



Forest Fire Scar Detection From Time-series Sentinel-1 Observations Based On Coherence Prediction Using Recurrent Neural Network

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Abstract

- High-quality post-fire optical imagery is usually unavailable due to smoke/cloud cover. Therefore, it has become an interesting research topic to exploit satellite SAR data as an alternative in forest fire scar detection since its acquisition is independent of weather condition and solar illumination.
- Using SAR backscatter intensity for multi-temporal change detection may lead to false positives in mountainous terrain with significant undulation, due to complex scattering mechanisms and geometric distortions in SAR imagery. Meanwhile, the coherence feature derived by InSAR has also been employed for change detection. Nevertheless, coherence exhibits uncertainty due to the non-stationary properties of forest vegetation, and thus false alarms may become a dominant problem in the detection results.
- To address above problems, we proposes a semi-supervised deep learning framework based on time-series SAR coherence analysis, which optimizes forest vegetation coherence prediction through a Convolutional-Recurrent Neural Network (CNN-RNN) temporal prediction model. The method utilizes the redundant characteristics of time-series SAR coherence, combines CNN for extracting multi-dimensional (spatial, temporal, and polarimetric) features, and models the dynamic evolution patterns of coherence sequences through RNN, thereby predicting vegetation coherence states under undisturbed conditions. The difference between predicted results and actual observation data is used to accurately extract change areas.

Study area

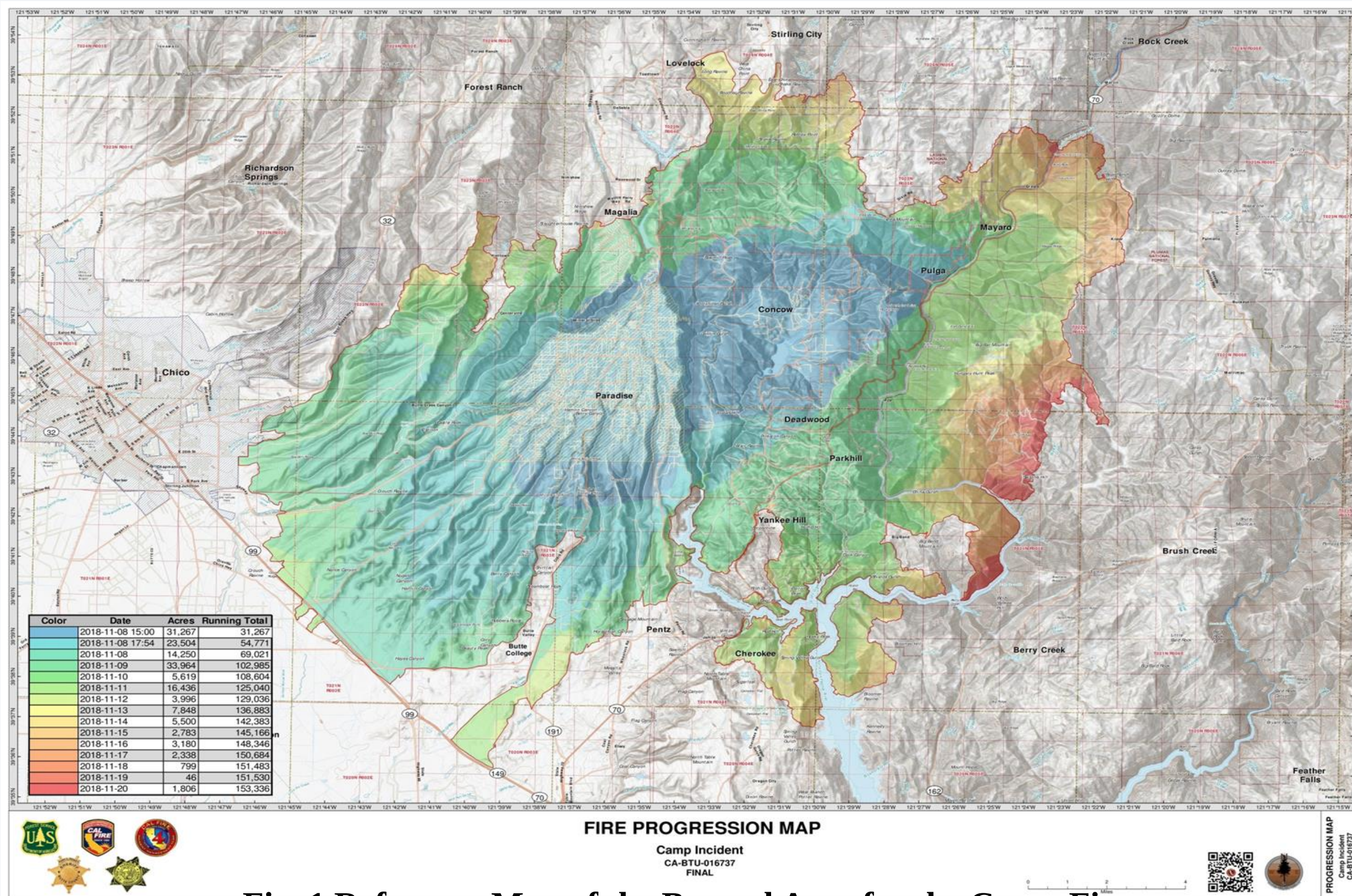


Fig. 1 Reference Map of the Burned Area for the Camp Fire. (Image Source: California Department of Forestry and Fire Protection)

Method

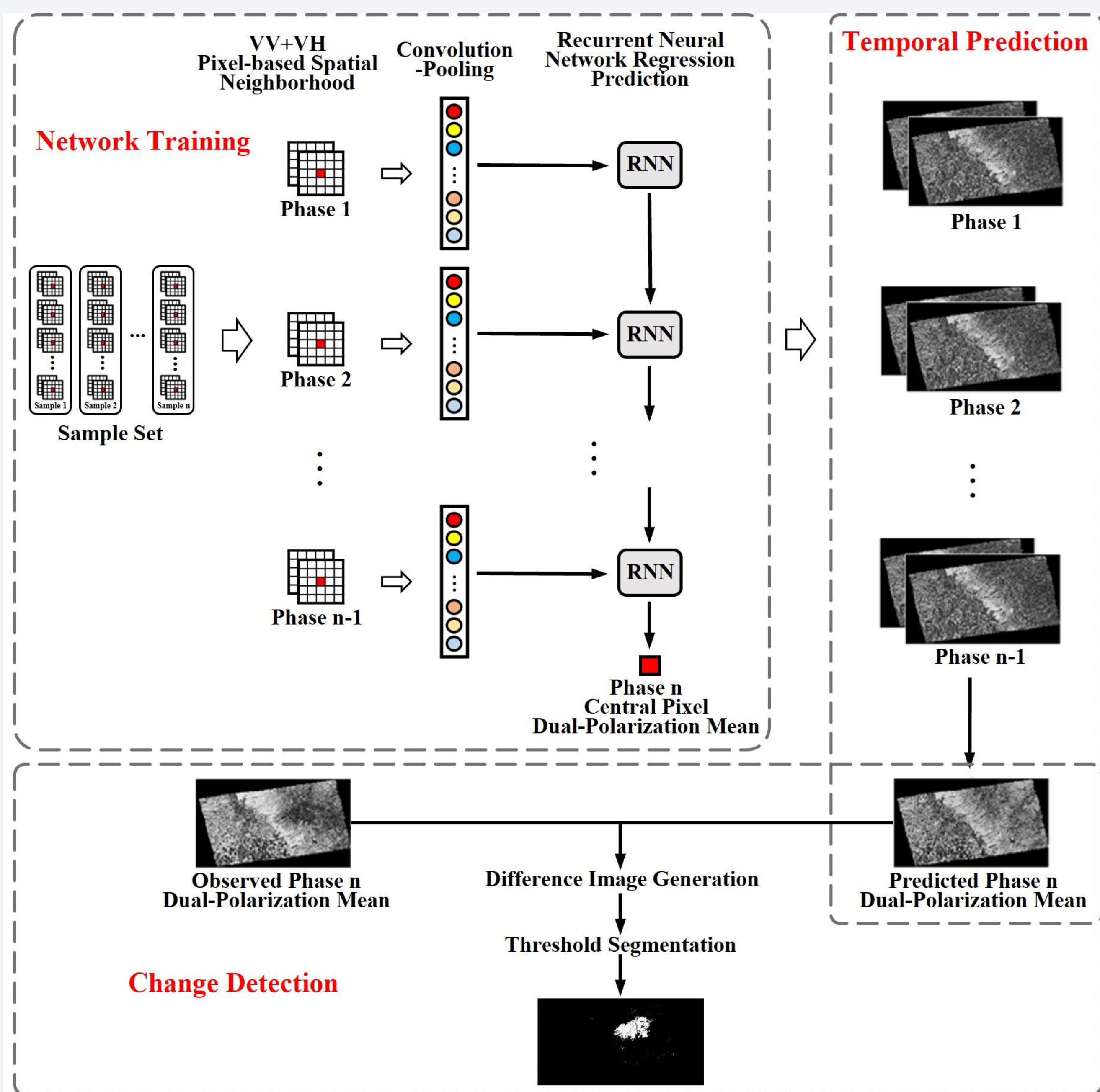


Fig. 2 Change Detection Framework Based on CNN-RNN Predictive Model.

- By leveraging convolutional neural networks (CNNs), spatial neighborhoods and polarimetric features of SAR pixels are convolved to extract multi-dimensional feature representations, enabling comprehensive spatio-temporal-polarimetric characterization of pixel sequences.

Conclusion

- This study leverages a CNN-RNN to integrate spatial, temporal, and polarimetric features, training on forest vegetation coherence sequences for undisturbed coherence prediction and precise change extent delineation.
- Compared with traditional bi-temporal methods, the proposed framework significantly reduces errors introduced by uncertain expressions of vegetation coherence. The CNN-RNN model incorporating multi-dimensional features ensures prediction accuracy while maintaining detail preservation capability.

Result

Two sets of comparative experiments were conducted:

Tab. 1 Description of Comparative Experiments.

Comparative Experiments	Method	Method Description
Based on Observed Datasets	Method 1: Variance Operator	Dual-polarization + Time-series variance operator + Threshold segmentation
	Method 2: Optimal Image Selection	Selection of pre-fire optimal coherence image (Phase 4) + Dual-polarization + Difference operator + Threshold segmentation
Based on Multi-Modal Image Features	Method 3: Linear Regression	Dual-Polarization + Linear Regression Prediction + Difference Operator + Threshold Segmentation
	Method 4: Pixel-based BiLSTM (VV)	Single pixel + Single-polarization (VV) + BiLSTM + Difference operator + Threshold segmentation
	Method 5: Spatially-neighbored Pixel-based BiLSTM (VV)	5×5 spatial neighborhood + Single-polarization (VV) + BiLSTM + Difference operator + Threshold segmentation

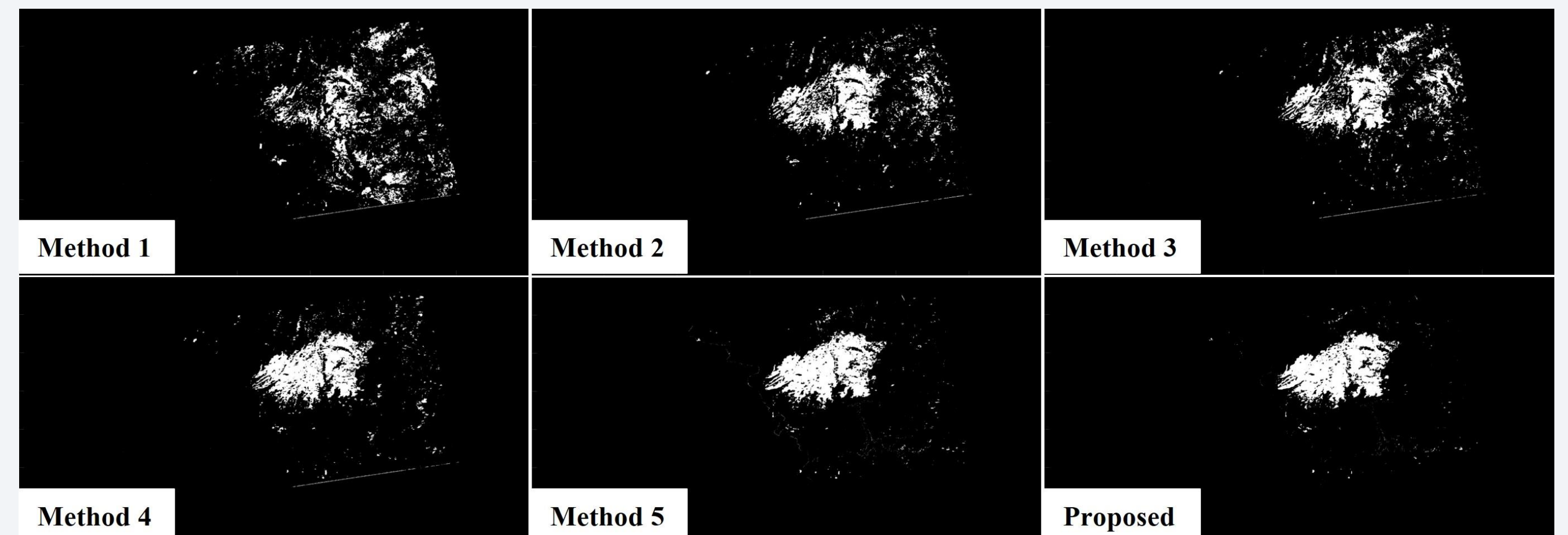


Fig. 3 Change Detection Results for Phase 6 (2018.11.05-2018.11.11) of the Camp Fire.

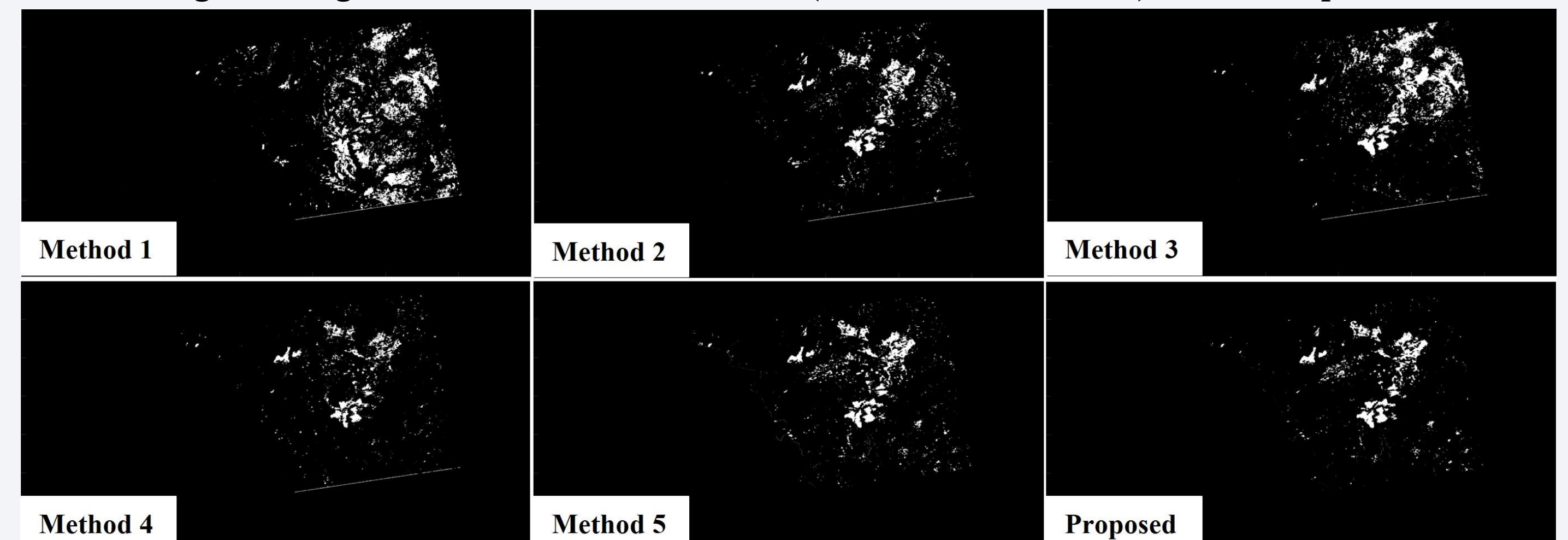


Fig. 4 Change Detection Results for Phase 7 (2018.11.11-2018.11.17) of the Camp Fire.

- Overall, the evaluation results for Phase 6 outperform those for Phase 7. This is primarily attributed to the fact that Phase 7 corresponds to the middle to late stages of the wildfire, characterized by dispersed spatial changes, a smaller scale of variation, and uncertainties such as human intervention.
- In comparison to Methods 1-3, the change patches extracted using deep learning-based time series prediction methods exhibit more complete shapes, reduced noise levels, and a clearer representation of the wildfire-affected areas and their evolutionary trends.

Tab. 2 Quantitative Evaluation Table of Camp Wildfire Change Detection Results.

Phase	Metric	Method 1	Method 2	Method 3	Method 4	Method 5	Proposed Method
Phase 6	Pr	0.3444	0.7120	0.6072	0.9065	0.9500	0.9774
	Re	0.3448	0.6061	0.5840	0.7300	0.7441	0.7604
	Acc	0.8858	0.9444	0.9309	0.9699	0.9743	0.9774
	Kappa	0.2820	0.6247	0.5576	0.7926	0.8208	0.8422
Phase 7	Pr	0.1246	0.6135	0.4701	0.7044	0.6293	0.7152
	Re	0.3209	0.6765	0.6307	0.5059	0.6916	0.6917
	Acc	0.9106	0.9771	0.9671	0.9785	0.9782	0.9822
	Kappa	0.1418	0.6317	0.5220	0.5781	0.6477	0.6941

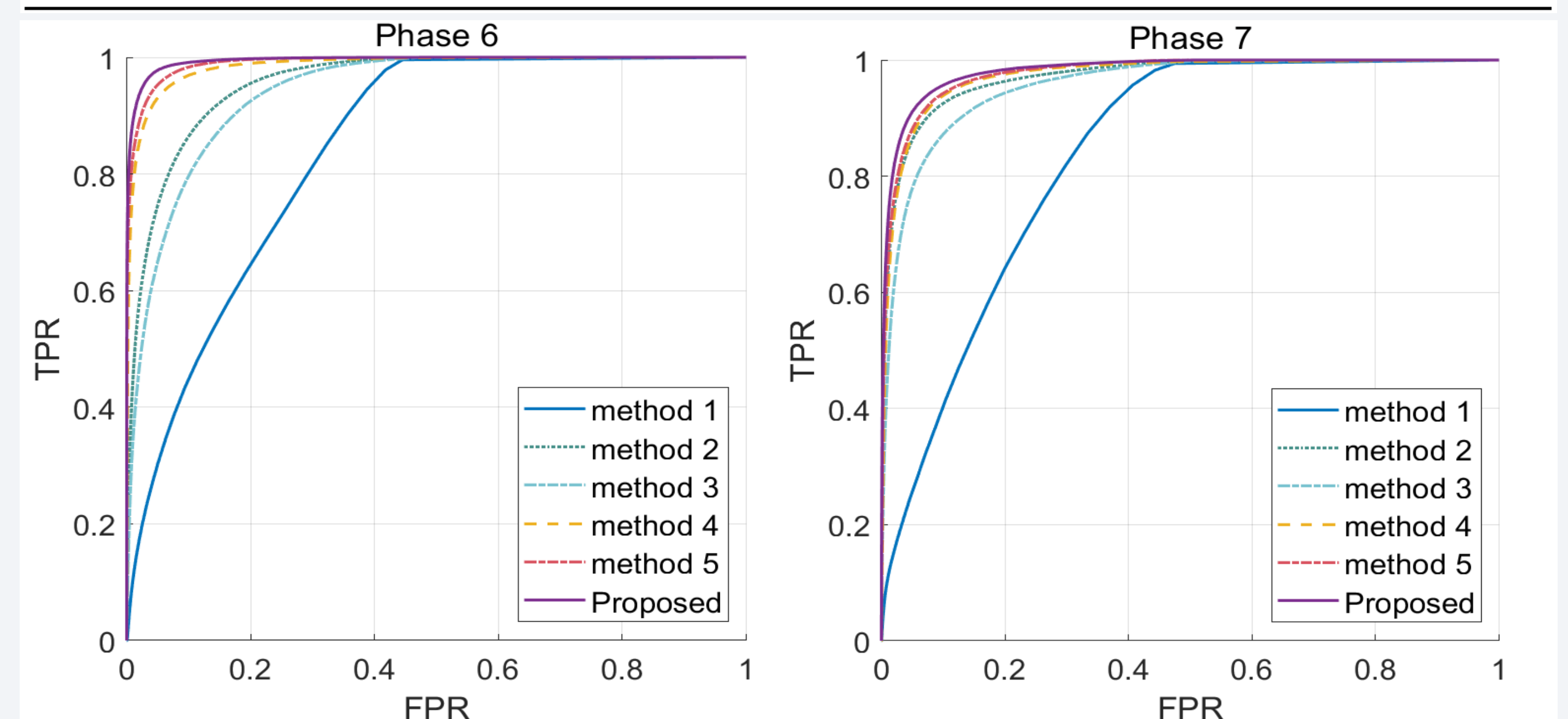


Fig. 5 ROC Curves of Comparative Methods.

- The curve of the proposed method is closer to the top-left corner (0,1), indicating its effectiveness in reducing false alarms and missed detections, and demonstrating superior overall performance.
- The AUC values of curves for Method 4, Method 5, and the proposed method increase progressively, suggesting that spatial local features and polarimetric features contribute to improvements in both time series prediction and change detection.