Advanced POLSAR

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Outline

- ✓ Classifiers
  - ✓ Cloude-Pottier
  - ✓ Wishart
- ✓ Applications
  - ✓ Ship detection
- ✓ Compact polarimetry
  - ✓ Raney decomposition

Summary of basic concepts

Reminder: single and partial target representation

Single Targets

Scattering matrix:

$$[S]=\begin{pmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{pmatrix}$$

Scattering vector:

$$\underline{k}=\frac{1}{2}Trace\left([S]\Psi\right)=[k_1,k_2,k_3,k_4]^T$$

Backscattering & reciprocity

$$\underline{k}=\frac{1}{2}Trace\left([S]\Psi\right)=[k_1,k_2,k_3]^T$$

Scattering mechanism:

$$\underline{\omega}=\underline{k}/|\underline{k}|$$

Partial Targets

The second order statistics are necessary.

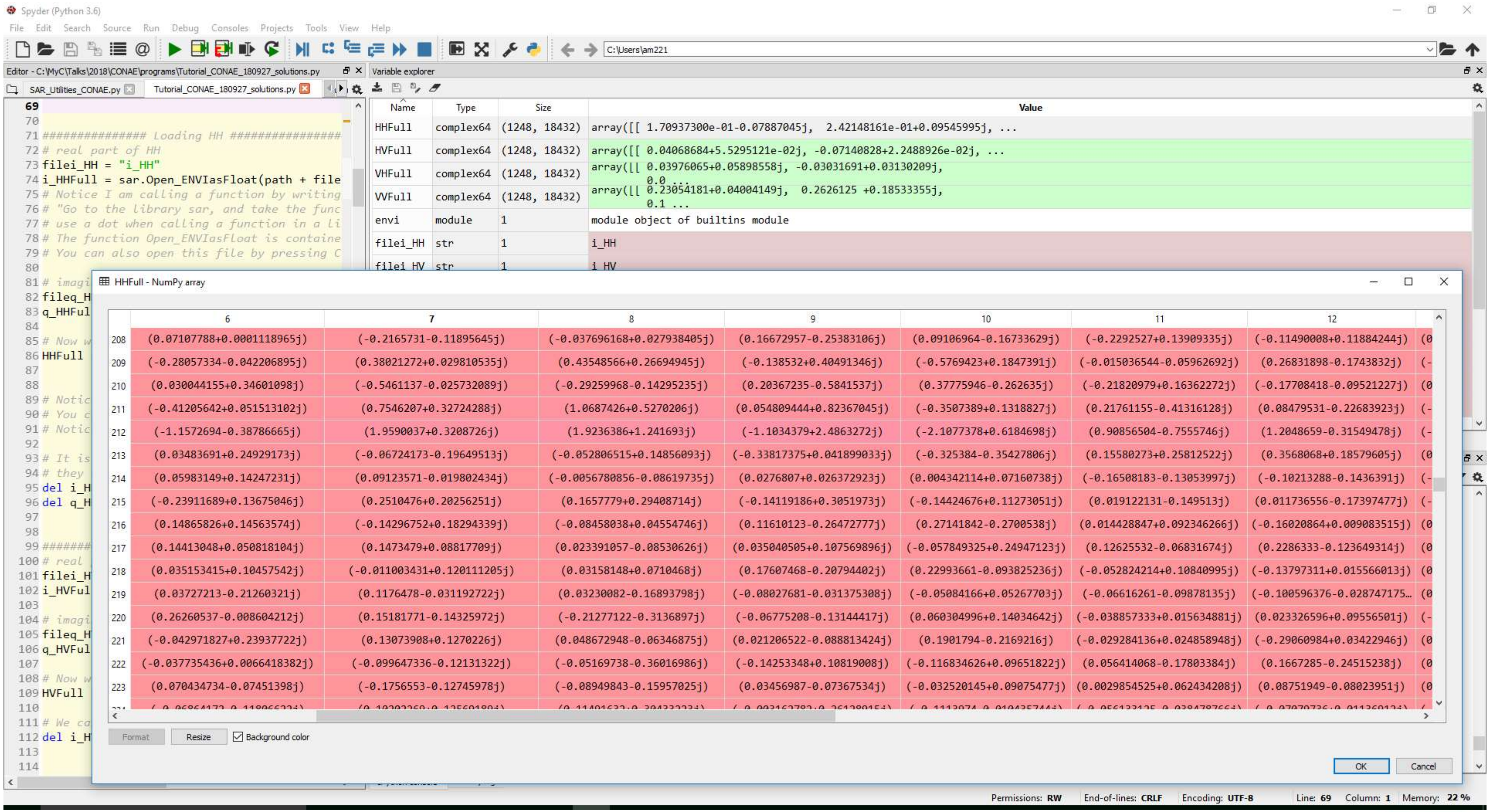
$$[C_3]=\left\langle \underline{k}\cdot\underline{k}^{+}\right\rangle$$

Covariance matrix:

$$[C_3]=\begin{bmatrix} \langle |k_1|^2\rangle & \langle k_1k_2^*\rangle & \langle k_1k_3^*\rangle \\ \langle k_2k_1^*\rangle & \langle |k_2|^2\rangle & \langle k_2k_3^*\rangle \\ \langle k_3k_1^*\rangle & \langle k_3k_2^*\rangle & \langle |k_3|^2\rangle \end{bmatrix}$$

Scattering matrix

Data are stored in complex form, that is real plus imaginary part



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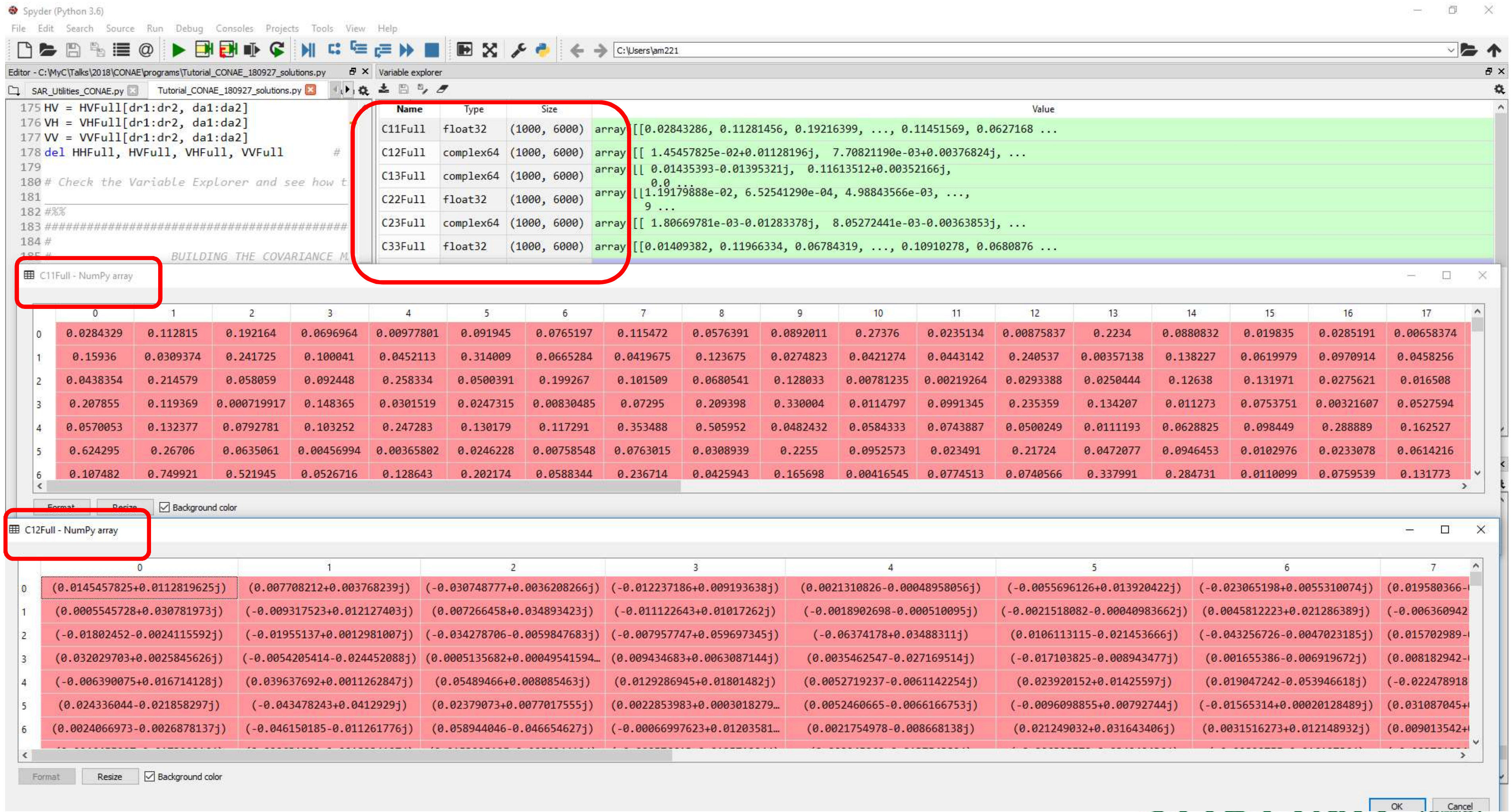
Covariance matrix

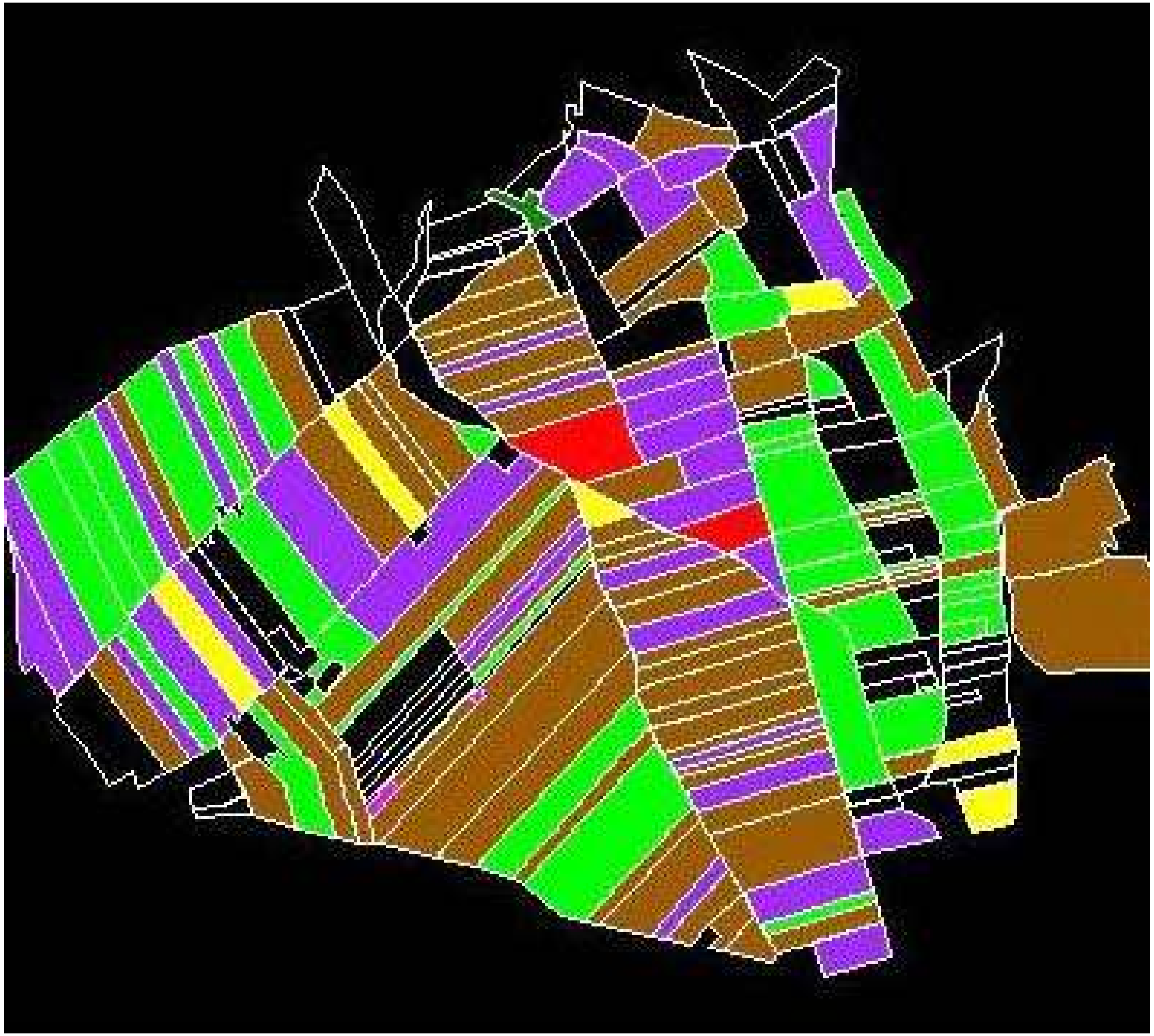
- ✓ An easy way to use this is by creating one image each element of the covariance matrix
- ✓ Pay attention that cross-diagonal elements are Complex numbers.



Classifiers

What is classification/segmentation?

Example of Land Cover



Making a classifier with Cloude-Pottier: H and A

- ✓ We can create **4 classes**. Each of them will have a strong value in one specific combination of Entropy (H) and Anisotropy (A):

1. **One mechanism**: This has high values of **(1-H)(1-A)**, since **t**his means that H and A are small. It is when only one dominant target is in the scene, e.g. a corner reflector.

2. **Two Mechanisms**: This has high values of **HA**, since H and A are big. It is when the process is confused, but there are only 2 strong scatterers, e.g. a dihedral and trihedral reflector in the same averaging window.

3. **One "almost dominant" Mechanism**: This has high values in **(1-H)A**, since H is high but A is big. It is when one scatterer dominates, but the others are not too small and not the same, e.g. some agricultural fields or buildings (i.e. strong dihedral from the wall and weaker surface from the roof).

4. **Three (or more) mechanisms**: This has high values in **H(1-A)**, since H is high and A is low. It is when the polarimetric behaviour is highly confused since there are many scatteres, e.g. a forest.

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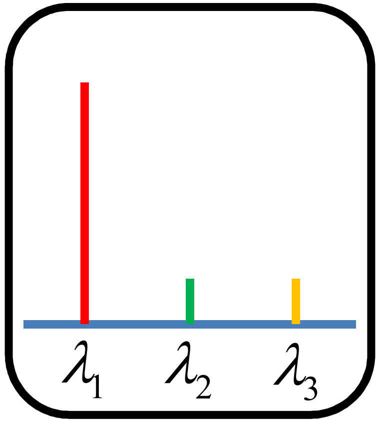
Making a classifier with Cloude-Pottier: H and A

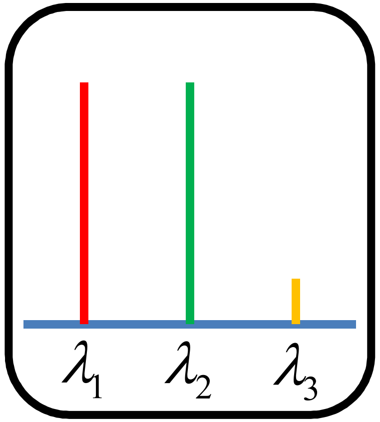
It is similar to decomposing the total power P (coming from the target) in several components:

$$P = P(1-H)(1-A) + PHA + P(1-H)A + PH(1-A)$$

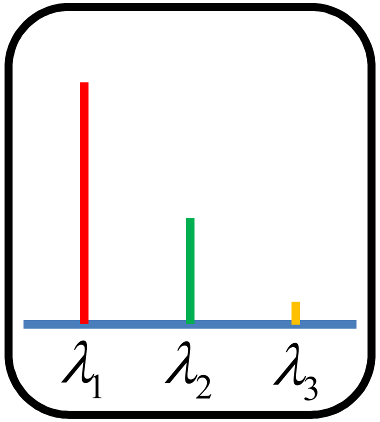
1 dominant



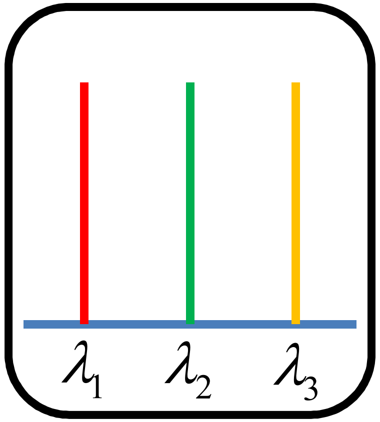
2 mechanisms with same strength



2 strong mechanisms, but one dominates



3 or more mechanisms



λ_i are the eigenvalues

Cloude-Pottier classification scheme: H and alpha

Here we want to introduce **α** in the classifier. We can plot entropy against **α** and separate the obtained feature space in 9 portions.

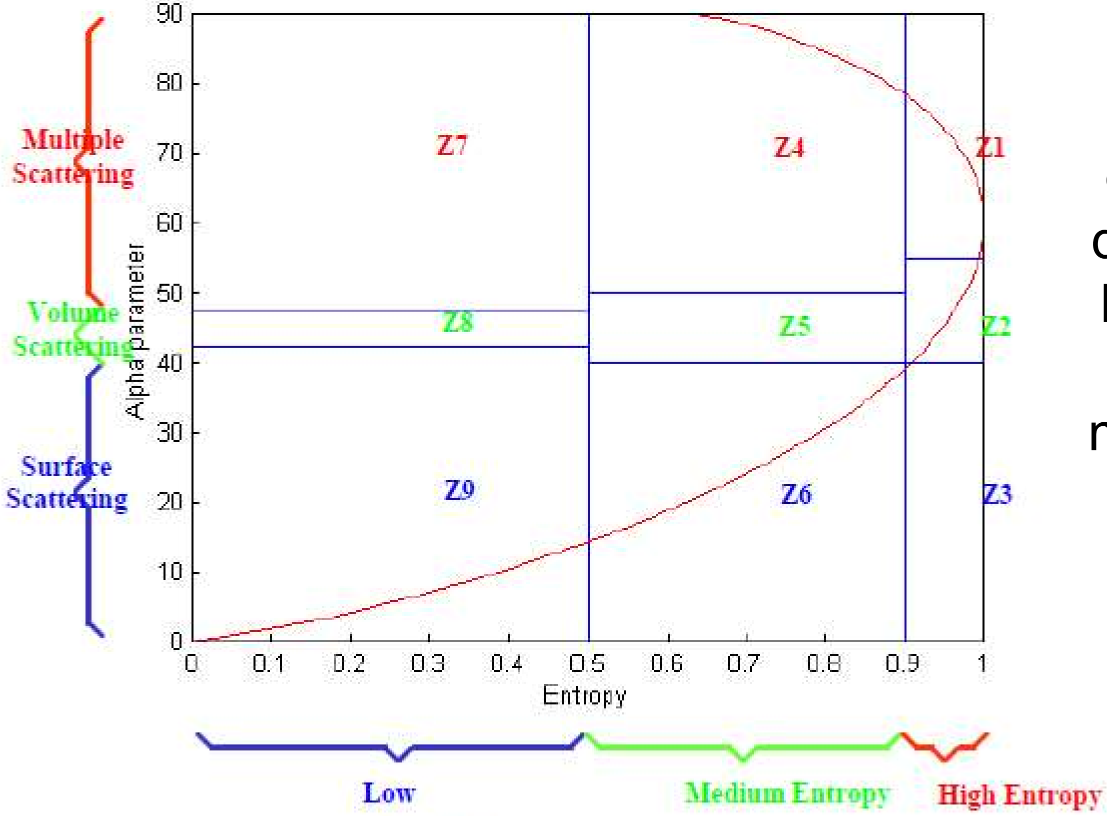


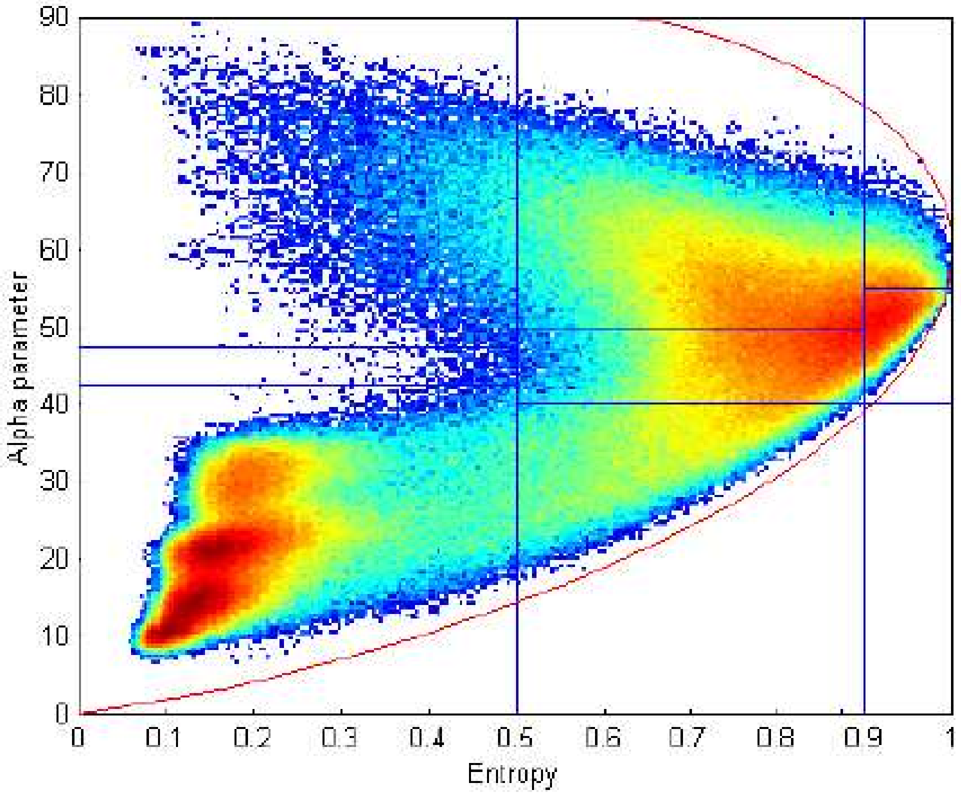
Fig. 13a : The H / α classification plane.

Alpha always ends up to **60** degrees when **H=1**. It can be proved mathematically

$$\hat{\alpha} = \sum_{i=1}^{3} \left(P_i \alpha_i \right)$$

Checking it on data: an example of histogram

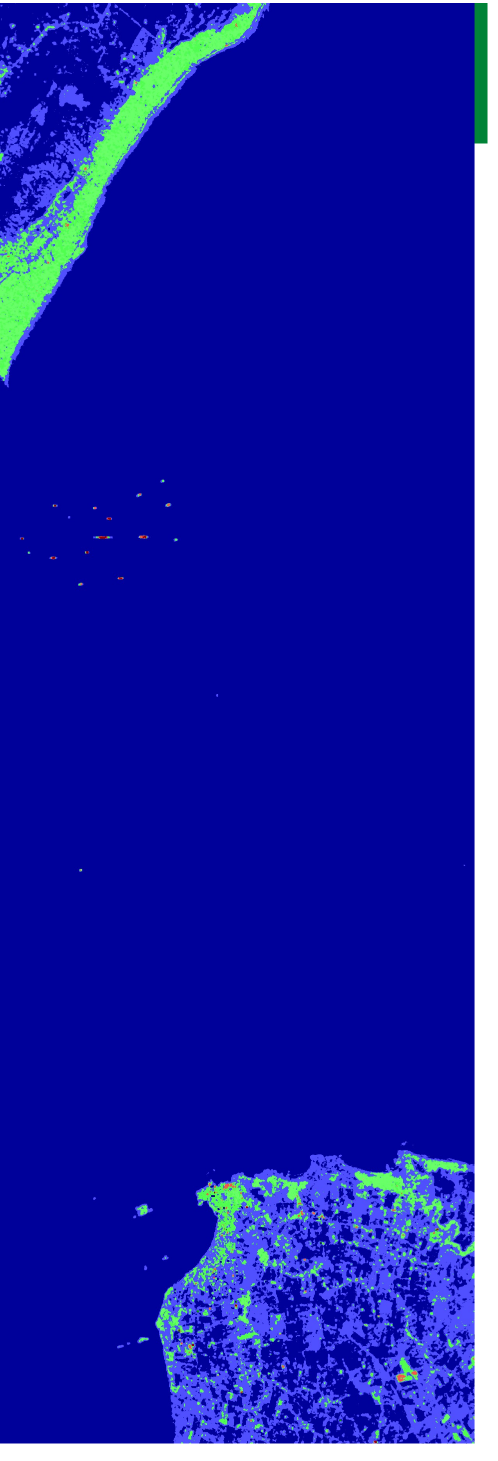
The 2D feature space proposed previously can be used to produce a 2D histogram of the data (we plot the actual value of **α** and entropy as in the data). As expected they are all inside the mathematically feasible area.



Results of classification

The classifier is able to recognise that the sea is a unique class.

Some areas on the land also belong to the same class. A reason may be that they behave like surfaces. Supervised classifiers may work better on those areas.



Statistically based

Why statistical classifier

- ✓ The classifier proposed previously is considering the physical behaviour of scatterers but it does not take into account the statistical variation of the image pixels
- ✓ In order to do this we need to know the pdf of the covariance (or coherency) matrix.
- ✓ This is a **Wishart** distribution.

L: number of independent looks

p: number of polarisation channels

Matrix Trace

$$f_T\left([T]/[T_m]\right) = \frac{L^{Lp}\left|[T]\right|^{L-p} \mathrm{e}^{-LTr\left([T_m]^{-1}[T]\right)}}{\pi^{\frac{p(p-1)}{2}}\Gamma(L)\ldots\Gamma(L-p+1)\left|[T_m]\right|^{L}}$$

pdf of the covariance matrix

Conditional to a specific class

Gamma function

Matrix determinant

The Wishart distance

- ✓ In order to set a statistical test from a known distribution, we need to define a **Distance.** This will tell us when two distributions look the same or not.

- ✓ A standard procedure is to use the **Bayesian Theorem** to calculate the Likelihood that a class is there and maximise it (**Maximum Likelihood Estimator, MLE**).

- ✓ The result of the MLE is a *distance between the pixels under analysis and the theoretical distribution of our class*. If the pixels seems similar to what we expect is our class, than the distance to that class is small.

$[T_m]$: Class
$[T]$: Test
$Tr()$: Trace
$|.|$: Determinant

Distance

$$d_m([T]) \square Tr\left([T_m]^{-1}[T]\right) + \ln\left(|[T_m]|\right)$$

$$[T] \in [T_m] \quad \text{if} \quad d_m([T]) < d_j([T]) \quad \forall j \neq m$$

The Wishart distance: iterative

- ✓ You can also decide to apply the classifier **iterately**. This generally provides *smoother results*… and it was tested, and seems to perform better.
- ✓ After the first classification, *the training dataset* (the coherency matrices of the classes) *are recalculated* (averaging the pixels in the same class result of the first classification) and another classification is performed
- ✓ The iteration continues till a **condition** is not met (i.e. there are very few pixels that changed their classes)

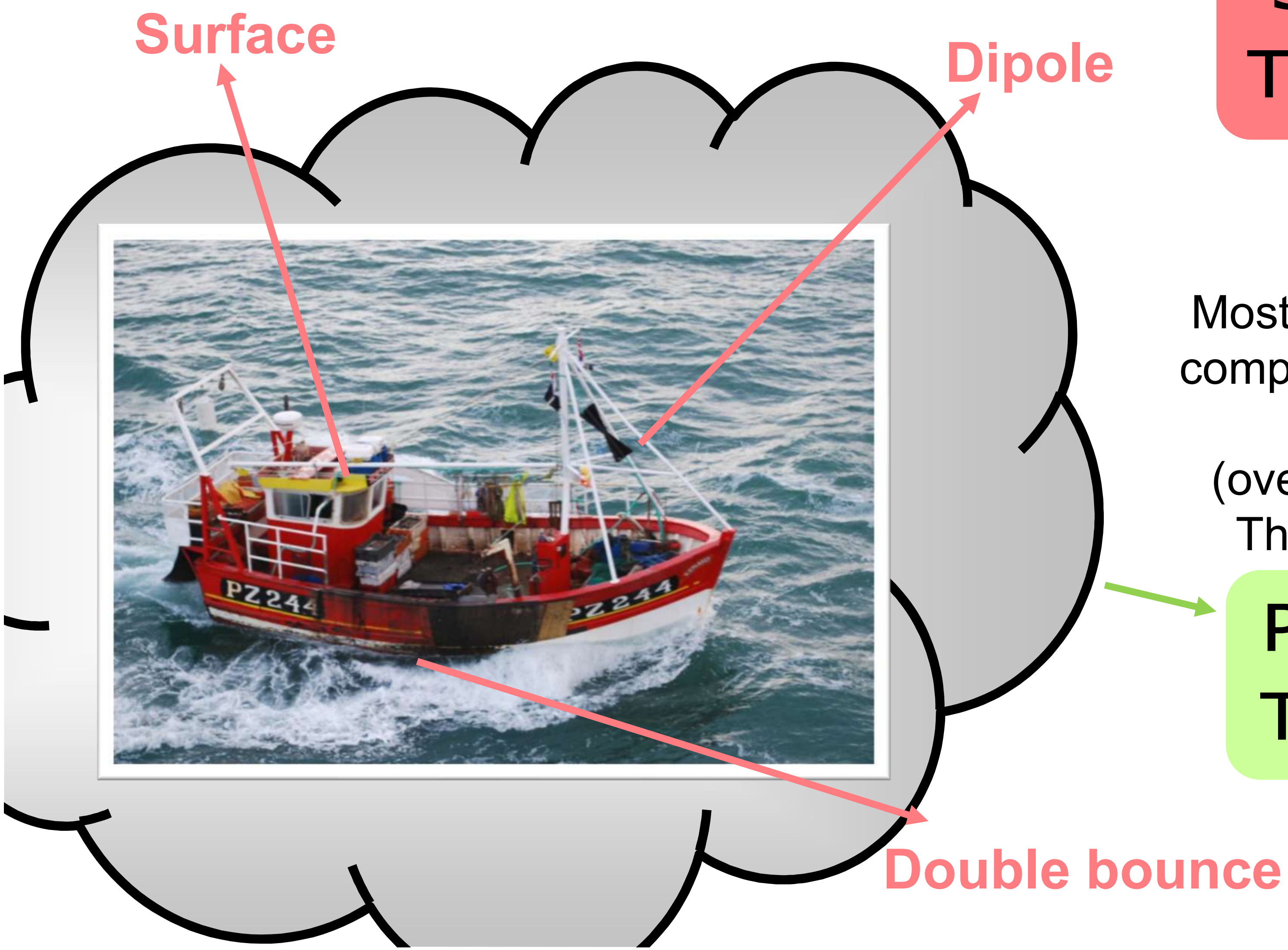
Maritime Applications:
ship detection

Scattering from sea and ships

Scattering from sea and ships

Is a ship a single target?

It is a collection of single targets

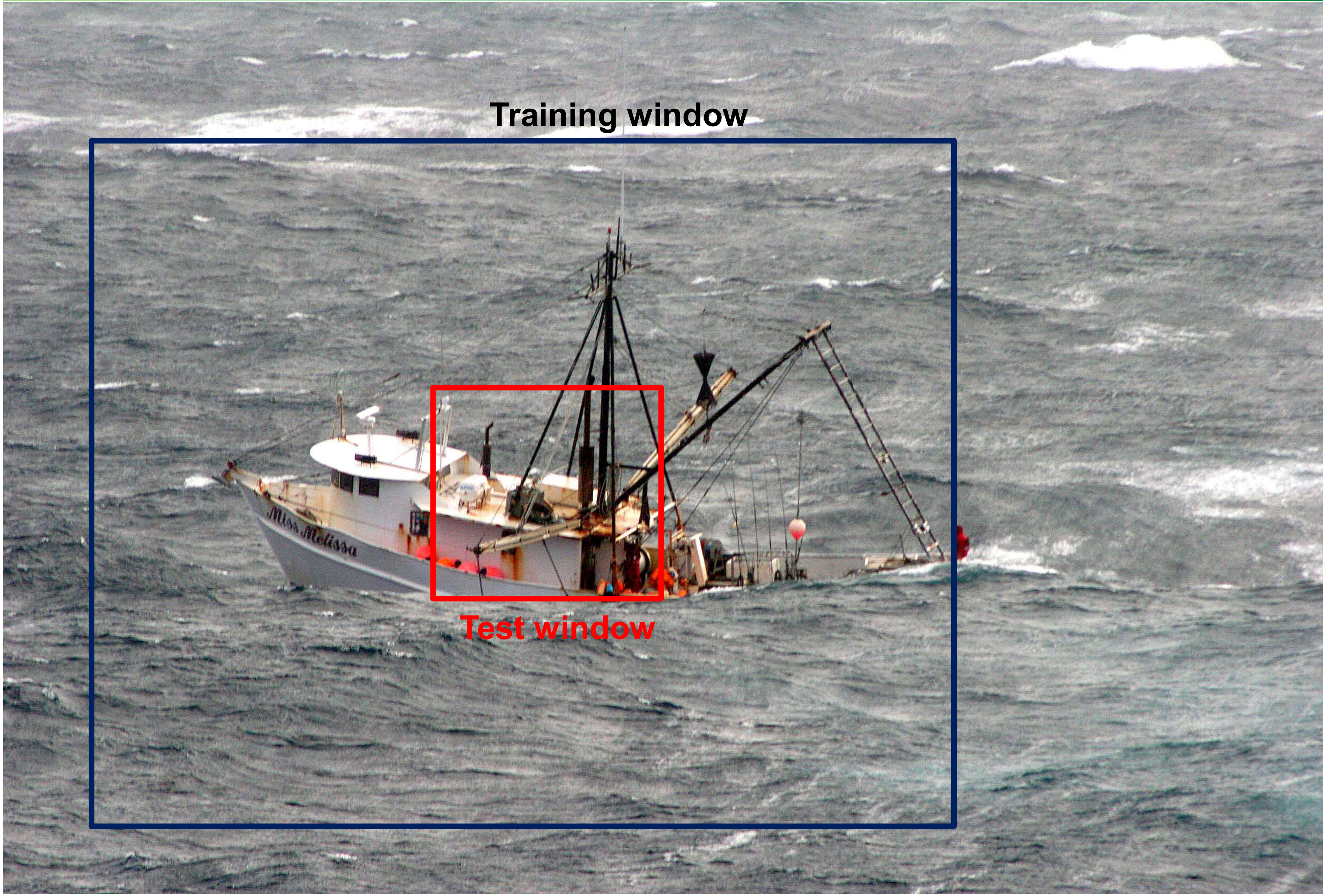


Single Targets

Most real targets are composed by **several** scatterers (over more pixels). They appear as:

Partial Targets

Evaluating differences between sea and ships



Polarimetric Notch Filter (PNF)

The algorithm is based on the *Geometrical Perturbation - Partial Target Detector,* however here, it is reversed and focused on the complementary space.

The **sea** is the **clutter** and the **rest** is the **target of interest**

$$P_{Sea} = \left| \underline{t}^{*T} \cdot \hat{\underline{t}}_{Sea} \right|^2$$

$$\boxed{\gamma_n = \frac{1}{\sqrt{1 + \dfrac{RedR}{P_{tot} - P_{Sea}}}} > T_n}$$

$$P_{tot} = \left| \underline{t}^{*T} \cdot \underline{t} \right|^2$$

Partial scattering vector:

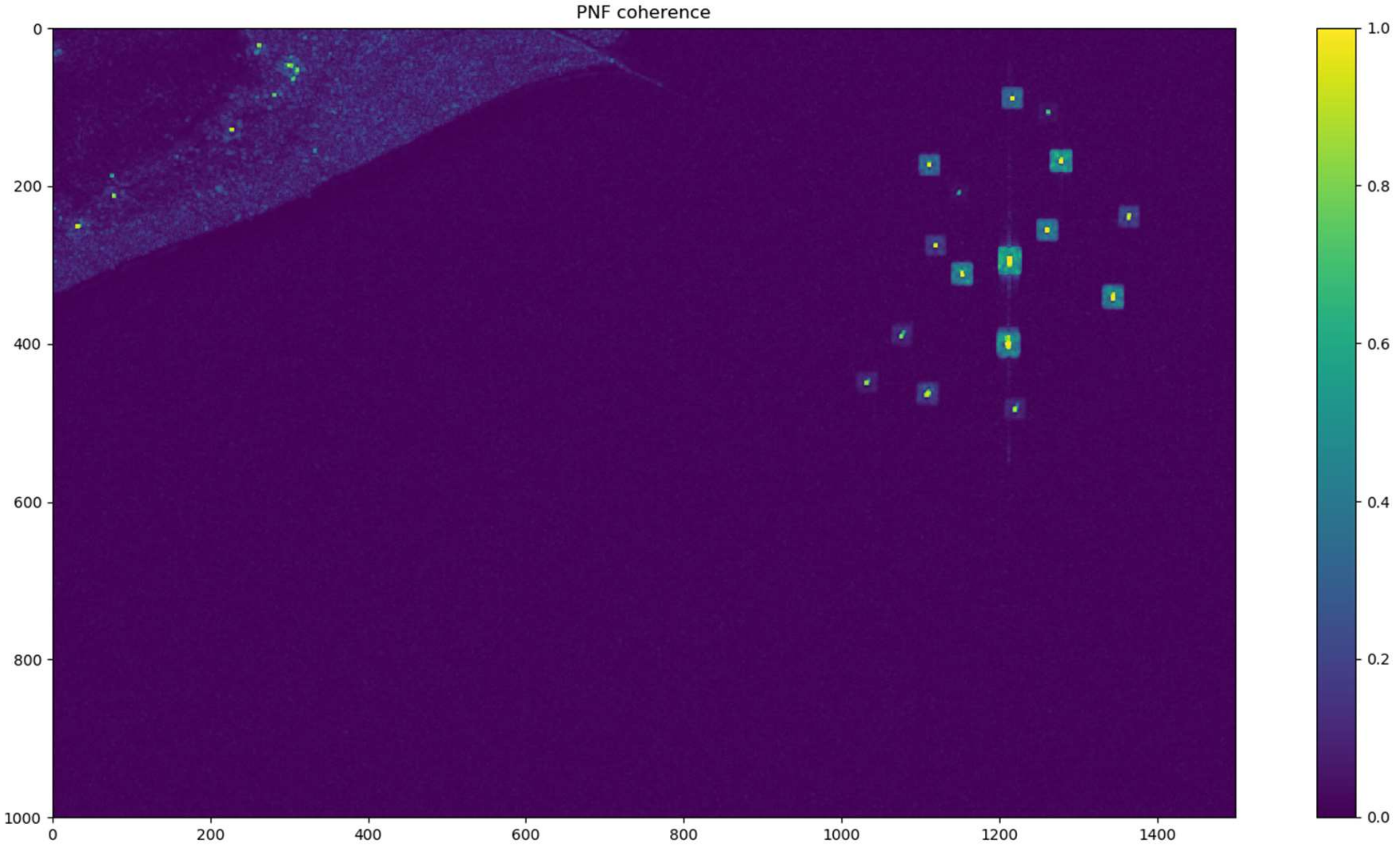
$$\underline{t} = \left[\underline{\omega}_1^{*T} [C] \underline{\omega}_1, \underline{\omega}_2^{*T} [C] \underline{\omega}_2, \underline{\omega}_3^{*T} [C] \underline{\omega}_3, \underline{\omega}_1^{*T} [C] \underline{\omega}_2, \underline{\omega}_1^{*T} [C] \underline{\omega}_3, \underline{\omega}_2^{*T} [C] \underline{\omega}_3 \right]^T$$

$$\hat{\underline{t}}_{sea} = \frac{\underline{t}_{sea}}{\left\| \underline{t}_{sea} \right\|}$$: target to reject (Null)

Marino, A., Cloude, S. R. and Woodhouse, I. H., “Detecting depolarized targets using a new geometrical perturbation filter,” IEEE TGRS, Vol. 50(10), pp 3787-3799, 2012.

Marino, A., "A Notch Filter for Ship Detection With Polarimetric SAR Data," IEEE JSTARS, early access, pp.1-14

Detectors: PNF



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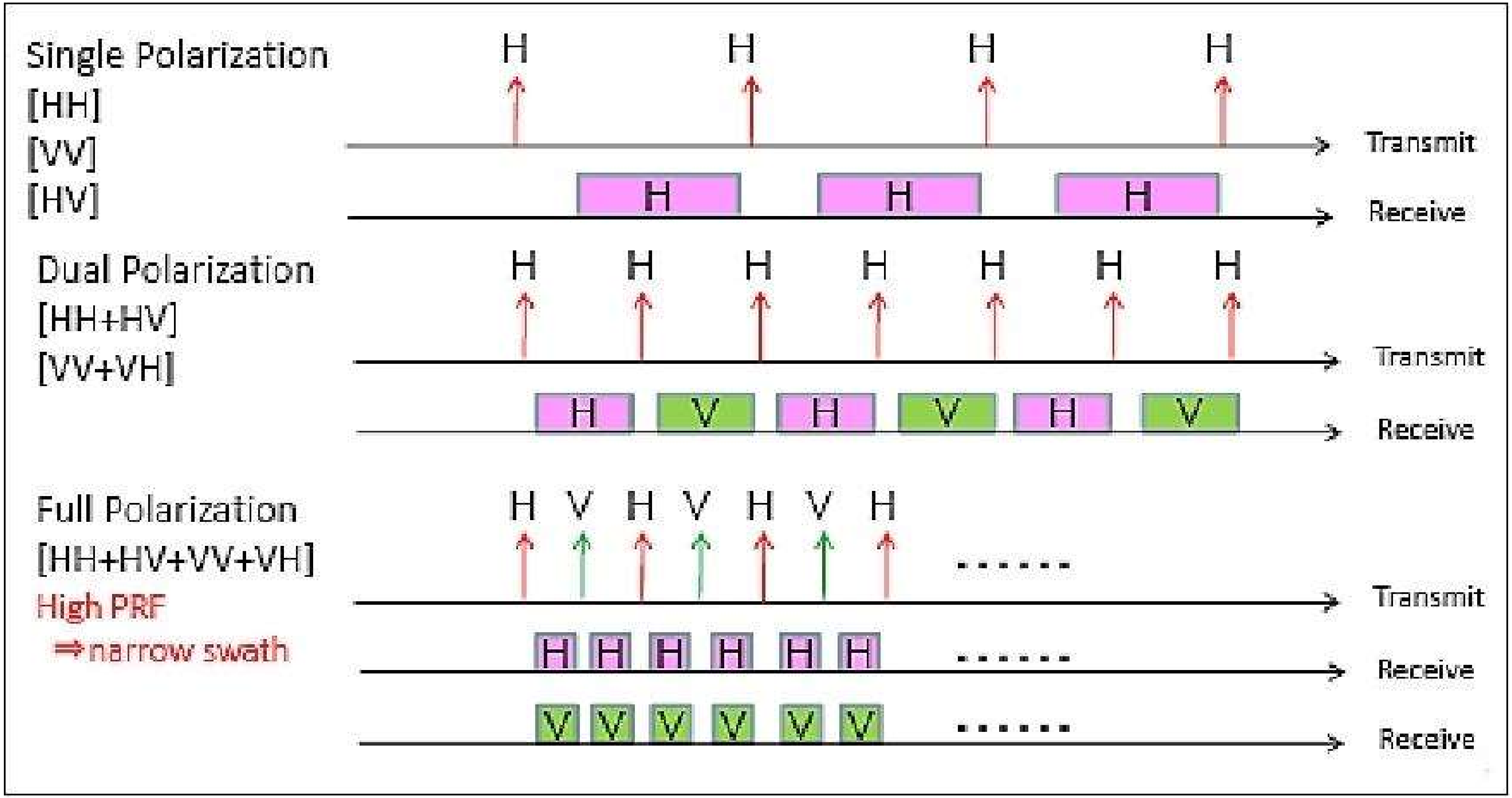
Compact pol

Aquiring quad pol data

Depending on the system, we may have the following drawbacks:

- ✓ Loss of resolution
- ✓ Los of signal to noise ratio
- ✓ Higher PRF
- ✓ Loss of area covered

Courtesy: JAXA

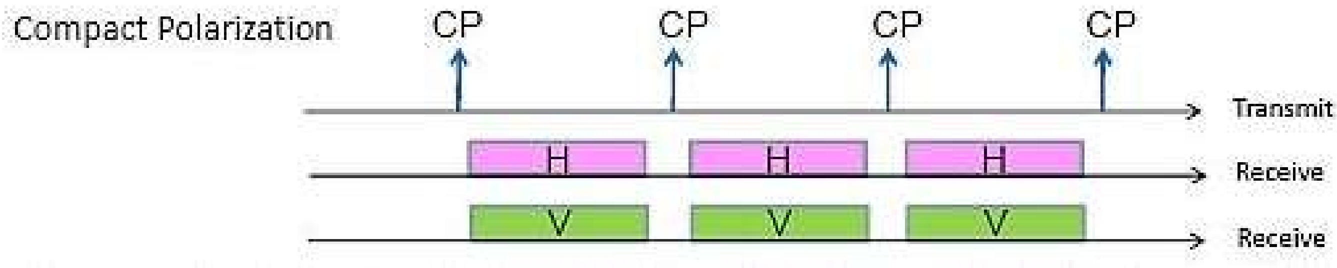


Compact pol

The idea is to send a **different** polarisation and receive linear horizontal and vertical.

For the **Hybrid** mode on SAOCOM the transmitted polarisation is circular.

In this way we combine somehow the information of different polarisation channels.



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Stokes vector

Since we have always the same transmitter, we can apply a “Wave analysis” of the polarisation for the receivers.

Beside building a scattering and a covariance, we could also use the Stokes vectors.

$$S_0 =< |E_H|^2 + |E_V|^2 > +N_0 = S_0$$

$$S_1 =< |E_H|^2 - |E_V|^2 > = mS_0 cos2\phi cos2\chi$$

$$S_2 = 2Re < E_H \ E_V^* > = mS_0 sin2\phi cos2\chi$$

$$S_3 = -2Im < E_H \ E_V^* \geq = -mS_0 sin2\chi$$

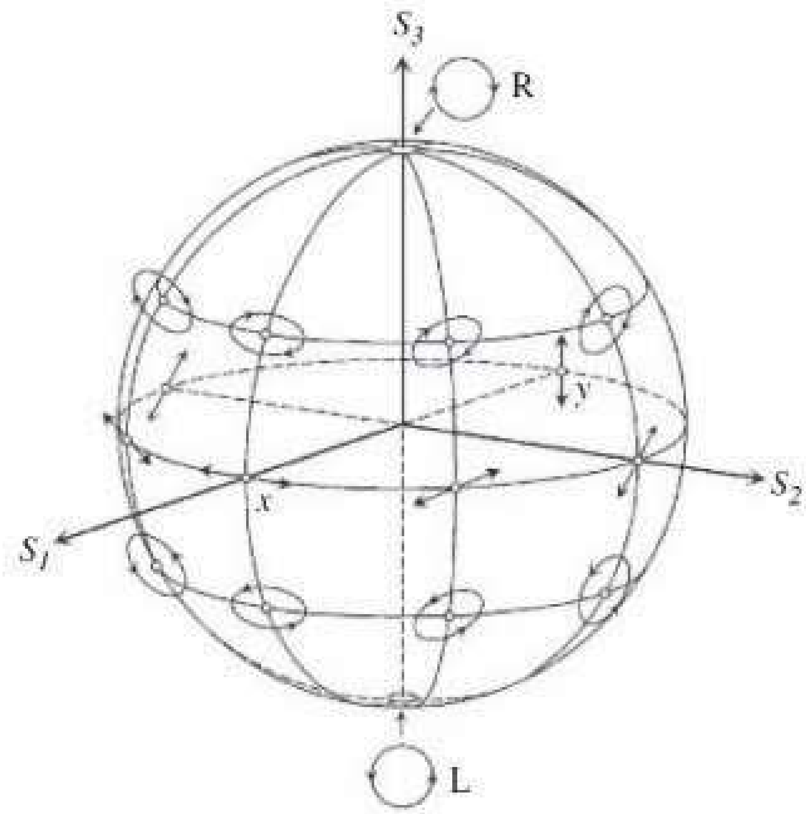
Poincare sphere parameters

Components of received waves

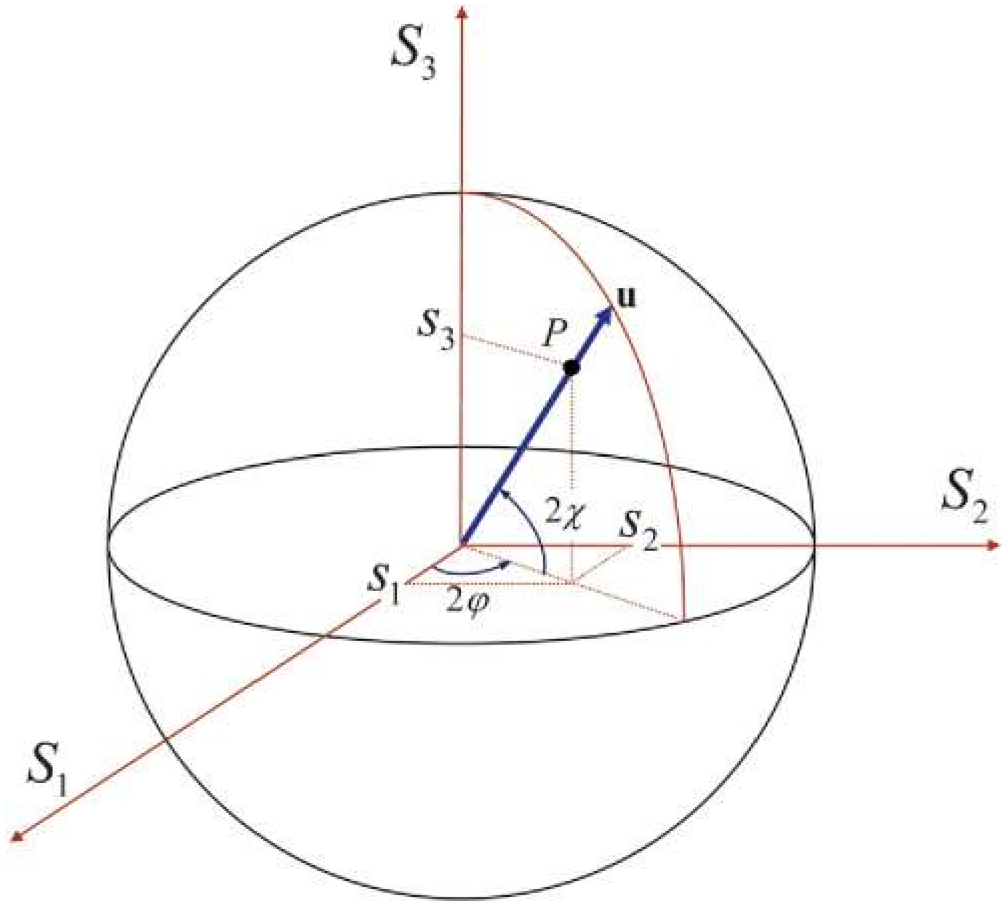
Poincare Sphere

We can represent stokes vector on the Poincare Sphere

State of polarisation



Poincare sphere



The Huynen fork

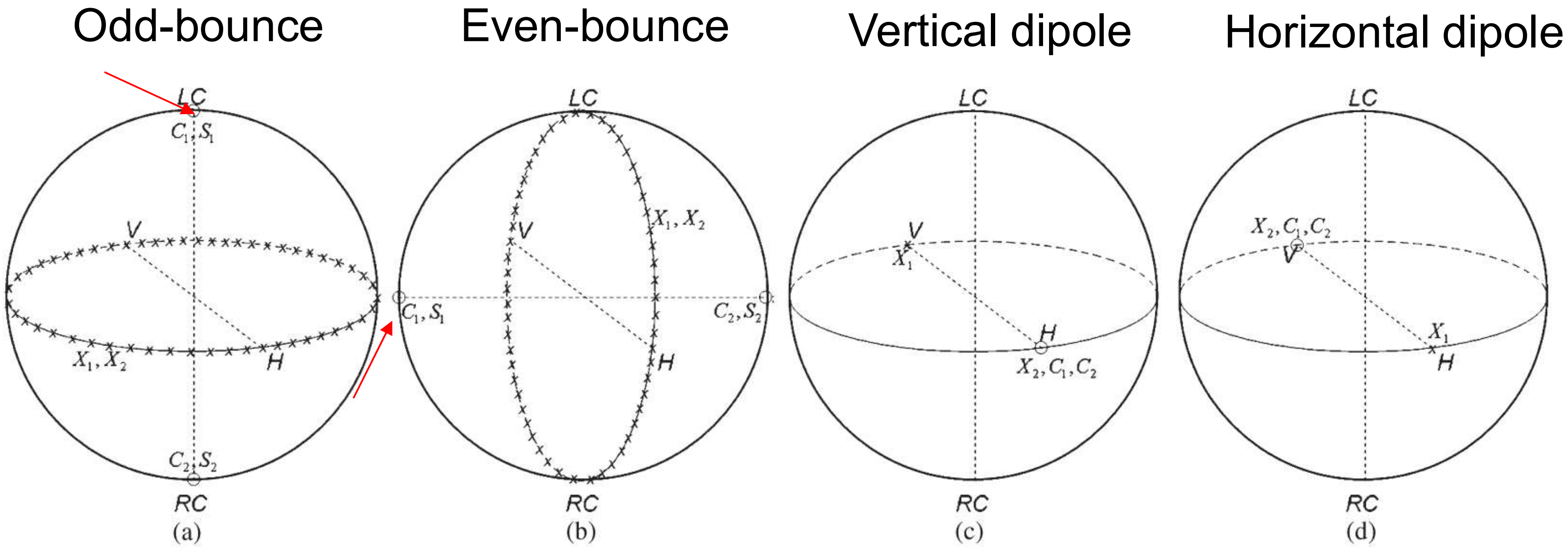


Fig. 6. Poincaré representation of single target detected. (a) Odd bounce. (b) Even bounce. (c) Vertical dipole. (d) Horizontal dipole.

Marino, Armando; Cloude, Shane and Woodhouse, Iain (2010). A polarimetric target detector using the Huynen fork. IEEE Transactions on Geoscience and Remote Sensing, 48(5) pp. 2357–2366.

Poincare Parameters

Degree of polarisation

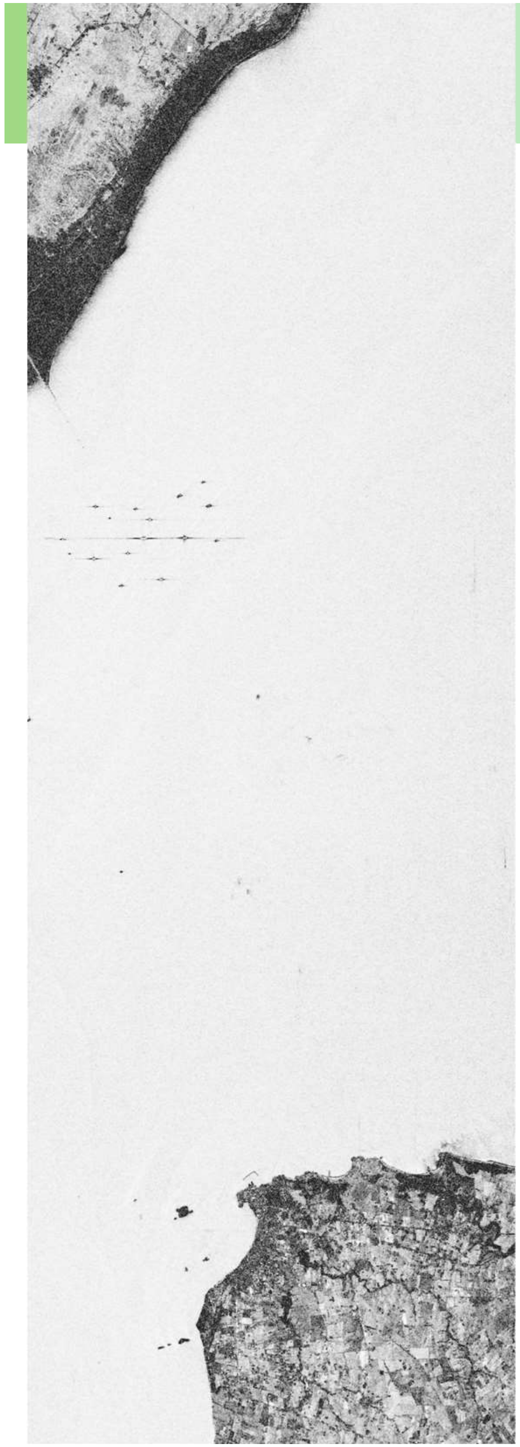
$$m = \frac{\sqrt{S_1^2 + S_2^2 + S_3^2}}{S_0}$$

Angle

$$sin2\chi = -\frac{S_3}{mS_0}$$

- ✓ They provide physical information of targets: e.g. *m* was used for oil and ship detection
- ✓ We can use this to do a target decomposition: **Raney Decomposition**

$$Red = \sqrt{mS_0(1 + sin2\chi)/2}$$
$$Green = \sqrt{S_0(1 - m)}$$
$$Blue = \sqrt{mS_0(1 - sin2\chi)/2}$$

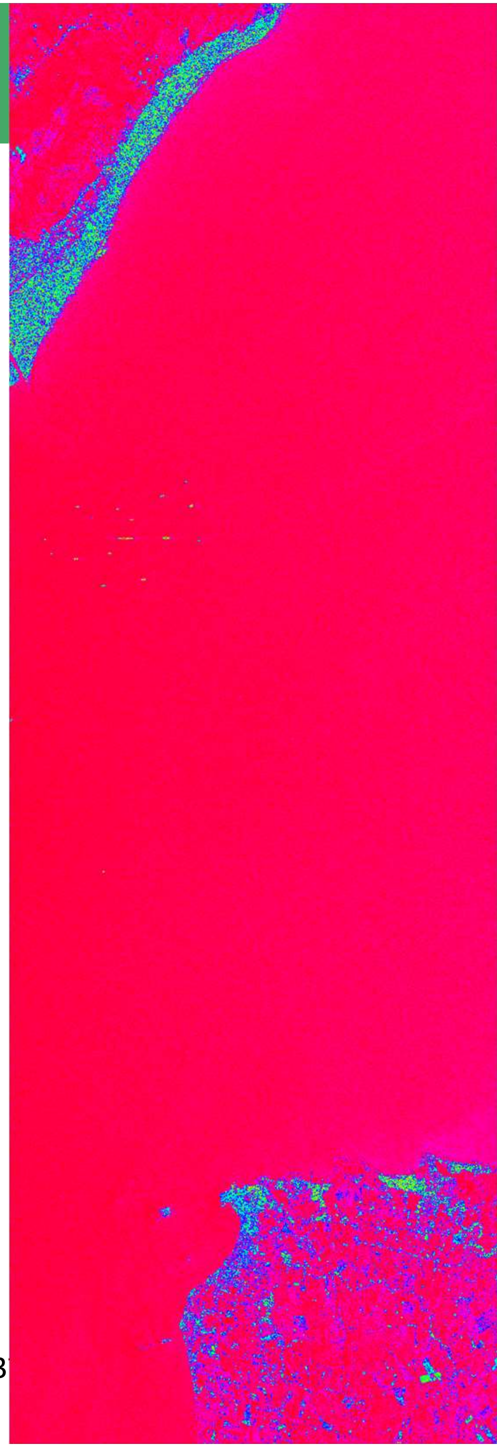


ALOS-1: Buenos Aires

m

The ***m*** parameters is able to identify the sea as a polarised target and the ship as depolarisers (because composed by many scattering mechanisms). This is a result analogue to the entropy

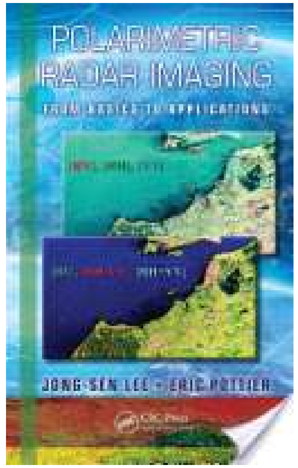
χ



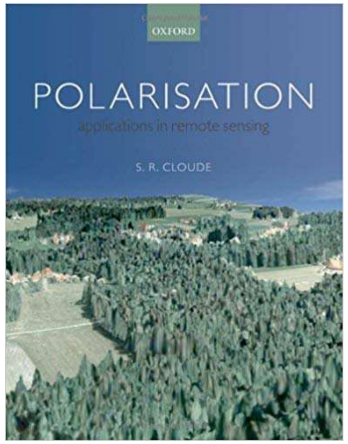
Any questions?

Possible further readings

Polarimetric Radar Imaging: From Basics to Applications
Jong-Sen Lee, Eric Pottier
CRC Press, 2009 - Technology & Engineering



Polarisation: Applications in Remote Sensing, by Shane Cloude, 2009, Oxford Press



Further readings