

ORIGINAL RESEARCH

Combined intensity and coherent change detection with four classes for laboratory multistatic polarimetric synthetic aperture radar

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Abstract

Satellites and drone swarms can be used to collect multistatic Synthetic Aperture Radar (SAR) images. Synthetic Aperture Radar images can be used for Intelligence Surveillance and Reconnaissance. One method is to use Coherent Change Detection (CCD) to identify changes such as objects or tracks in the scene. This paper investigates a two-stage change detector, formed using intensity change and CCD images, extended to laboratory measured multistatic SAR data. A variety of performance metrics are used to quantitatively assess the results. Bistatic results are compared to a variety of multistatic and fully polarimetric results. The improvement in performance of multistatic and fully polarimetric images over bistatic images is shown. Additionally challenges and limitations of using multistatic datasets are highlighted.

KEYWORDS

multistatic radar, polarimetric radar, radar imaging, radar interferometry, synthetic aperture radar, ultra wideband radar

1 | INTRODUCTION

Synthetic Aperture Radar (SAR) provides reconnaissance and surveillance of the earth's surface for all weather, during the day and night. Synthetic Aperture Radar Coherent Change Detection (CCD) allows for the detection of very small scene changes between two SAR images, such as vehicle tracks [1–4].

This research is applicable to multistatic satellite constellations. A multistatic SAR satellite constellation being developed by the United Kingdom Ministry of Defence under the name Project Oberon [5]. This work is also relevant to multistatic SAR drone swarms, which operate in SAR near field configurations [6, 7].

The research is supported by measurements at the Cranfield University Ground-Based Synthetic Aperture Radar (GBSAR) laboratory [8, 9], where antennas are scanned within two vertical rectangular apertures, which allow a great deal of flexibility and fine control of SAR geometries for the scene.

This paper investigates the use of a two-stage change detector [10–12] extended to multistatic and fully polarimetric

(near field) data [13, 14]. Several methods of forming the multistatic and fully polarimetric change detection images are used. These are presented in Sections 3.2 and 3.3. These images are analysed using a variety of performance metrics, which are presented in Section 3.4. The multistatic trajectories have a baseline between the mission and reference trajectories. This baseline leads to additional decorrelations [8, 15], which can be detected by the change detection algorithm. This can result in the actual change being obscured. This paper investigates how well different methods of forming multistatic change detection images are able to compensate for these decorrelations and produce a change detection image which is easy to interpret and captures the structure of the change.

1.1 | Coherent Change Detection

Coherent Change Detection is calculated as a normalised cross correlation [15–17]. The magnitude, $\hat{\gamma}$, is referred to as the sample coherence. Where S_1 and S_2 are the two complex

images being compared and N is the number of pixels within a window sampled over the two images. The pixel index is k .

$$\hat{\gamma} = \frac{\left| \sum_{k=1}^N S_1(k) S_2^*(k) \right|}{\sqrt{\sum_{k=1}^N |S_1(k)|^2 \sum_{k=1}^N |S_2(k)|^2}} \quad (1)$$

Forming good quality high contrast CCD results are reliant on high coherence between the SAR images [17, 18]. This coherence can be reduced by natural processes such as wind and rain [15, 18–20].

Conducting rapid repeated passes would allow for monitoring developing situations in a timely manner.

Bistatic (and multistatic) radar geometries involve having the transmitter and receiver substantially separated, and multistatic geometries are comprised of multiple simultaneous bistatic collections. Multistatic SAR can have several advantages, such as providing improved cross range resolution [21, 22], and Signal-to-Noise Ratio [23], although the choice of which trajectories to combine significantly affects these [24].

Multistatic SAR satellite constellations may allow the collection of more timely change detection images to be formed using SAR image collections from differing trajectories, thus reducing the repeat pass time [25, 26]. However, the CCD's may be subject to varying degrees of coherence due to differing baselines and other effects such as multipath and different scattering due to a change in geometry [8].

For high coherence and an improved change detection capability, the repeat pass geometries should be chosen to provide a high degree of spatial frequency (K-space) support overlap [17, 27, 28], yet it has been found that this alone is insufficient to guarantee high coherence and good CCD contrast [8].

Multistatic CCD images can be formed in two ways. Either as a coherent summation where multiple SAR images are combined or using 'sorting'. This paper uses sorting to refer to taking the maximum, mean or minimum sorting [13, 14] for each pixel and is explained in detail in Section 3.3.2. The use of sorting multiple bistatic CCD images rather than coherent summation multistatic may be useful in certain scenarios. These may be where a multistatic collection is conducted but the positioning accuracy of the antennas is poor. This could be, for example, a swarm of Uncrewed Air Systems with a transmitter [6, 29, 30] in the swarm or with a large illuminator [29, 31].

1.2 | Non-coherent change detection

Non-coherent change detection (NCCD) allows for the detection of large scene changes. It is a comparison of the backscatter powers (amplitude squared) [15].

$$NCCD = |S_1(k)|^2 - |S_2(k)|^2 \quad (2)$$

2 | MULTIDIMENSIONAL CHANGE DETECTION

2.1 | Multidimensional Coherent Change Detection

The multistatic fully polarimetric SAR data is multidimensional and can be combined in different ways [13, 24]. In this paper, multidimensional is used to describe a scenario where several change detection images are available for the same change and area. In this paper, the dimensions for the multistatic data consist of multiple bistatic collections and four polarisations.

Prior work has investigated the performance of different multistatic combinations [13] as well as augmenting the CCD and NCCD with polarimetric decompositions [14].

2.1.1 | Polarimetric Coherent Change Detection

Polarimetry relates to the incident and scattered orientation of the Electro-Magnetic (EM) waves [2, 13, 32]. These are often described in terms of two orthogonal vectors; vertical (V) and horizontal (H). By convention, the nomenclature received–transmitted is used. Thus, a wave transmitted in the vertical and received in the horizontal polarisation would be called HV. This dataset employed here is fully polarimetric and uses the two co-polar polarisations VV and HH as well as the cross-polar polarisations HV and VH.

Radar polarimetry uses the vector nature of EM waves to produce and analyse the content of images. Polarimetry can provide information on the scattering mechanisms present in the scene [2]. Polarimetric SAR CCD has also been shown to improve CCD images [2, 13, 32].

2.2 | Two-stage detector definition

A two-stage change detector was presented in [10, 12], with Ref. [11] performing analysis on the theoretical performance. These detectors are described as 'combined intensity and CCD', shortened to CI-CCD in this paper. For the NCCD, changes are detected due to a difference in amplitude in the images. This typically indicates large scale scene changes. Smaller scene changes typically do not result in a change in intensity, but rather phase [15, 17]. To detect these changes, CCD is used.

The two-stage CI-CCD detector, introduced in Refs. [10, 12], is shown below in Figure 1 (replicated from [10]). Here S_1 and S_2 represent the reference and mission trajectories.

For the intensity change detection, the difference in intensities (σ) is calculated. This difference is then compared against a threshold T_{NCCD} . Differences exceeding this threshold are labelled as changes. The CCD, as described in Section 1.1 results in a coherence value, $\hat{\gamma}$. This value is also

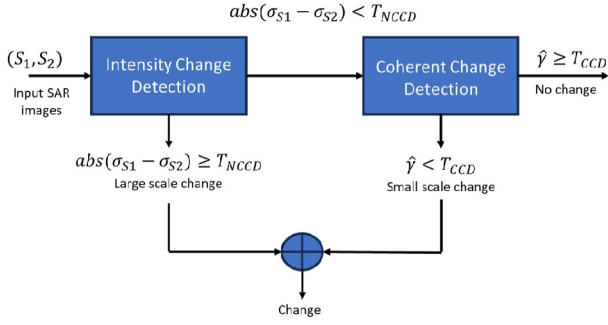


FIGURE 1 The block diagram of the CI-CCD detector introduced in [10, 12]. The figure is replicated from [10]. The figure is replicated from [10]. The figure shows the Intensity and Coherent Change Detection (CCD) stages as well as how thresholding is used.

compared against a threshold T_{CCD} . In this case, values exceeding the threshold (close to 1) are labelled as unchanged, whereas pixels with a value below the threshold are labelled as changes. If a change is detected in either the CCD or NCCD images, then the output image shows a change for that pixel. The output of the detector is a binary value indicating a change or no change.

3 | METHODOLOGY

3.1 | GBSAR laboratory

Bistatic SAR measurements were conducted at the Cranfield University Ground-Based SAR laboratory (GBSAR lab) [33]. The scene consisted of a gravel rectangle of 3.4×4 m and is shown in Figure 2. The measurements were conducted with a Vector Network Analyser (VNA), with a centre frequency of 8.3 GHz and bandwidth of 3.4 GHz. Due to the use of a single VNA, there were no signal synchronisation issues associated with the bistatic measurements, often a significant issue for practical remote bistatic SAR sensing [26]. The SAR geometries used were constrained using the available transmitter and receiver rectangular apertures pictured in Figure 3, where the scene dimensions and SAR geometries measured are also shown. The transmitter aperture had a width of 3.5 m, and the receiver aperture a width of 2.4 m. The vertical extent of both apertures was 1.46 m.

The multistatic data was collected for several geometries. In each case, the transmitter moved along the red trajectory. The receivers were located in one of the 6 positions. These are referred to as R1–6 (see Figure 3). The bistatic geometries are referred to as TR1–6.

The SAR data was collected for two collections. In the first, the reference, the scene was unchanged. In the second, called the mission, the letters ‘GBSAR’ were traced onto the scene. This was done by gently disturbing the gravel for use in change detection performance evaluation.

For the reference collection TR1, TR2 and TR3 were used. For the mission collection TR4, TR5 and TR6 were used.



FIGURE 2 Image shows the Ground-Based Synthetic Aperture Radar (GBSAR) system in a bistatic configuration, with a gravel rectangle as the scene.

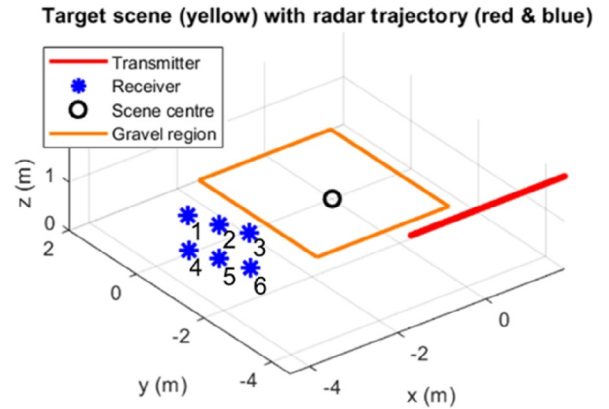


FIGURE 3 Diagram showing the radar trajectories used in the data collection. The transmitter trajectory is shown in red, the multiple fixed receiver positions in blue and the gravel region is shown in orange. The receivers are numbered 1–6 and are referred to as R1 through to R6.

Transceiver scan geometry parameters are listed in Table 1. It is noted that the grazing and bistatic angles are spatially variant over the scene, and the values provided in the table are calculated to the centre of the scene and gravel region. The resolutions were calculated using the Bistatic Equivalent Monostatic rather than the midpoints. This results in different co-ordinates to the transceiver midpoints. Using the incorrect geometry can lead to image distortions or incorrect resolution estimates [34, 35].

From the Reference and Mission multistatic collections, three pairs of bistatic geometries were used for CCD creation as follows: TR1 and TR4, TR2 and TR5, and TR3 and TR6 (effectively receiver columns). These allowed the formation of three bistatic CCD images for each of the two collections. The three CCDs were combined to form multistatic CCD images in different ways.

3.2 | Multistatic image formation

A multistatic SAR image is formed using the coherent summation of bistatic SAR images. These SAR images were formed using a bistatic generalisation of the Back Projection Algorithm [36]. In addition to multistatic SAR images,

		TR1	TR2	TR3	TR4	TR5	TR6
Bistatic angle, β ($^\circ$)		64.2	57.4	50.8	66.6	59.6	52.8
Grazing angle, ψ ($^\circ$)	Tx	22.9	22.9	22.9	22.9	22.9	22.9
	Rx	22.1	22.1	22.8	14.5	14.5	14.2
Range (m)	Tx	4.95	4.95	4.95	4.95	4.95	4.95
	Rx	5.24	5.25	5.32	5.01	5.00	5.08
Transmitter height (m)		1.92	1.92	1.92	1.92	1.92	1.92
Receiver height (m)		1.97	1.97	1.97	1.50	1.50	1.50
BEM resolution	Range (cm)	4.21	4.17	4.13	4.06	4.03	4.01
	Cross-range (cm)	4.36	4.38	4.40	4.40	4.41	4.41

Tx denotes the transmitter, Rx the receiver, and Bistatic Equivalent Monostatic (BEM) the BEM values for the transceiver trajectories. Ranges are in the respective slant planes. Resolutions are in the ground plane and estimated at the scene centre.

TABLE 1 Table showing the scan geometry parameters for the six bistatic trajectories.

multistatic CCD and NCCD images are used in this paper. These may be either from multistatic SAR images or a combination of bistatic CCD/NCCD images from a multistatic SAR collection. A multistatic CCD or NCCD image formed from (coherent summation) multistatic SAR images is referred to as a ‘Coh sum’ image in the results plots. Multistatic CCD images formed using multiple bistatic CCD or NCCD images are referred to as ‘max’, ‘mean’ or ‘min’ in the results plots depending upon the procedure implemented.

For the CCD images, a maximum image has the maximum coherence value for each pixel between the different CCD images being compared (a maximum image results in the minimum number of detections). Conversely, a minimum image has the lowest coherence (and the highest number of detections). This nomenclature is also used for the NCCD images.

The CI-CCD images are named after the CCD images used in the formation. However, in the NCCD images, a higher value corresponds to a greater change.

Therefore, to maximise the coherence or detections, the following combinations were used for the CI-CCD images:

- Max two-stage - Max CCD, Min NCCD
- Mean two-stage - Mean CCD, Mean NCCD
- Min two-stage -Min CCD, Max NCCD

3.3 | Two-stage CI-CCD detector

3.3.1 | Detector architecture

The detector architecture maintains similarities with the two-stage CI-CCD detector outlined in Section 2.2, albeit with some modifications. As shown in Figure 1, a change detected in the NCCD image is classified as a change. If no change is detected, then the CCD image coherence value is compared against a threshold.

This architecture was modified to include four classes: definite change, probable change, probable no change and

definite no change. The change detection for the NCCD images remains binary, as shown in Section 2.2. This is because the NCCD process detects large scale changes. As the CCD process is more sensitive four classes have been used to reduce the impact of edge case detections on the performance metrics. These classes are outlined in Equation (3). Here ρ is the value of the CI-CCD detection pixel and T the change/no change threshold. t is the tolerance and defines the size of the probable change/no change bins.

$$\rho = \begin{cases} 1 & \hat{\gamma} \geq (T + t) \\ 0.5 & (T + t) > \hat{\gamma} \geq T \\ -0.5 & (T - t) < \hat{\gamma} < T \\ -1 & \hat{\gamma} \leq (T - t) \end{cases} \quad \rho = \begin{cases} 1 & \text{Def. no change} \\ 0.5 & \text{Prob. no change} \\ -0.5 & \text{Prob. change} \\ -1 & \text{Def. change} \end{cases} \quad (3)$$

This is then shown visually in a flowchart in Figure 4.

3.3.2 | Pre and post CI-CCD sorting

Sorting occurs at two different stages. This sorting takes the maximum, mean or minimum value per pixel and forms new images. This occurs either before or after the CI-CCD detection. This is shown in two flowcharts (Figures 5 and 6).

CI-CCD images formed when the sorting has occurred before the two-stage detection step are referred to as pre-2S-sorted. Multistatic CI-CCD image can be formed by sorting (maximum, mean or minimum) of bistatic CI-CCD images. These are referred to as post-2S-sorted images.

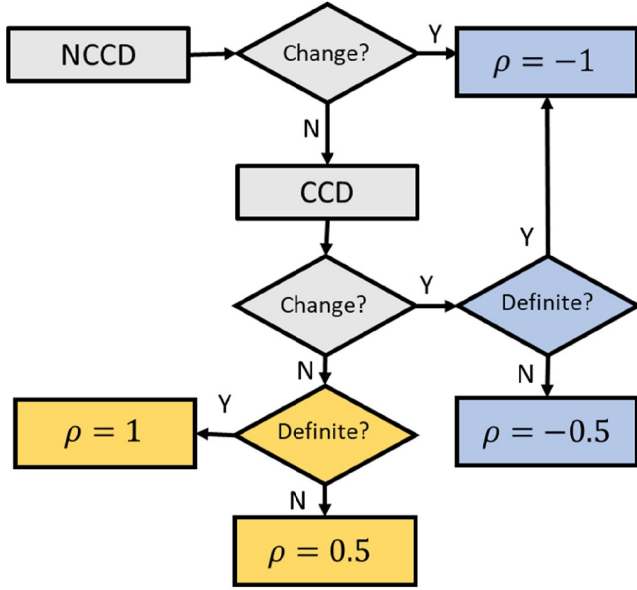


FIGURE 4 Flow diagram of the two-stage CI-CCD detector. Boxes in blue show where a change has been detected. Areas in yellow indicate no change. These reflect the colours in the CI-CCD images (such as Figure 7).

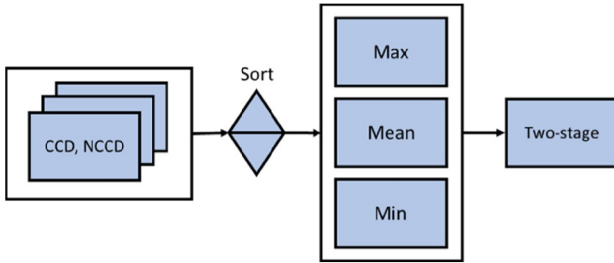


FIGURE 5 Flow chart showing the processing steps for forming 'pre-2S-sorted' CI-CCD images.

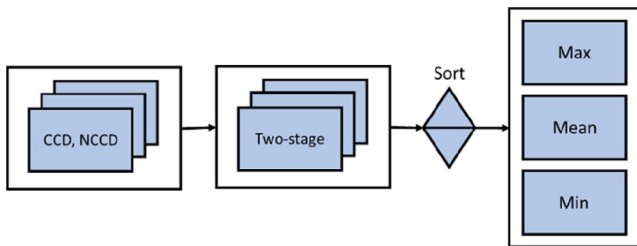


FIGURE 6 Flow chart showing the processing steps for forming 'post-2S-sorted' CI-CCD images.

3.3.3 | Master image

The Master CI-CCD images were formed from exact repeated trajectories, unlike the test CI-CCD images which used dissimilar receiver positions. For example, TR1 against TR1, whereas the results use different trajectories such as TR1 against TR4. This resulted in very high coherence for the areas where no change occurred, as there would not be decorrelations present due to the baseline [15] or Radar Cross Section,

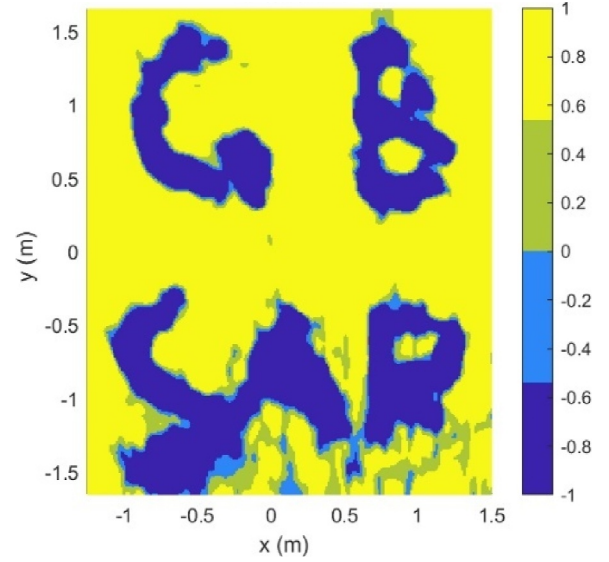


FIGURE 7 Two-stage master CI-CCD image for the pre-2S-sorting images. Here blue indicates a change and yellow indicates no change.

term [8]. The master images were calculated from the mean of the individual bistatic master CI-CCD images. These were then discretised (see equation (4)). The letters 'GBSAR' were clearly visible in the master images.

$$\rho_{Discrete} = \begin{cases} 1 & \rho > 0.5 \\ 0.5 & 0 < \rho \leq 0.5 \\ -0.5 & 0 > \rho \geq -0.5 \\ -1 & \rho < -0.5 \end{cases} \quad (4)$$

Two master CI-CCD images were formed (Figures 7 and 8), one for the pre-2S-sorted images and one for the post-2S-sorted images. These master images were formed with the same threshold for change, $T = 0.91$. The tolerance, t was set to 0.02.

This threshold was chosen as it resulted in two master images which captured the change. This value was chosen using both qualitative and quantitative measures of quality. At 0.91, both the Pre-2S-sorting and Post-2S-sorting images had a high Root Mean Squared (RMS) contrast values [37]. A lower threshold resulted in the 'GBSAR' letters in the pre-2S-sorting image being too large, and too many changes being detected on the lower area of the gravel. A higher tolerance resulted in too few detections of change in the Post-2S-sorting master image.

3.4 | Performance metrics

Performance metrics such as the Probability of Detection (POD), Critical Success Index (CSI) and the False Alarm Ratio (FAR) were used in the evaluation of the CCD images. These

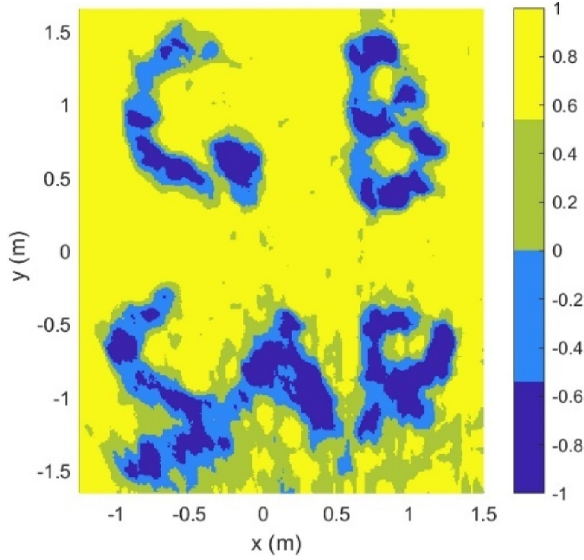


FIGURE 8 Two-stage master CI-CCD image for the post-2S-sorting images. Here blue indicates a change and yellow indicates no change.

metrics are often used in the evaluation of space weather predictive models [38, 39].

These were calculated using a confusion matrix (Table 2). Here T and F mean true and false respectively, and P and N mean positive (change) and negative (no-change) in the CCD image [38, 40].

3.4.1 | Adjustments to the performance metrics

Conventionally, a two-class detection is used. This leaves no room for ambiguous cases. As such, this paper utilises a four-class system. This was done to better take advantage of the multidimensional data available, and to reduce the impact of borderline cases. This necessitated a new confusion matrix, shown in Table 3.

3.4.2 | Performance metrics

Using the confusion matrix (Table 3), several performance metrics can be calculated. The formulae for the metrics are shown in Table 4. Additional metrics such as the Root Mean Squared Error (RMSE) (to be defined below) use the difference in CI-CCD (ρ) image values between the test and master images, instead of a confusion matrix. These formulae are defined below [38–44]:

- Probability of Detection (POD). This metric gives a value of [0,1] and is the proportion of true positive predictions compared to the number of events. A value approaching 1 indicates most events were detected, and a value approaching 0 indicates most events were missed.
- The Critical Success index (CSI) shares some similarities with the POD. It compares the number of correct forecasts to the number of correct forecasts, false alarms and misses. It is not

TABLE 2 Confusion matrix, showing the conditions that correspond to TP, TN, FP and FN.

Confusion Matrix		Event Observed	
		Yes	No
Event Forecast	Yes	TP	FP
	No	FN	TN

Note: Here TP means true positive and TN means true negative. FP means false positive and FN means false negative.

TABLE 3 Modified confusion matrix for the four class images.

Confusion Matrix		Master image			
		$\rho = -1$	$\rho = -0.5$	$\rho = 0.5$	$\rho = 1$
Test image	$\rho = -1$	TP = 1	TP=0.75	FP=0.75	FP=1
	$\rho = -0.5$	TP=0.75	TP=1	FP=0.5	FP=0.75
	$\rho = 0.5$	FN=0.75	FN=0.5	TN=1	TN=0.75
	$\rho = 1$	FN=1	FN=0.75	TN=0.75	TN=1

Note: Here TP means true positive and TN means true negative. FP means false positive and FN means false negative.

TABLE 4 Table showing the different performance metrics used in this paper.

Probability of Detection (POD)	
Value range: [0,1]	
$POD = \frac{TP}{TP + FN}$	(5)
Critical Success Index (CSI)	
Value range: [0,1]	
$CSI = \frac{TP}{TP + FP + FN}$	(6)
False Alarm Ratio (FAR)	
Value range: [0,1]	
$FAR = \frac{FP}{TP + FP}$	(7)
Proportion Correct (PC)	
Value range: [0,1]	
$PC = \frac{TP + TN}{TP + TN + FP + FN}$	(8)
Heidke Skill Score (HSS)	
Value range: $[-\infty, 1]$	
$HSS = \frac{2 * (TP * TN - FP * FN)}{(TP + FN)(FT + TN) + (TP + FP)(FP + TN)}$	(9)
Matthews's Correlation Coefficient (MCC)	
Value range: $[-1,1]$	
$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP) * (TP + FN) * (TN + FP) * (TN + FN)}}$	(10)
Root Mean Squared Error (RMSE)	
Value range: $[0, \infty]$	
$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Predicted_i - Actual_i)^2}$	(11)

affected by the number of correct negative forecasts. A value approaching 1 indicates a perfect forecast.

- The False Alarm Ratio (FAR) compares the number of false alarms with the number of forecast events. Here a value of 1 indicates all forecast events were false. This is sometimes confused with the False Alarm Rate $FAR_{rate} = FP / (TN + FP)$ [45].
- The Proportion Correct (PC) provides a measure of the number of accurate forecasts of events compared to the total number. A value approaching 1 indicates most forecasts were true, a value approaching 0 indicates most were wrong.
- The Heidke Skill Score (HSS) shares some similarities with the Success Rate ($SR = 1 - FAR_{rate}$); however, it also accounts for the random forecasts. The HSS outputs a value of $-\infty$ to 1. No incorrect forecasts would result in a value of $+1$. No correct forecasts would give a value of $-\infty$. A value of 0 would indicate 'no skill', and performance close to random guesses.
- The Matthew's Correlation Coefficient (MCC) is an alternative to Pearson's Correlation Coefficient (R) but is less affected by unbalanced datasets. A value of 1 represents perfect classification, and -1 represents perfect misclassification. Similarly, to the HSS, a value of 0 represents a classification similar to the expected value (random or no skill).
- The RMS Error (RMSE) quantifies the error between the test and master images. It is commonly used to evaluate performance precision, although does not indicate whether errors are in positive or negative.

The Universal Image Quality Index (UIQI) UIQI was also used [4, 46, 47]. It consists of four metrics:

$$Q = Q_1 \cdot Q_2 \cdot Q_3 \quad (12)$$

Here Q is a measure of the overall similarity. Q_1 can be seen as a measure of the structural similarity of the images. Q_2 represents the similarity of the image mean. Q_3 denotes the similarity of the image constants [4, 46, 47].

4 | RESULTS

Two methods of forming the max, mean and min images were discussed in section 3.3.2. As such graphs are presented for both the pre-2S-sorting and post-2S-sorting. It should be noted that the bistatic and coherent summation multistatic CI-CCD images are the same, as they were not produced using the pre/post-2S-sorting method. Instead a single pair of SAR images was formed and then change detection was performed. There will be some difference in the numerical values of the performance metrics due to the difference in master images.

4.1 | RGB colour composite images

Colour composite images can be formed to illustrate the impact of using multiple radar geometries and polarisations.

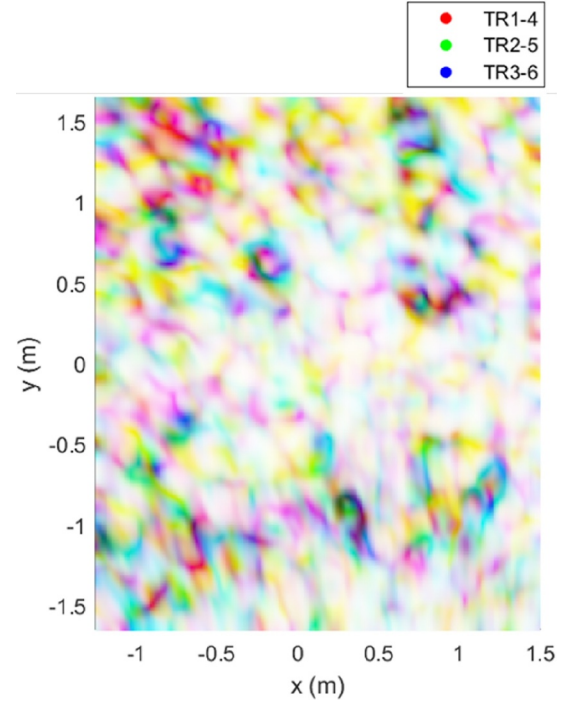


FIGURE 9 Colour composite (RGB) Coherent Change Detection (CCD) image for the three bistatic transceiver pairs. The image is VV polarised.

Three CCD images are used; thus, each pixel has three sets of values ranging from zero to one. These then define the Red Green Blue (RGB) value of each pixel.

In Figure 9, each colour RGB corresponds to a pair of receiver positions. Pixels that are white exhibit high coherence across all radar position pairs. However, inspecting the image shows that the coherence in a given pixel may be lower for one or two positions, leading to a brightly coloured image.

Figure 10 shows another colour composite, this time for all polarisations, but only one position. This again shows a significant degree of variability between the two co-polar terms (VV and HH) and the combined cross-polar terms ((VH + HV)/2).

4.2 | Normalisation

The performance metrics were plotted on spider plots. To improve the reader's ability to compare the performance of the different methodologies the performance values have been normalised to the maximum value.

This was done by finding the maximum value for each metric and dividing all values in that metric by the maximum value. The maximum values are shown below in Table 5. As such, each spider plot uses values of 0–1.

The formula for the normalisation is shown in Equation (6). Here x represents a particular performance metric (e.g. False Alarm Ratio, HSS, etc.). All the values of this particular metric (bistatic, multistatic, fully polarimetric, etc.) are represented by X . x_i is the value of a given performance metric and a particular image formation technique. For example, a maximum fully polarimetric multistatic image. This value is

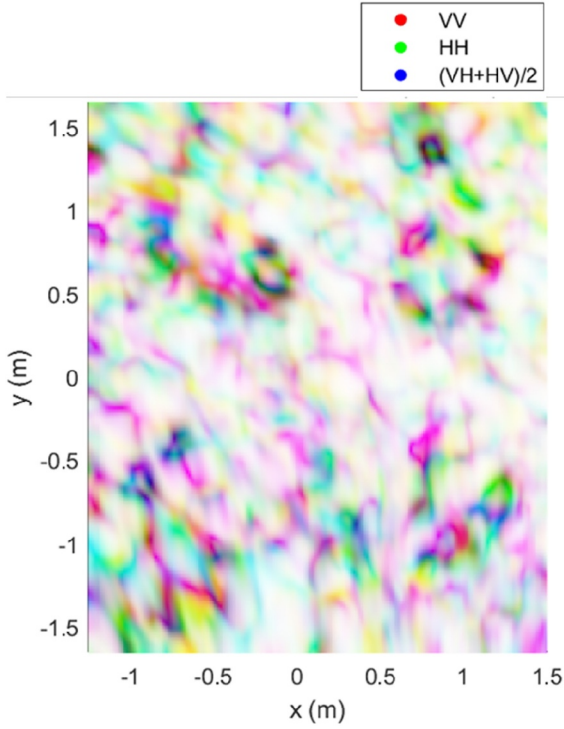


FIGURE 10 Colour composite (RGB) Coherent Change Detection (CCD) image for the four polarisations. Image is formed using TR1-4. The co-polar polarisations VV and HH are shown in red and green respectively. An average of the two cross-polar CCD images is shown in blue.

TABLE 5 Table showing the maximum values for each of the different performance metrics.

PC	0.833	RMSE	1.655
POD	1.000	FAR	0.763
CSI	0.457	UIQI - Q	0.584
MCC	0.507	UIQI - Q1	0.682
HSS	0.500		

then normalised using the maximum value of X . The normalised value of x_i is represented by a tilde; $\tilde{x}_i$.

$$\tilde{x}_i = \frac{x_i}{\max(X)} ; \text{ where } X = [x_1, x_2, \dots, x_N] \quad (13)$$

After the normalisation, the FAR and RMSE data presentation was modified further. The value of the normalised FAR and RMSE (now with values ranging from 0 to 1) was subtracted from 1. This was done so that a value closer to the outside of the spider plot (1) indicates better performance.

4.3 | Bistatic and multistatic

Bistatic and multistatic performance can be compared. These are shown for the pre-2S-sorting (Figure 11) and the post-2S-sorting (Figure 12).

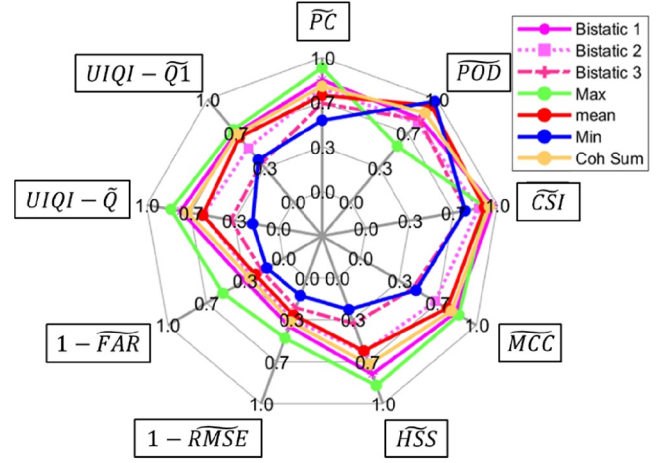


FIGURE 11 Spider plot showing the normalised performance of the three bistatic positions against the multistatic pre-2S-sorting and coherent summation. This is for the VV polarisation.

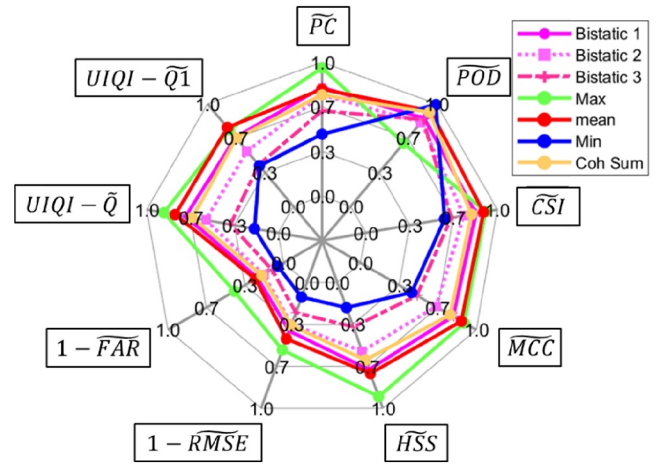


FIGURE 12 Spider plot showing the normalised performance of the three bistatic positions against the multistatic post-2S-sorting and coherent summation. This is for the VV polarisation.

The pre-2S-sorting, for the VV polarisation (Figure 11), shows that the maximum multistatic performs well in many metrics, except the POD and CSI. This is likely because the high number of no-change events being classified, resulting in a high number of false negatives. The coherent summation multistatic performs similarly to the best bistatic metrics. The max and mean exhibit quite poor performance, although do maintain a high POD. This shows the value of using multiple performance metrics.

The behaviour of the post-2S-sorting (Figure 12) is different to the pre-2S-sorting. The minimum performs worse than in the previous set of images. The mean now demonstrates superior performance to the coherent summation. The performance of the max image is quite similar.

It is also important when assessing performance to examine the outputs. This helps explain the performance seen in the graphs above. Figures 13 and 14 show eight CI-CCD images. Comparing the output change detection images

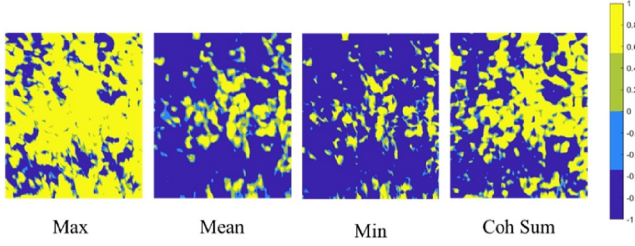


FIGURE 13 Set of four CI-CCD images formed using the pre-2S-sorting dataset for the VV polarisation.

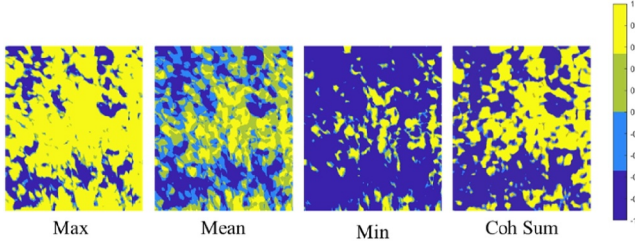


FIGURE 14 Set of four CI-CCD images formed using the post-2S-sorting dataset for the VV polarisation.

helps explain why the performance of the mean and min were quite similar (Figure 11). Inspecting the mean and min images in Figure 13 shows that they appear very similar. The mean image in Figure 14 however shows the ‘GBSAR’ much more clearly. In the pre-2S-sorting, many definite changes are detected, however in the post-2S-sorting significantly fewer are.

4.4 | Multistatic comparisons

The different multistatic images can be compared. These are plotted in Figures 15 and 16. These images show the trend seen in Section 4.1.3 holds true across the polarisations.

4.5 | Polarisations

The polarisations can also be investigated. Plotting the bistatic performance metrics in Figures 17 and 18. This shows that there is a variance in performance across polarisation. This is particularly evident for the MCC and HSS metrics.

Fully polarimetric images can be formed in the same way as the multistatic images. The results for these are presented in Figures 19 and 20. These figures use TR1 as the reference and TR4 as the mission trajectory.

Similarly, to the bistatic results, the minimum images performed worse than the single polarisation images, except for POD. The coherent summation performs at a similar level to the poorest single polarisation (HH). The maximum performs well, except for POD. It has high PC, UIQI, MCC and HSS values. The mean varies in performance as seen in Section 4.1.3. For the pre-2S-sorting, it exhibits similar performance to

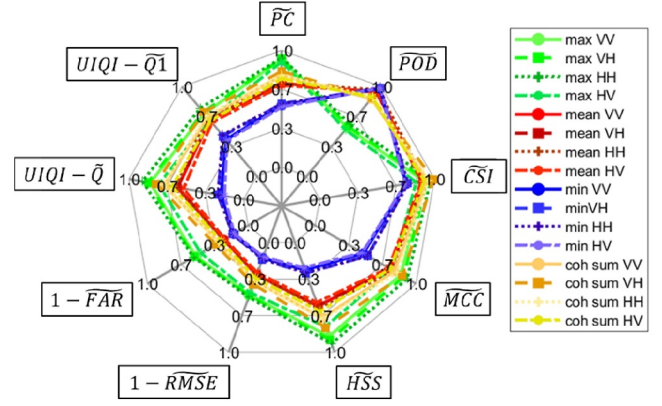


FIGURE 15 Spider plot showing the normalised performance of the pre-2S-sorting multistatic images across the four polarisations.

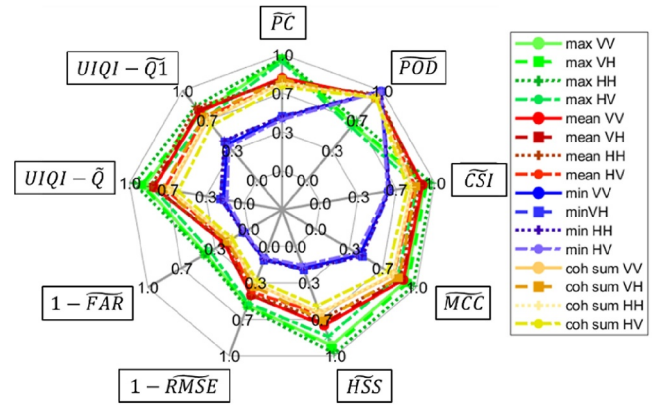


FIGURE 16 Spider plot showing the normalised performance of the post-2S-sorting multistatic images across the four polarisations.

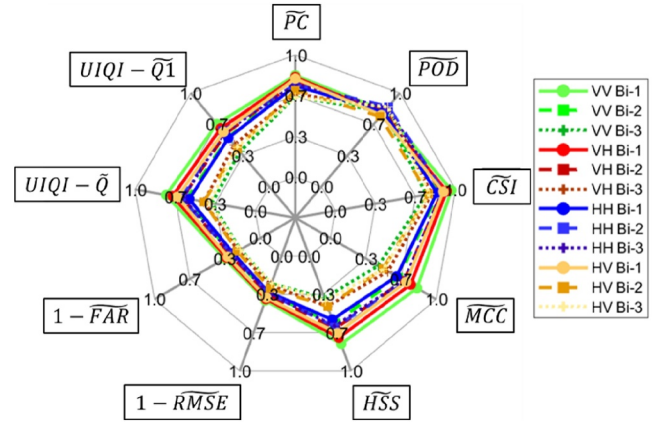


FIGURE 17 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared against the pre-2S-sorting master.

the single polarisation; however, for the post-2S-sorting, it performs similarly to the max, although it has a higher POD at a cost of a lower PC and higher FAR.

Fully polarimetric multistatic images can also be formed. Figures 21 and 22 compare the bistatic fully polarimetric

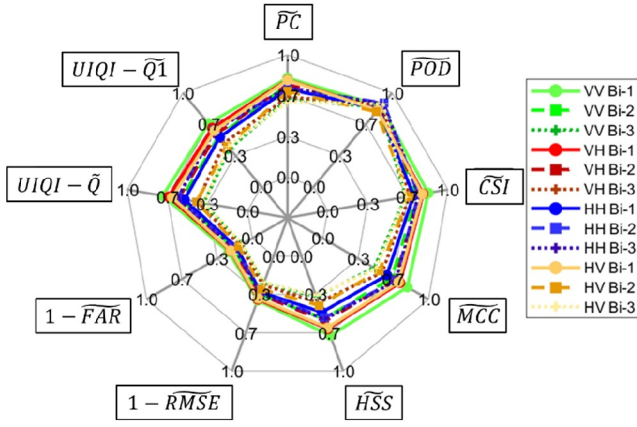


FIGURE 18 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared against the post-2S-sorting master.

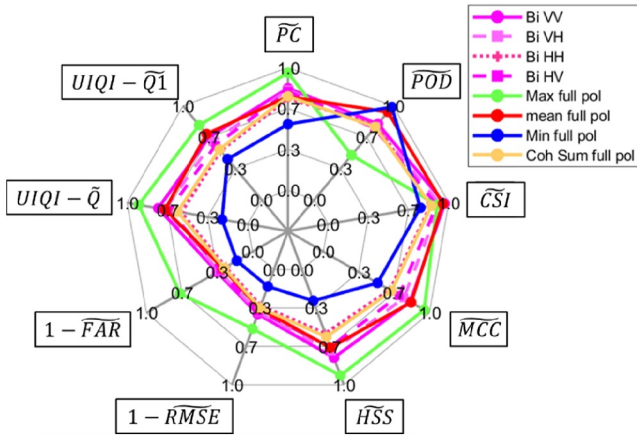


FIGURE 19 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared and four fully polarimetric CI-CCD images. Formed using pre-2S-sorting and radar positions TR1 and TR4.

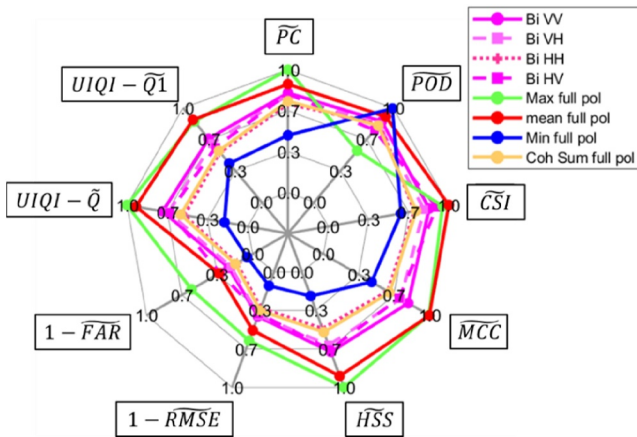


FIGURE 20 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared and four fully polarimetric CI-CCD images. Formed using post-2S-sorting and radar positions TR1 and TR4.

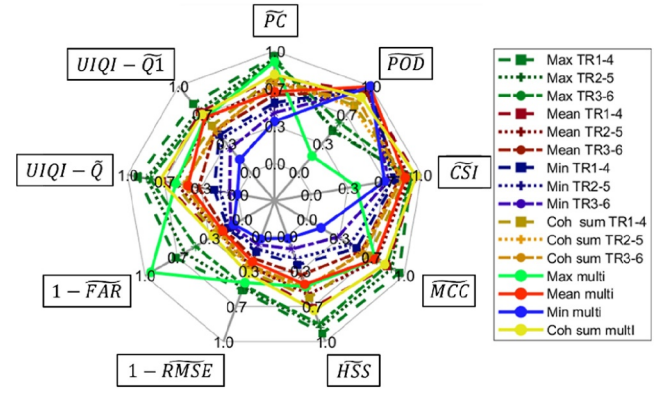


FIGURE 21 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared and multistatic fully polarimetric CI-CCD images. Formed using pre-2S-sorting.

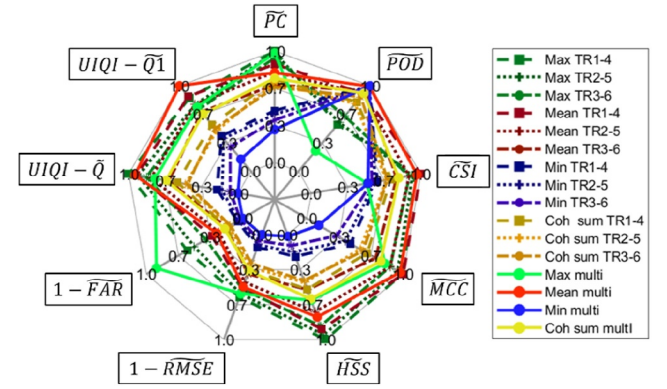


FIGURE 22 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared and multistatic fully polarimetric CI-CCD images. Formed using post-2S-sorting.

performance metrics with the multistatic fully polarimetric performance.

In the pre-2S-sorting results (Figure 21), the max multistatic performs significantly worse than the bistatic maximum. It is believed this is due to too many images being used and thus changes being obscured. This effect is lessened in the post-2S-sorting results (Figure 22). In both, the pre- and post-2S-sorting results the multistatic minimum performs worse than the bistatic. This is likely for the same reason as the maximum; too many images, which in this case cause too many changes to be detected.

The mean performs quite poorly for the pre-2S-sorting results (Figure 21), with the multistatic performing worse than the bistatic means. In the post-2S-sorting results (Figure 22), the performance is quite good, particularly with regards to the UIQI, CSI and POD. It also has a low FAR and RMSE. The multistatic is worse than some bistatic max and mean images for the HSS and FAR and is outperformed by the maximum in PC.

The coherent summation performs similarly to the maximum (bistatic and multistatic). It shows improvement over the bistatic coherent summation. For the pre-2S-sorting

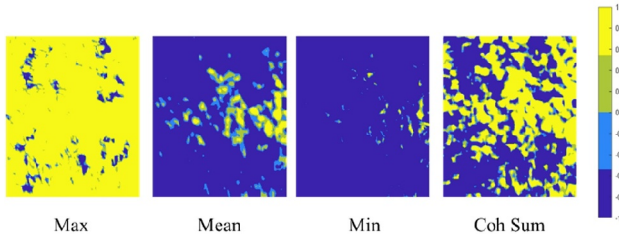


FIGURE 23 Set of four CI-CCD images formed using the pre-2S-sorting dataset for the full polarisation multistatic.

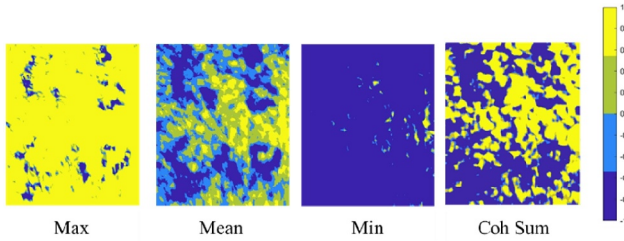


FIGURE 24 Set of four CI-CCD images formed using the post-2S-sorting dataset for the full polarisation multistatic.

results (Figure 21), it exceeds it in POD and CSI but performs worse for the other metrics. It has a higher HSS and MCC than the multistatic pre-2S-sorting, but not the bistatic. In the post-2S-sorting results (Figure 22), it is additionally outperformed by the bistatic and multistatic mean.

We can again inspect the output fully polarimetric and multistatic CI-CCD images shown in Figure 23 (pre-2S-sorting) and Figure 24 (post-2S-sorting). The letters ‘GBSAR’ are quite visible in the maximum image, so despite a relatively low POD, it is readable. It is also clearer than in the single pol (VV) images (Figures 13 and 14).

The minimum images perform very poorly and are covered in strong detections of change. As such, it is clear why the metrics are so poor.

The mean for the pre-2S-sorting (Figure 23) is quite similar to the minimum of the two figures below, as such it is clear why the performance metrics are similar to the minimum. The post-2S-sorting mean image (Figure 24) however clearly shows the ‘GBSAR’ letters. The four classes help here in making the letters more legible.

An enlarged image of the mean full polarisation multistatic post-2S-sorting (from Figure 24) is shown in Figure 25.

The coherent summation images do show the letters, although the false alarms make the G and S hard to make out.

The master images and the mean pre- and post-2S-sorting mean images are formed in a similar manner. Although the number and geometry of trajectories were significantly different. In the master images (Figures 7 and 8), the pre-2S-sorting image has a higher contrast and appears visually clearer than the post-2S-sorting master image. This is reversed when looking at the results (Figures 23 and 24). Here the post-2S-sorting image is significantly clearer. This is believed to be from the input images. It is hypothesised this is due to the

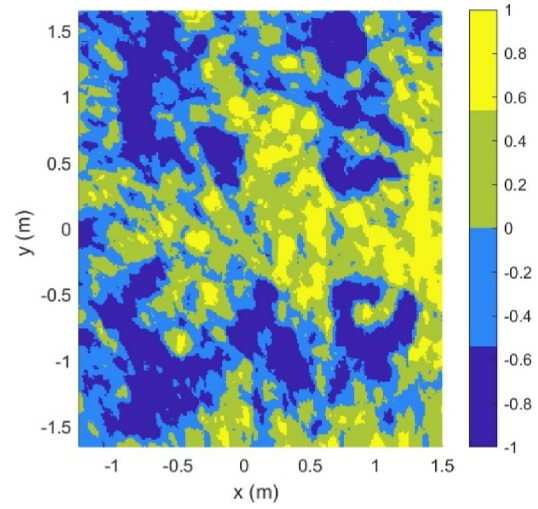


FIGURE 25 CI-CCD for the mean full polarisation multistatic post-2S-sorting (from Figure 24).

TABLE 6 Table showing the averaged performance metrics of the bistatic images compared to the pre-2S-sorting master image.

	VV	VH	HH	HV
TR1-TR4	0.7	0.67	0.58	0.64
TR2-TR5	0.59	0.62	0.62	0.5
TR3-TR6	0.47	0.52	0.52	0.49

image formation pipeline. The bistatic master images have a high degree of similarity as they were formed using exactly repeated trajectories. Thus, averaging before image formation, results in a high contrast result. The post-2S-sorting averages a series of discrete values rather than a continuous series within 0–1, as such there is a greater possibility of a reduced contrast.

However, for the test images, the trajectories are no longer repeating, as such additional decorrelations are present. These additional decorrelations lower the coherence of the CCD images used in the pre-2S-sorting, which then results in a higher number of changes being detected.

4.6 | Results summary

To provide an overview and summary the mean of the values of the performance indices was taken for each of the CI-CCD images. These are shown in the tables below and use the colourmap provided below.

This provides a single value of performance to summarise the results; however, it is biased by the choice of metrics.



Table 6 and Table 7 present the bistatic averaged performance metrics for the post-2S-sorting and pre-2S-sorting,

TABLE 7 Table showing the averaged performance metrics of the bistatic images compared to the post-2S-sorting master image.

	VV	VH	HH	HV
TR1-TR4	0.67	0.63	0.54	0.61
TR2-TR5	0.57	0.58	0.58	0.49
TR3-TR6	0.45	0.48	0.59	0.46

TABLE 8 Table showing the averaged performance metrics of the multistatic and fully polarimetric CI-CCD images formed using the pre-2S-sorting.

		Max	Mean	Min	Coh-Sum
Bistatic full pol	TR1-TR4	0.79	0.68	0.45	0.59
	TR2-TR5	0.74	0.61	0.41	0.54
	TR3-TR6	0.72	0.5	0.35	0.55
Multi single pol	VV	0.73	0.63	0.43	0.67
	VH	0.75	0.62	0.45	0.72
	HH	0.78	0.64	0.45	0.68
	HV	0.68	0.6	0.42	0.64
Multi fully polarimetric		0.58	0.58	0.27	0.68

TABLE 9 Table showing the averaged performance metrics of the multistatic and fully polarimetric CI-CCD images formed using the post-2S-sorting.

		Max	Mean	Min	Coh-Sum
Bistatic full pol	TR1-TR4	0.84	0.81	0.31	0.56
	TR2-TR5	0.79	0.72	0.36	0.51
	TR3-TR6	0.74	0.61	0.31	0.52
Multi single pol	VV	0.76	0.72	0.38	0.64
	VH	0.78	0.71	0.4	0.67
	HH	0.82	0.71	0.4	0.63
	HV	0.71	0.66	0.36	0.59
Multi fully polarimetric		0.68	0.8	0.23	0.63

respectively. These results are presented for all four polarisations.

Table 8 and Table 9 present the multistatic averaged performance metrics for the post-2S-sorting and pre-2S-sorting, respectively.

It can be seen that the highest values for the averaged performance metrics are found in Table 9. These are higher than those found in Tables 6–8.

The maximum bistatic fully polarimetric for TR1-TR4 resulted in the highest average performance metric value. This

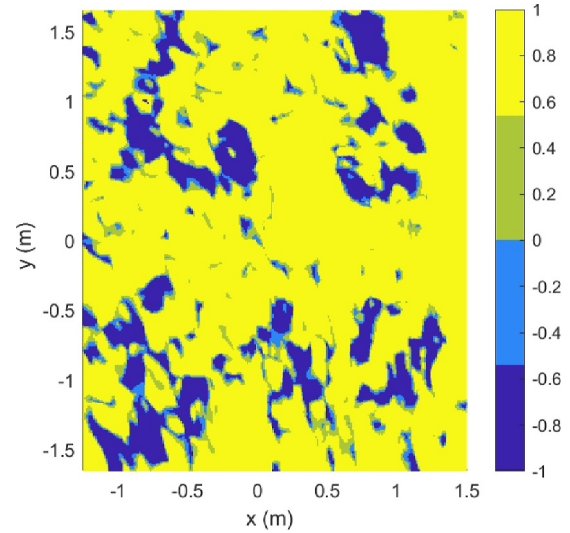


FIGURE 26 CI-CCD image for the bistatic TR1-TR4, fully polarimetric maximum (post-2S-sorting). This image showed a high average performance of 0.84 in Table 9.

image is shown in Figure 25. Compared to Figure 26, which also performed well it shows a lower number of detections.

5 | DISCUSSION

This paper has investigated the performance of different multistatic combinations for change detection quantitatively using a variety of performance metrics as well as qualitatively.

The use of multiple performance metrics combined with inspecting the output images has been shown to help characterise performance. These metrics do not just show how well a detector performed, but its tendency towards over or under detection and how well it captures the structure of the disturbance. For example, the metrics showed how the performance of the mean images was improved in the post-2S-sorting compared to the pre-2S-sorting (Section 4.1.3). This could then be visually seen as well in the CI-CCD images.

It has been shown that multistatic and multipolar change detection can lead to improved change detection performance. However, the manner in which the multistatic CI-CCD image was formed has a significant impact on performance. Coherent summation did not lead to the best performing change detection images. Instead multistatic change detection images formed incoherently using bistatic images was shown to perform better. An additional consideration is whether the sorting is performed pre or post the CI-CCD stage, and what manner of sorting was chosen. The variance in performance due to the former was most clearly demonstrated by the mean images which performed much better for the post-2S-sorting than for the pre-2S-sorting. The variance due to the type of sorting was evident in all the CI-CCD images, where the max, mean and min images displayed significant variation in detections.

Overall, the multistatic maximum and mean Post-2S-sorting images performed the best. The fully polarimetric multistatic mean Pos-2S-sorted image also exhibited good performance,

with very high Q values, although was outperformed in some metrics by some fully polarimetric bistatic images.

The minimum images were the best at detecting the presence of a change (high POD). However, the minimum images suffered from a poor FAR and did not capture the shape of the disturbance as shown by the Q, MCC and HSS values. The maximum images resulted in a significantly lower POD; however, the shape of the GBSAR letters was much more evident. This was reflected in high Q, MCC and HSS values.

The maximum and minimum images however showed a degradation in performance for the fully polarimetric multistatic images. This is hypothesised to be from too many images being used, this leading to a dominance of outliers (either change or no change) in the sorting. This would then obscure the structure of the disturbance track. In the multistatic fully polarimetric case, the mean post-2S-sorting image performed well and was more robust at negating the impact of outliers.

6 | CONCLUSION

This paper has investigated the performance of different multistatic combinations for change detection.

From the spider plots and the averaged performance tables (Section 4.1.6), some conclusions can be drawn.

Post-2S-sorting results in improved performance compared to pre-2S sorting.

Maximum post-2S-sorting images could offer good performance as shown in Table 9; however, for the fully polarimetric multistatic maximum image, the outliers (no change) become too dominant and degrade performance. Therefore, the maximum may be vulnerable to missing a large number of possible detections (low POD) when large numbers of images are used.

The mean images post-2S-sorting images performed quite well and were more robust to outliers.

The difference between the best performing maximum and mean images in Table 9 is quite small and does not represent a significant difference in performance.

The coherent summation performed worse than the maximum and mean images. This suggests processing a multistatic dataset bistatically, then forming a multistatic CI-CCD image will improve detection performance. The minimum images performed very poorly.

Overall, the mean post-2S-sorting performed well and is robust against outliers for larger volumes of images. Maximum post-2S-sorting images can perform well too but are more vulnerable to outliers and a low POD.

It is acknowledged that the values of the performance metrics relate to the master image used, and the number of detections present. Additionally, whilst it is hypothesised, these conclusions are valid for other multistatic change detection scenarios, only a single scene and disturbance investigated here.

Future work should investigate scenes of greater complexity, layover and/or varying topography. Multiband or multispectral change detection could also be investigated w.r.t multistatic SAR. Change detection algorithms trimmed,

weighted or winsorised means [48, 49] may offer improved performance by eliminating outliers.

AUTHOR CONTRIBUTION

Alexander Hagelberg: Conceptualization; Formal analysis; Investigation; Methodology; Software; Validation; Writing – original draft; Writing – review & editing. **Daniel Andre:** Funding acquisition; Methodology; Project administration; Resources; Software; Supervision; Writing – review & editing. **Mark Finnis:** Resources; Software.

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CONFLICT OF INTEREST STATEMENT

There is no conflict of interest that we are aware of.

DATA AVAILABILITY STATEMENT

Radar trajectory co-ordinates will be made available on the CORD repository. Synthetic Aperture Radar data is the subject of ongoing research but may be made available on request to the corresponding author or the Cranfield GBSAR group.

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