Research on Multi-temporal Cloud Removal Using D-S Evidence Theory and Cloud Segmentation Model

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Background & Problems

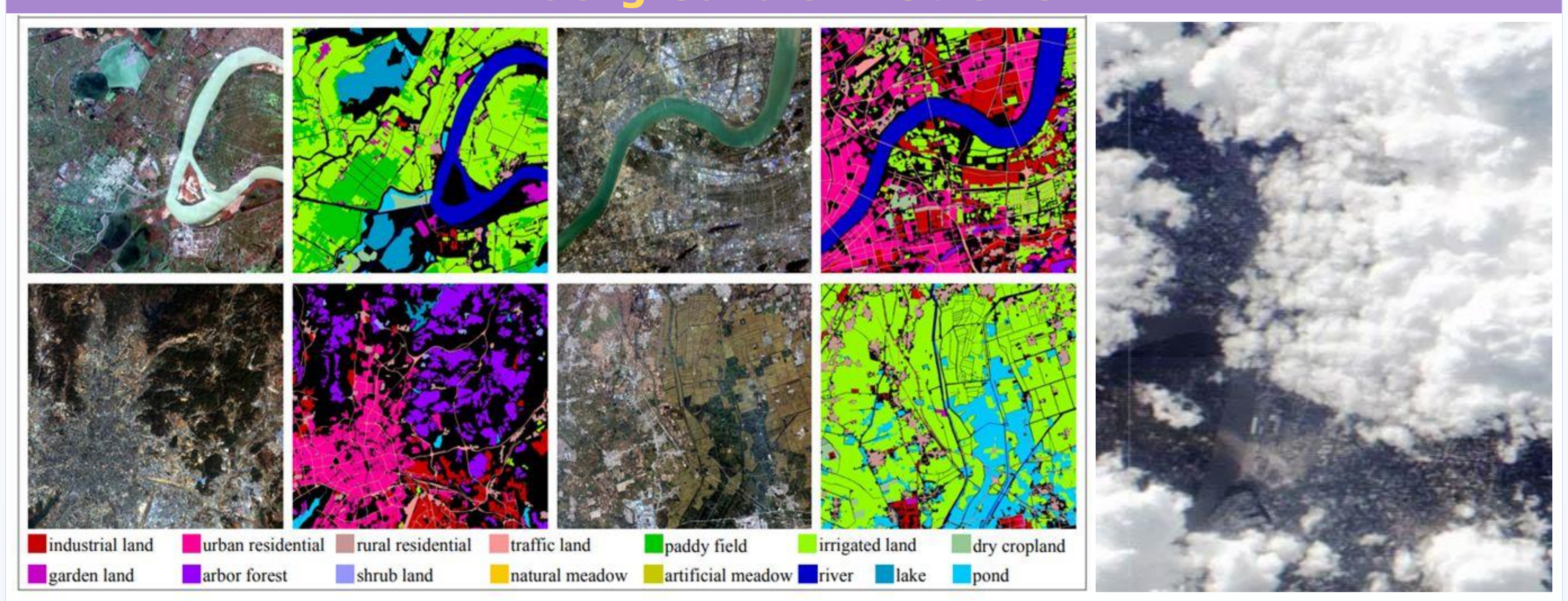


Fig.1 Application of remote sensing images.

Our contributions & Advantages

1. We introduced **color prior knowledge** to improve detection (Cloud-net) performance.
2. We designed a cloud removal rule that can effectively fuse **multi-temporal** remote sensing images, based on the **D-S evidence theory**.
3. We applied our method to **real satellite remote sensing images** and achieved a significant cloud removal performance.

Advantages:

1. Our method do not require cloudless images as the reference.
2. Our method can be applied to real remote sensing images containing thick clouds with a surprising performance (reducing the average percentage of **cloud noise from 30%-40% to 2%-8% on GaoFen-4 (GF-4) satellite images**).
3. Our method can deal with images with a high percentage of **cloud noise**.

Cloud segmentation network

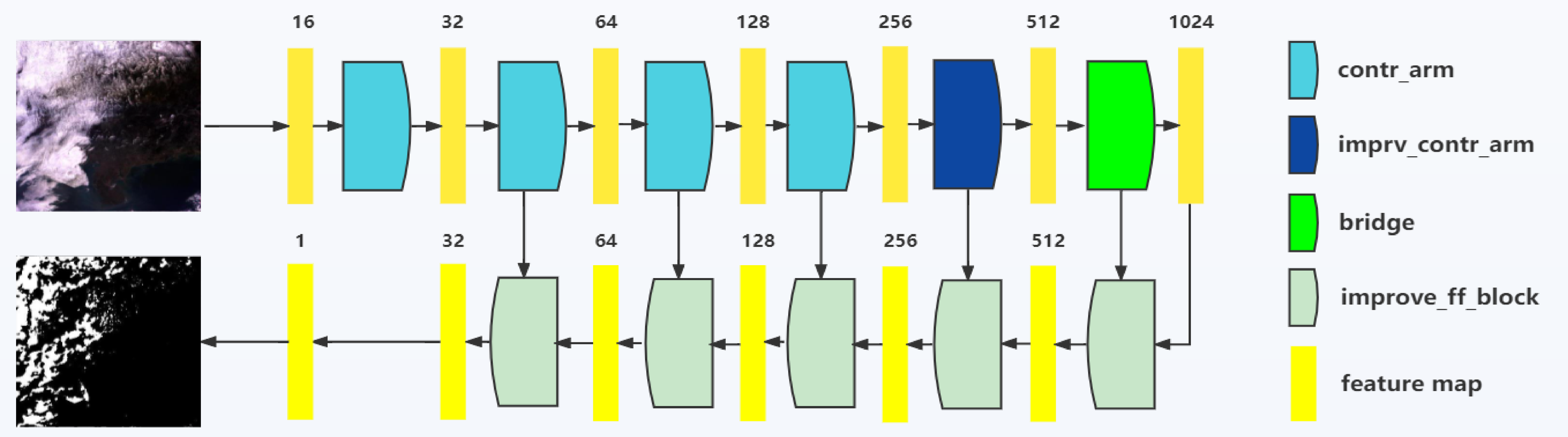
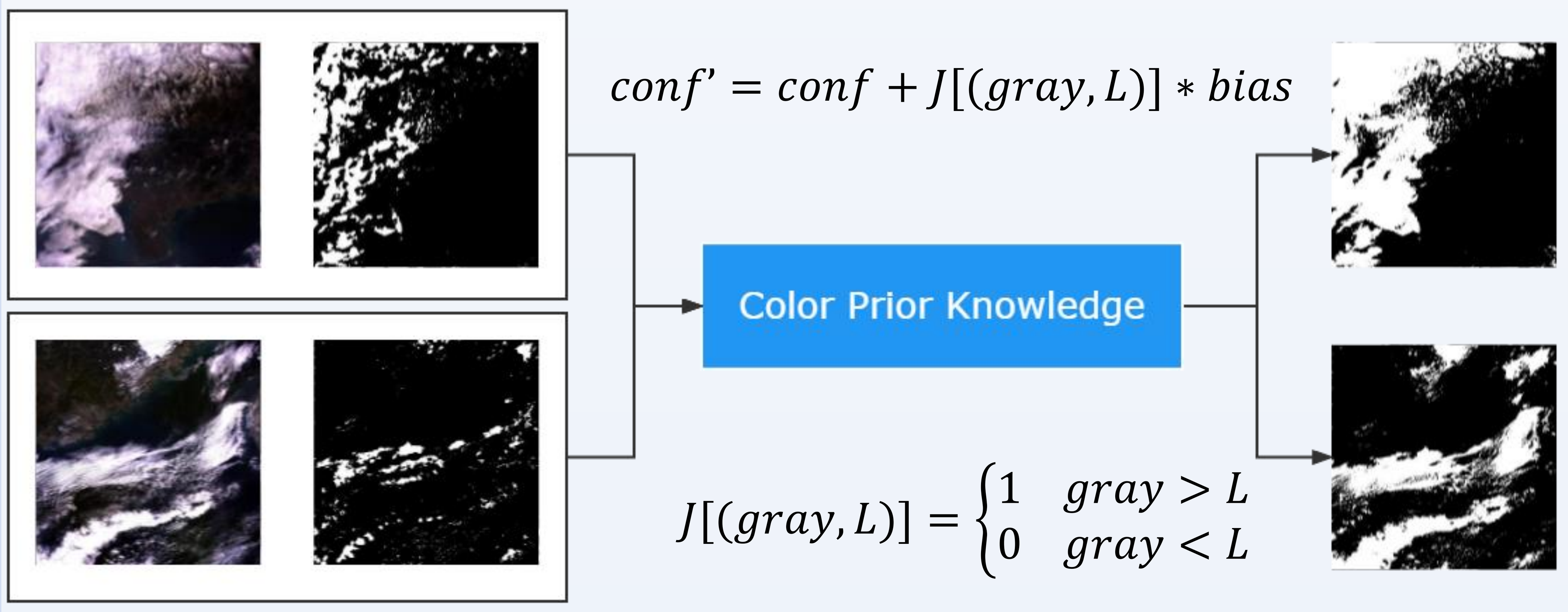


Fig.2 Structure of the Cloud-net model [1]. Inputs: 384×384 image with 4 channels (RGB and NIR). Outputs: cloud confidence.

Color prior knowledge & D-S Evidence fusion method



$$conf' = conf + J[(gray, L)] * bias$$

$$J[(gray, L)] = \begin{cases} 1 & gray > L \\ 0 & gray < L \end{cases}$$

Fig.3 Effect of the color prior knowledge

$$Pla(OC) = \frac{1}{K} \sum_{A_1 \cap A_2 \cap \cdots \cap A_q = C} m_1(A_1) m_2(A_2) \dots m_q(A_q)$$

$$Pla(OCL) = \frac{1}{K} \sum_{A_1 \cap A_2 \cap \cdots \cap A_q = CL} m_1(A_1) m_2(A_2) \dots m_q(A_q)$$

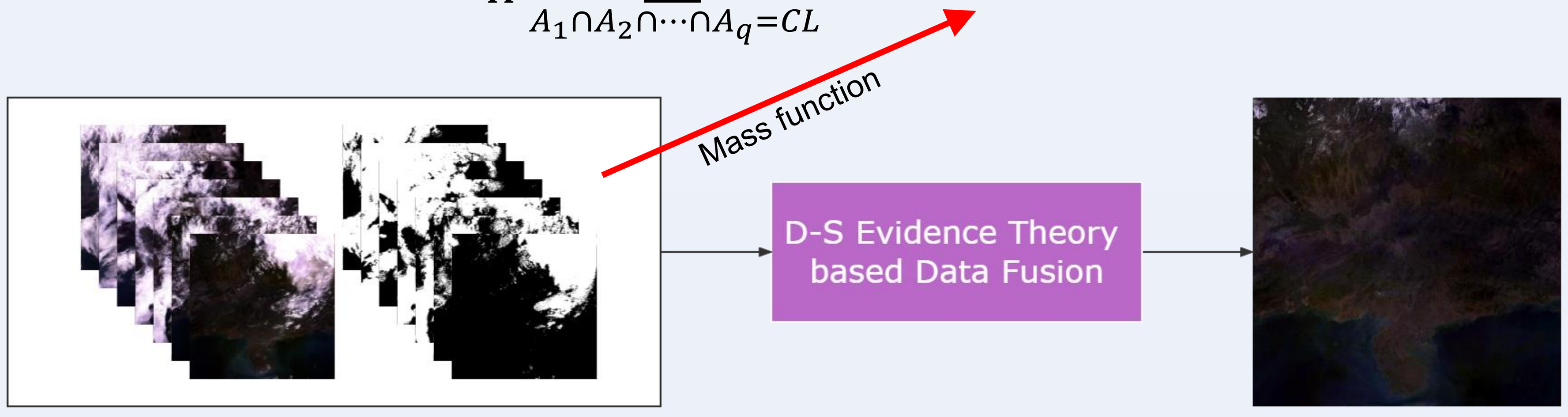


Fig.4 Effect of the D-S evidence theory[2] based data fusion

Ablation study

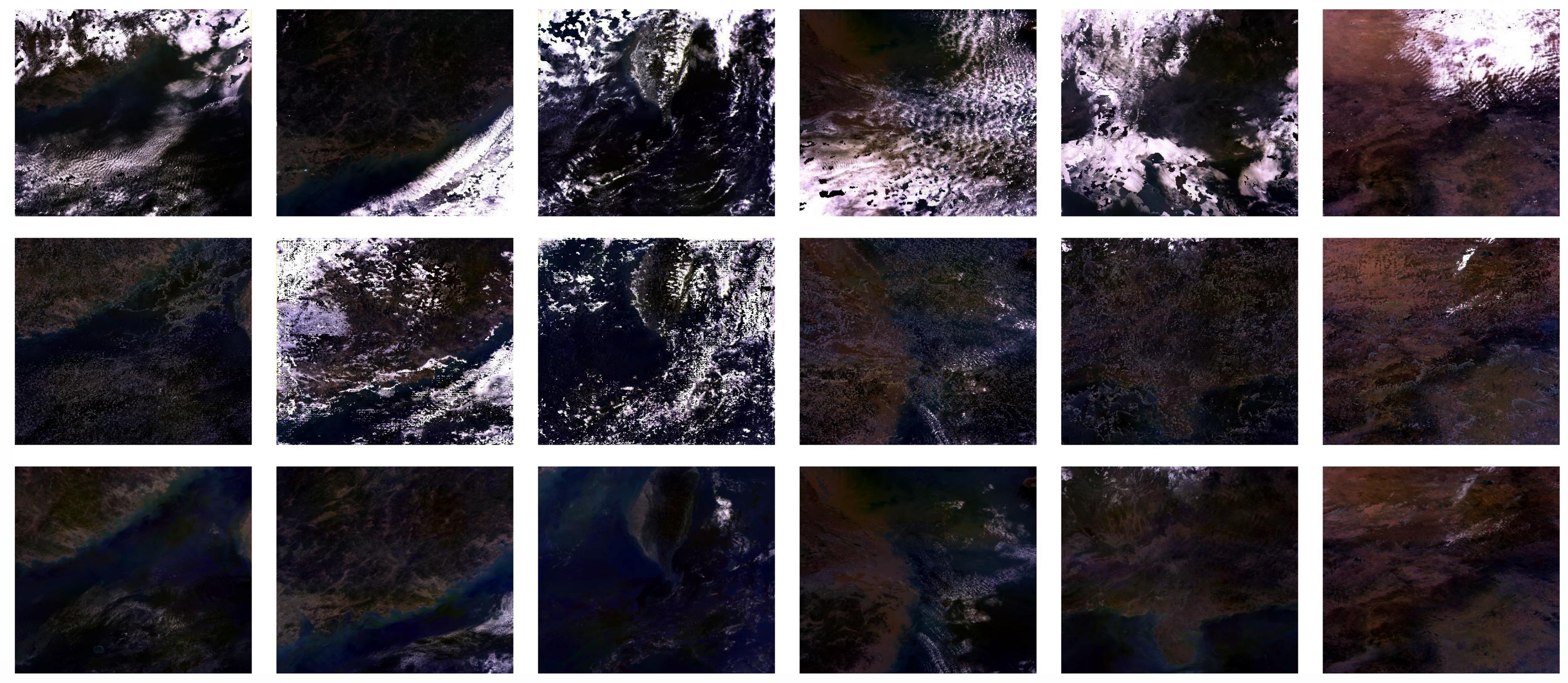


Fig.5 Row 1: outputs without the prior knowledge. Row 2: outputs without the D-S evidence theory. Row 3: outputs with all components.

Cloud removal results

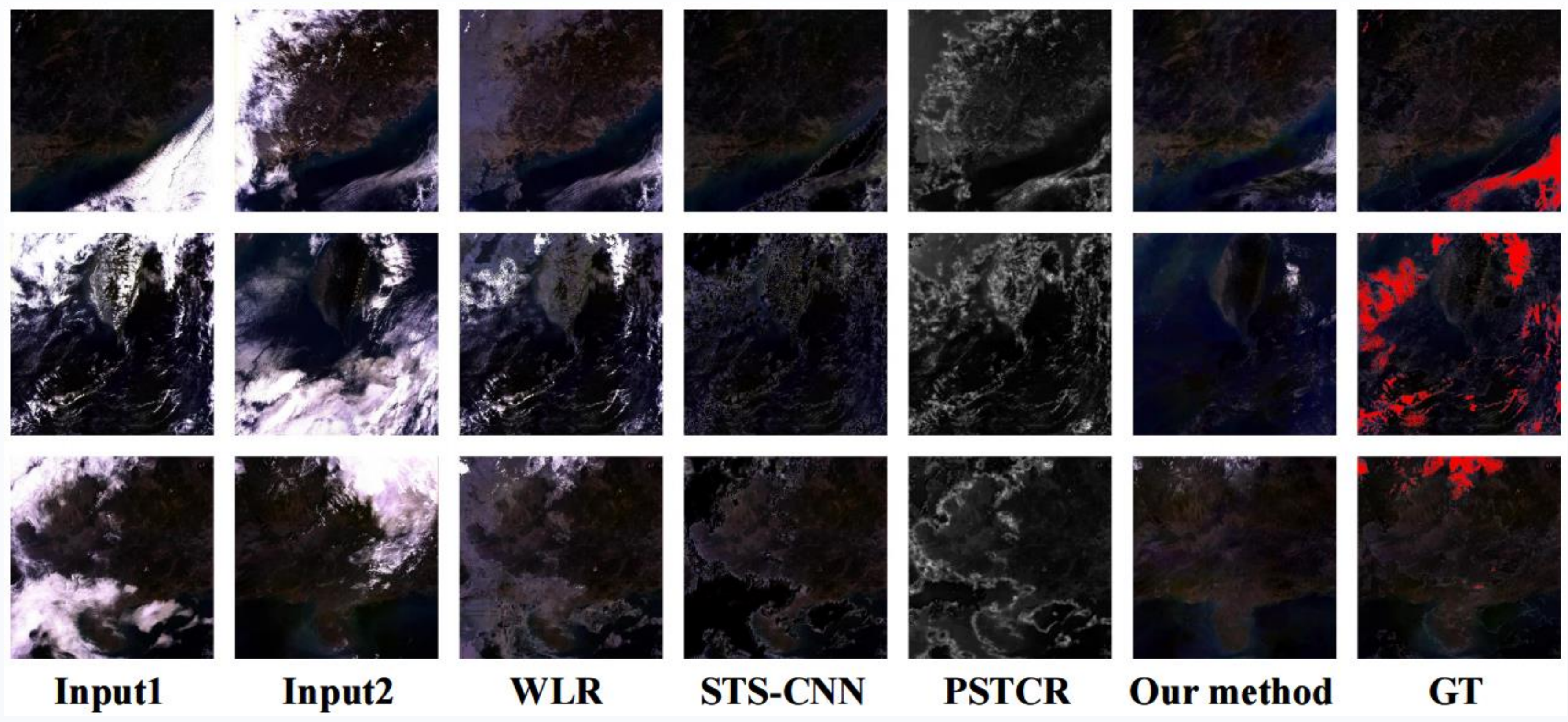


Fig.6 Comparison against different cloud removal methods on test images.

Table.1 Estimated cloud rates before and after cloud removal. The cloud rate: number of cloud pixels/number of total pixels of output images.

Area/Cloud rate	WLR[3]	STS-CNN[4]	PSTCR[5]	**Our method**
1	22.51%	23.07%	20.49%	**2.55%**
2	33.90%	15.44%	24.59%	**2.66%**
3	28.35%	26.89%	22.76%	**2.14%**
4	33.86%	24.74%	29.79%	**7.37%**
5	31.13%	26.75%	25.85%	**2.67%**
6	31.79%	29.32%	17.51%	**1.76%**

Table.2 Comparison of MSE against different cloud removal methods on test images.

Area/MSE	WLR[3]	STS-CNN[4]	PSTCR[5]	**Our method**
1	0.0552	0.0931	0.0844	**0.0501**
2	0.1152	0.0200	0.1204	**0.0191**
3	1.066	0.8268	0.9092	**0.7813**
4	0.1484	0.0886	0.2025	**0.0335**
5	1.115	0.7198	0.8202	**0.6664**
6	0.832	0.1190	0.0416	**0.0348**

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