



Robust SAR Coherence Estimation for Low-Coherence Regions Using Machine Learning

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Abstract

Synthetic Aperture Radar (SAR) coherence estimation plays a crucial role in surface deformation monitoring and change detection, with its accuracy directly affecting the reliability of subsequent interferometric measurements. SAR images are sensitive to noise in low coherence areas. Traditional coherence estimators have large deviations under low coherence and small sample conditions and cannot reliably characterize the characteristics of changing areas. To address these critical limitations, This paper proposes a new method that combines machine learning with weighted coherence statistics, and the complex numerical integration and bootstrap sampling process are avoided through automated non-parametric statistical inference. The ratio change statistics that characterize the intensity difference are introduced to improve the covariance matrix and used as training features to avoid the limitation of the image equal variance assumption, further improving the accuracy and computational efficiency of the estimation. Experimental results show that the proposed method has a more robust coherence estimation capability in small sample size and low coherence regions, and improves the contrast in low coherence areas; this method has broad application potential, especially in scenarios where fast and efficient estimation of coherence amplitude is required.

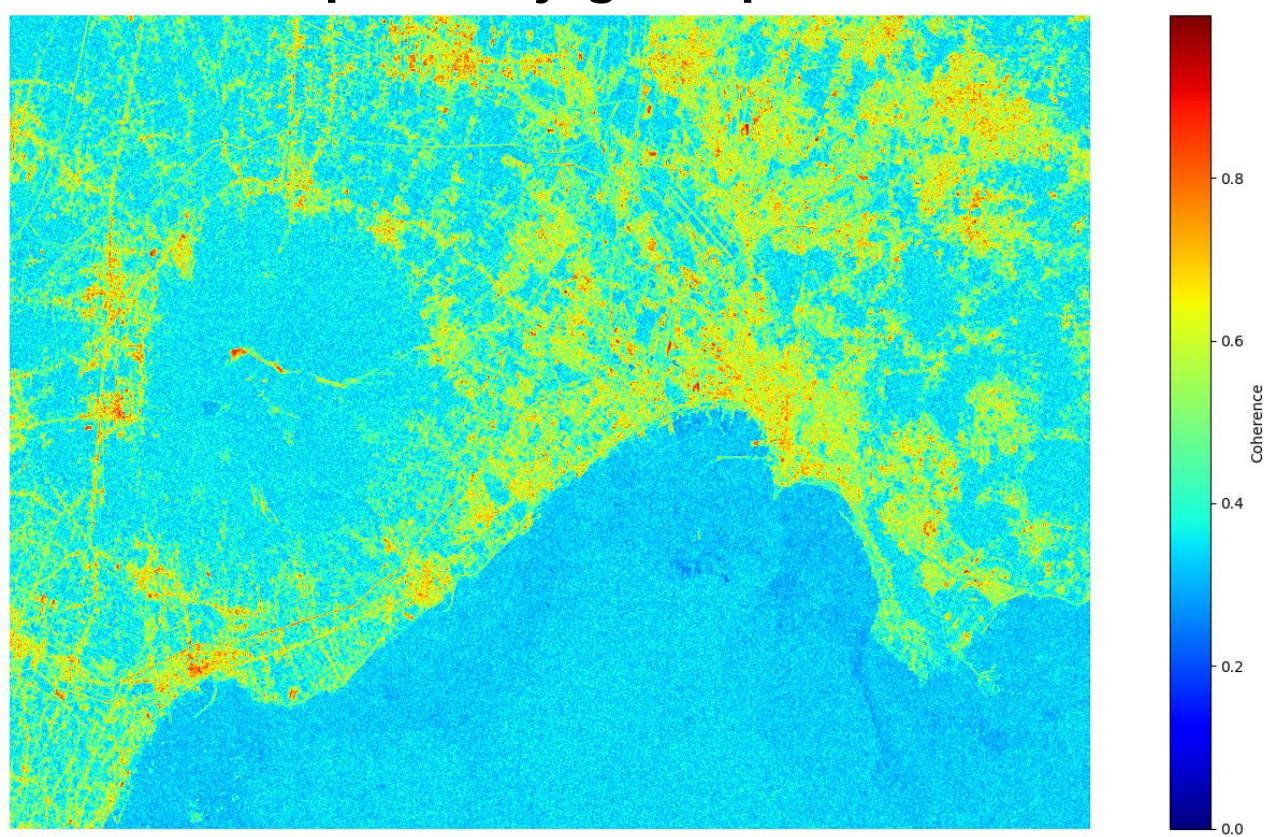
Index Terms—SAR coherence estimation, machine learning, low coherence, small sample sizes

Introduction

Synthetic Aperture Radar (SAR) coherence quantifies the phase stability between two complex SAR acquisitions over the same area, serving as a cornerstone for interferometric applications^[1]. Computed as the magnitude of the complex cross-correlation coefficient:

$$\gamma_a = \frac{|\sum_{k=1}^N f_k^* g_k|}{\sqrt{\sum_{k=1}^N f_k^* f_k \sum_{k=1}^N g_k^* g_k}}$$

where f_k, g_k are complex pixel values and N is the sample size, The symbol * is the complex conjugate operator.



Coherence image of Napoli area from TerraSAR-X data (γ_a)

The value range is 0~1, A value of $\gamma=1$ indicates perfect phase stability (e.g., stable urban structures), while $\gamma=0$ implies complete decorrelation (e.g., flooded vegetation or rapid surface disruption).

The task at hand is to estimate the coherence from a sample of size N . However, the challenge is the significant bias and variance of the estimates, especially when dealing with small coherences and small sample sizes.

At the same time, SAR images are sensitive to noise in low coherence areas^[2]. The traditional coherence statistic γ_a has significant deviations under low coherence and small sample conditions, making it difficult to effectively characterize the characteristics of the changing area. To this end, this paper proposes a new method that integrates machine learning and weighted coherence statistics. Through the intensity difference ratio feature and non-parametric statistical inference, the estimation accuracy and robustness of the low coherence area are improved.

Objectives

- Demonstrate the principle and method of ML coherence estimation.
- Combined with the weighted coherence estimator^[3], the covariance matrix in the complex circular Gaussian distribution is improved.
- The new ML coherence estimation has the potential to better highlight the change area.

Methods

This study proposes a robust coherence estimation method based on joint optimization of weighted coherence and machine learning. As shown in Figure 2, the method mainly consists of the following four parts:

(1)Generate simulated data based on complex circular Gaussian and new covariance matrix: The covariance matrix Σ_w is constructed by presetting uniformly distributed amplitudes a_1, a_2 , interference phase ϕ_0 and coherence value γ , setting the Σ_w to a positive definite value and then perform singular value decomposition (SVD).

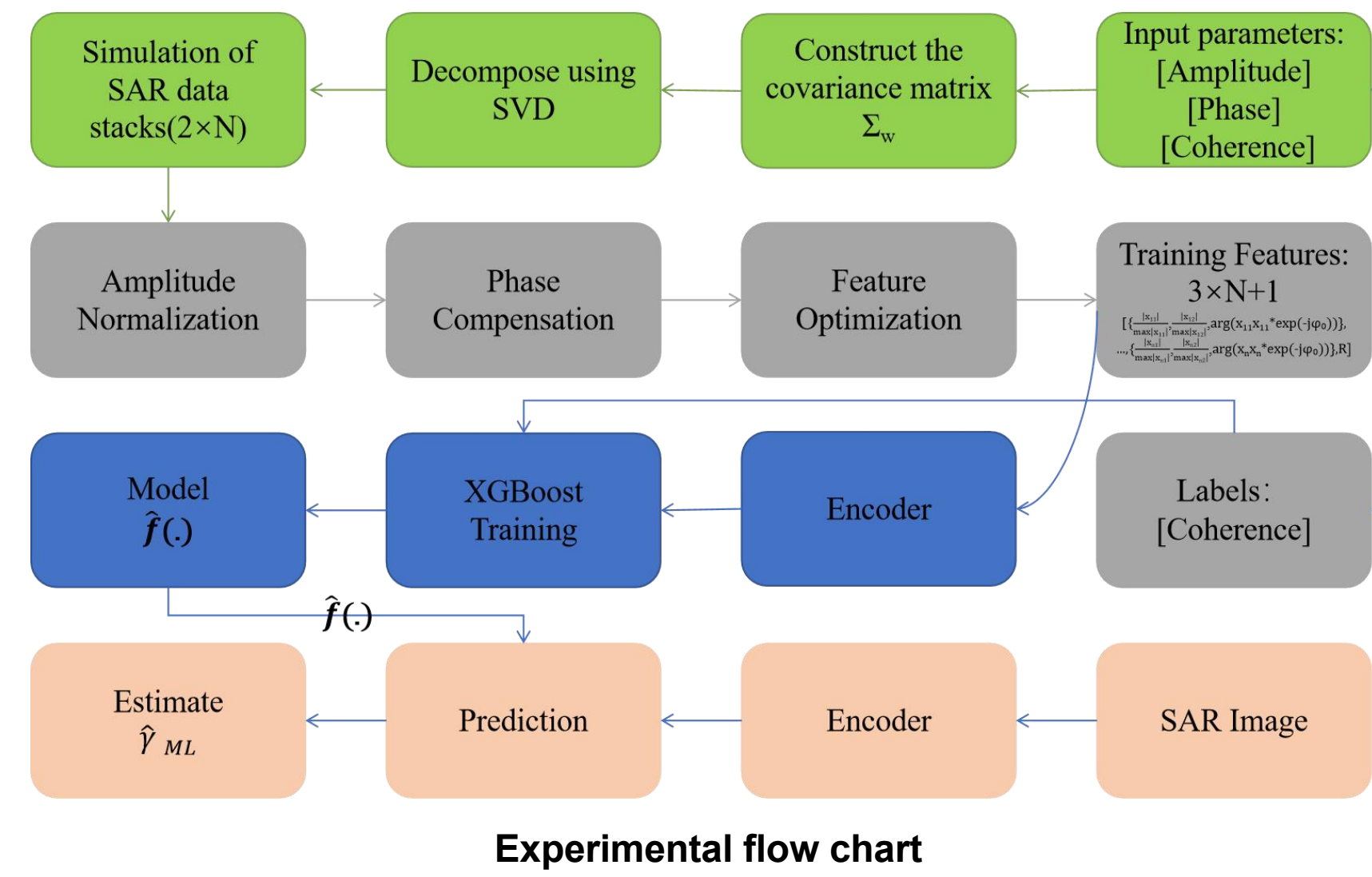
$$\Sigma_w = cov(X_1, X_2) = \begin{pmatrix} a_1^2 & \rho e^{j\phi_0} \\ \rho e^{-j\phi_0} & a_2^2 \end{pmatrix}, \rho = \frac{\gamma}{2} \left(\sqrt{R} \cdot a_1^2 + \frac{a_2^2}{\sqrt{R}} \right), R = \frac{a_1^2}{a_2^2}$$

A complex matrix $Z \in \mathbb{C}^{2 \times N}$ consisting of independent complex circular Gaussian (CCG) random variables is constructed and combined with the SVD decomposition results to generate simulated SAR data.

(2)Feature optimization and conversion into machine learning training data: The simulated data are preprocessed, including amplitude normalization and phase compensation, and finally converted into a feature vector consisting of $(3N + 1)$ parameters.

(3)Generate 10**7 sets of simulated data samples covering different coherence value ranges, and the coherence estimation model is trained based on the machine learning model XGBoost^[4].

(4)Use the trained model γ_{ML} to estimate the coherence of SAR data.



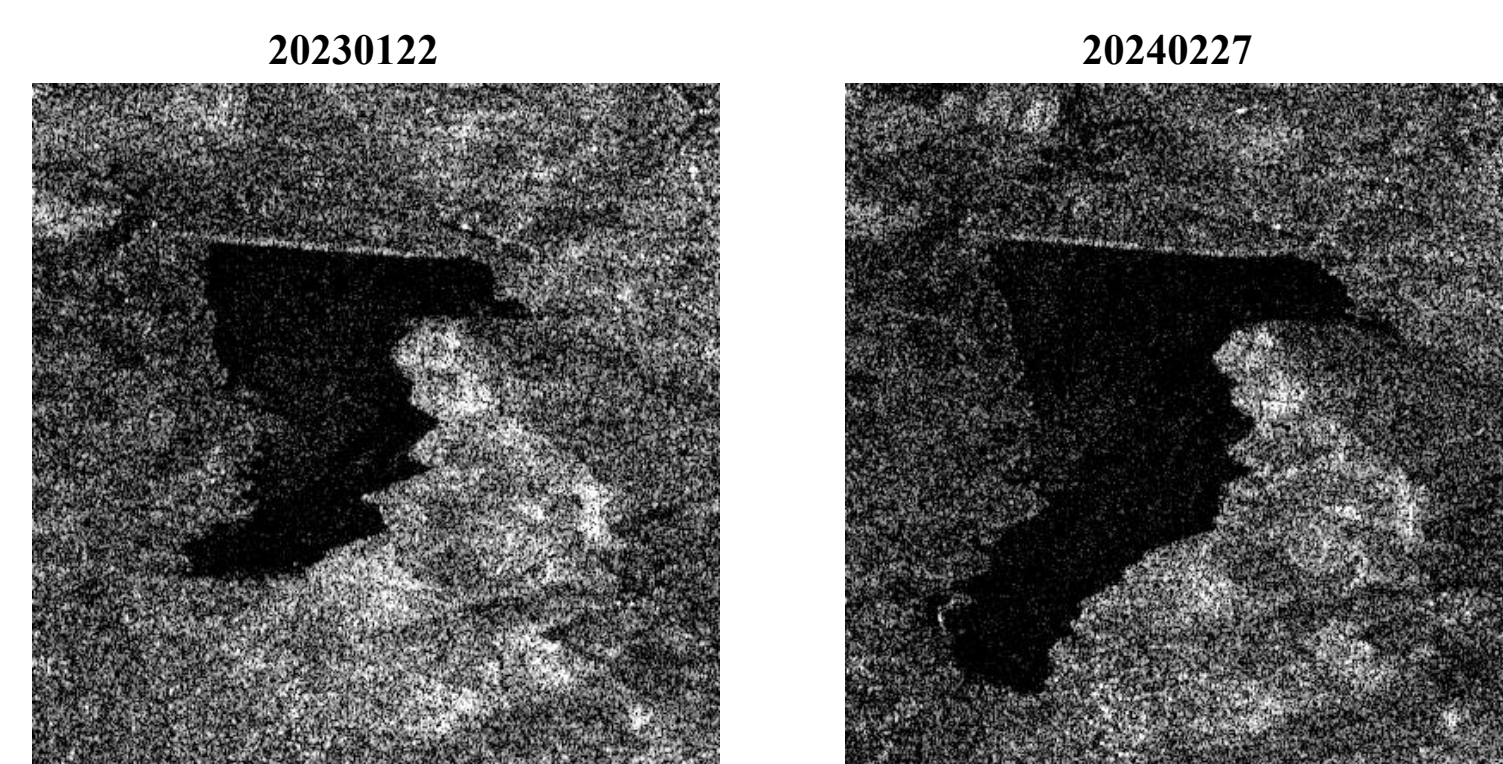
Results

In order to evaluate the effectiveness of the coherence estimation of the proposed estimator and its applicability in satellite SAR images, three sets of comparative analysis were performed. In the experiments, Sentinel1-A (S1A) and TerraSAR-X (TSX) and TanDEM-X (TDX) images from different sensors were used. They are used to detect changes in different areas: Dataset 1 is used to detect sensitive changes in the water area of the dam area, Dataset 2 is used to detect changes in the cultivated area, and Dataset 3 is used to identify changes in the built-up area. Table 1 shows the detailed information of the images.

Table 1

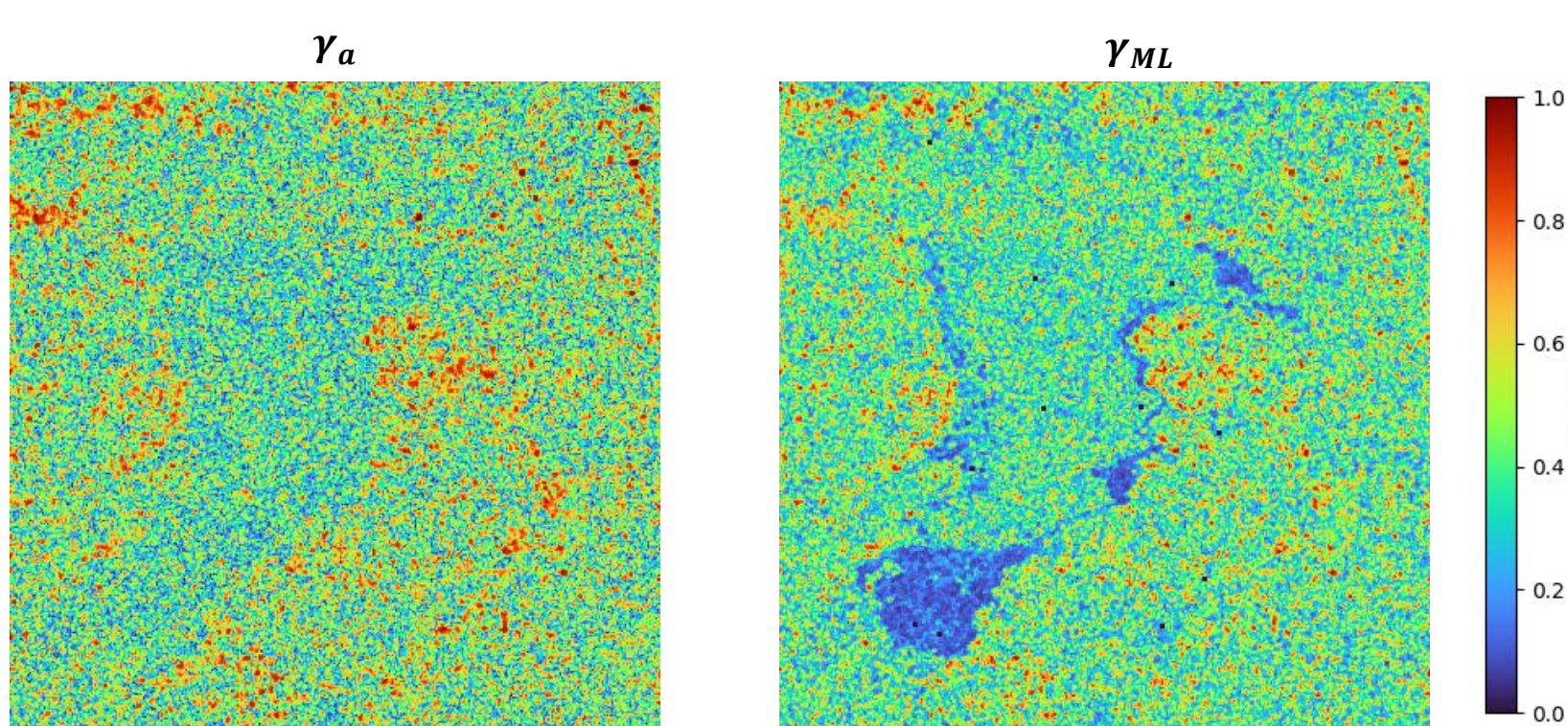
Set	sensor	Angle	Date	Res	IM	Size
1	S1A	33.91°	22/01/2023	20m	IW	400*400
	S1A	33.92°	27/02/2024	20m	IW	400*400
2	TDX-1	21.39°	10/07/2023	3m	SM	1010*700
	TSX-1	21.38°	03/10/2024	3m	SM	1010*700
3	TDX-1	21.39°	10/07/2023	3m	SM	600*600
	TSX-1	21.38°	03/10/2024	3m	SM	600*600

Set1: This area is mainly a typical water system distribution belt within the dam's influence area. Affected by the periodic drainage scheduling of the reservoir, the main land cover types in the study area show significant dynamic changes, frequently changing from seasonal water bodies to land.



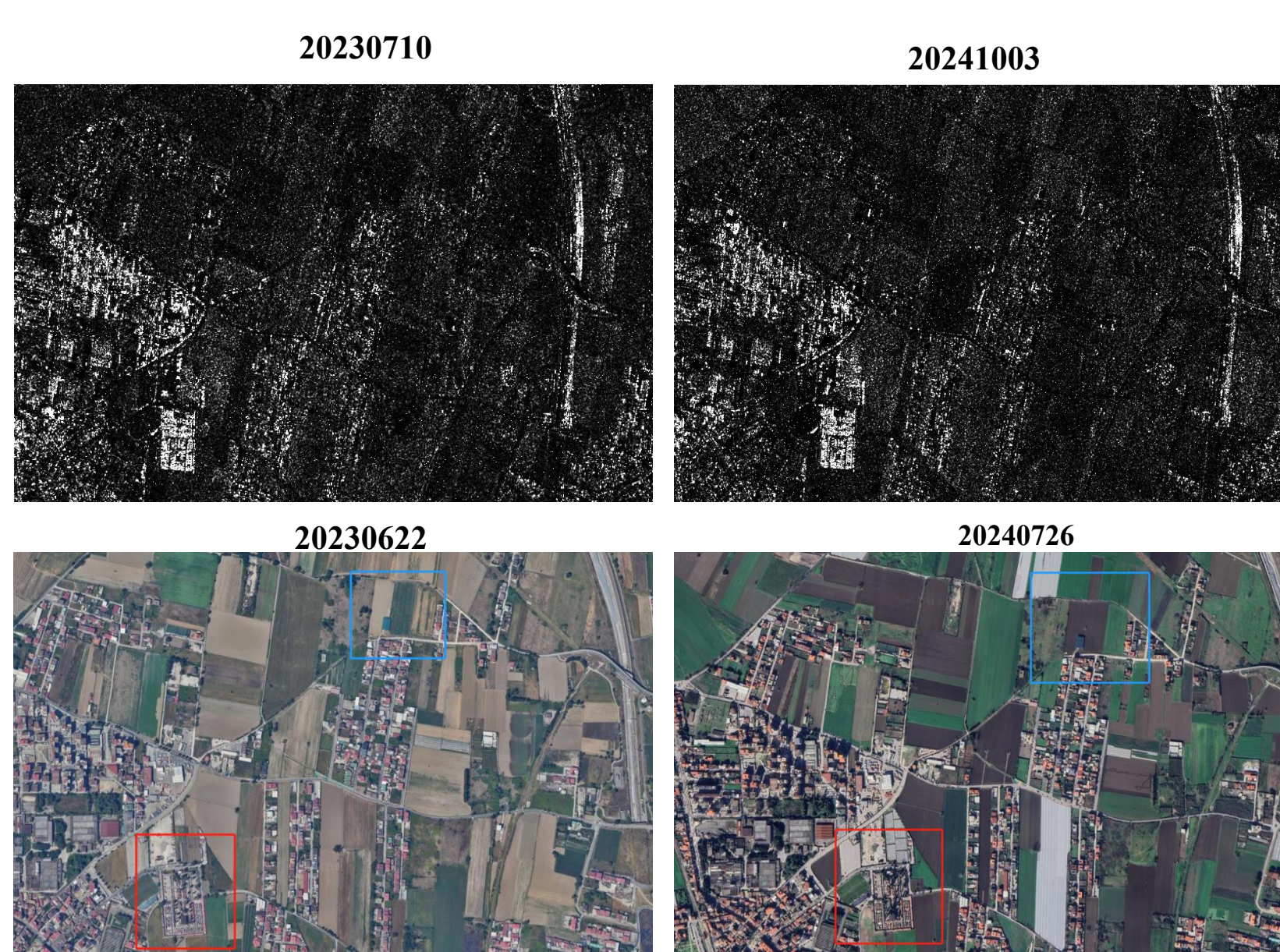
SAR amplitude image of Set1

We use the classic coherence formula and the method in this paper to estimate the coherence of this scene(window size is 3*3), and the results are as follows:

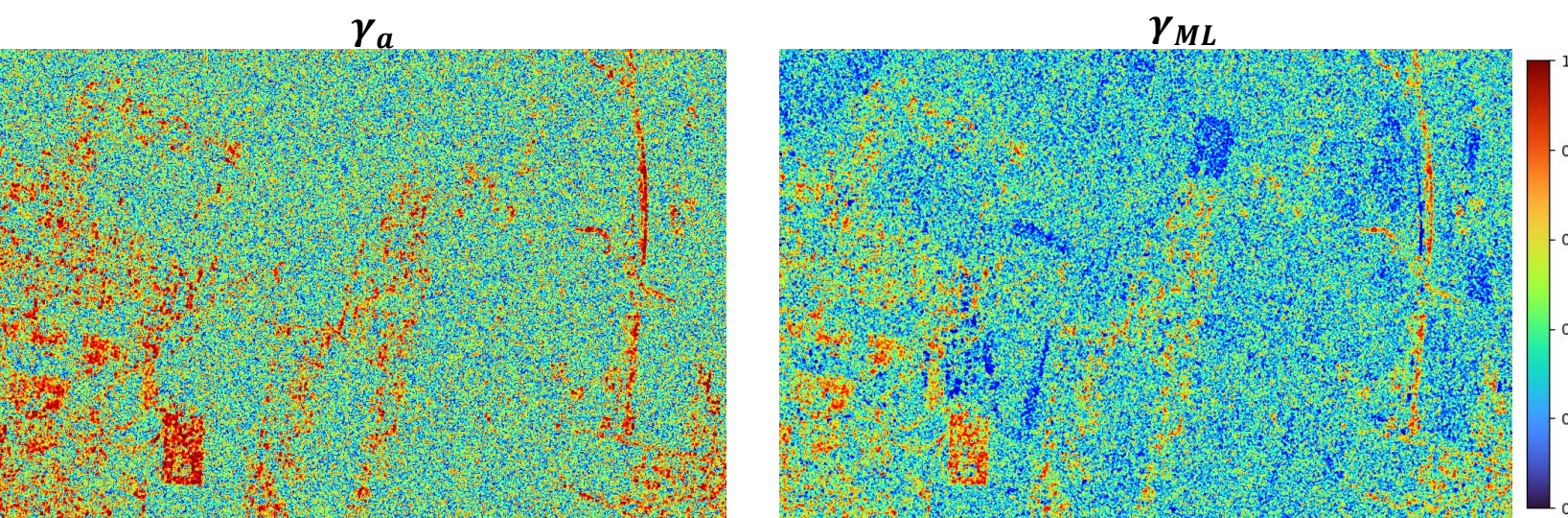


Coherence results of γ_a and γ_{ML} for Set1

Set2: This area is a suburb around the city. Affected by human agricultural activities, the main surface cover types in the study area show periodic changes, from wasteland to cultivated land.

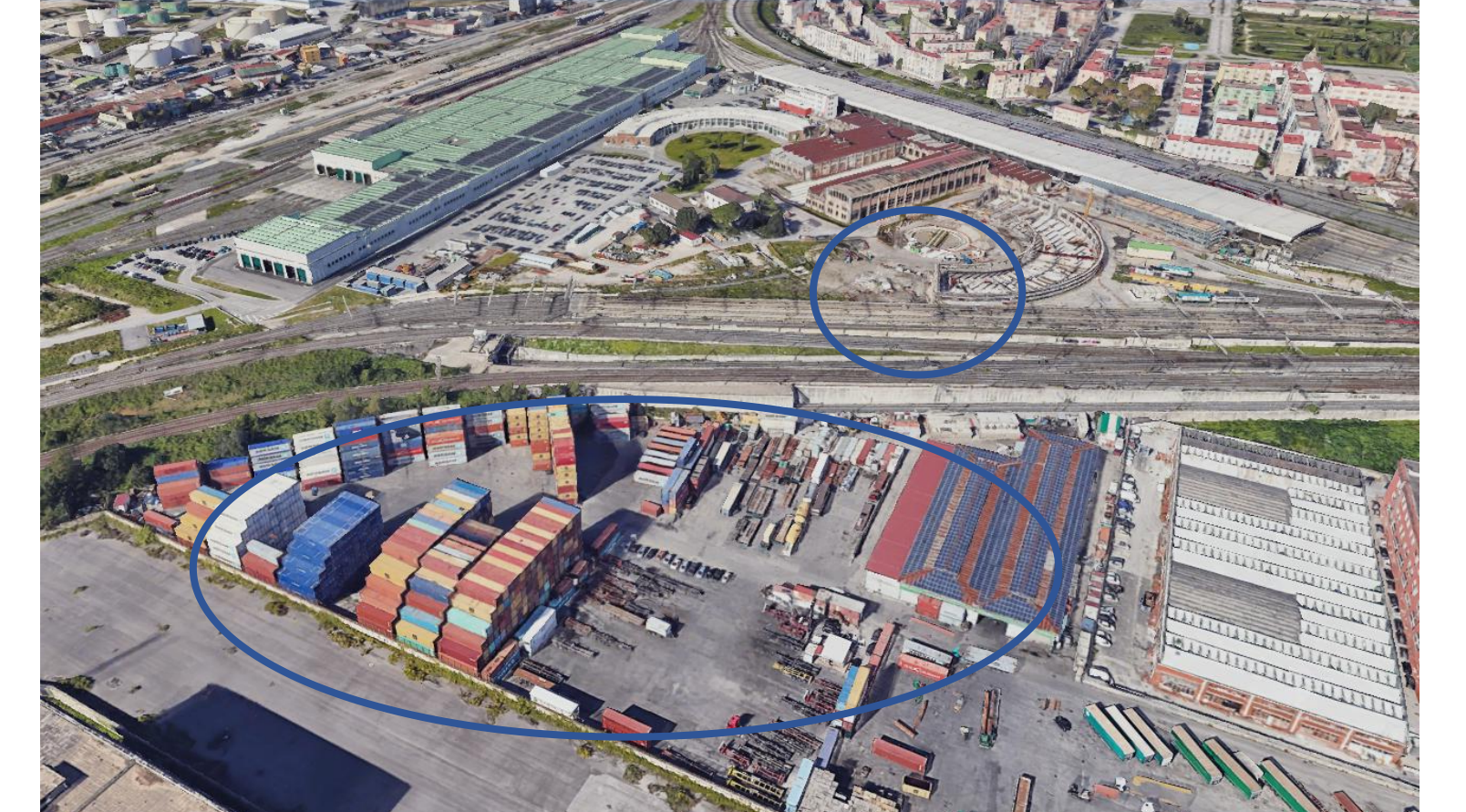


SAR amplitude image and Optical image (from Google Earth) of Set2



Coherence results of γ_a and γ_{ML} for Set2

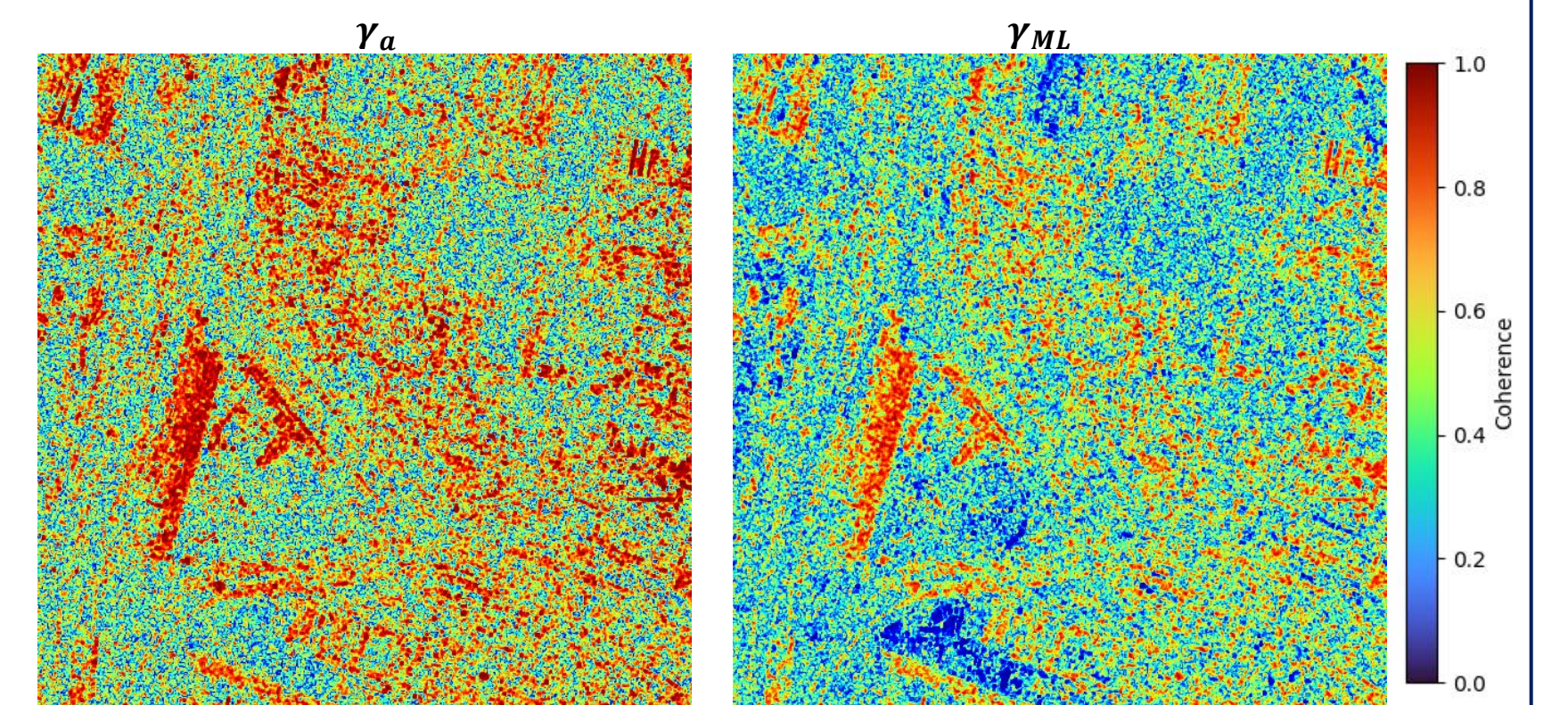
Set3: As a typical port city area, the coherence of construction sites and cargo yards in the study area are expected to be significantly lower than those in stable terrain areas due to the spatiotemporal decoherence effect of surface scatterers.



Three-dimensional landscape of Set3 (from Google Earth)



SAR intensity image of Set3 (log10 scale)

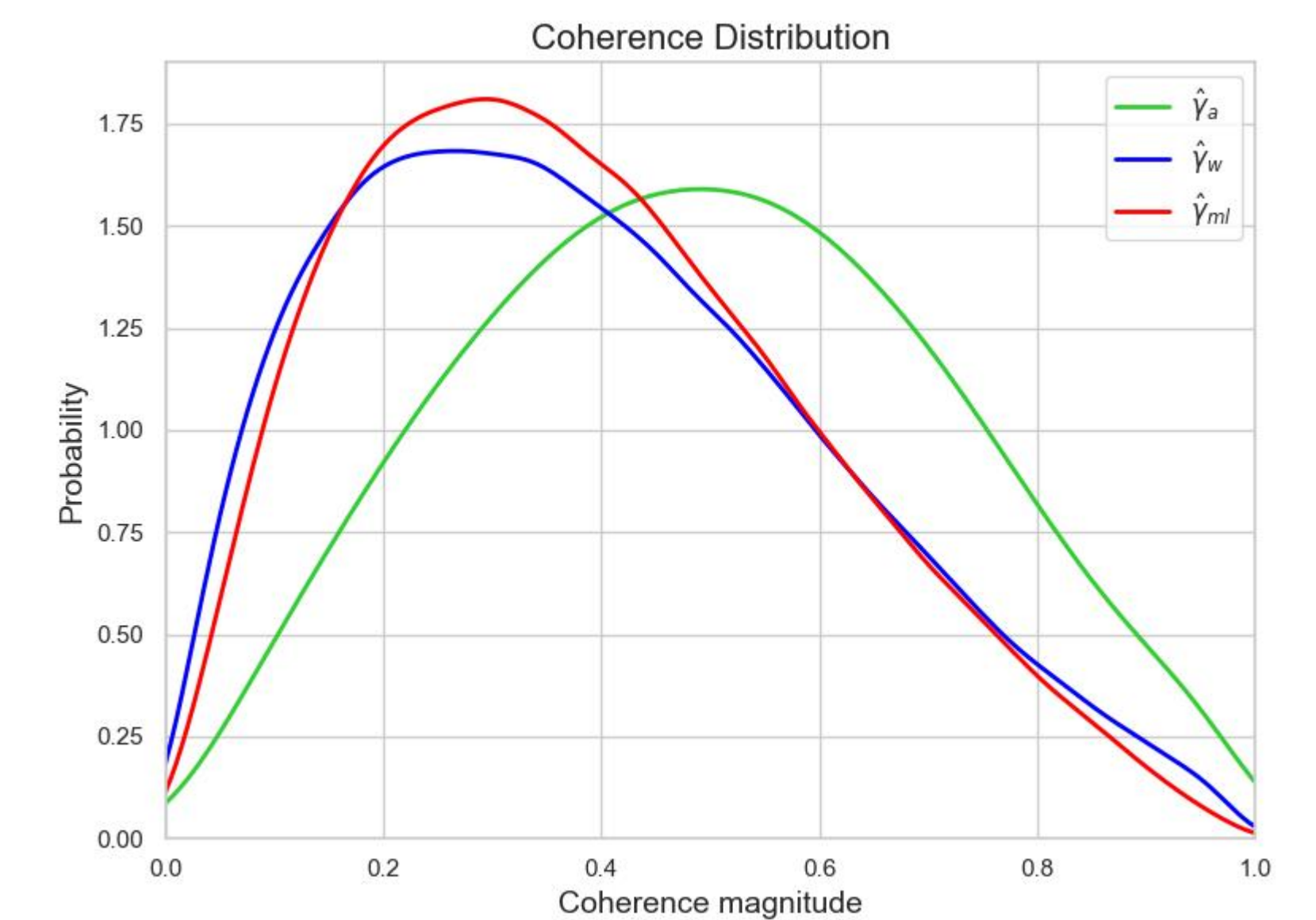


Coherence results of γ_a and γ_{ML} for Set3

Discussion

Experimental verification at different resolutions and in different scenes (water systems, farmlands, and buildings) shows that the proposed method can effectively enhance the coherence attenuation characteristics of the changing area, making the changing area show a more significant coherence reduction.

Based on the data of Dataset 2, we compared the performance of the γ_a and γ_{ML} algorithms with the proposed method in coherence estimation. The results show that the proposed method has better robustness and can better distinguish between decorrelation caused by changes and low coherence caused by other factors.



Histogram fitting probability curve of the coherence image.

Conclusions

This paper proposes a new SAR coherence estimation method that integrates intensity difference ratio features and machine learning. Compared with traditional methods, this method effectively solves the problems of large estimation bias and high variance in low coherence areas under small sample conditions. Experimental results show that: (1) in low coherence scenes, this method can accurately detect the coherence attenuation characteristics corresponding to the surface change area; (2) the contrast of the low coherence area is significantly improved. This method provides a new technical idea for small sample SAR interferometry processing and has important application value in fields such as surface deformation monitoring.

References

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