

An Universal and Index-Agnostic Bitemporal Indicator for Unsupervised Environmental Change Detection from Multispectral Satellite Data



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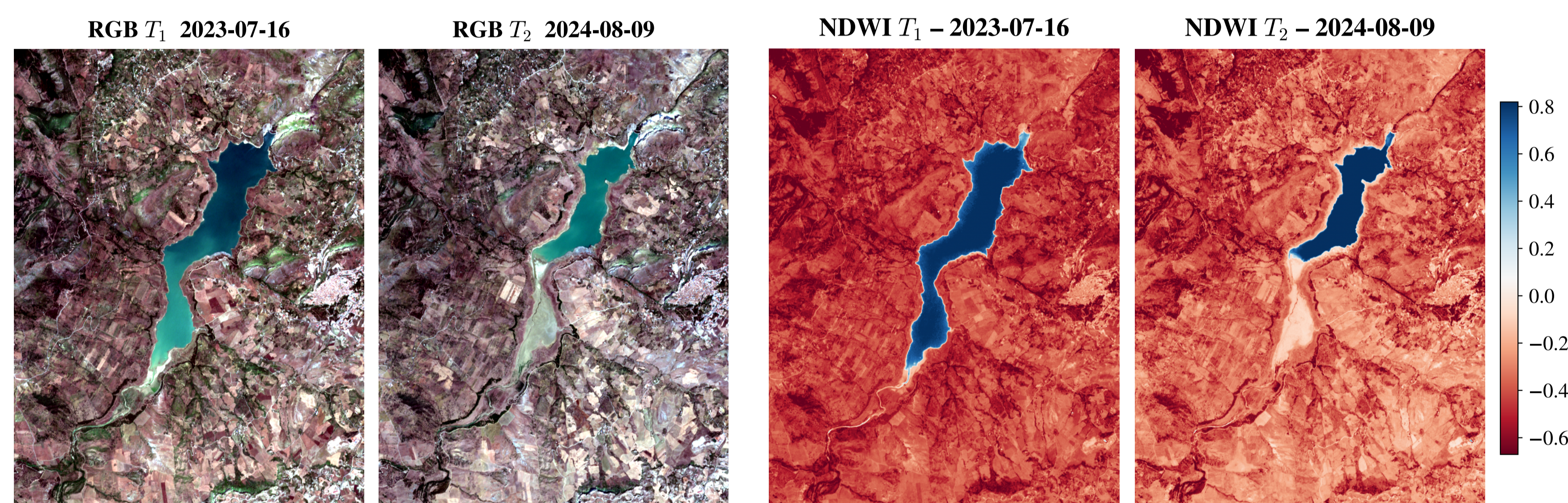
Introduction

Earth Observation monitoring is often hindered by the scarcity of ground-truth data required for Deep Learning [1], while traditional unsupervised methods struggle with radiometric and seasonal noise [2]. To bridge this gap, we introduce the **Bitemporal Spatial Autocorrelation (BSAC)** framework. Assuming stable landscapes preserve their spatial dependence [3], BSAC quantifies change through the *loss of symmetry* in the autocorrelation matrix across multiple lags.

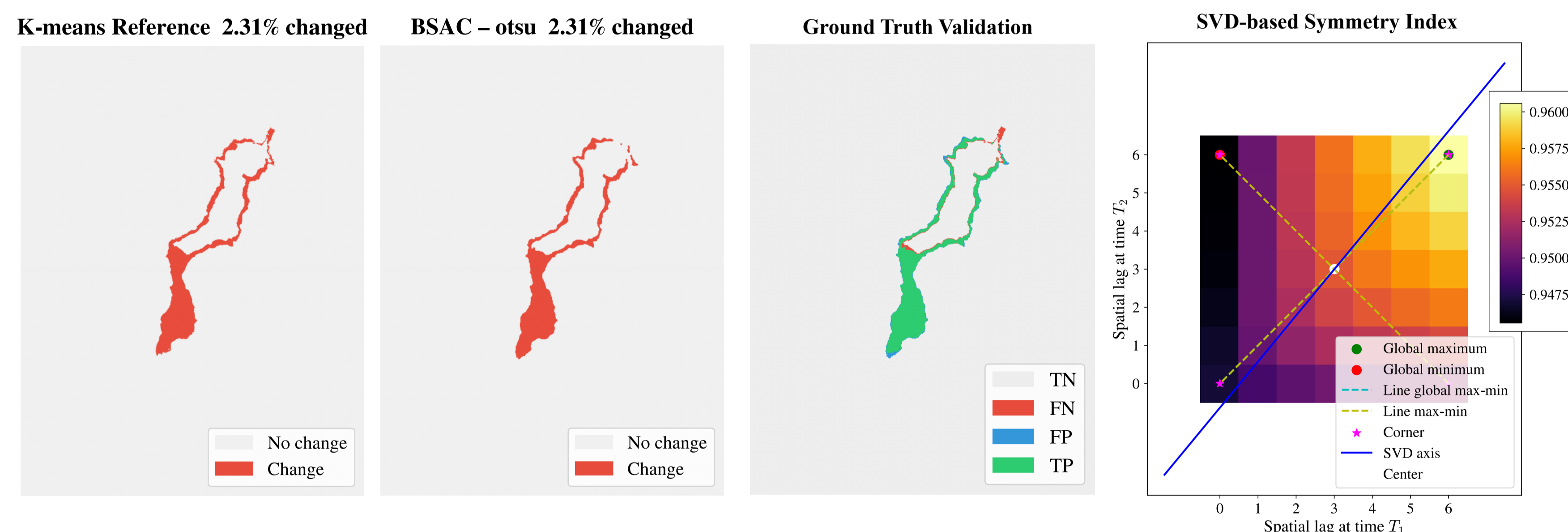
Validated across diverse environmental scenarios and showcased here on the 2024 desiccation of *Lake Rosamarina* near Caccamo (PA - Italy), this index-agnostic framework leverages sparse-matrix operations to achieve high computational scalability. By extracting three reproducible, training-free change metrics, BSAC equips National Statistical Offices with a robust, fully unsupervised tool for environmental reporting in data-scarce regions [4].

Results

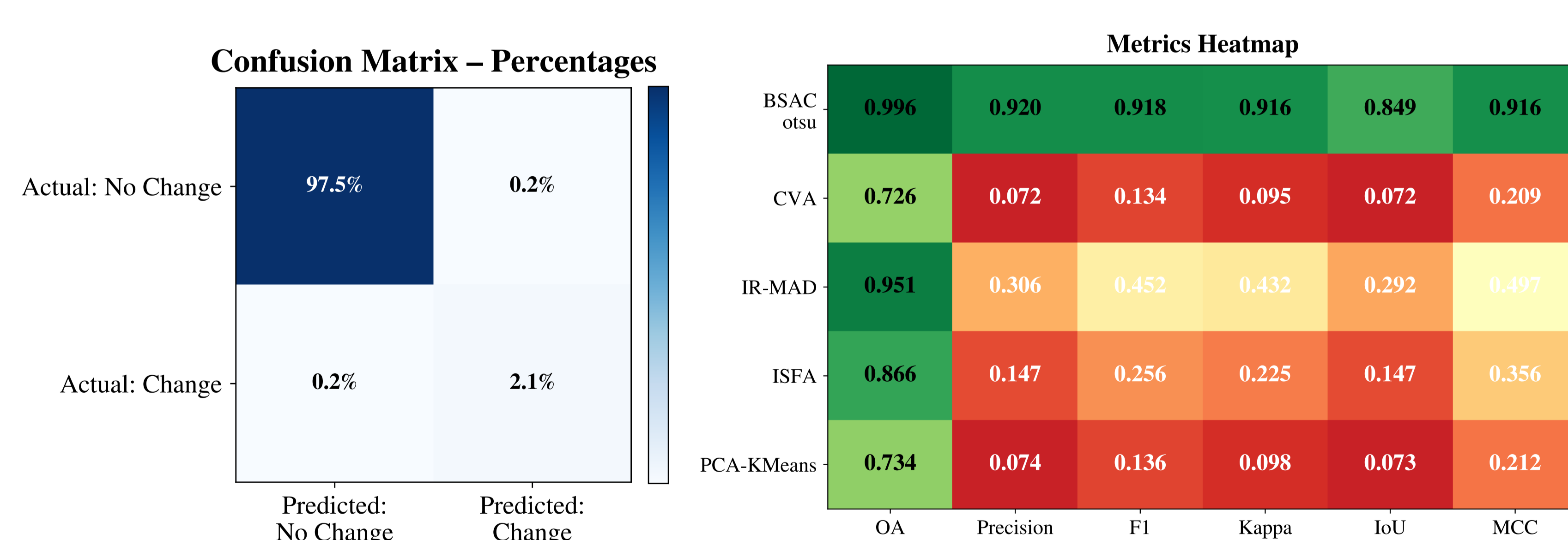
A. Input Data – Lake Rosamarina, Sicily (Italy)



B. Change Maps and Change Detection via BSAC



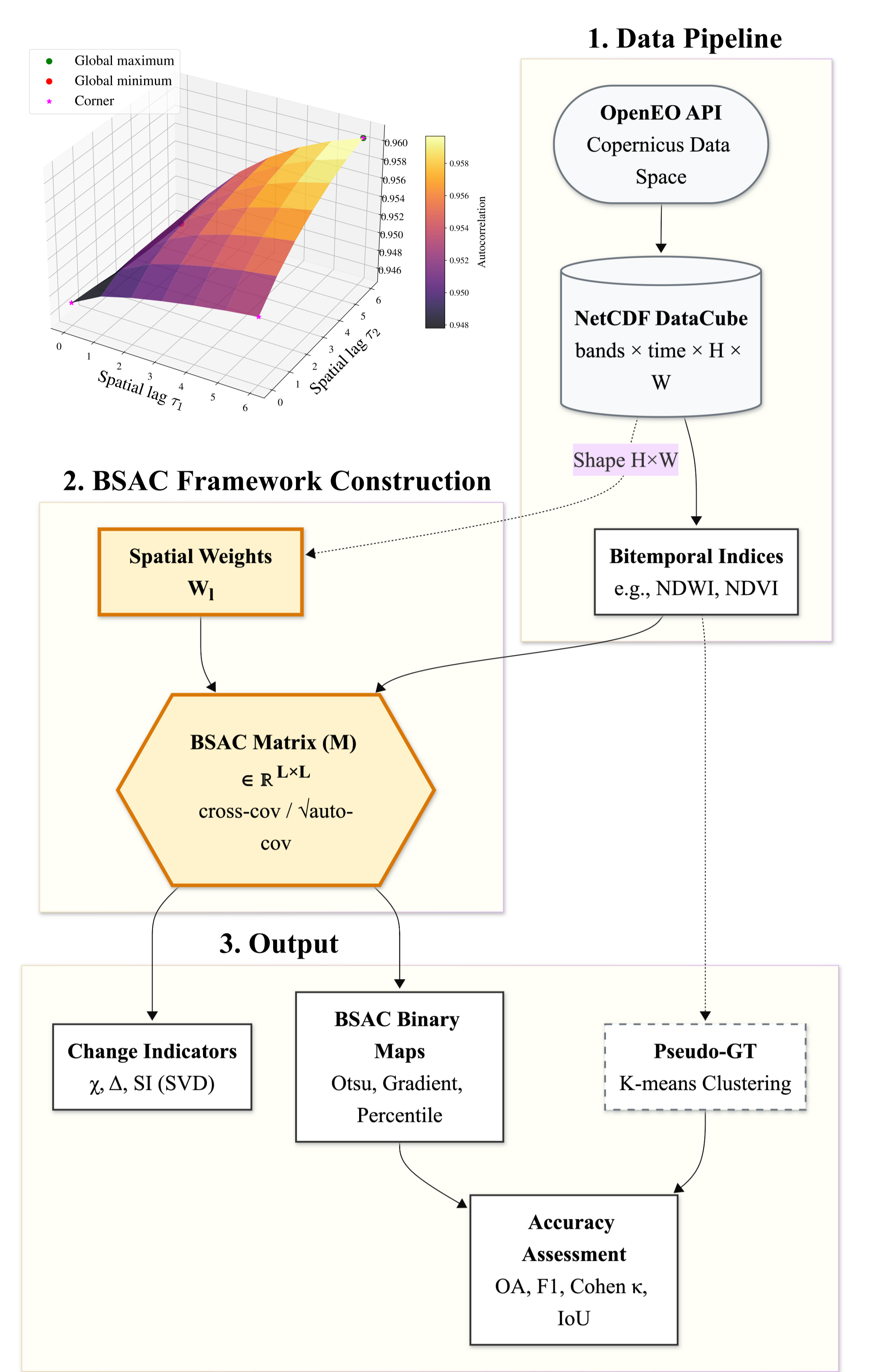
C. Comparison and Results Metrics



Conclusions & Future Work

- **Unsupervised & Index-Agnostic:** Quantifies structural shifts without training data, operating on any pre-computed multispectral index.
- **Robustness:** Outperforms classical statistical methods by intrinsically filtering radiometric noise and artifacts.
- **Future Work - SAR Fusion:** Extending to multi-modal tensor fusion with Sentinel-1 SAR

BSAC Matrix Pipeline



Methodological Core

1. Topological Projection

Maps spectral index z_t into L spatial scales via sparse Moore adjacency matrix W as $\tilde{z}_t^{(l)} = W_l z_t$ [5]

2. Bitemporal Spatial Autocorrelation Matrix

Encodes cross-scale structural predictions, capturing macroscopic landscape shifts and isolating local pixel-level fluctuations:

$$M[l,k] = \frac{\text{Cov}(\tilde{z}_{t_1}^{(l)}, \tilde{z}_{t_2}^{(k)})}{\sigma(\tilde{z}_{t_1}^{(l)})\sigma(\tilde{z}_{t_2}^{(k)})}$$

3. Symmetry Breaking Indicators

Quantifies topological disruption via three metrics

- Stability Trigger ($\chi \in \{0, 1\}$):** Flags non-stationary events (diagonal dominance violation).
- Asymmetry Magnitude Δ :** Measures change severity: $\Delta = \frac{1}{L} \|\mathcal{M} - \mathcal{M}^T\|_F$
- Symmetry Index ($SI \in [0, 1]$):** Evaluates structural self-similarity via SVD, measuring the angular deviation of the principal axis from the diagonal.

References

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