



# Change Detection Algorithm with Hardware Constraints

Prof. Ingo Sander<sup>1</sup>, Postdoc Marcello Costa<sup>2</sup>

October 1, 2024 — <sup>1</sup>KTH Royal Institute of Technology, <sup>2</sup>Cisb Saab



# Contents

Problem Introduction and Background

Change Detection Algorithm: 2D-AR( $n$ ) on Synchronous MoC

CASE I: Change Detection on CARABAS-II

Change Detection on Synchronous MoC → rapid data analysis:

1. **Elementary Change Detection Model:** → Low complexity and power consumption, memory requirements, and parallelized structure<sup>1</sup>
2. **Time-series methods**<sup>2</sup> → ARIMA, PCA, SVM, Random Forest, NN, K-means, GLM, EM, SVD, XGboost, LSTM,..
3. **Temporal dataset: Ultra-wideband (UWB) SAR** → stable scatters in time, random motions of targets in the clutter as a first-order autoregressive AR(1) process

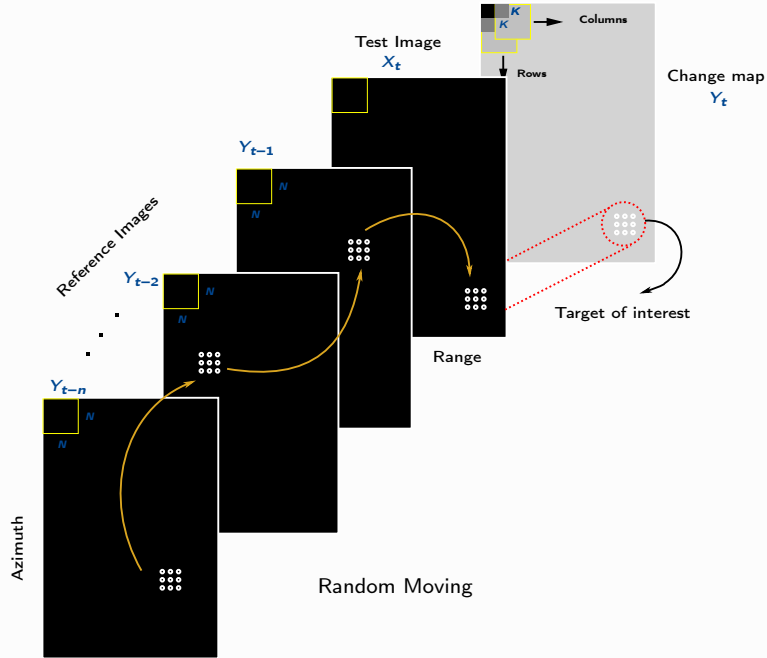
---

<sup>1</sup>Rabhi *et al.*, “Patterns and skeletons for parallel and distributed computing,” Springer Science & Business Media, 2003.

<sup>2</sup>Wu, Suya, et al. “Quickest Change Detection for Unnormalized Statistical Models,” *IEEE Trans. on Inf. Theory*, v. 70, n. 2, pp. 1220-1232, 2024.

Time series Prediction:

$$\hat{Y}_t = f(X_t, Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}) + \epsilon_t, \quad (1)$$



Combinational solution: 1-lag

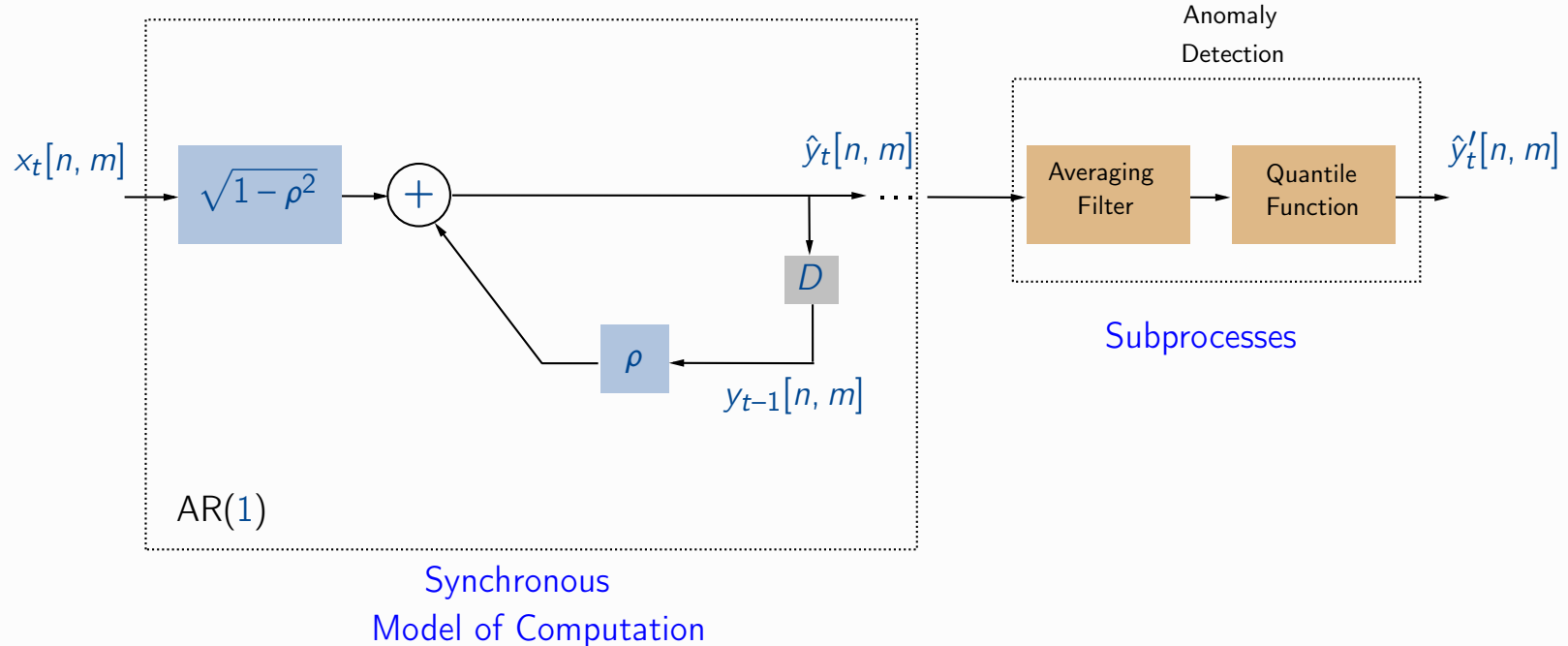
$X_t$	$Y_{t-1}$	Change
0	0	No change
0	1	No change
1	0	Change
1	1	No change

Note: Anomaly = 1, background = 0.



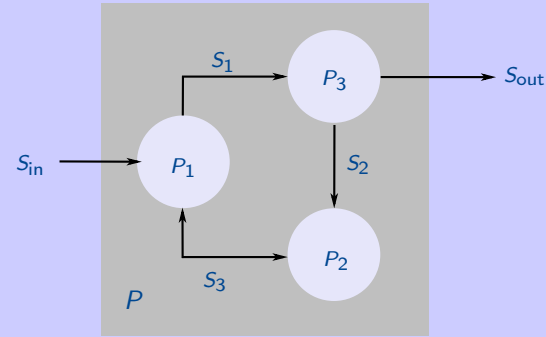
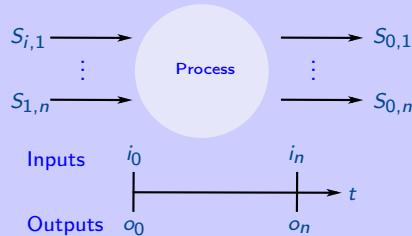
# Change Detection Algorithm: 2D-AR( $n$ ) on Synchronous MoC

## Time-Spatial Implementation:



**Synchronous MoC<sup>5</sup>:** Synchronized parallel components, running in successive computation steps, where all components perform some quantum of computation.

1. Output is synchronous with input
2. Internal actions are instantaneous



<sup>5</sup>Albert Benveniste and Gérard Berry. "The synchronous approach to reactive and real-time systems," *Proceedings of the IEEE*, 79(9):1270–1282, September 1991.

## Change Detection with AR Model

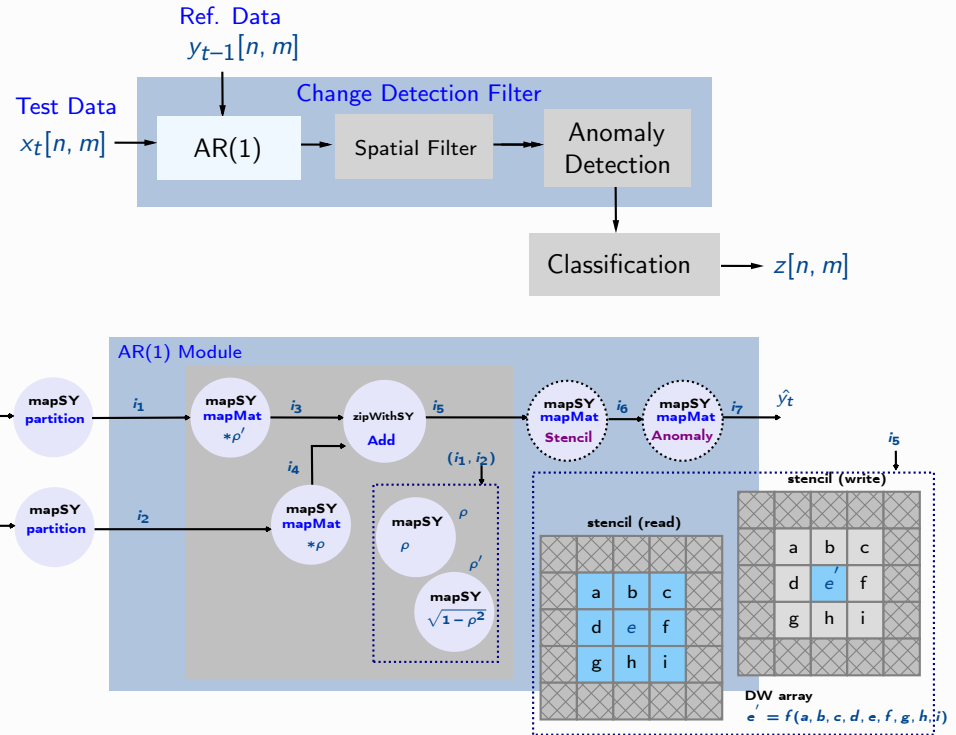
### ► ForSyDe Framework<sup>5</sup>/Haskell

Synchronous MoC constructors:

- Combinational  $\rightarrow$  zipWithSY, mapSY
- Delay  $\rightarrow$  delaySY
- Sequential  $\rightarrow$  mooreSY, mealySY

Parallel stencil computation

- Data.Massiv.ArrayFramework<sup>6</sup>



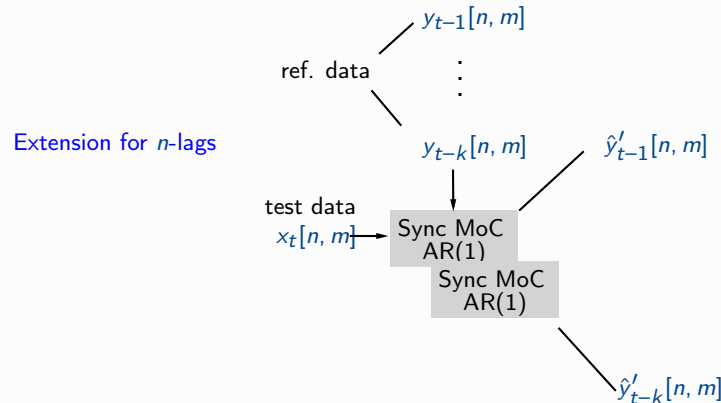
<sup>5</sup><https://forsyde.github.io/>

<sup>6</sup><https://hackage.haskell.org/package/massiv>



## Extension: $n$ -lags Model

- Hardware efforts  $\times$  detection performance are balanced over high-parallelized Sync MoC structure by  $[N, k]$  selection, enabling fast data analysis.
- Extension for a Markov chain in multitemporal ( $n$ -lags) improves the detection performance (considering relevant statistical dependencies), replicating the elementary MoC structure.

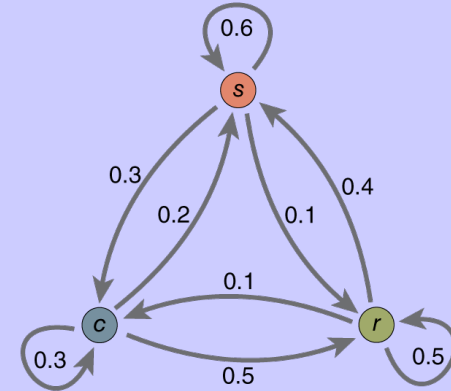


## $n$ -lags Model

Markov-chain: all states are observable and probabilities converge over time  
(dependencies are included)

$$r_{i,j}[n] = \sum_k r_{i,k}[n-1]P_{k,j}$$

$\left\{ \begin{array}{ll} r_{i,j}[n] \rightarrow & \text{Prediction going to state } i \text{ to } j \\ r_{i,k}[n-1] \rightarrow & \text{recursion from state } i \text{ to } k \\ P_{k,j} \rightarrow & \text{Transition probability from state } k \text{ to } j \end{array} \right.$



where  $r_{i,j}[n] \Rightarrow \hat{y}'_t$  for each incremental lag.

Proposition:  $n$ -lags 2D-AR Model on Markov-Chain.

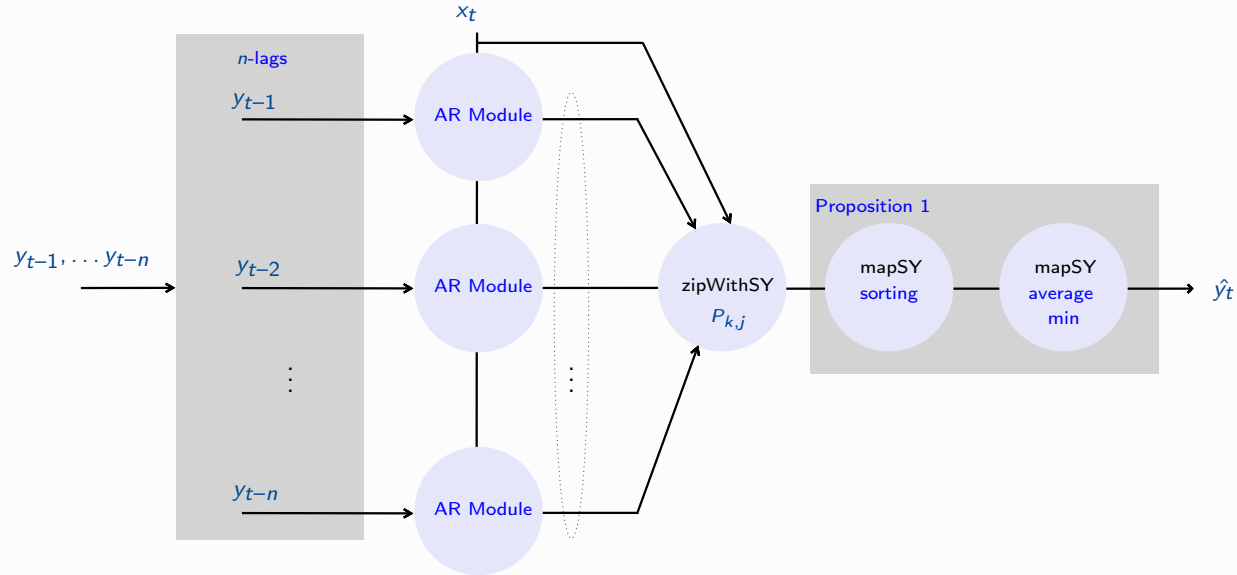
Let  $r_{i,j}[n]$  be the prediction extracted from a Markov chain. For change detection, Let  $\tilde{r}_{i,j}^\ell[n]$  denote the set of interest involving AR(1) subject to the lowest probability. Then we will the unique sequence

$$\tilde{r}_{i,j}^\ell[n] = \bigcup_{i=0}^{\ell-1} \min\{r_{i,j}[n] \setminus \tilde{r}_{i,j}^\ell[n]\}, \quad (2)$$

which represents the most likely available lags to detect changes anomalies in  $r_{i,j}[n]$  with minimum false alarms.

□

## Synchronous MoC on ForSyDe

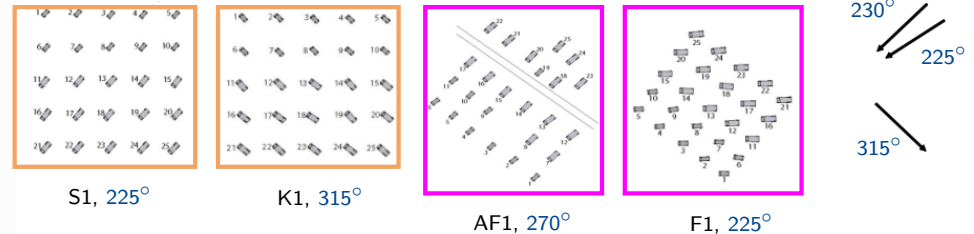
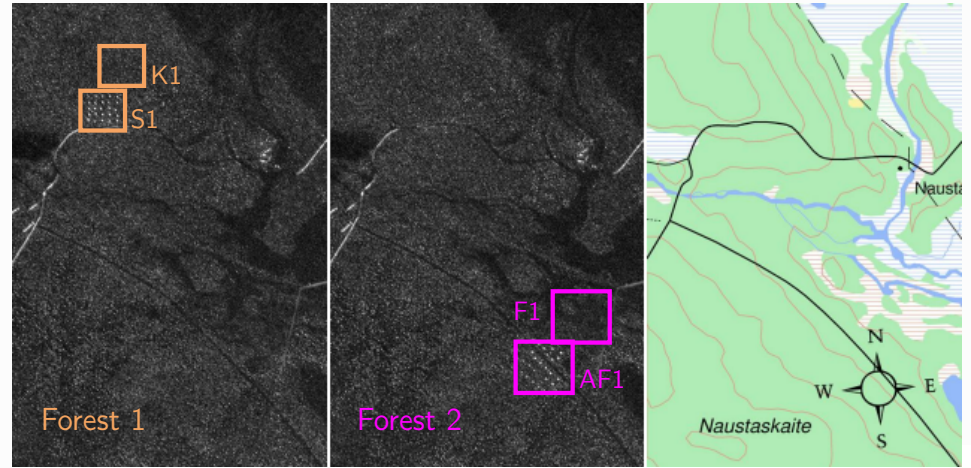




# CASE I: Change Detection on CARABAS-II

## CARABAS-II dataset<sup>7</sup>:

- 24 images: magnitude VHF (20 – 90 MHz) SAR HH-polarized with 1 m resolution ( $2 \times 3 \text{ km}^2$ )
- 4 Targets position: S1, K1, F1, and AF1
- 6 passes: 3 Flight directions under ground RFI sources ON/OFF
- Application: Through-foliage detection



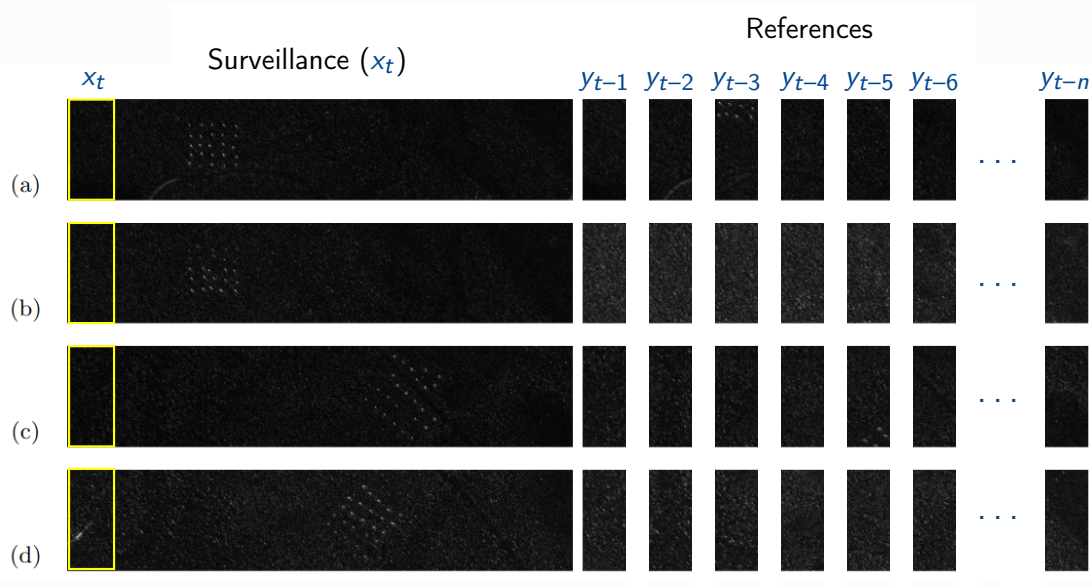
<sup>7</sup>Ulander, L.M, et al. "Change detection for low-frequency sar ground surveillance," *IEE Proceedings-Radar, Sonar and Navigation* , 152(6), pp. 413–420, 2005.

## CASE I: Change Detection on CARABAS-II

Exp. No.	Surveillance image		Reference image		Known Targets	Area [km <sup>2</sup> ]
	Mission	Pass	Mission	Pass		
1	2	1	3	1	25	6
2	3	1	4	1	25	6
3	4	1	5	1	25	6
4	5	1	2	1	25	6
5	2	2	4	2	25	6
6	3	2	5	2	25	6
7	4	2	2	2	25	6
8	5	2	3	2	25	6
9	2	3	5	3	25	6
10	3	3	2	3	25	6
11	4	3	3	3	25	6
12	5	3	4	3	25	6
13	2	4	3	4	25	6
14	3	4	4	4	25	6
15	4	4	5	4	25	6
16	5	4	2	4	25	6
17	2	5	4	5	25	6
18	3	5	5	5	25	6
19	4	5	2	5	25	6
20	5	5	3	5	25	6
21	2	6	5	6	25	6
22	3	6	2	6	25	6
23	4	6	3	6	25	6
24	5	6	4	6	25	6
Total					600	144

Include all lags  $y(t-n)$  to improve the prediction model

Campaign sample data:  $2 \times 0.5$  km (15%)

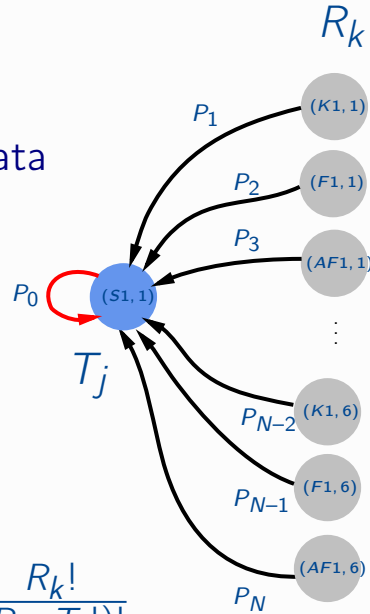


## CASE I: Change Detection on CARABAS-II

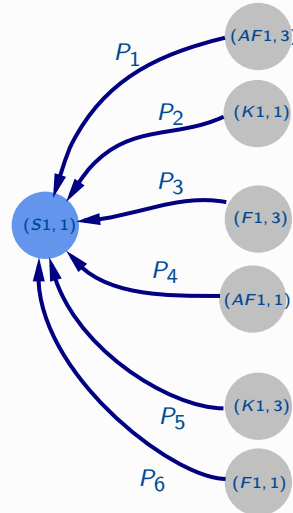
R: reference data

T: test data

$$P_{k,j} = \prod_{j=1}^J \prod_{k=1}^K \frac{R_k!}{(R_k - T_j)!}$$



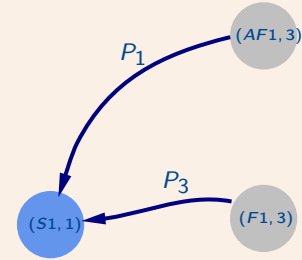
Best pairs



Decision Criteria

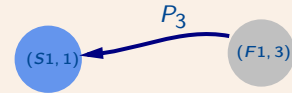
1

Mean:  $\hat{l}_{CD} = \frac{1}{2} \tilde{r}_{i,j}^2[n]$



2

Min:  $\hat{l}_{CD} = \tilde{r}_{i,j}^1[n]$





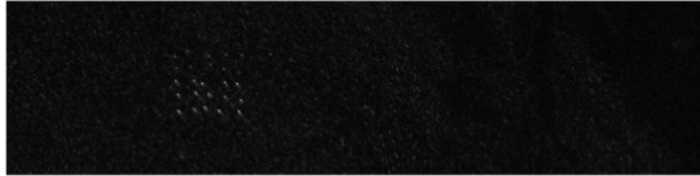
## CASE I: Change Detection on CARABAS-II

$2 \times 0.5 \text{ km}^2$  (15%);  $N = 40$ ;  $\text{AR}(n)$ ,  $n = [1, 6]$

### Pair 11

#### Surveillance 1

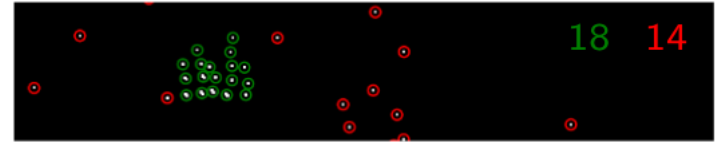
(a)



(b)



(c)



GLRT

(d)



AR(1)

(e)

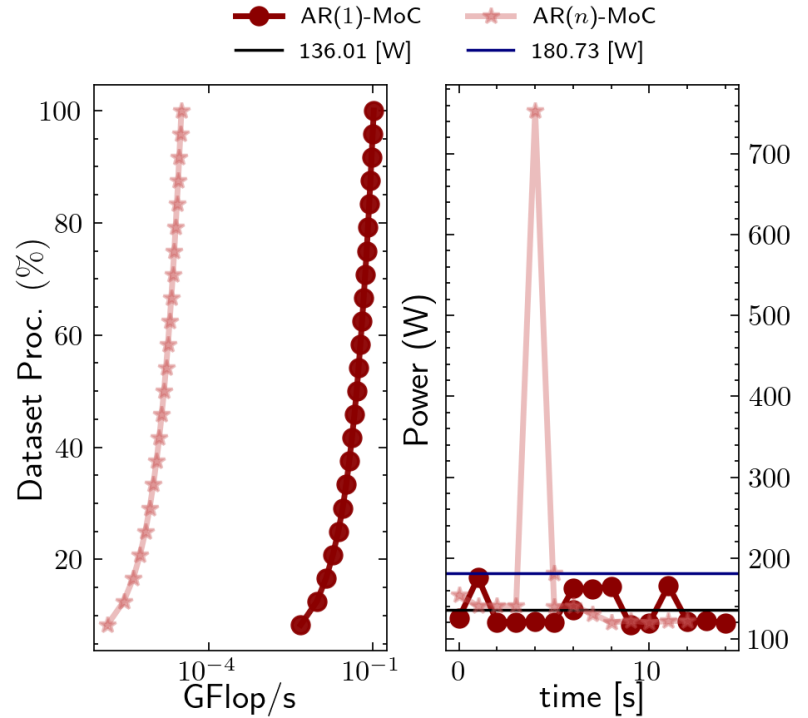


AR(n)

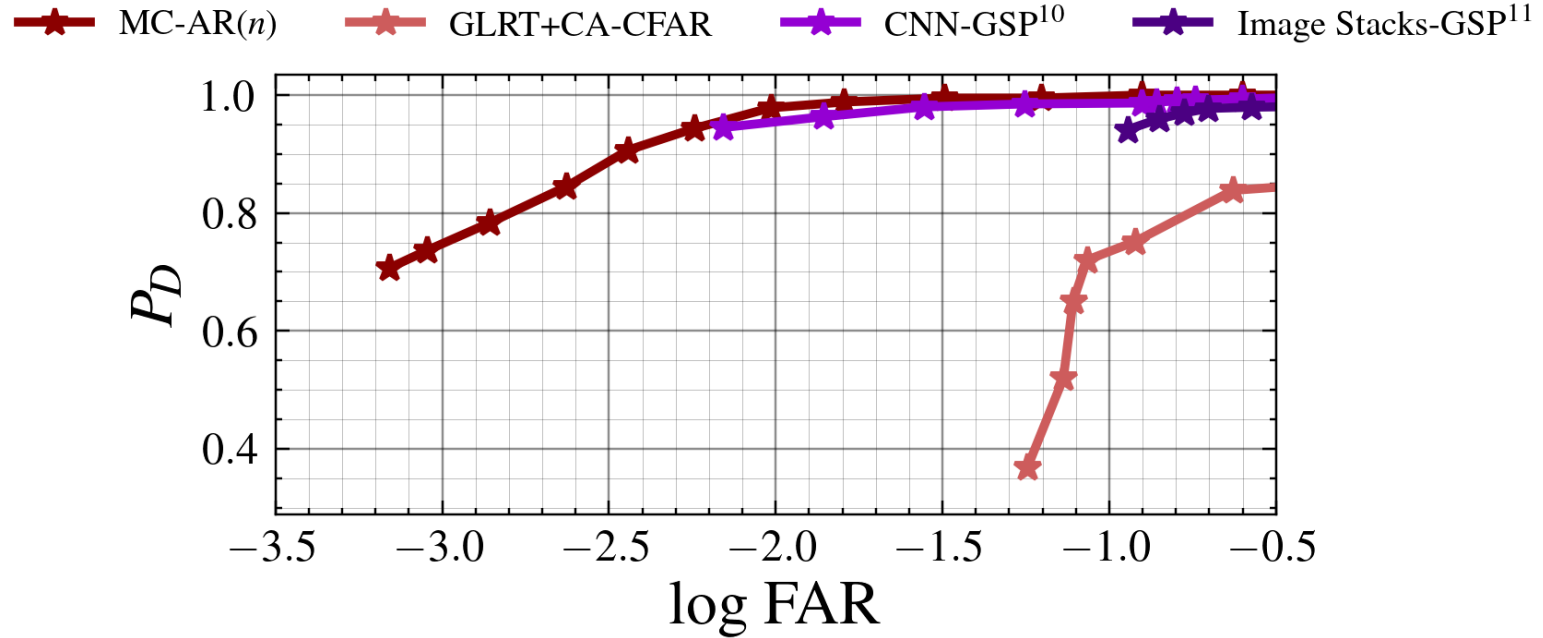
## Energy-Complexity Performance

Instance	AR(1)		AR(n)/6	
	GLRT	CFAR	sf	q-ECDF
Complexity	$\mathcal{O}(N^2)$	$\mathcal{O}(N^2 k^2)$	$\mathcal{O}(N^2 k^2)$	$\mathcal{O}(N^2 \log N^2)$
Runtime (sec)	8.47	242.60	10.65	7.00

Note: sf = spatial filtering stage with averaging filter.



## CASE I: Change Detection on CARABAS-II



<sup>10</sup>Vinholi, J.G., et al., 'Change Detection Based on Convolutional Neural Networks Using Stacks of Wavelength-Resolution Synthetic Aperture Radar Images,' in IEEE TGRS, vol. 60, pp. 1-14, 2022.

<sup>11</sup>Palm, B.G., et al., "Wavelength-Resolution SAR Ground Scene Prediction Based on Image Stack," Sensors 2020, 20(7).

## Conclusions

- The generalized  $n$ -lags model has potential detection improvement over high-parallelized structure.
- Embedded SW application for heterogeneous architectures: CPUs, GPU or FPGA.
- Notes:

$$\tilde{r}_{i,j}^{\ell}[n] = \bigcup_{i=0}^{\ell-1} \min\{r_{i,j}[n] \setminus \tilde{r}_{i,j}^{\ell}[n]\} \rightarrow \text{Generalized model,}$$

$$\begin{cases} \ell = 1 \Rightarrow \text{best bi-temporal AR}(1) \\ \ell \mid \min PFA \Rightarrow \ell < k \end{cases}$$

## Next Steps

1. Target architectures

2. Parallel scheduling

3. Test performance

