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Thick Cloud Removal for Sentinel-2 Time-series Images via Combining Deep Prior and Low-Rank Tensor Completion

Qiang Zhang

Wuhan University

https://qzhang95.github.io

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igarss BRUSSELS 2021

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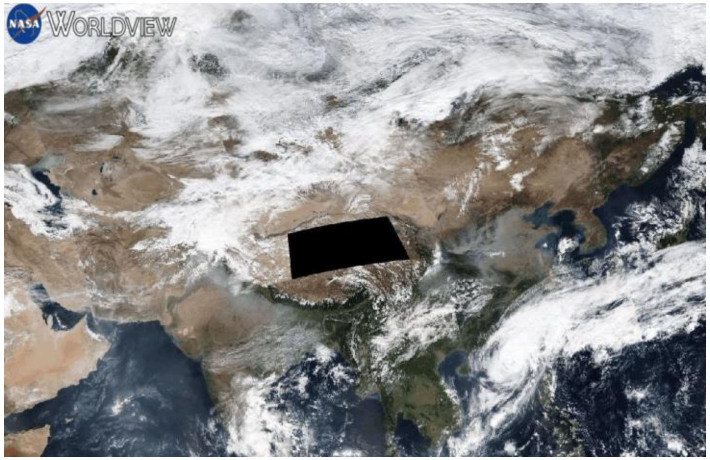
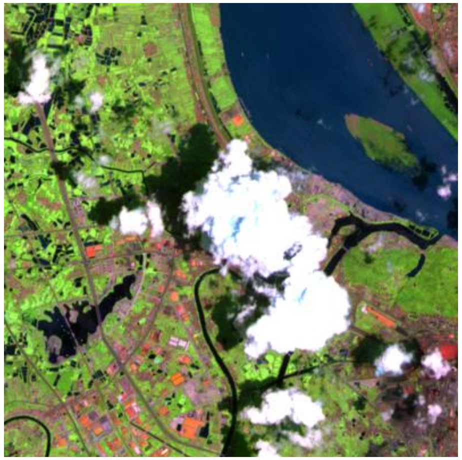
Outline

1 Background

Thick Cloud Removal



Thick Cloud Covering



Sentinel-2 MSI

GF-1 WFV

Thick cloud greatly reduce data usability!

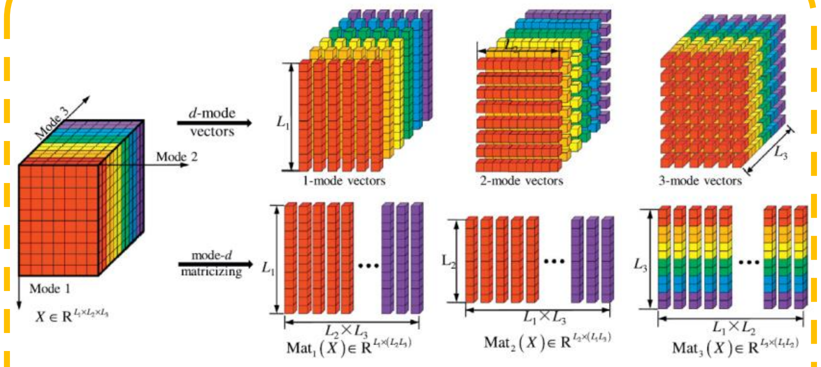
→

Multitemporal images
Thick Cloud Removal

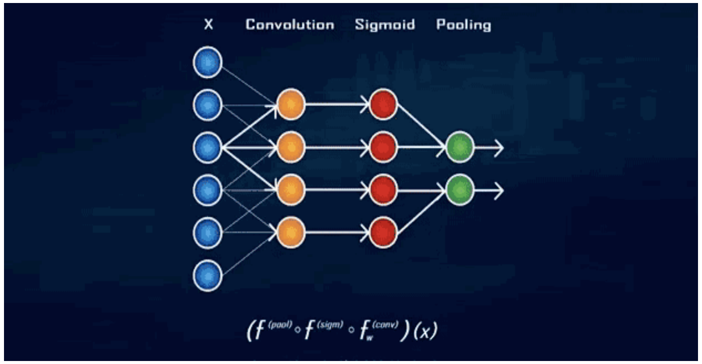
- □ Model Driven Strategy: Sparse, Low-rank, Non-local…
- □ Data Driven Strategy: Deep Learning based-methods…

1 Background

Motivations



Model-Driven



Data-Driven

- **Inherent Characteristics**
- Sensitive Parameter
- Complex Optimization

- **Powerful Feature Expression**
- Large Training Labels
- Overfitting Effects

Complementing Each Other for Thick Cloud Removal?

Model-Driven + **Data-Driven**

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Outline

2 Methodology

Notation & Preprocessing

Tensor: $\mathcal{X} \in \mathbb{R}^{r_1 \times r_2 \times r_3 \cdots}$ **Matrix:** $\mathbf{X} \in \mathbb{R}^{r_1 \times r_2}$ **Vector:** $\mathbf{x} \in \mathbb{R}^{r_1}$

Time-series Cloudy Images

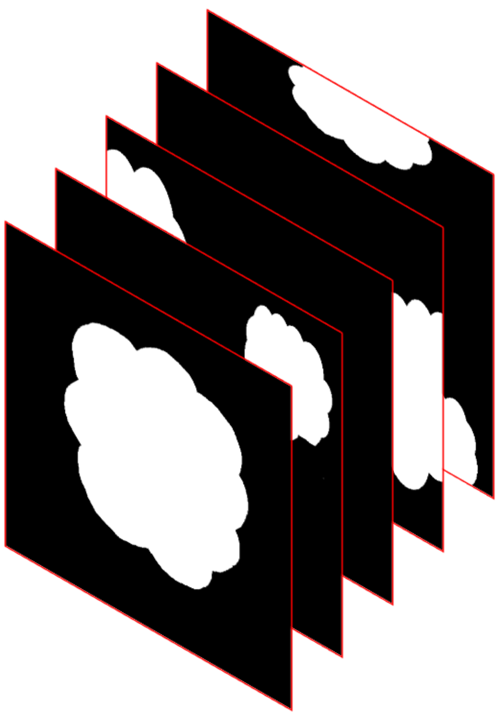
$\mathcal{Y} \in \mathbb{R}^{w \times h \times t}$

Getting Accurate Cloud Location

Cloud Detection [1]

[1] Li et al., *ISPRS P&RS*, 2019.

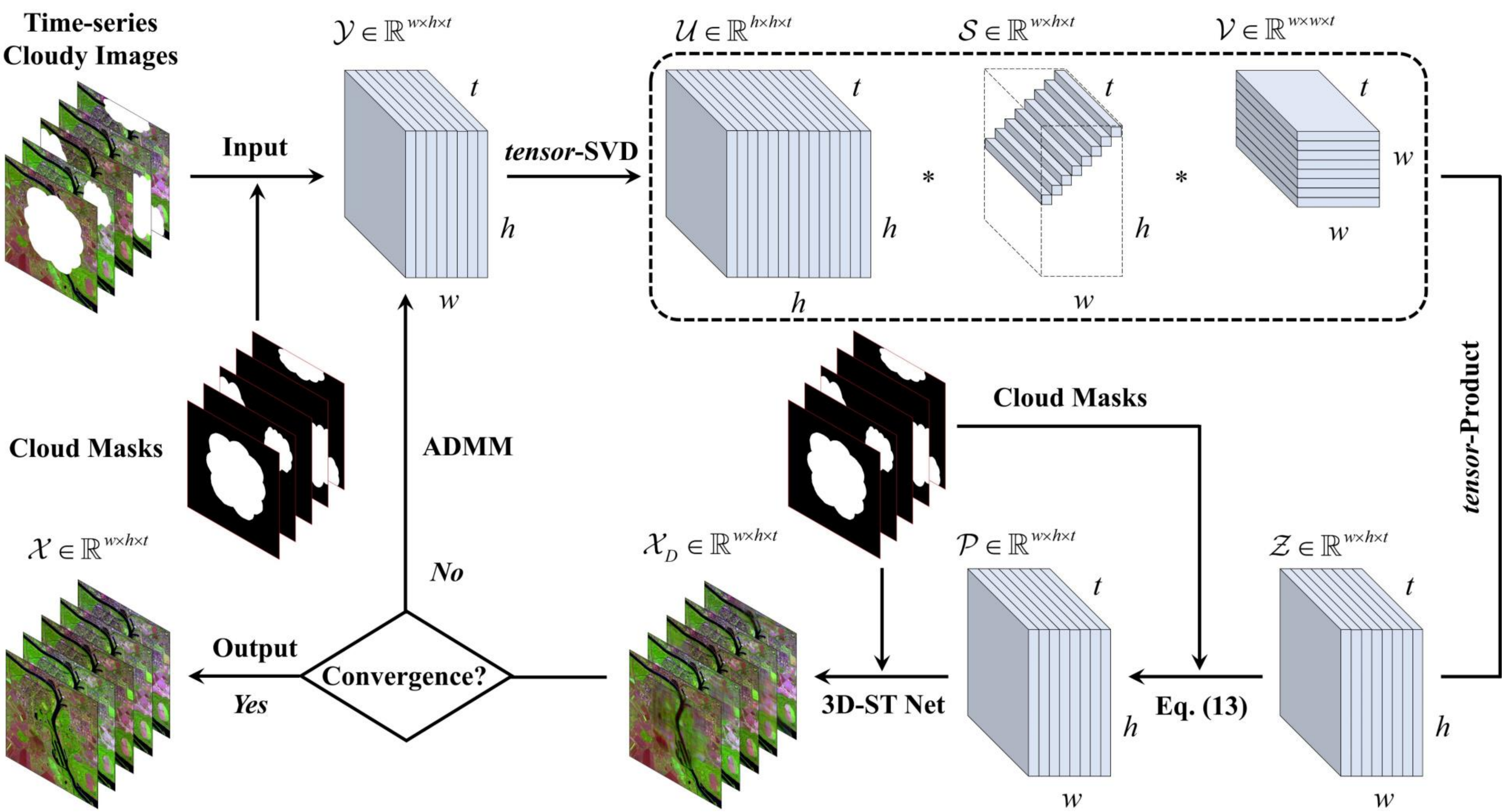
Cloud Masks



$\mathcal{M} \in \mathbb{R}^{w \times h \times t}$

2 Methodology

Flowchart

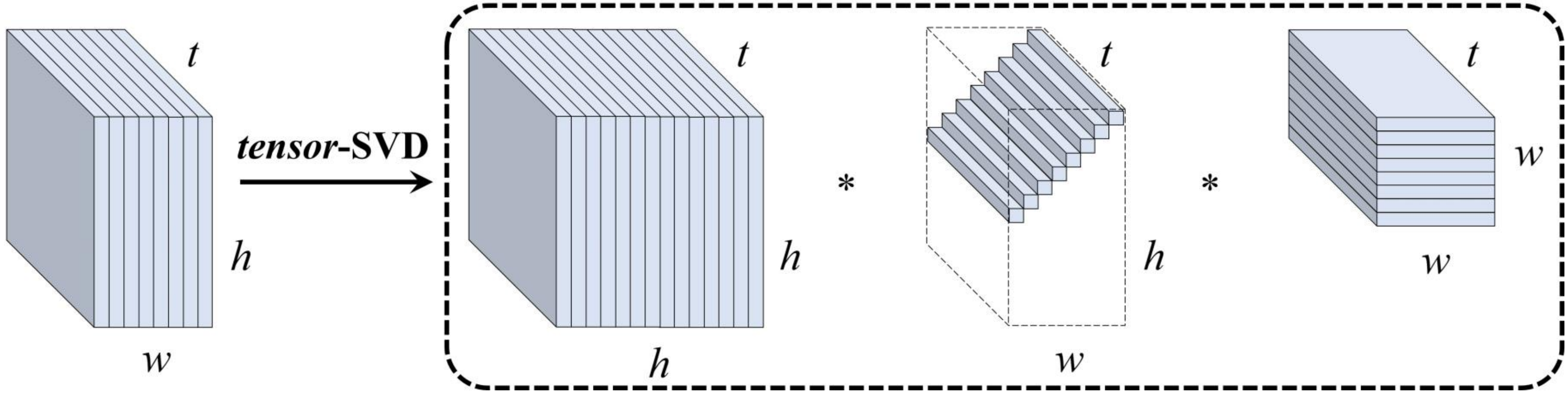


2 Methodology

Tensor-SVD

$$\mathcal{Y} = \mathcal{U} * \mathcal{S} * \mathcal{V}^{\mathrm{T}}$$

$\mathcal{Y} \in \mathbb{R}^{w \times h \times t}$ $\mathcal{U} \in \mathbb{R}^{h \times h \times t}$ $\mathcal{S} \in \mathbb{R}^{w \times h \times t}$ $\mathcal{V} \in \mathbb{R}^{w \times w \times t}$



$$(\mathbf{U}_i, \mathbf{S}_i, \mathbf{V}_i^{\mathrm{T}}) = SVD(\mathbf{Y}_i) \rightarrow i = 1, 2, 3$$

$$r = rank_{tubal}(\mathcal{Y}) = \max(D(\bar{\mathbf{S}}_1), D(\bar{\mathbf{S}}_2), D(\bar{\mathbf{S}}_3))$$

Simplified

FFT/IFFT

$$\bar{\mathcal{U}} = \mathcal{U}(:, 1:r, :)$$

$$\bar{\mathcal{S}} = \mathcal{S}(1:r, 1:r, :)$$

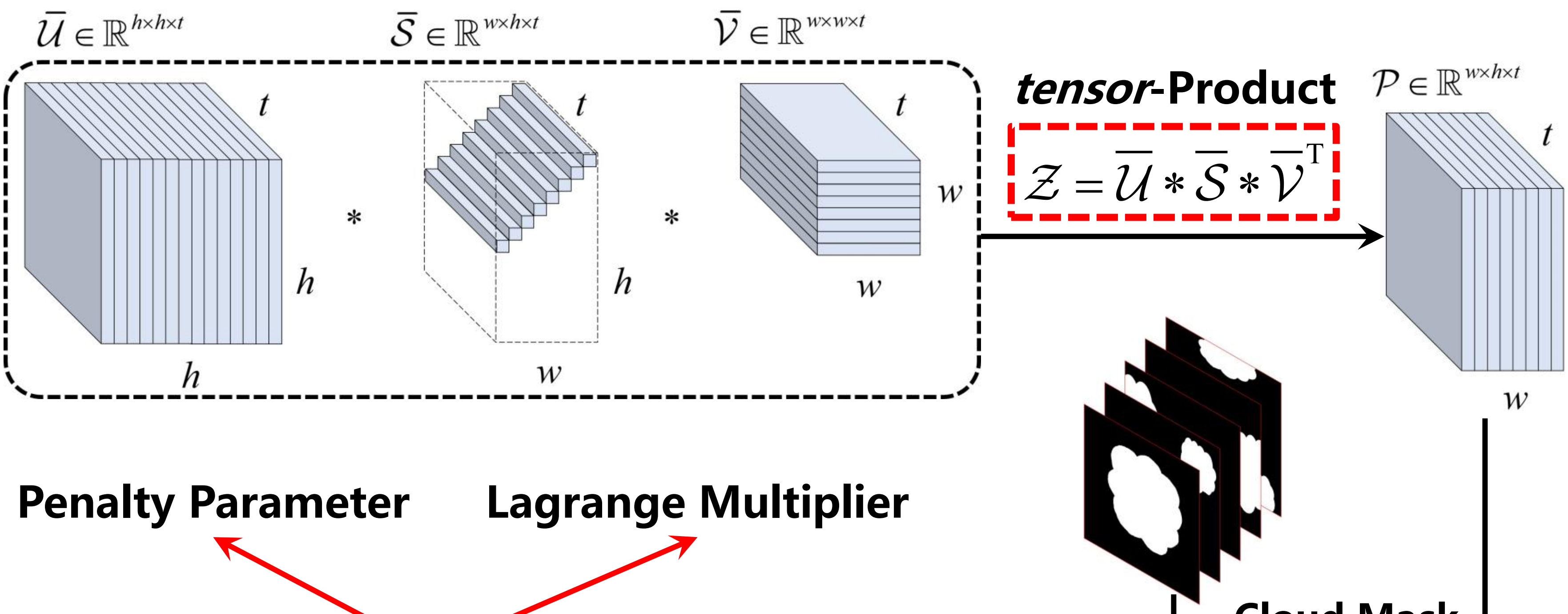
$$\bar{\mathcal{V}} = \mathcal{V}(:, 1:r, :)$$

Tensor Tubal Rank:
Maximum number of non-zero tubes

2 Methodology

Tensor-Product

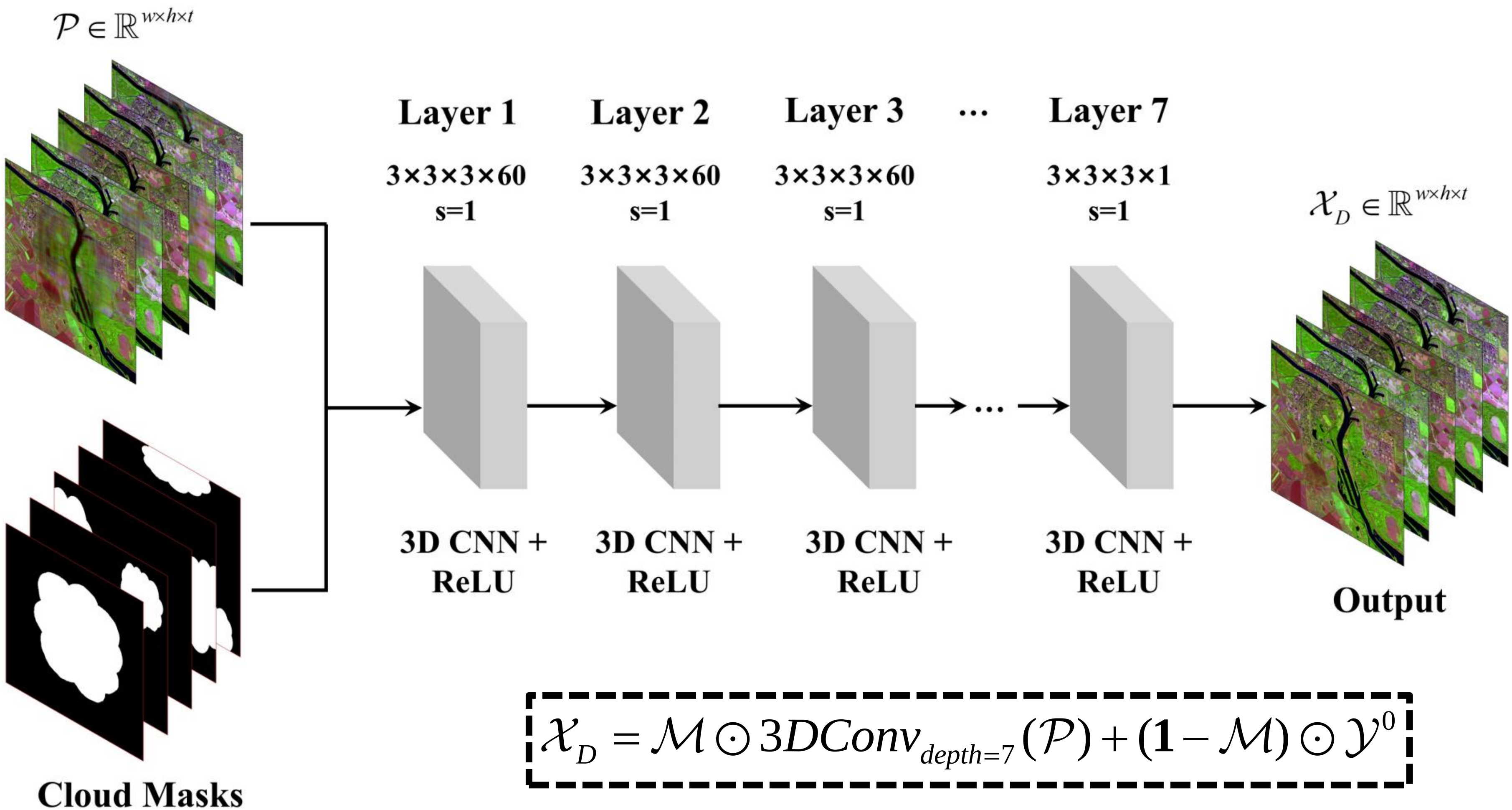
Definition of Tensor-Product: $\mathcal{B}_3(i,j,:)=\mathcal{B}_1 * \mathcal{B}_2=\sum_{k=1}^{n_2}\mathcal{B}_1(i,k,:)\odot\mathcal{B}_2(k,j,:)$



$$\mathcal{P}=\mathcal{M}\odot(\mathcal{Z}+\beta\cdot\mathcal{Q})+(\mathbf{1}-\mathcal{M})\odot\mathcal{Y}^0$$

2 Methodology

Deep Spatio-Temporal Prior



$$\mathcal{X}_D = \mathcal{M} \odot 3DConv_{depth=7}(\mathcal{P}) + (\mathbf{1} - \mathcal{M}) \odot \mathcal{Y}^0$$

2 Methodology

Network Training

Jointly Global-Regional Loss:

$$\mathcal{L} = \mu_1 \cdot \mathcal{L}_g + \mu_2 \cdot \mathcal{L}_r + (1 - \mu_1 - \mu_2) \cdot \mathcal{L}_{TV}$$

TV Loss

Global Loss

$$\mathcal{L}_g = \frac{1}{2N} \sum_{n=1}^{N} \left\| \mathcal{X}_D^{(n)} - \mathcal{X}^{(n)} \right\|_2^2$$

$$\mathcal{L}_r = \frac{1}{2N} \sum_{n=1}^{N} \frac{1}{sum(\mathcal{M}^{(n)})} \left\| \mathcal{M}^{(n)} \odot \mathcal{X}_D^{(n)} - \mathcal{M}^{(n)} \odot \mathcal{X}^{(n)} \right\|_2^2$$

Local Loss

$$\mathcal{L}_{TV} = \frac{1}{2N} \sum_{n=1}^{N} \sum_{i,j} \frac{1}{sum(\mathcal{M}^{(n)})} \sqrt{(\mathcal{X}_{D(i,j+1,:)}^{(n)} - \mathcal{X}_{D(i,j,:)}^{(n)})^2 + (\mathcal{X}_{D(i+1,j,:)}^{(n)} - \mathcal{X}_{D(i,j,:)}^{(n)})^2}$$

ADMM Optimization

Algorithm 1 Combined Deep 3D Spatio-temporal Prior with Low-rank Tensor SVD for Thick Cloud Removal via ADMM

Input: Time-series cloudy images $\mathcal{Y}$, corresponding cloud masks $\mathcal{M}$

Initialization: $\mathcal{Y}^0 = (\mathbf{1} - \mathcal{M}) \odot \mathcal{Y}$, $\mathcal{X}_D^0 = \mathcal{Y}^0$, $\mathcal{Q}^0 = \mathbf{0}$, $\beta^0 = 0.02$, $\beta_{\max} = 1$, $\eta = 1.3$, $\varepsilon = 1e-5$, $k = 1$, $k_{\max} = 20$

1: **while** not converged and $k \leq k_{\max}$ **do**
2: Updating $\overline{\mathcal{U}}^k$, $\overline{\mathcal{S}}^k$, and $\overline{\mathcal{V}}^k$ via (7) to (11)
3: Updating $\mathcal{Z}^k$ via (12)
4: Updating $\mathcal{P}^k$ via (13)
5: Updating $\mathcal{X}_D^k$ via (14)
6: Updating $\mathcal{Y}^k$, $\mathcal{Q}^k$, and β^k via (15), (16), and (17), respectively
7: If $\|\mathcal{X}_D^k - \mathcal{X}_D^{k-1}\|_F / \|\mathcal{X}_D^{k-1}\|_F < \varepsilon$, stop iteration
8: $k = k + 1$
9: **end while**

Output: The construction cloud-free result $\mathcal{X}$=$\mathcal{X}_D^k$

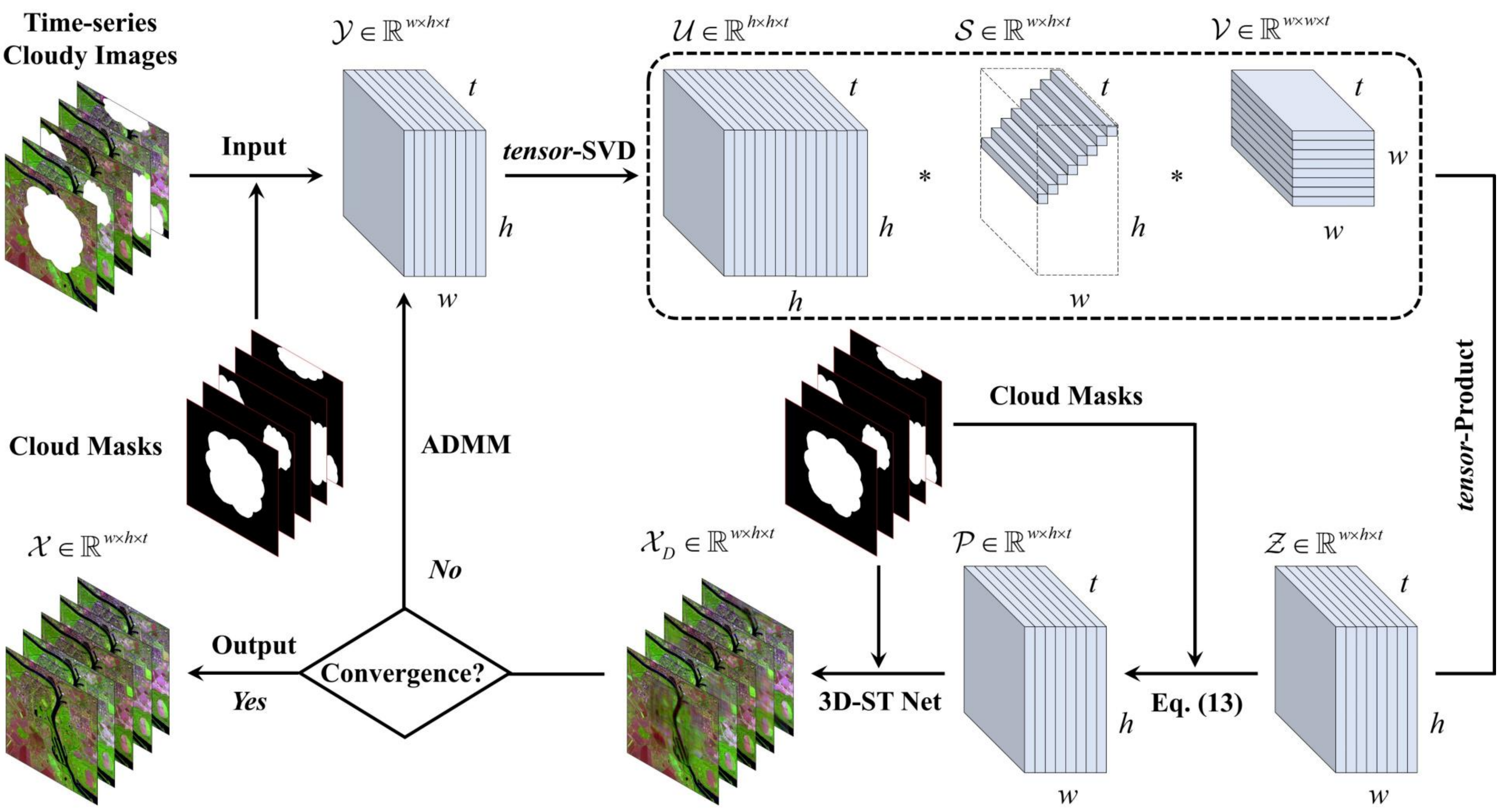
$$\boxed{\mathcal{Y}^k = \mathcal{X}_D^{k-1} - 1/\beta^{k-1} \cdot \mathcal{Q}^{k-1}}$$

$$\boxed{\mathcal{Q}^k = \mathcal{Q}^{k-1} + \beta^{k-1} \cdot (\mathcal{Y}^k - \mathcal{X}_D^k)}$$

$$\boxed{\beta^k = \min(\eta \cdot \beta^{k-1}, \beta_{\max})}$$

2 Methodology

Flowchart

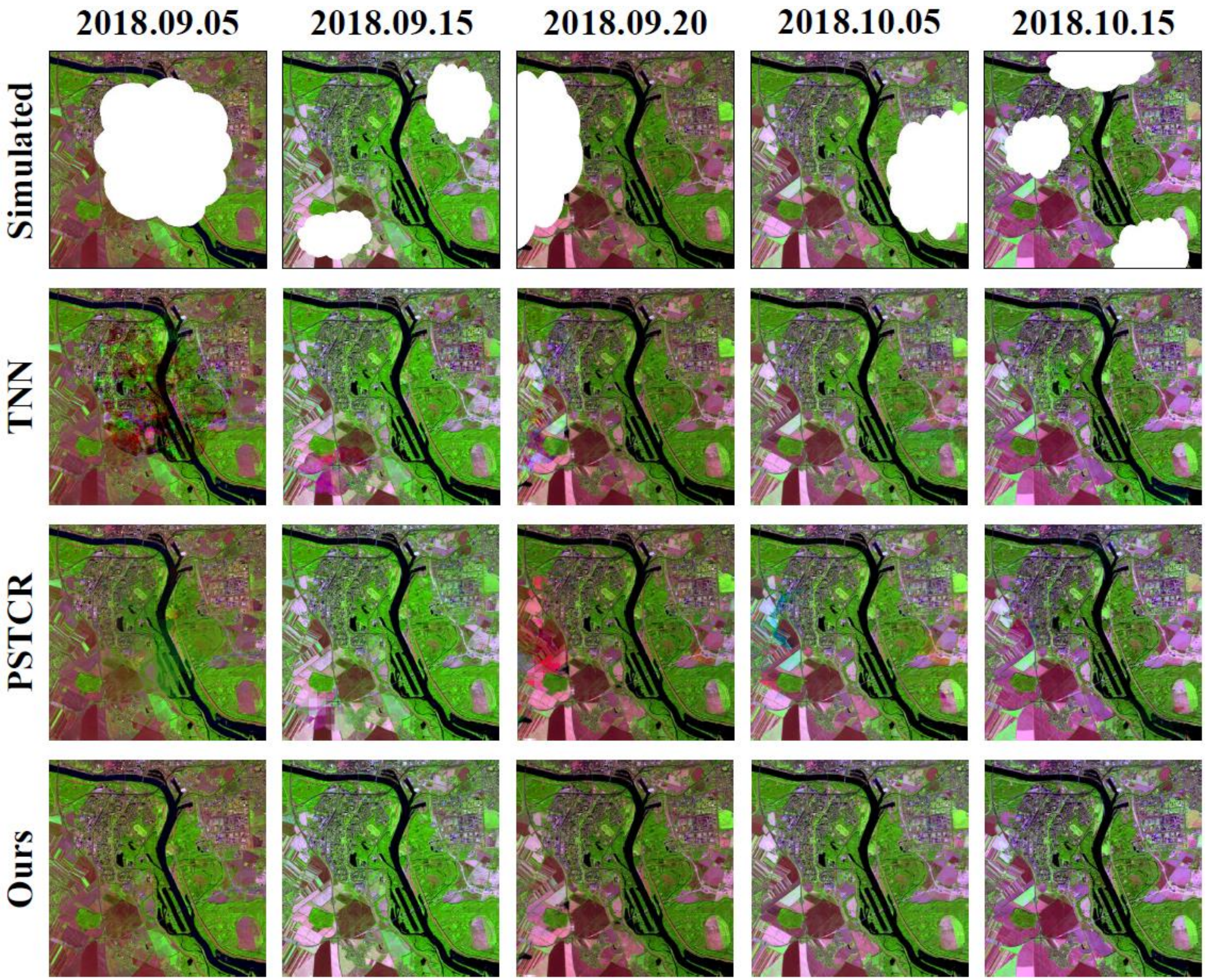


Outline

1. Background
2. Methodology
3. **Experiments**
4. Conclusion

3 Experiments

Simulated Results (Sentinel-2 MSI)



Method Type

Low Rank Tensor-based

Deep Learning-based

Combined

3 Experiments

Evaluation Indexes

Evaluation indexes of Sentinel-2 MSI simulated experiments 1

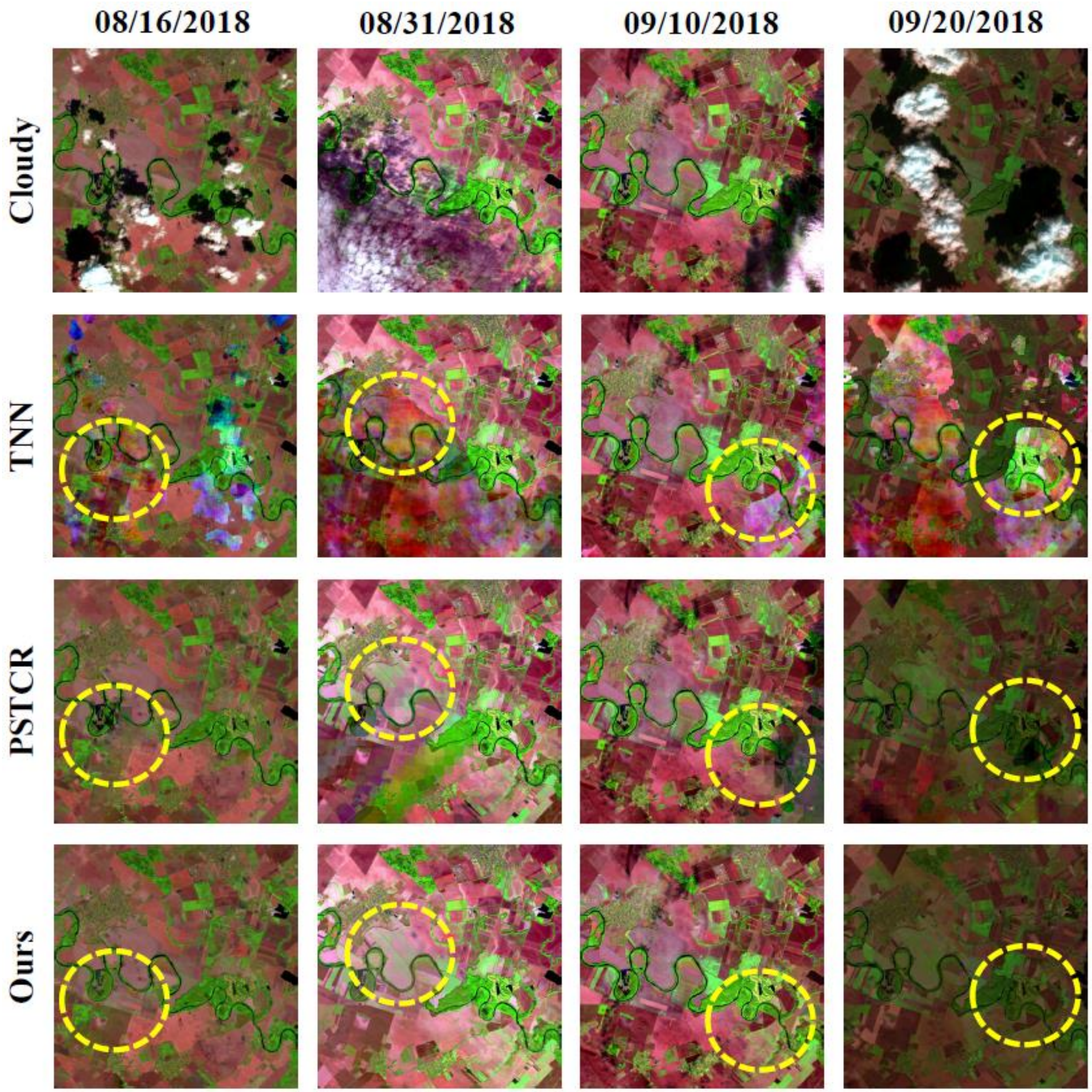
Method	CC	SSIM	RMSE	SAM
Cloudy	0.6628	0.7845	0.1983	9.6431
HaLRTC	0.7857	0.8563	0.1246	6.2878
TNN	0.9553	0.9386	0.0571	1.4984
PSTCR	0.9648	0.9412	0.0509	1.2375
Proposed	0.9817	0.9658	0.0383	0.9424

Evaluation indexes of Sentinel-2 MSI simulated experiments 2

Method	CC	SSIM	RSE	SAM
Cloudy	0.6448	0.7535	0.2129	8.2129
HaLRTC	0.7689	0.8346	0.1453	5.2369
TNN	0.9163	0.8826	0.0837	1.6856
PSTCR	0.9675	0.8943	0.0558	1.5294
Proposed	0.9842	0.9359	0.0426	1.1828

3 Experiments

Real Results (Sentinel-2 MSI)



Method Type

Low Rank Tensor-based

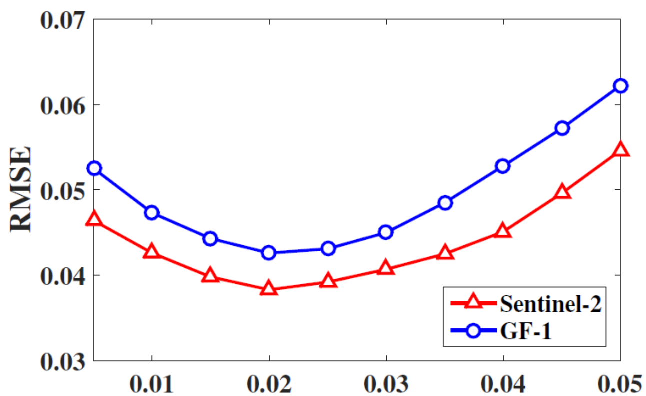
Deep Learning-based

Combined

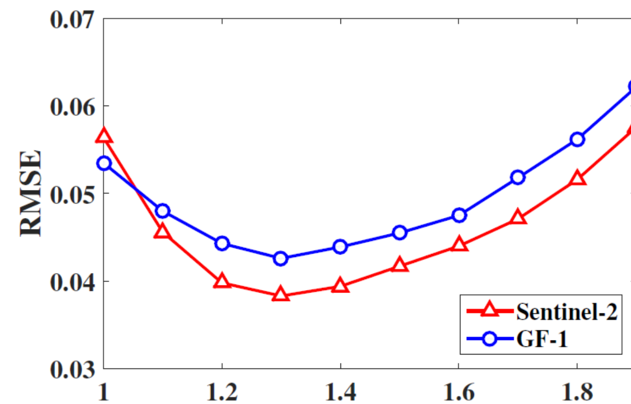
3 Experiments

Parameter Sensitivity

Scaling Factor & Step Threshold

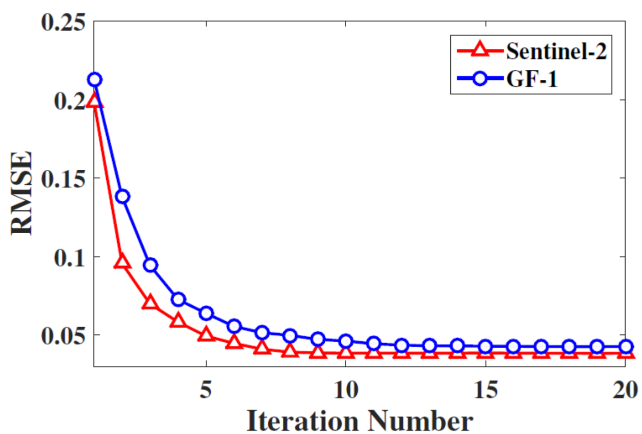


(a) Scaling factor β^0

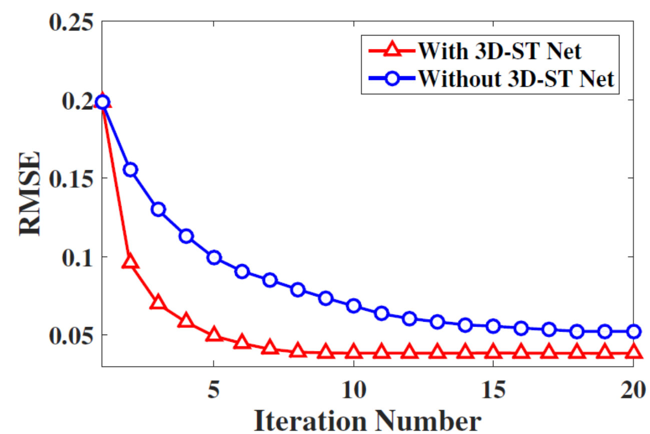


(b) Step threshold η

ADMM & 3D-ST Net



(a) ADMM iteration optimization



(b) With/without 3D-ST Net

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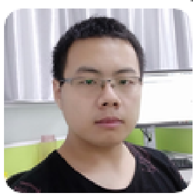
4 Conclusion

- **Combining Deep Spatio-temporal Prior with Low-Rank Tensor SVD (DP-LRTSVD) for thick cloud removal in multitemporal images**

- **DP-LRTSVD jointly utilizes the low-rank characteristic and deep spatio-temporal prior under the ADMM optimization framework**

- **DP-LRTSVD can simultaneously deal with time-series cloudy Sentinel-2 images, without ensuring cloud-free image**

We have released our time-series cloudy Sentinel-2 dataset (including cloud/shadow mask) at https://qzhang95.github.io!



Code & Dataset

Thanks!

Qiang Zhang
https://qzhang95.github.io

LIESMARS, Wuhan University