

# A Location Scale Based CFAR Detection Framework for FOPEN SAR Images

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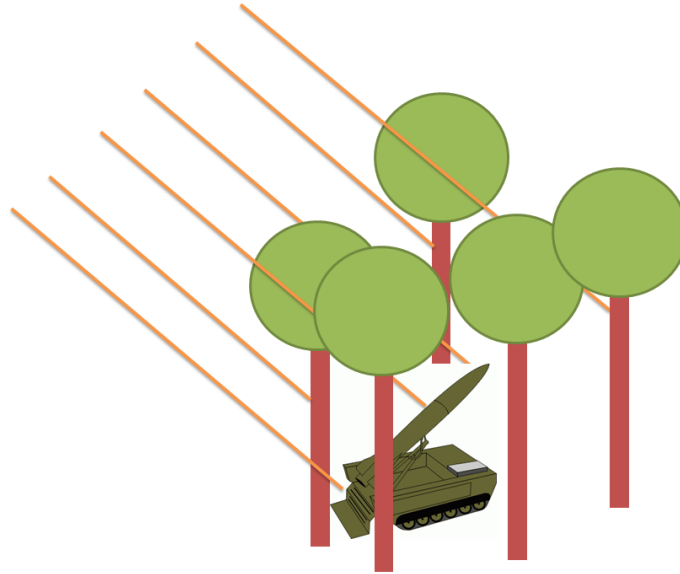


# Outline



- Introduction
- Multi-Model CFAR Detection in LS Environment
- Background Characterization
- Performance analysis on Real Data
  - Extended Target Detection
- Conclusions

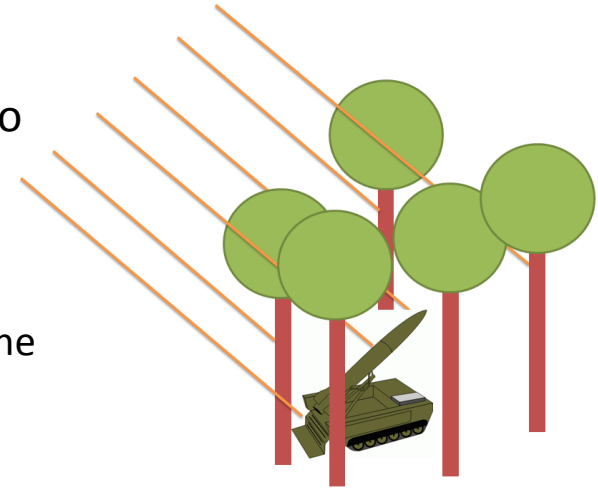
# Introduction



- Foliage Penetrating (FOPEN) Radar Imaging is a technique with high potential in defence applications thanks to its capability to see through foliage canopies;
- Due to the nature of the imaged scene, different challenges from “traditional” SAR images arise;
- The presence of trees, whose trunks reflect with relatively high intensity the radar signal, represents one of them;
- Trees reflection contributes to the clutter return that become more difficult to model;
- This makes difficult the application of standard detection techniques.

# Introduction

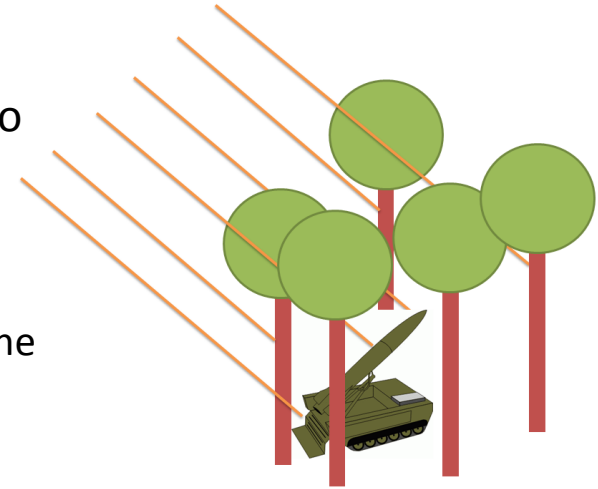
- For this specific family of background a general and closed form model is not available;
- However a statistical approach is desirable thanks to its reliability and capability to include control on performance;
- The problem of target detection consists of deciding on the possible presence of a target in a signal (i.e. SAR Image).



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- The detection problem can be formulated in the form of the following hypothesis test:

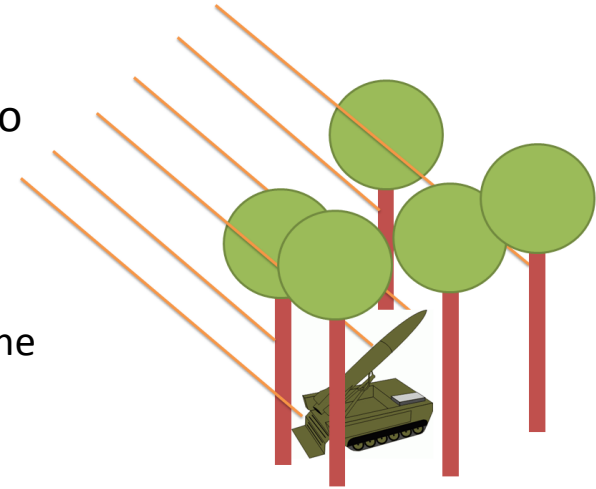
$$\begin{cases} H_B : X = B & \text{Target absent} \\ H_T : X = T & \text{Target present} \end{cases}$$

Where  $X$  is the random variable and  $T$  denotes the threshold value.

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- In this work we propose a Constant False Alarm Rate algorithm for detection of targets in foliage able to adapt the threshold and the distribution model to deal with this particular background type;

# Multi-Model CFAR Detection in LS Environment



- A general solution to the CFAR problem exists if the clutter distribution is of a Location-Scale family or if a parameter-free transformation can be found a general distribution in a Location-Scale type

# Multi-Model CFAR Detection in LS Environment



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A random variable  $X \sim LS(\theta_L, \theta_S)$  is of the location scale type, with location parameter  $\theta_L \in \mathbb{R}$  and scale parameter  $\theta_S > 0$  if any variable of the family can be obtained by an affine transformation of the standardized variable  $X_0 \sim LS(\theta_L = 0, \theta_S = 1)$ , namely

$$X = \theta_S X_0 + \theta_L$$



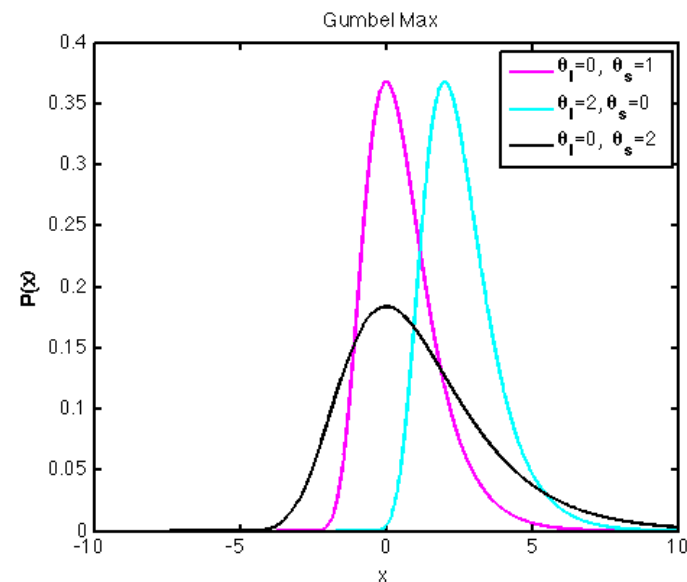
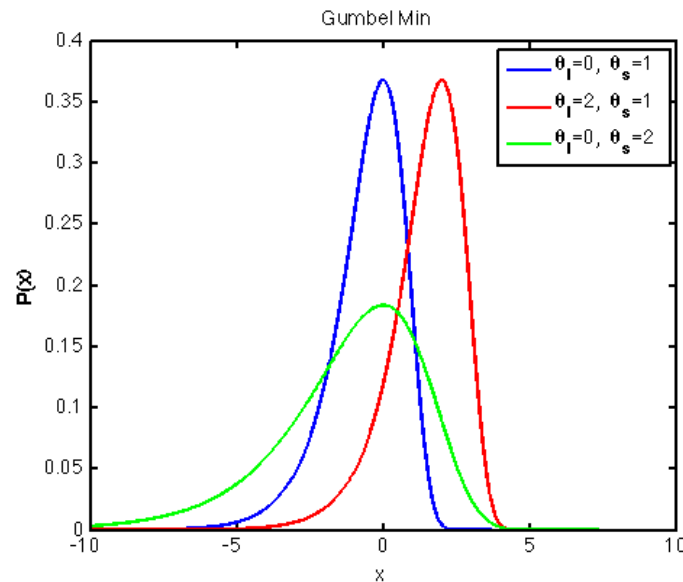
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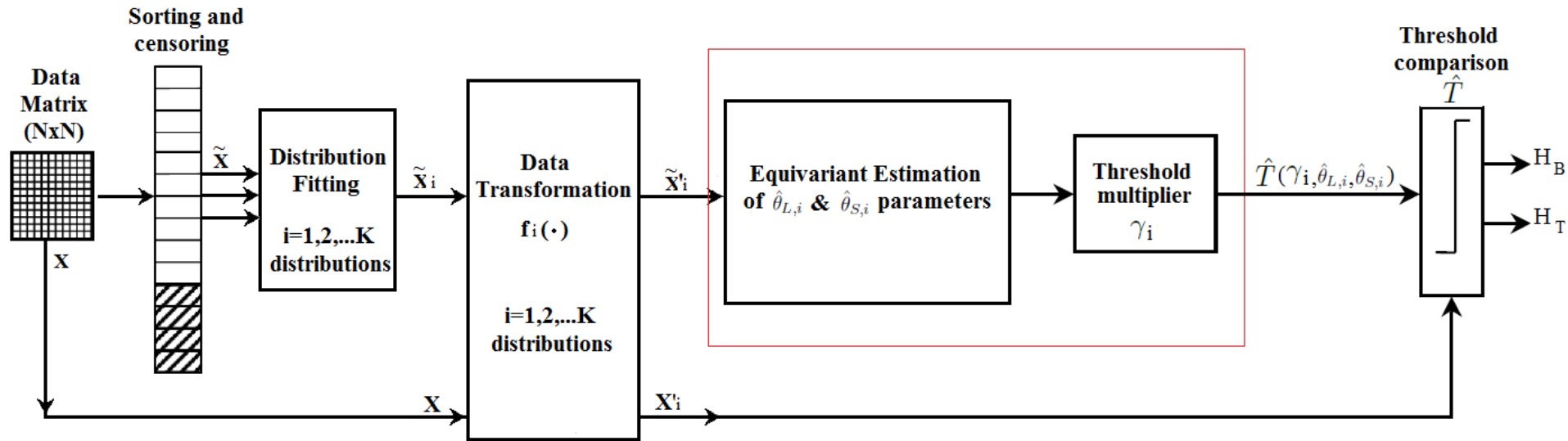
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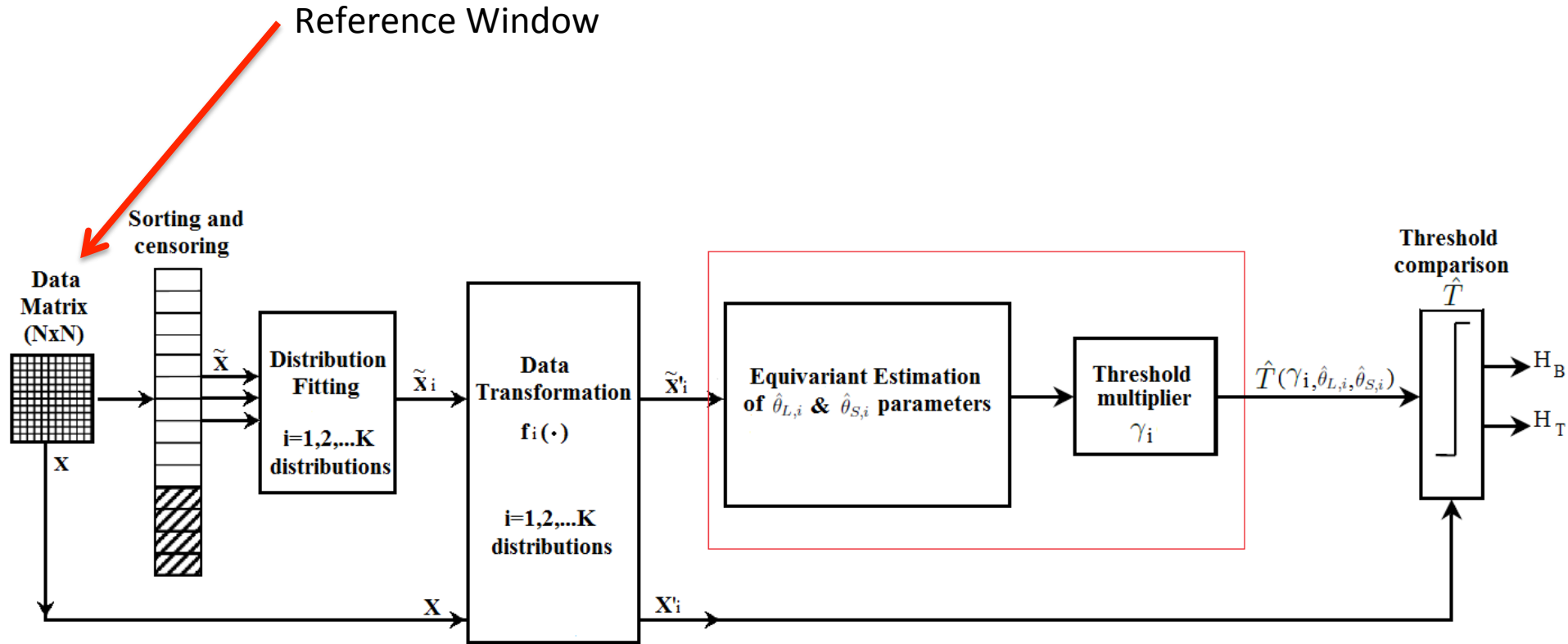
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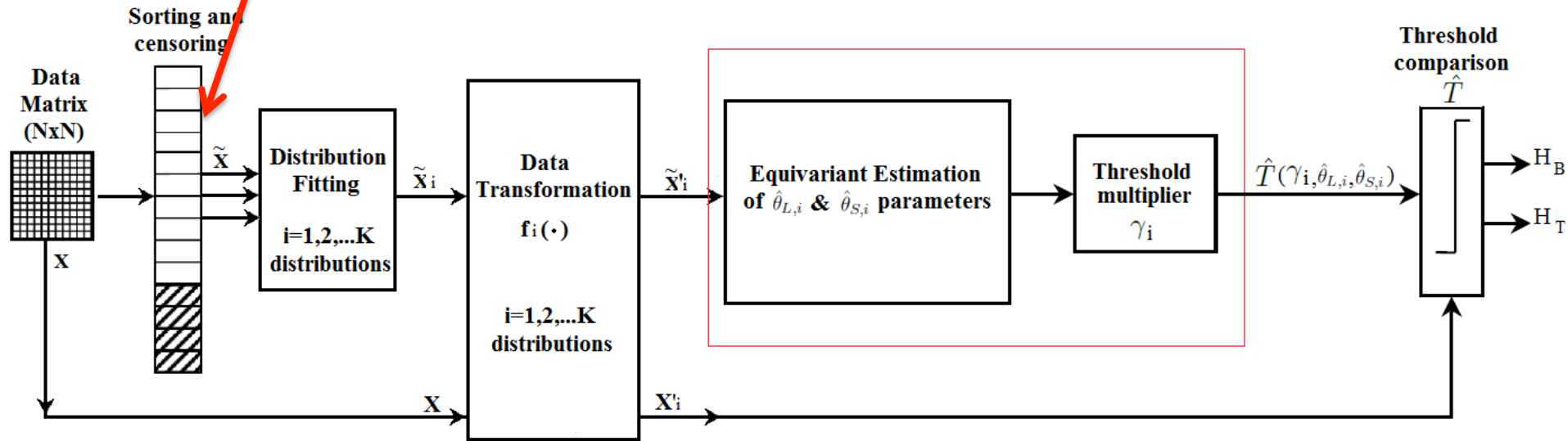
# Multi-Model CFAR Detection in LS Environment



# Multi-Model CFAR Detection in LS Environment



Censoring to avoid target self masking in the distribution parameters estimation process

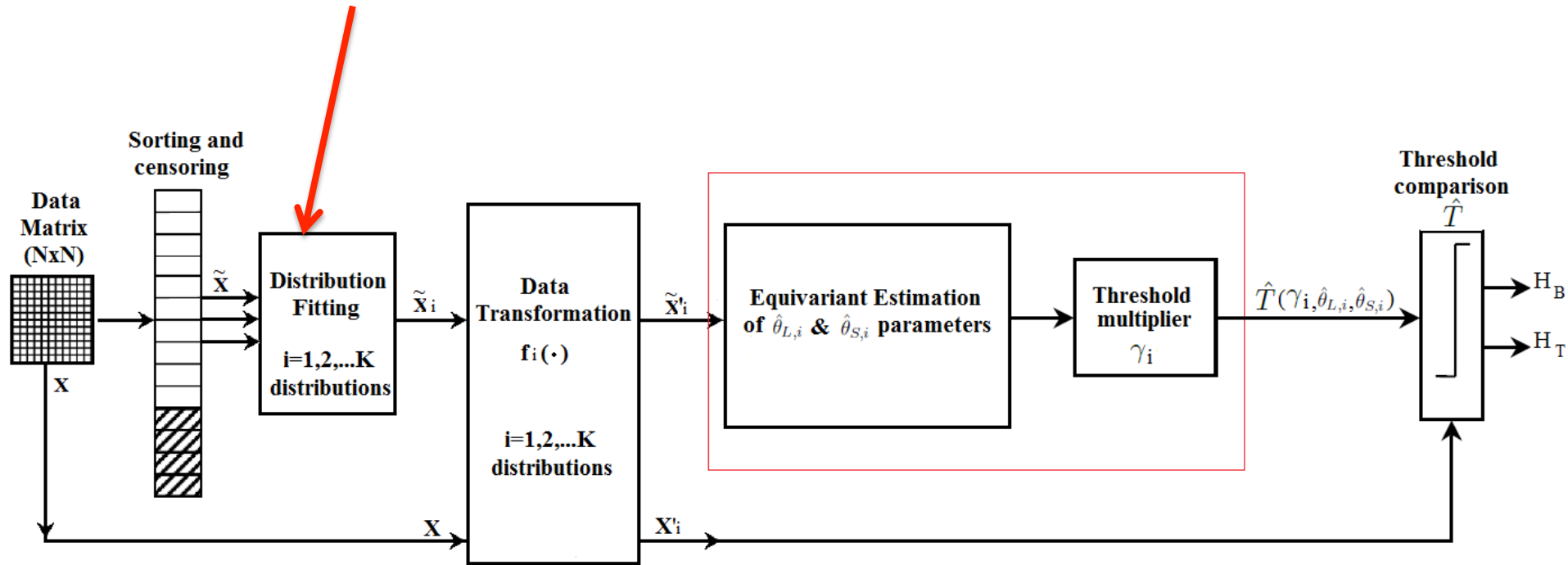


The pixels with highest values in the reference window are removed to avoid bias in the threshold estimation.

# Multi-Model CFAR Detection in LS Environment



## Background Characterization using Lilliefors Test



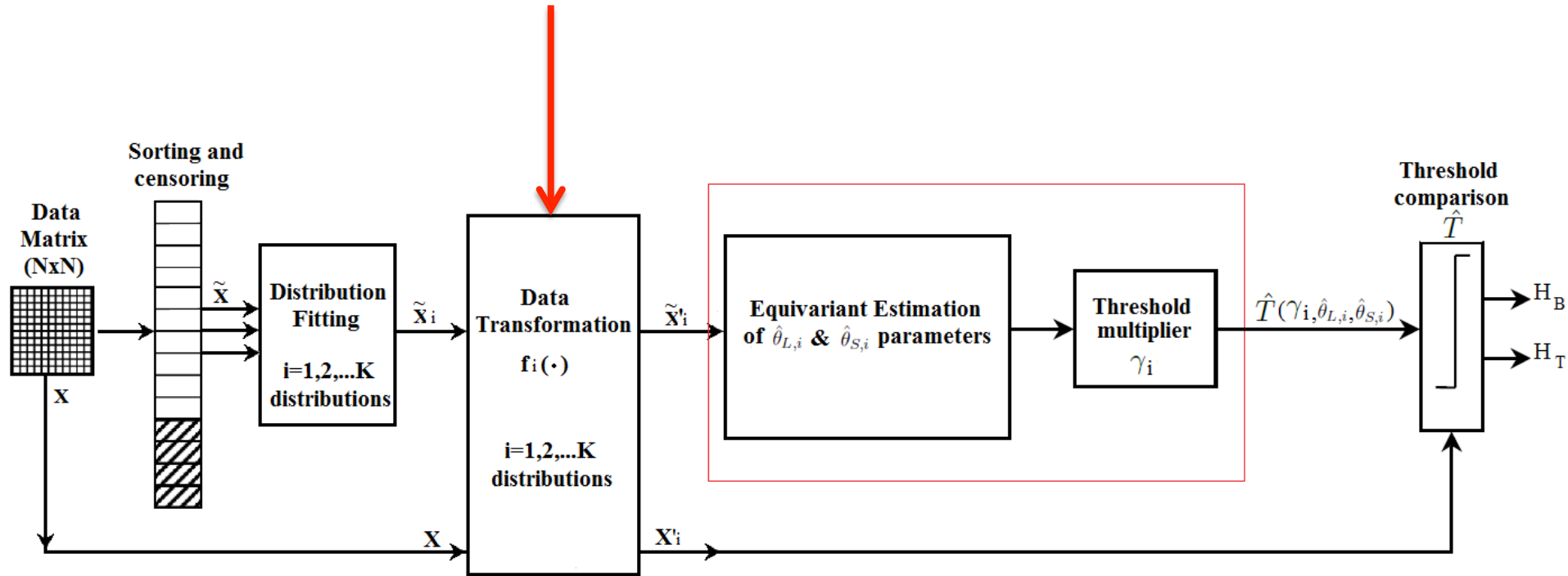
The background model is selected based on the location-scale distribution model that fits better the data or its non-parametric transformation;

Lilliefors test is a modified Kolmogorov-Smirnov test that is non-parametric and applicable in the unknown parameter case.

# Multi-Model CFAR Detection in LS Environment



Data transformation to make them LS

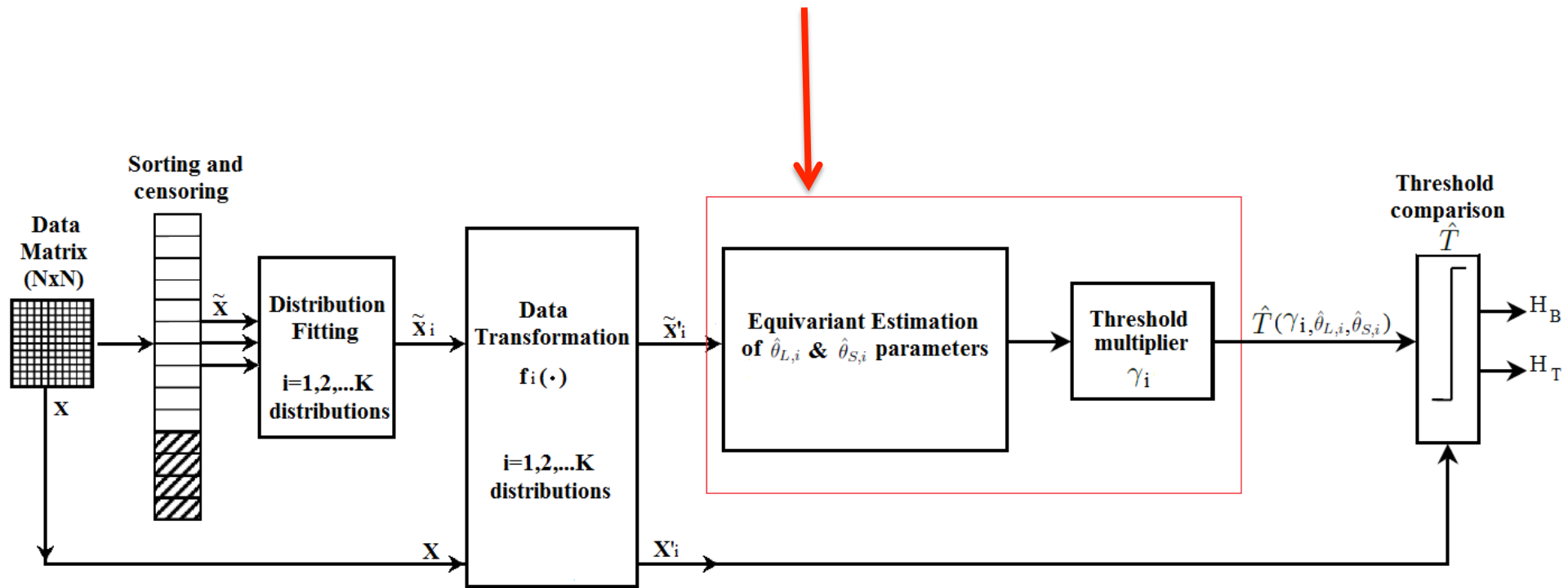


As the selected distribution might not be LS, then the data must be transformed to become LS.

# Multi-Model CFAR Detection in LS Environment



Model Specific block

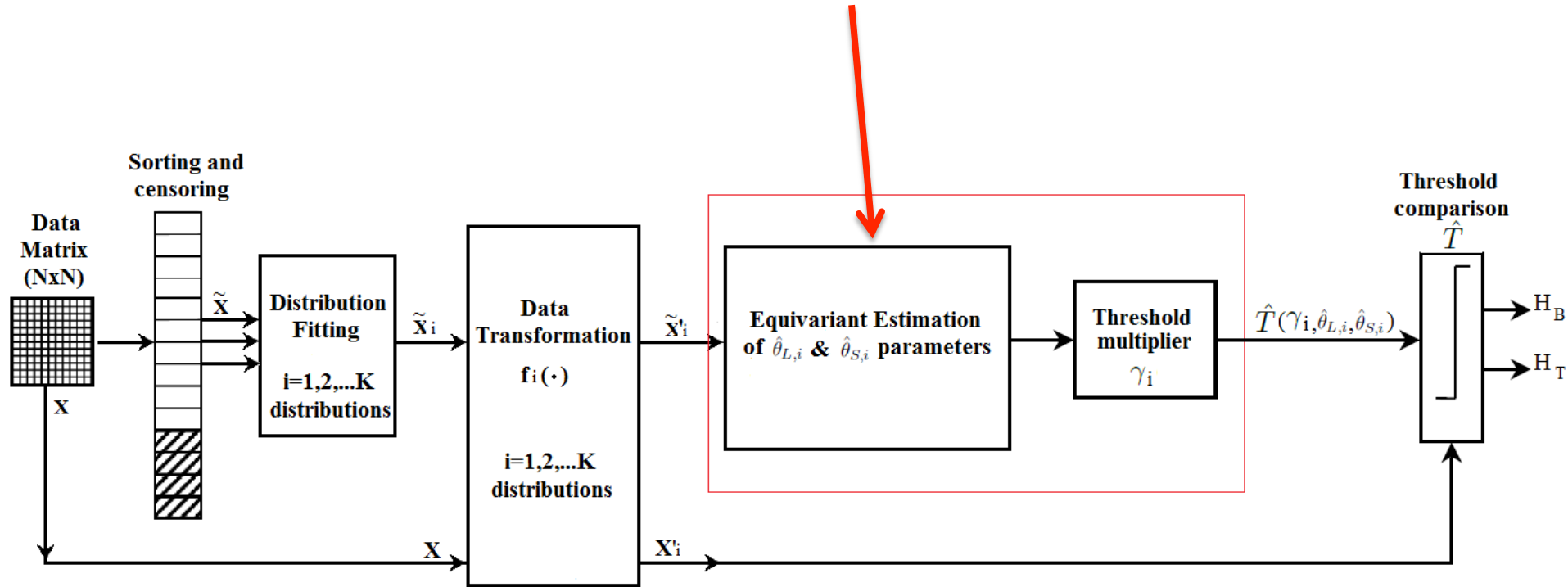


The parameter estimators depends on the statistical model adopted;

# Multi-Model CFAR Detection in LS Environment



## Location and Scale Parameters Estimation

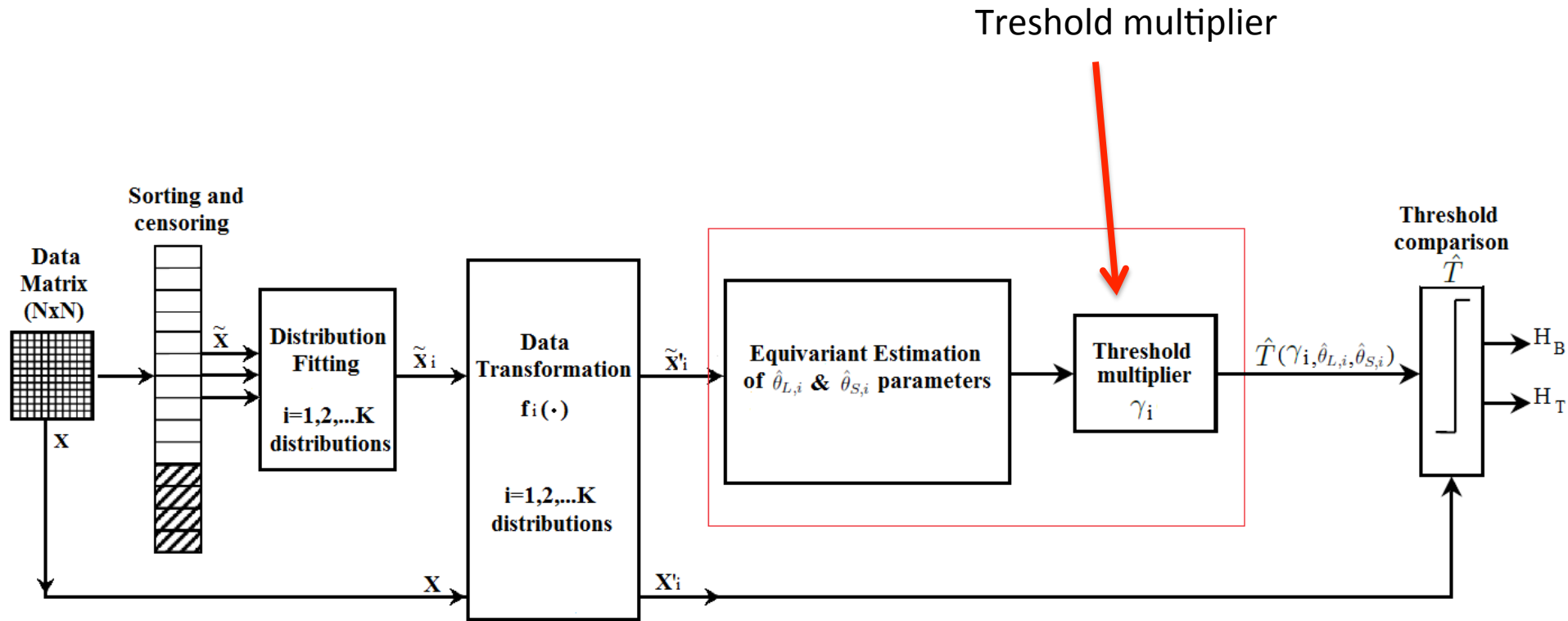


The Best Linear Unbiased Estimators are used to estimate location and scale parameters, minimizing the variance with unbiasedness constraint.

$$\begin{pmatrix} \hat{\theta}_{L,i} \\ \hat{\theta}_{S,i} \end{pmatrix} = (\mathbf{H}_i^T \mathbf{C}_{0,i}^{-1} \mathbf{H}_i)^{-1} \mathbf{H}_i^T \mathbf{C}_{0,i}^{-1} \tilde{\mathbf{X}}'_i, \quad \mathbf{H}_i = (\mathbf{1} \ \boldsymbol{\mu}_{0,i})$$



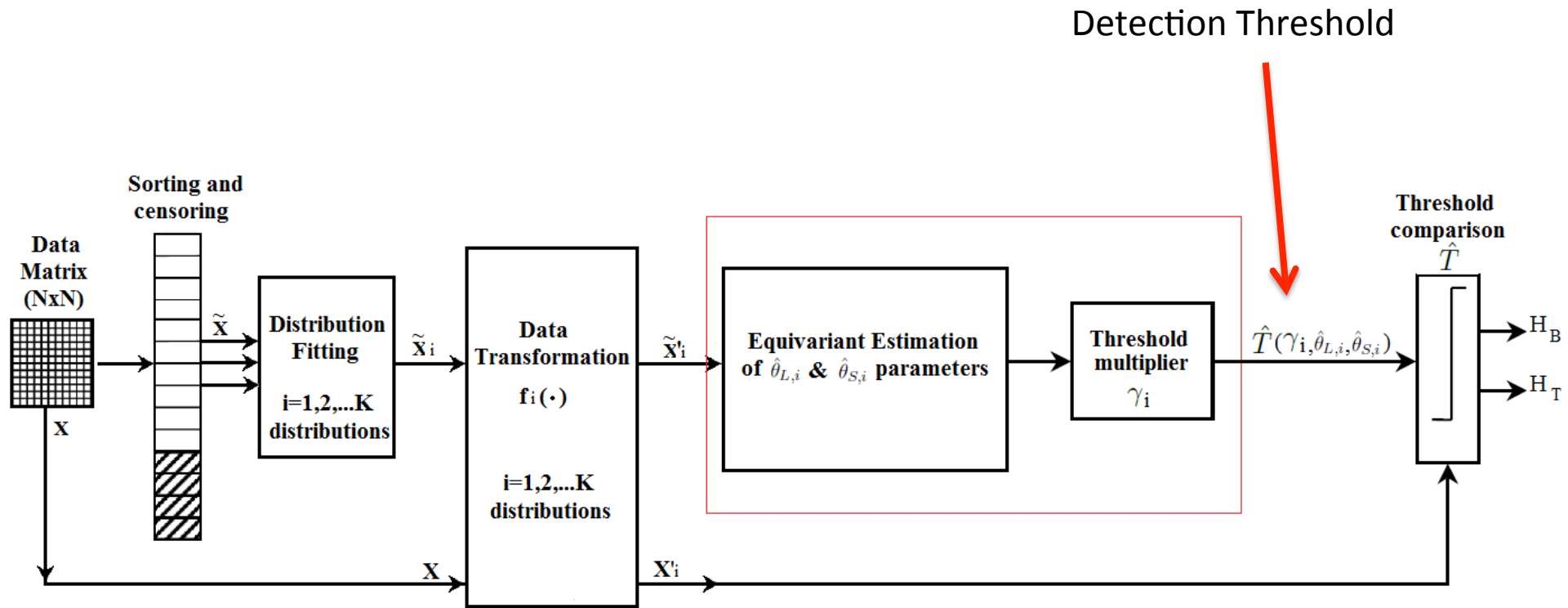
# Multi-Model CFAR Detection in LS Environment



The threshold multiplier ensures the false alarm probability for the given parameters and is the solution to the equation

$$P_{FA} = Pr \left\{ \frac{\tilde{X}'_i - \hat{\theta}_{L,i}}{\hat{\theta}_{S,i}} > \gamma_i \mid H_B \right\}$$

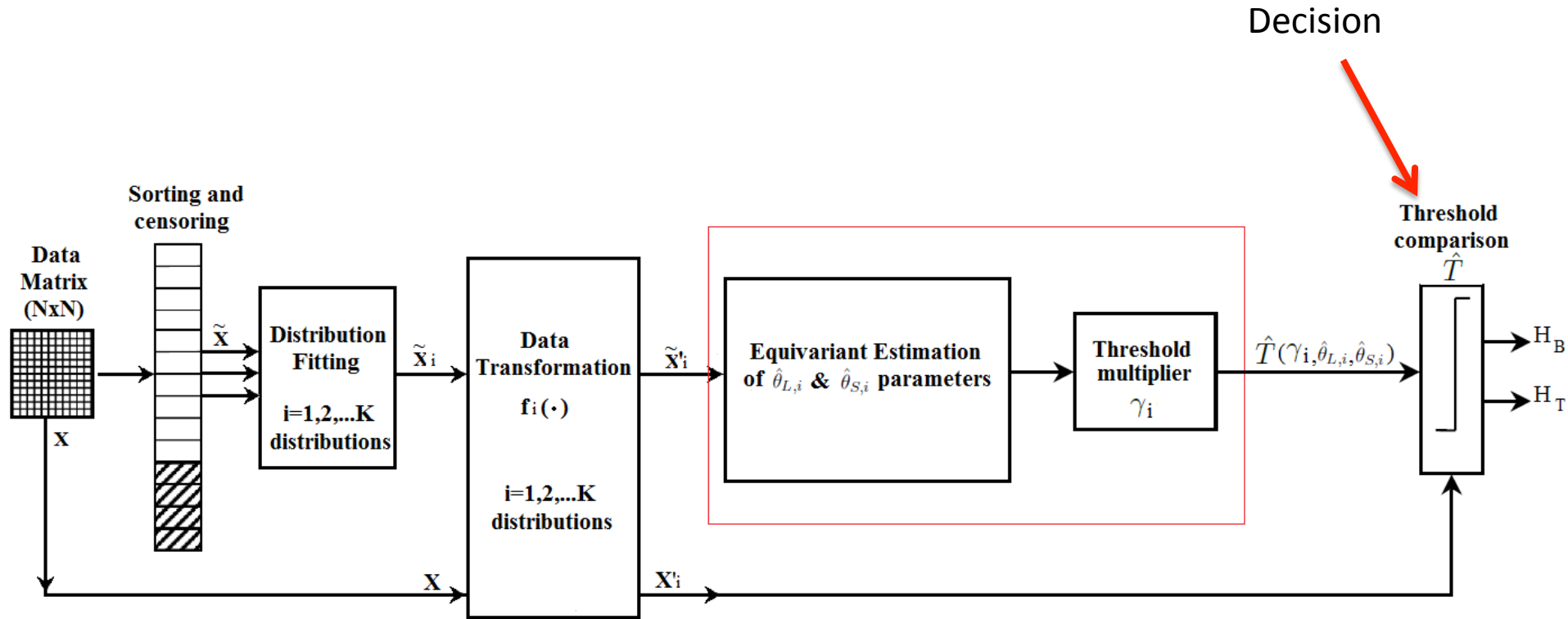
# Multi-Model CFAR Detection in LS Environment



The adaptive threshold is then obtained as

$$\hat{T}(\gamma_i, \hat{\theta}_{L,i}, \hat{\theta}_{S,i}) = \hat{\theta}_{S,i}(\tilde{X}'_i) \gamma_i + \hat{\theta}_{L,i}(\tilde{X}'_i).$$

# Multi-Model CFAR Detection in LS Environment



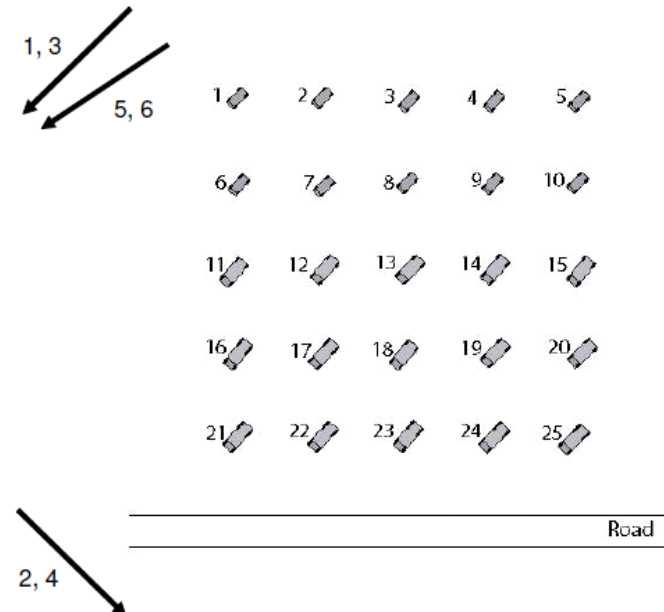
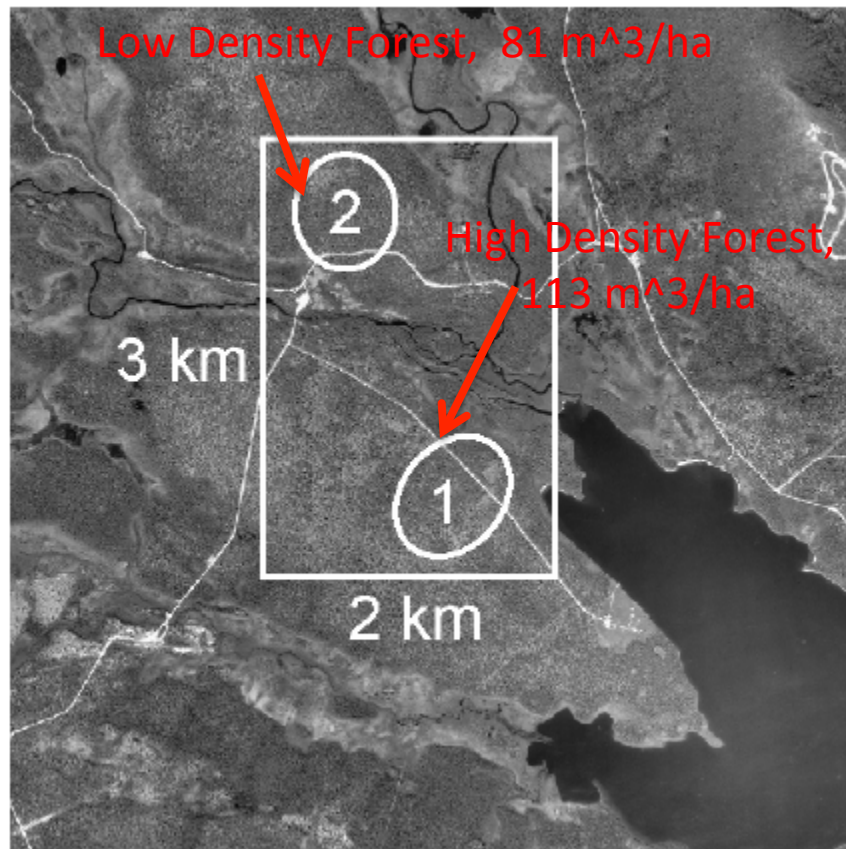
The threshold is compared with the uncensored data to perform the detection

$$X'_i \underset{H_B}{\overset{H_T}{\gtrless}} \hat{T}(\gamma_i, \hat{\theta}_{L,i}, \hat{\theta}_{S,i})$$

# Background Characterization



- A requirement of the proposed framework is that the background models are Location-Scale or Location-Scale transformable;
- The Carabas II dataset (intensity only) has been used for model selection and for performance analysis;



# Background Characterization

- Due to the presence of trees in the scenario distributions with light and heavy tails are preferred;



# Background Characterization



- Due to the presence of trees in the scenario distributions with light and heavy tails are preferred;
- The two distributions that resulted to provide the best fit are:

The Gumbel for Maximum distribution, whose CDF is:

$$F(\mathbf{x}; \theta_L, \theta_S) = \exp \left[ -\exp \left( -\frac{x - \theta_L}{\theta_S} \right) \right] \quad \theta_L \in \mathbb{R} \quad \theta_S > 0$$

and the Weibull distribution with CDF:

$$F(\mathbf{x}; \kappa, \lambda) = \begin{cases} 1 - e^{-\left(\frac{x}{\lambda}\right)^\kappa}, & \text{if } x \geq 0, \\ 0, & \text{if } x < 0. \end{cases}$$

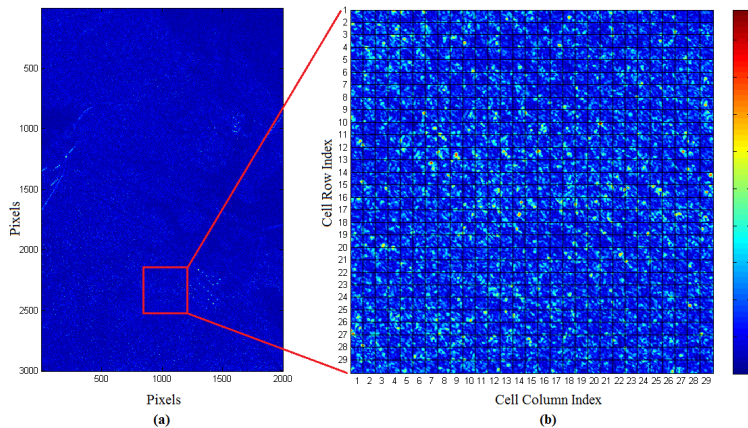
whose natural logarithm is a Gumbel for Minimum distribution, so it can be transformed in LS-type.

# Background Characterization

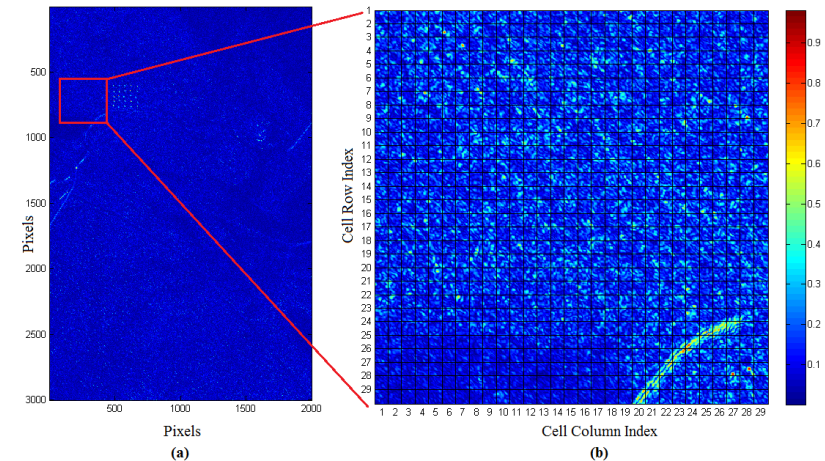


- For both high and low density forest the Lilliefors test was used in a single and multi-model approach;

## High density Forest



## Low density Forest



Gumbel Maximum	Multi-Model
96.91%	98.57%

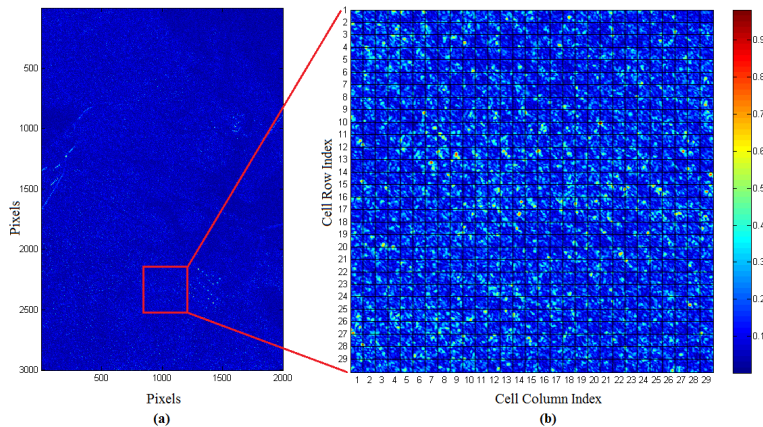
Weibull	Multi-Model
97.50%	99.16%

# CFAR Performance

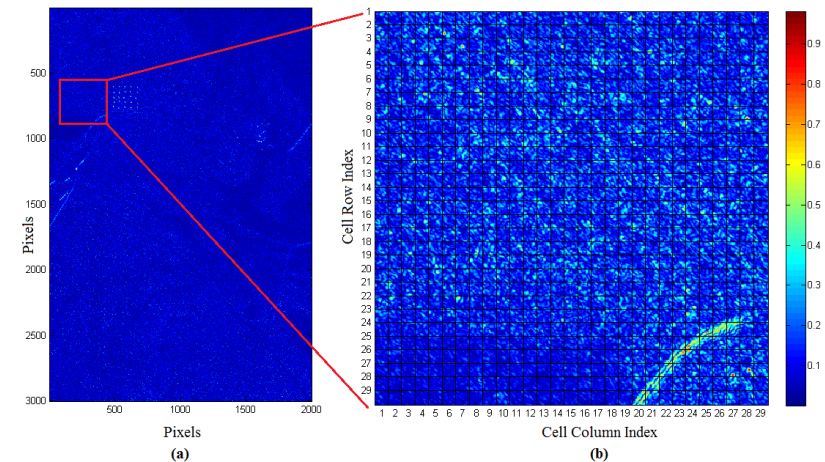


- In order to verify the CFAR property, the detection is performed in the target free areas (nominal  $P_{fa} = 10^{-4}$ );

High density Forest



Low density Forest



Censoring Depth	$P_{fa}$
0	$1.03 \times 10^{-4}$
32	$8.64 \times 10^{-4}$
64	$6.70 \times 10^{-4}$
96	$6.61 \times 10^{-4}$
128	$6.19 \times 10^{-4}$

Censoring Depth	$P_{fa}$
0	$5.08 \times 10^{-5}$
32	$1.43 \times 10^{-4}$
64	$1.52 \times 10^{-4}$
96	$6.01 \times 10^{-5}$
128	$8.32 \times 10^{-5}$

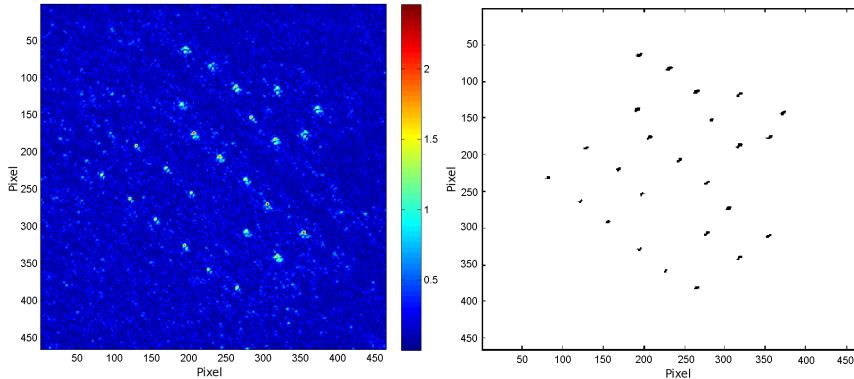


# Detection Performance

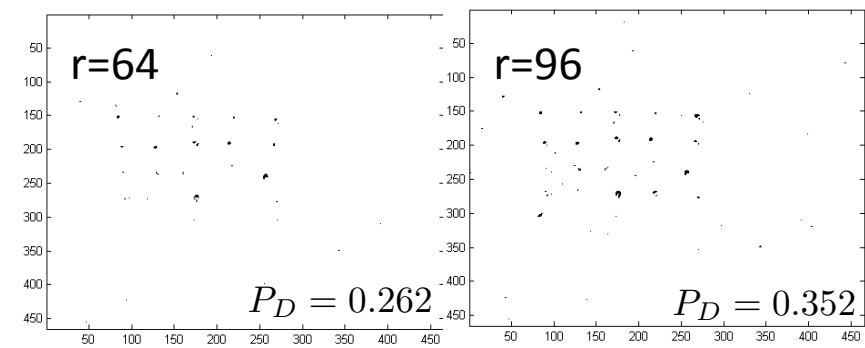
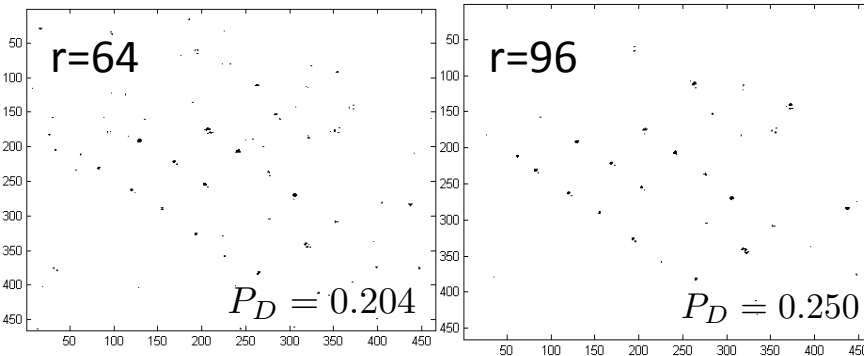
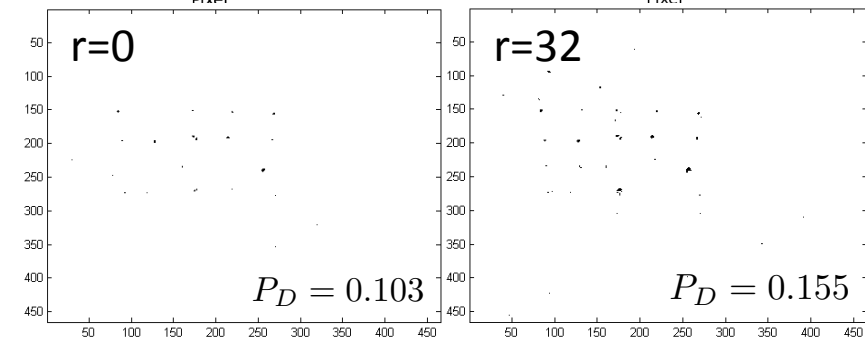
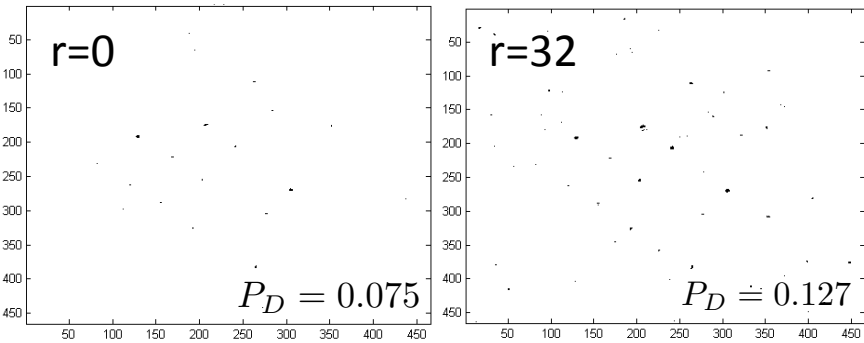
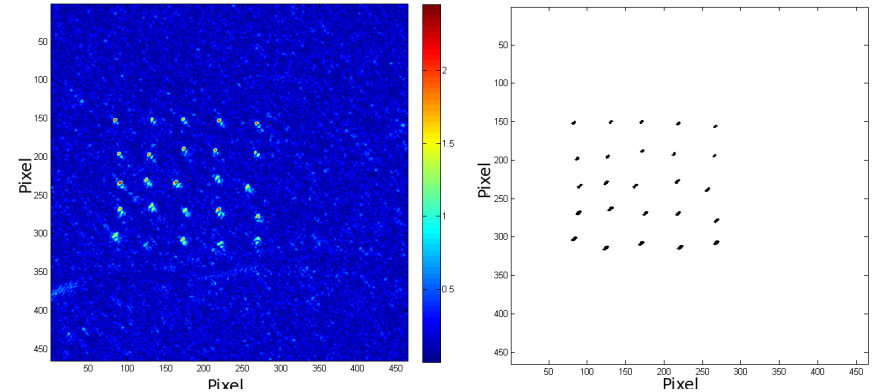
- In order to verify demonstrate the capability to detect targets, the algorithm is tested on the area containing vehicles hidden in foliage (nominal  $P_{fa} = 10^{-4}$ );



High density Forest



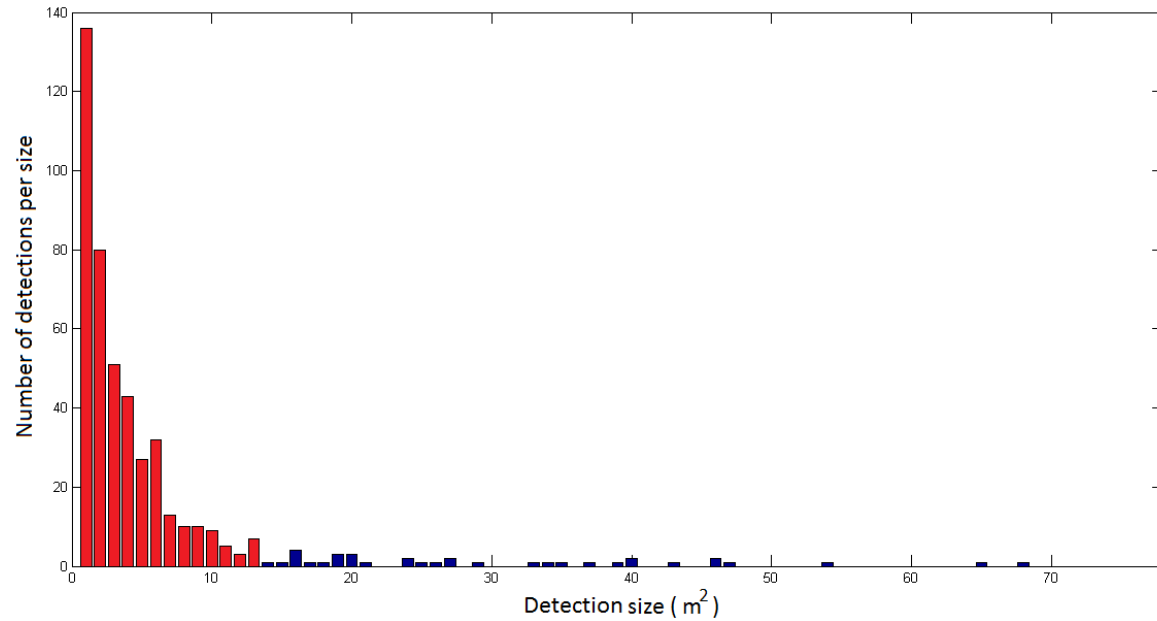
Low density Forest



# Extended Target Detection



If a clustering and a threshold on the target size are applied the probability of detection can be improved with mitigation of higher false alarms.



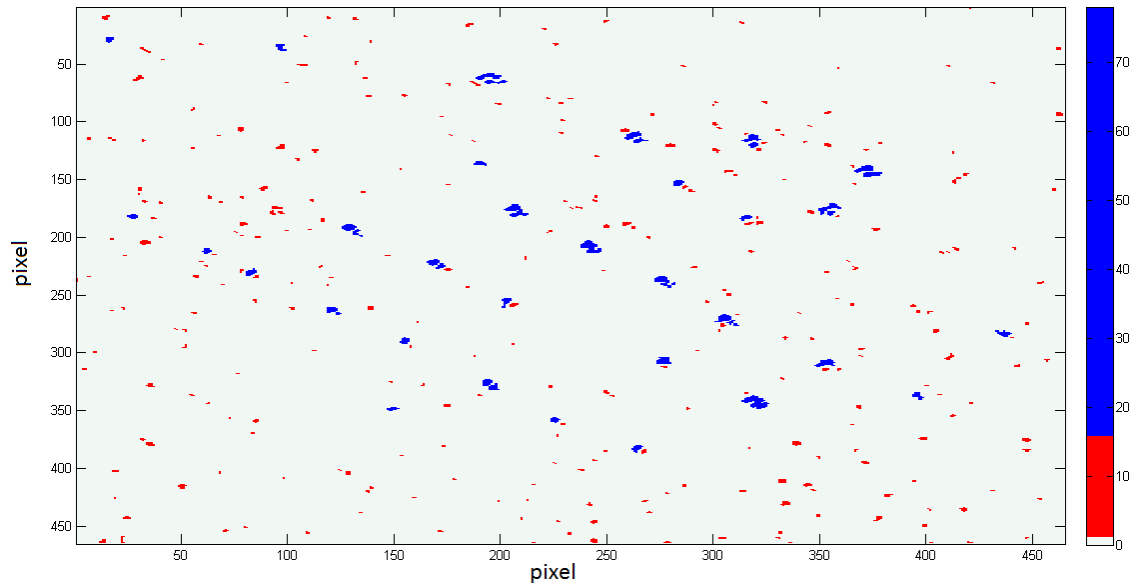
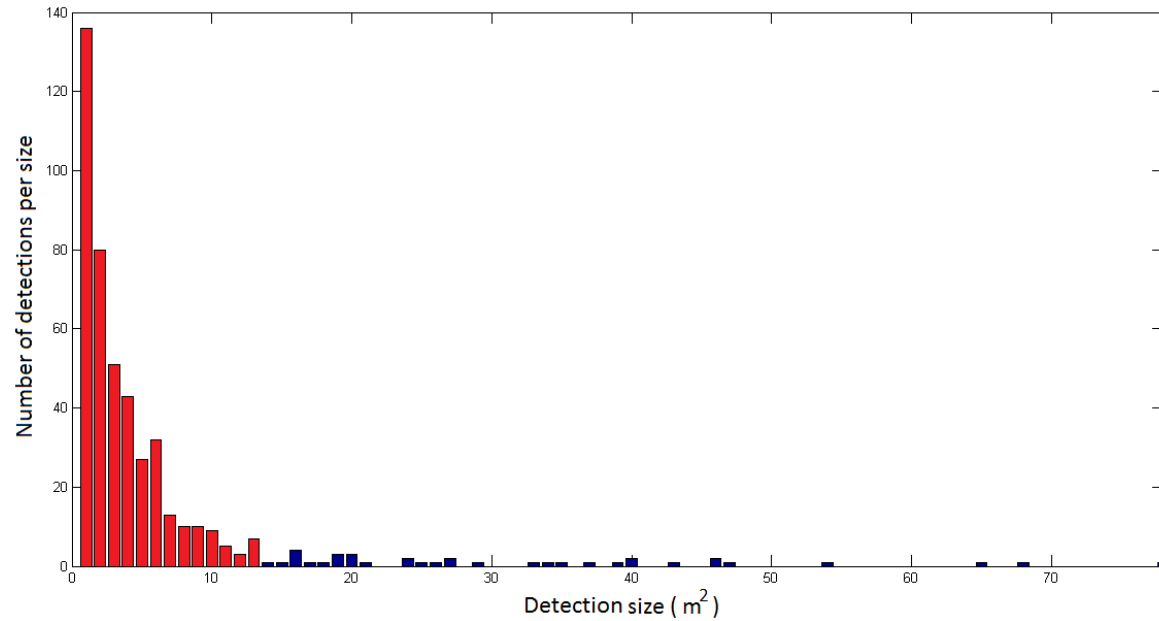
# Extended Target Detection



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Nominal $P_{fa} = 10^{-2}$	$P_D$	$P_{fa}$
No Clustering	0.5804	$1 \times 10^{-2}$
Clustering	0.5804	$3 \times 10^{-3}$

1 miss only = 96% of extended targets are at least partially detected.



# Conclusion



- A framework for CFAR detection in Foliage Penetration SAR images has been proposed;
- The proposed approach adapts both background model and threshold in order to maintain the CFAR property;
- The CFAR and detection performance have been assessed on real data with two forest densities;
- The framework demonstrated to successfully provide a control on the false alarm probability;
- The detection probability can be improved by exploiting domain knowledge information as in the case of extended target detection;
- Future work will deal with the extension of the framework to coherent CFAR detection.



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