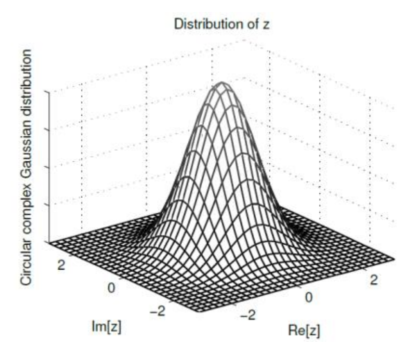
SAR data and statistics

- **Data: complex electro-magnetic field** $z = Ae^{j\varphi}$ **(amplitude** $A = |z|$ **, intensity** $I = A^2$ **)**

- **Speckle: coherent imagery, interferences**
  - Goodman model (rough surfaces)

$$p(z|\sigma^2) \triangleq p(\mathrm{Re}[z], \mathrm{Im}[z]|\sigma^2) = \frac{1}{\pi\sigma^2}\exp\left(-\frac{|z|^2}{\sigma^2}\right)$$



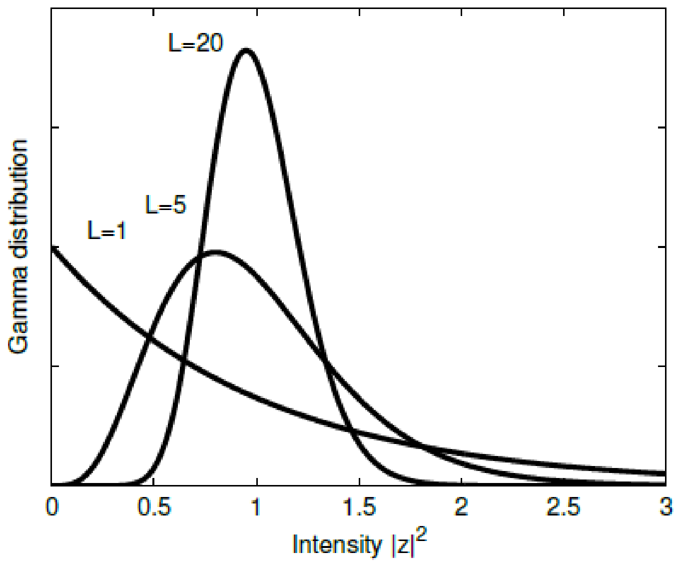


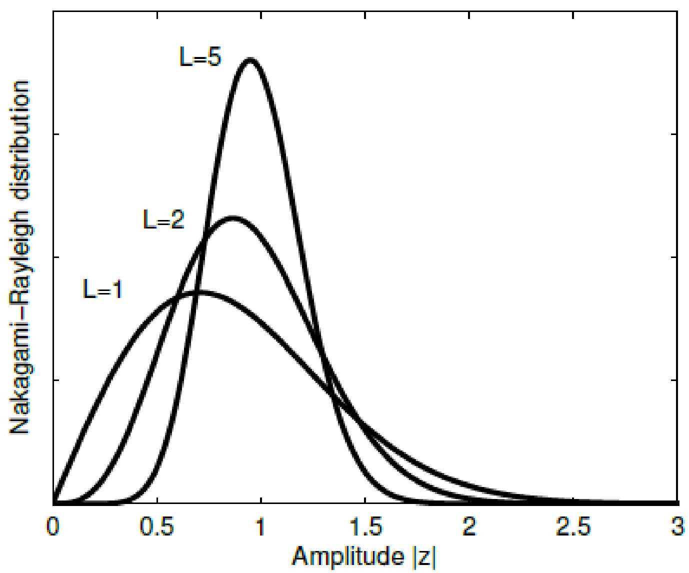
$$\sigma^2 = R$$

SAR data and statistics

One channel, Goodman model:

- Multi-look images: $I = \frac{1}{L}\sum_{i=1}^{L}|z_i|^2$
- Intensity distribution: Gamma
- Amplitude distributions: Rayleigh-Nakagami





SAR data and statistics

- **D channels, Goodman model:**
  - Vectorial data: $\mathbf{k} = (z_1, ..., z_D)^t$
  - Circular complex Gaussian distribution:

$$\boxed{\mathrm{p}(\boldsymbol{k}|\boldsymbol{\Sigma}) = \frac{1}{\pi^D \det(\boldsymbol{\Sigma})} \exp\left(-\boldsymbol{k}^\dagger \boldsymbol{\Sigma}^{-1} \boldsymbol{k}\right)}$$

$$\boldsymbol{\Sigma} = \mathbb{E}\{\boldsymbol{k}\boldsymbol{k}^\dagger\}$$

$$\boldsymbol{\Sigma} = \begin{pmatrix} R_1 & \sqrt{R_1}\sqrt{R_2}\gamma_{1,2}\exp(j\psi_{1,2}) & \cdots & \sqrt{R_1}\sqrt{R_D}\gamma_{1,D}\exp(j\psi_{1,D}) \\ \sqrt{R_1}\sqrt{R_2}\gamma_{1,2}\exp(-j\psi_{1,2}) & R_2 & & \sqrt{R_2}\sqrt{R_D}\gamma_{2,D}\exp(j\psi_{2,D}) \\ \vdots & & \ddots & \vdots \\ \sqrt{R_1}\sqrt{R_D}\gamma_{1,D}\exp(-j\psi_{1,D}) & \sqrt{R_2}\sqrt{R_D}\gamma_{2,D}\exp(-j\psi_{2,D}) & & R_D \end{pmatrix}$$

SAR data and statistics

- **Multi-look data, Goodman model: Wishart distribution**

$$C = \frac{1}{L}\sum_{i=1}^{L} \boldsymbol{k}_i \boldsymbol{k}_i^\dagger$$

$$\boxed{p(C|\boldsymbol{\Sigma}) = \frac{L^{LD}|C|^{L-D}}{\Gamma_D(L)|\boldsymbol{\Sigma}|^L}\exp\left(-L\,\mathrm{tr}(\boldsymbol{\Sigma}^{-1}C)\right)}$$

$$I_k = A_k^2 = \frac{1}{L}\sum_{i=1}^{L}|z_{i,k}|^2$$

$$d_{k,l}e^{j\phi_{k,l}} = \frac{\sum_{i=1}^{L} z_{i,k} z_{i,l}^*}{\sqrt{\sum_{i=1}^{L}|z_{i,k}|^2 \sum_{i=1}^{L}|z_{i,l}|^2}}$$

coherence

phase

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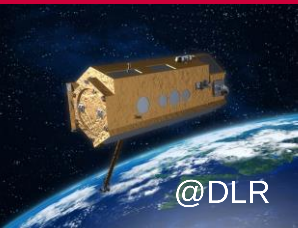
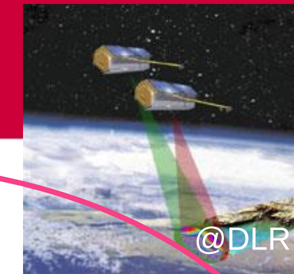


SAR data and statistics



D=1 $z = Ae^{j\varphi}$

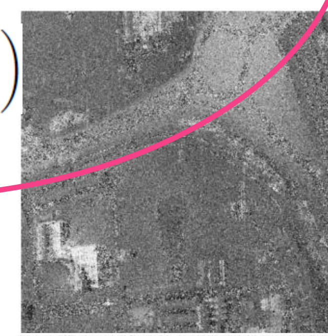
Amplitude data (classification, object recognition,…)

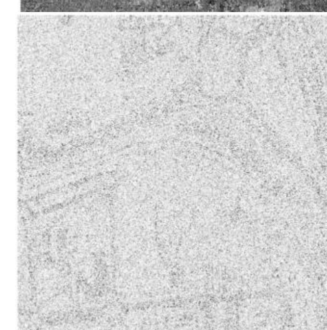
D=2 $\mathbf{k} = \begin{pmatrix} z_1 \\ z_2 \end{pmatrix}$

different incidence angles

Interferometric data: geometric information (elevation, movement)

$$\mathbf{\Sigma} = R \begin{pmatrix} 1 & \gamma_{1,2} e^{j\psi_{1,2}} \\ \gamma_{1,2} e^{-j\psi_{1,2}} & 1 \end{pmatrix}$$





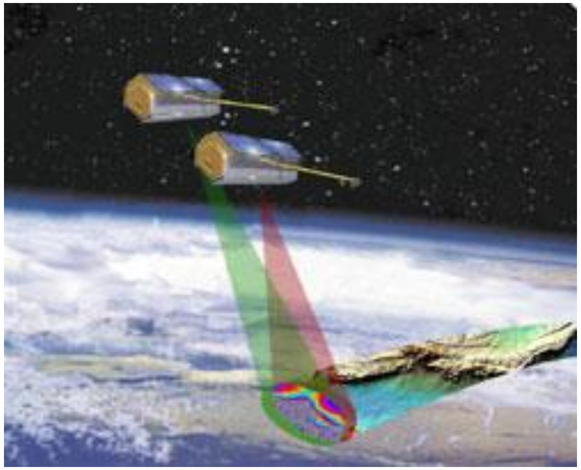
D=3 $\boldsymbol{k} = (z_{hh}, z_{vv}, \sqrt{2} z_{hv})^t$

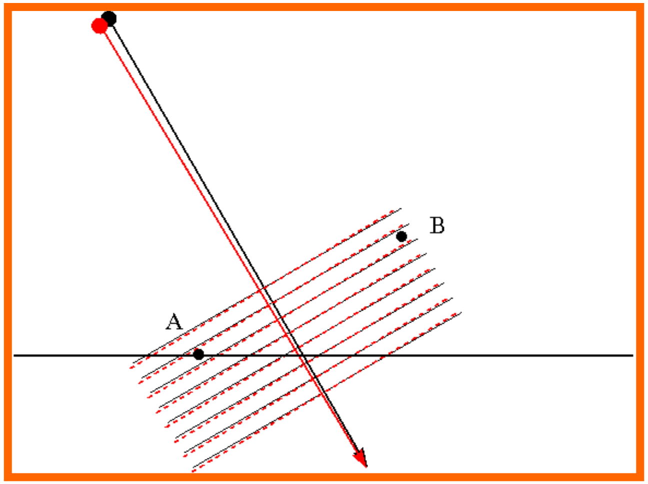
different polarizations

Polarimetric data

Backscattering mechanisms (classification, object recognition,…)

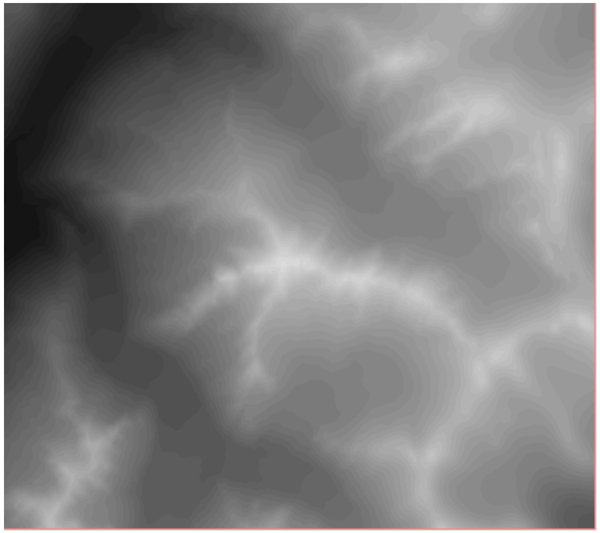
InSAR data

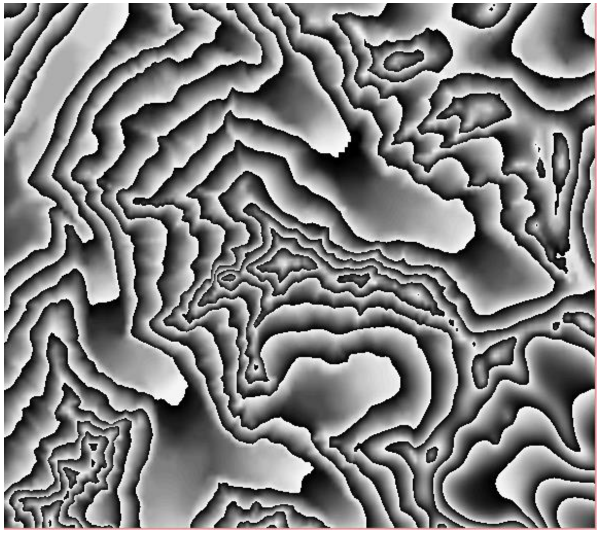




$$\phi = \frac{4\pi R}{\lambda} + \phi_{pr}$$

$$\phi_2 - \phi_1 = \frac{4\pi(R_2 - R_1)}{\lambda} = \psi_{1,2}$$





$$\psi_{1,2} = \frac{4\pi B_{\perp_{1,2}}}{R\sin(\theta)\lambda} h$$

$$\psi_{1,2} = \alpha_{geom_{1,2}} h$$

Probabilistic framework

Bayesian classification

- Two classes : water / background
- Distributions of the SAR signals taken into account
- Regularization term

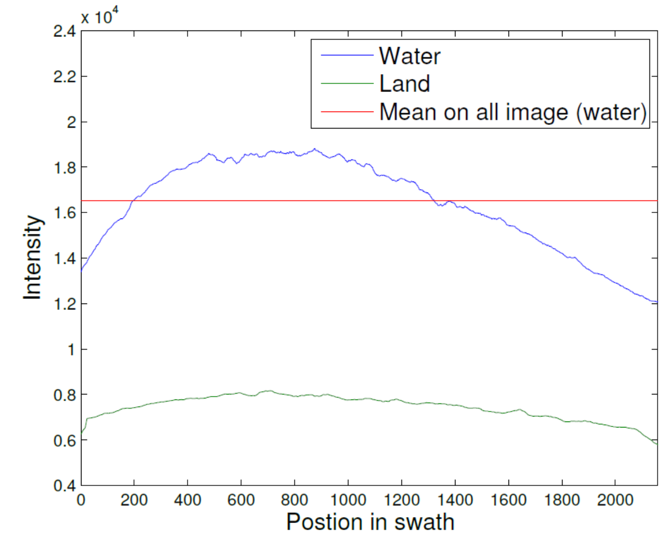
$$\boxed{\begin{aligned}\hat{\mathbf{u}} &= \arg\min_{\mathbf{u}} -\log\left(\mathrm{p}(\mathbf{v}|\mathbf{u})\right) - \log\left(\mathrm{p}(\mathbf{u})\right) \\ &= \arg\min_{\mathbf{u}} \mathcal{E}(\mathbf{u}),\end{aligned}}$$

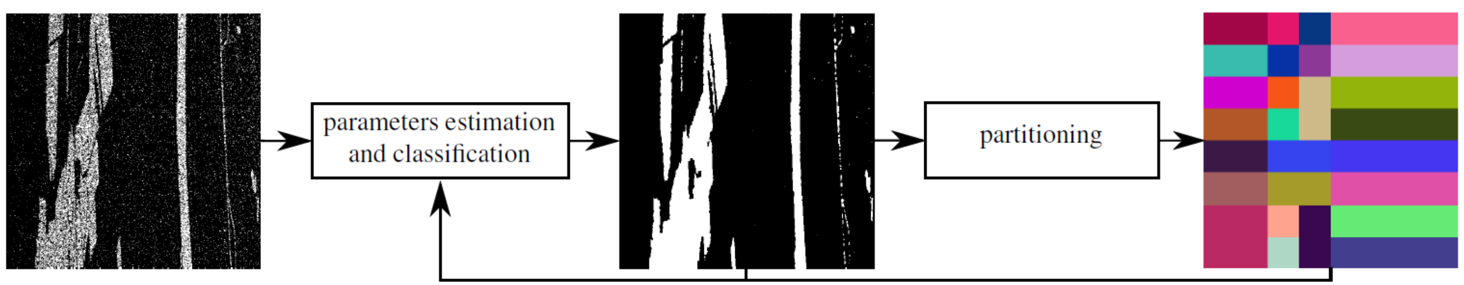
$$\begin{cases} -\log\left(\mathrm{p}(\mathbf{u})\right) = \sum \beta \; |u_s - u_t| \\ \mathrm{p}(V_s = v_s | U_s = i) = \dfrac{1}{\Gamma(L)} \dfrac{L}{\mu_i} \left(\dfrac{L v_s}{\mu_i}\right)^{L-1} e^{-\frac{L v_s}{\mu_i}} \end{cases}$$

Probabilistic framework

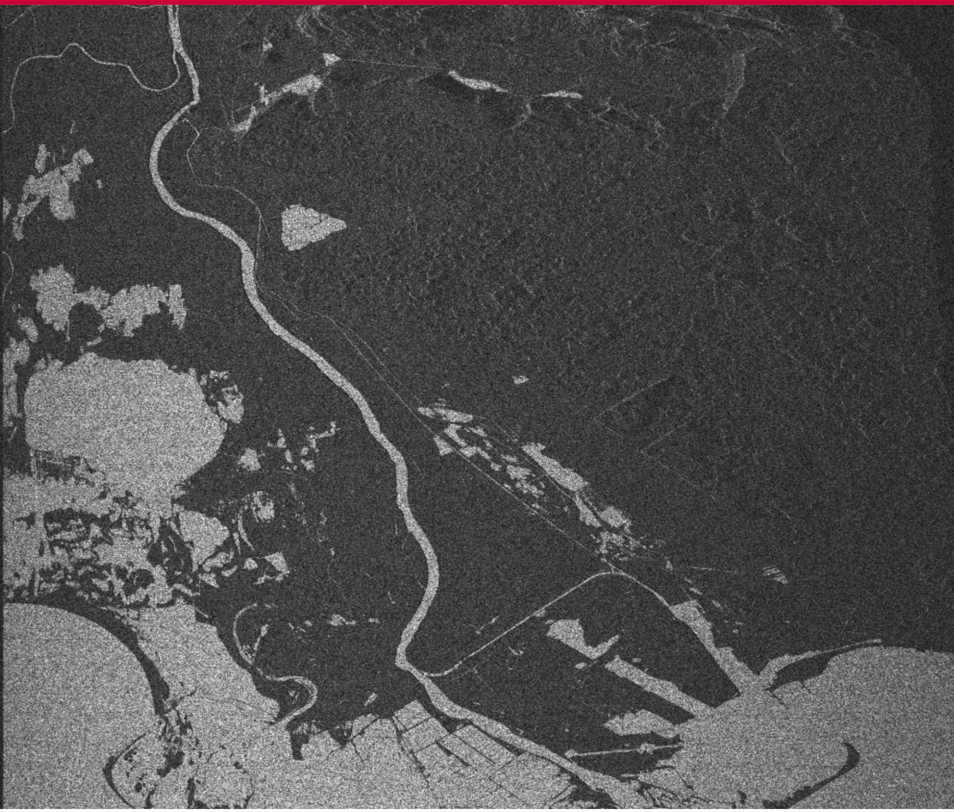
Refinement

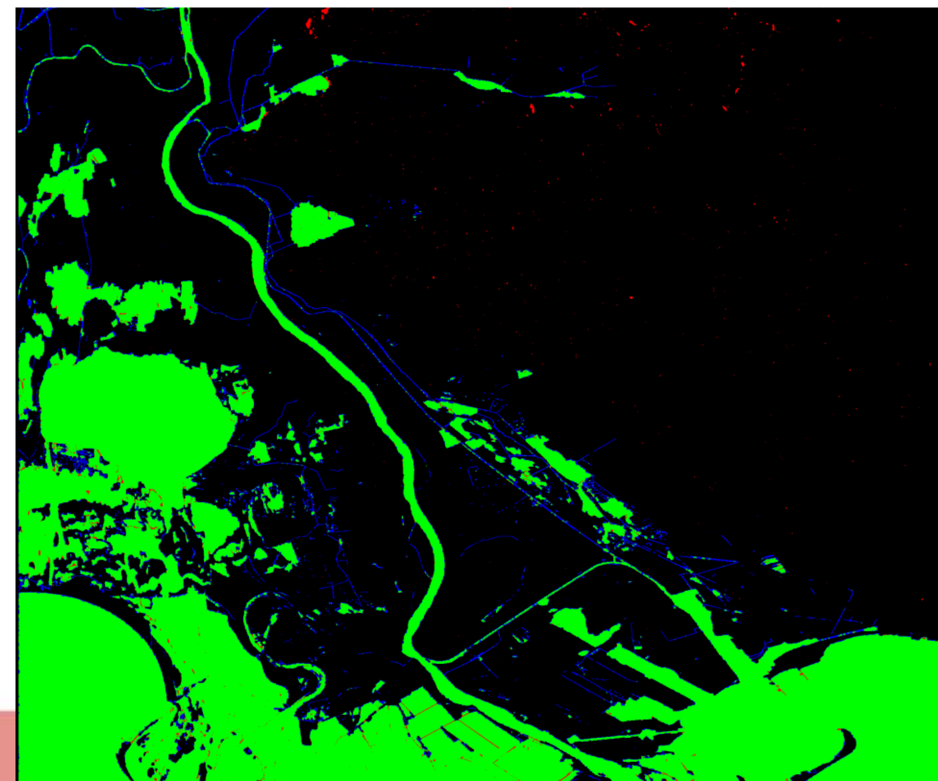
- Local learning of the class parameters
- Image partitioning for graph-cut based optimization





Initialization Classification Partition





Thèse S. Lobry

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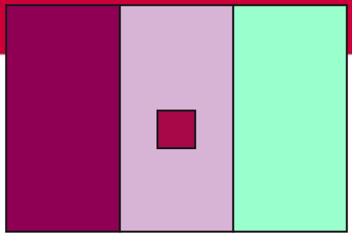
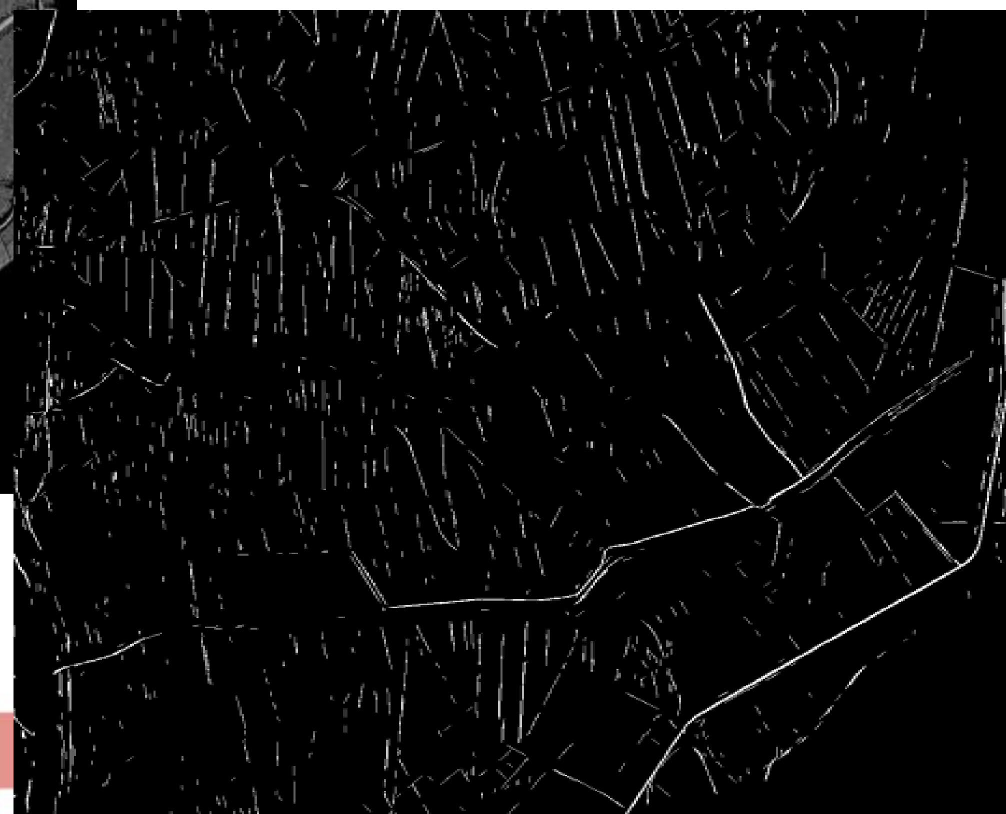
Fine network detection

- **Context:**
  - Adaptation of a road detection algorithm for SAR data
- **Method principle:**
  - Low-level line detector taking into account SAR statistics
  - High level step connecting the detected candidates (contextual information)

Step 1: Line detector

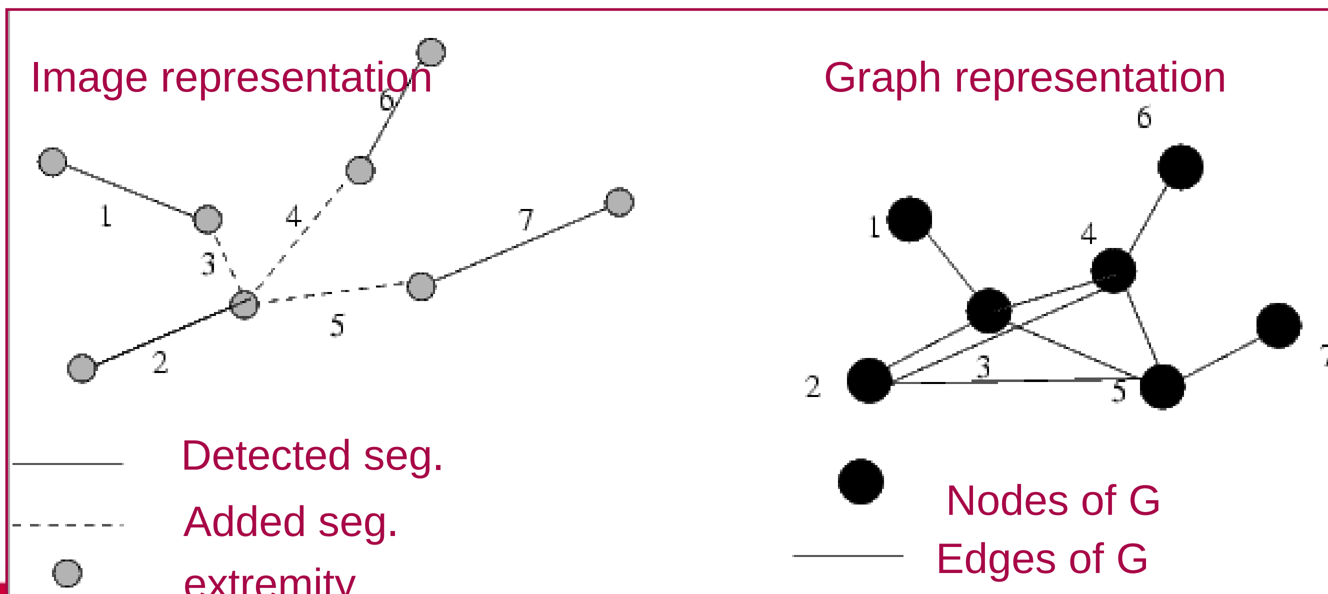


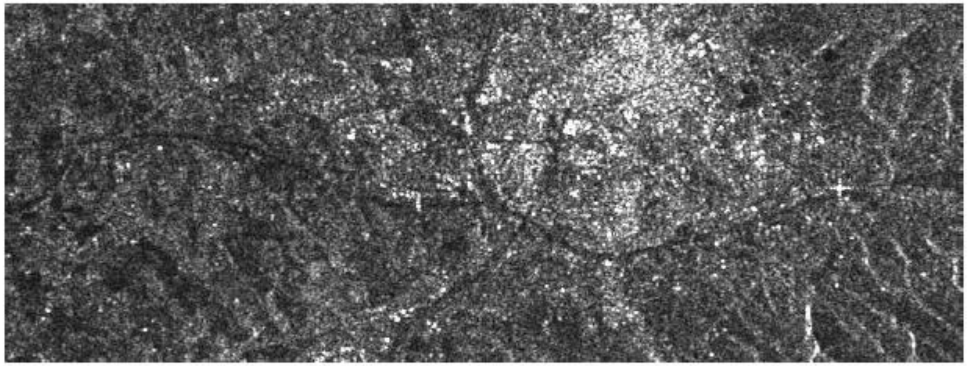
- **Speckle noise:**
  - Nakagami distribution of SAR amplitude data
  - Line detector based on the ratio of amplitude mean computed on stripes around the considered structure
  - Statistical analysis of the ditribution of the ratio-based line detector
  - In practice:
    - Width of the line between 3 and 5 pixels
    - 11 pixels length

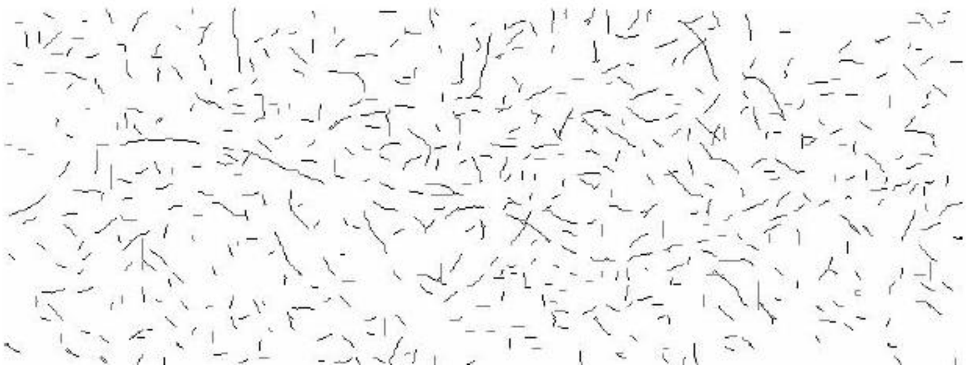


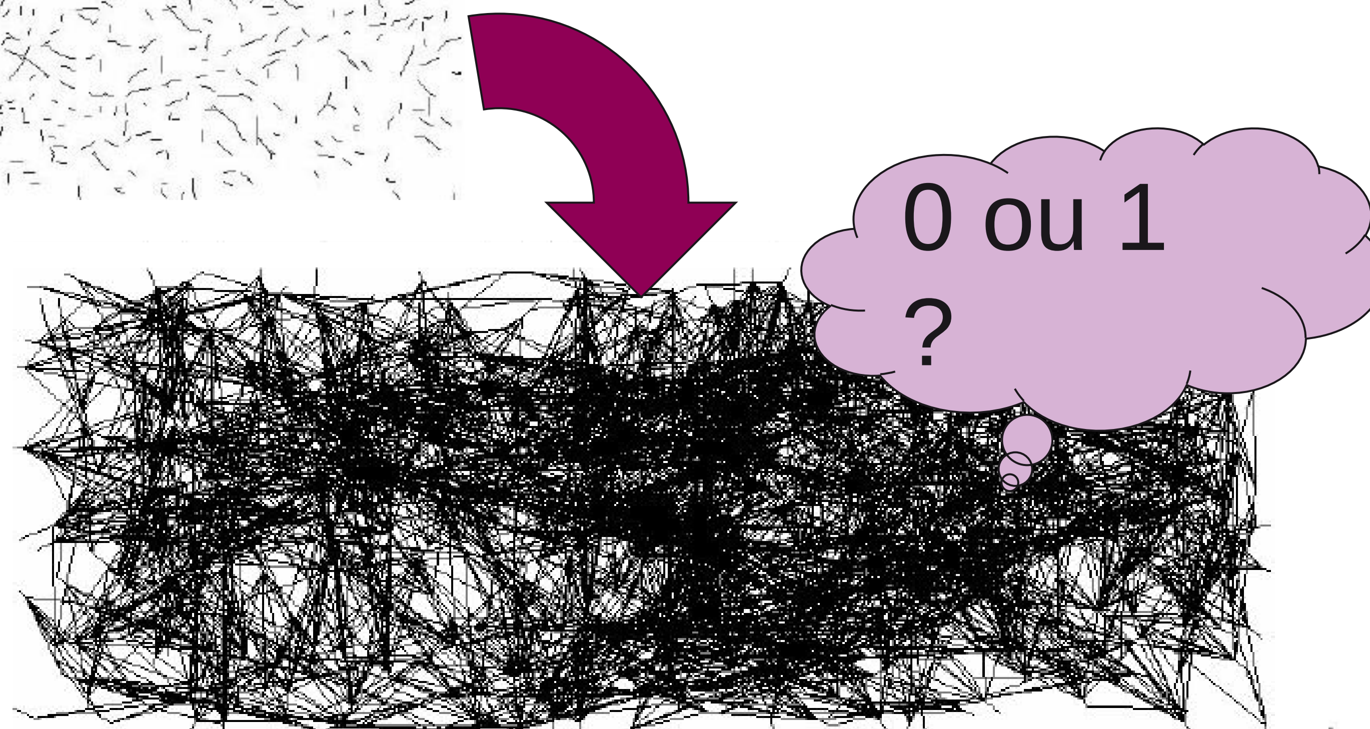
Step 2:Markov random field on a line graph

- **Graph construction:**
  - Line detection
  - Graph = segment graph using the detected segments and all the « possible » connexions (edge = 2 segments share an extremity)








0 ou 1
?

Step 2:Markov random field on a line graph

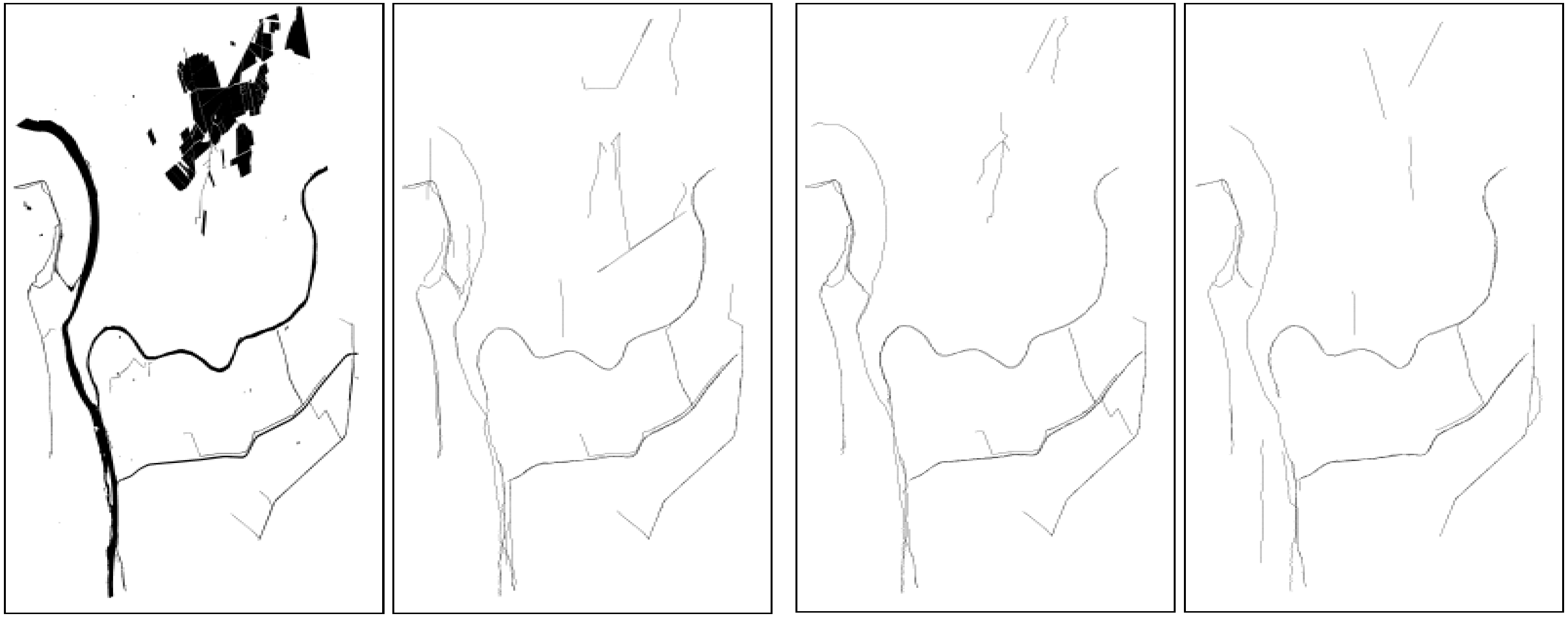
- **Markovian energy**
  - X binary field (road or not road label)
  - Y line detector responses observed in the SAR data

$$U(x \mid y) = \underbrace{\sum_s -\log P(y_s \mid x_s)}_{} + \underbrace{\sum_c V_c(x_c)}_{}$$

Likelihood of the observations for a given label
Computed using the line detector response along the segment

Prior information about the river shapes
•Riverss are long
•Curvature
•Few crossings

Some results



- **Quantitative evaluation (correctness / completeness):**
  - Water bodies / networks
  - Positioning problems between mask / detection

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- Conclusion and further works

Conclusion and further works

- **Joint analysis of phase / amplitude data**
  - Combining both information (using complex field distributions – phase / coherence / amplitude)
- **Introduction of « prior » information**
  - Reference mask deformation (level set)
  - Multi-temporal processing (class learning, algorithm initialization, multi-temporal denoising, …)
- **Constraint: huge amount of data**
  - Simple and fast algorithms to compute the products

References

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- R. Fjortoft et al. KaRIn on SWOT: Characteristics of Near-Nadir Ka-Band Interferometric SAR Imagery, IEEE TGRS, 2014.
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