



国防科技大学

National University of Defense Technology

CVPR  
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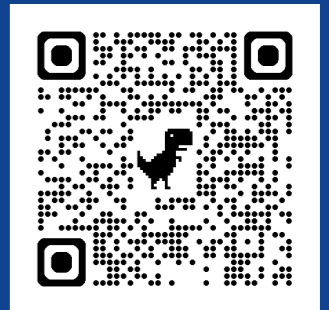


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# Local Precise Refinement: A Dual-Gated Mixture-of-Experts for Enhancing Foundation Model Generalization against Spectral Shifts

Xi Chen

<https://nudt-sawlab.github.io/SpectralMoE/>





# 1. Background & Motivation

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## Spectral Remote Sensing Imagery: Encompassing Hyperspectral, Multispectral, and RGB Data



**Hyperspectral**

Bands: 32  
Resolution: 10 m



**Multispectral**

Bands: 4  
Resolution: 4 m

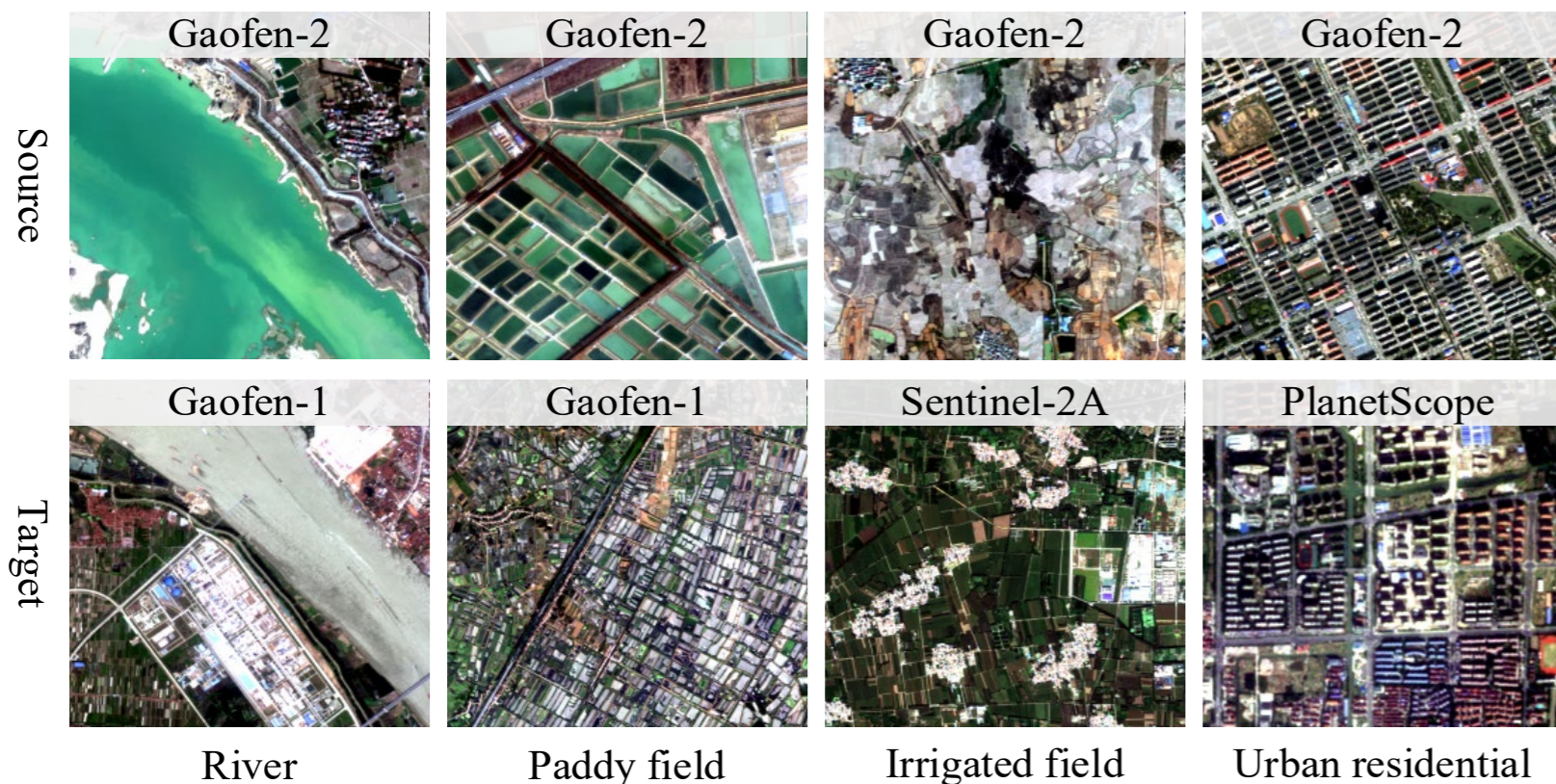


**RGB**

Bands: 3  
Resolution: 0.1 m

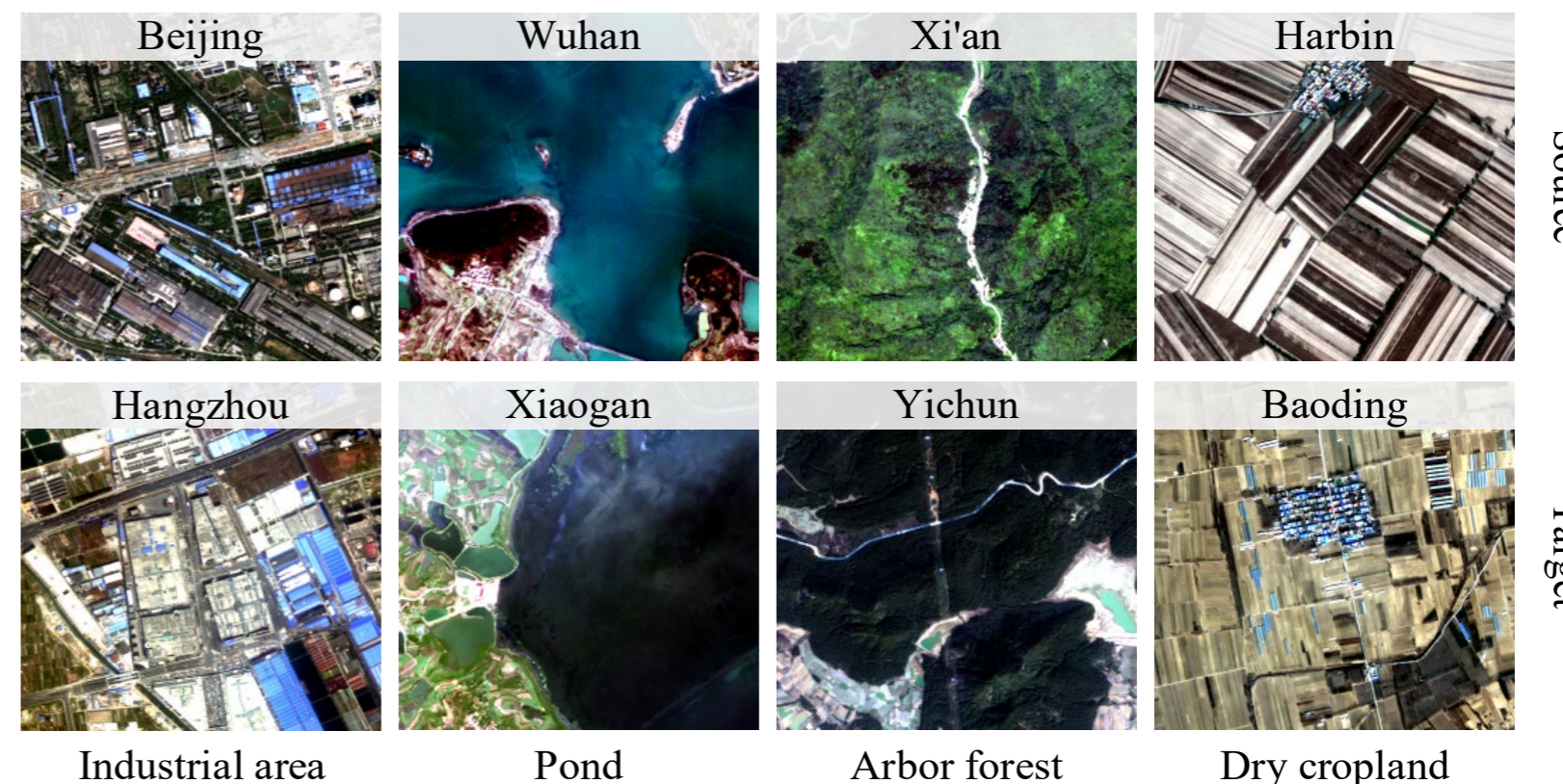
## Spectral Shifts in Practical Mapping: Cross-Sensor and Cross-Geospatial Variations

Cross-sensor



(a)

Cross-geospatial



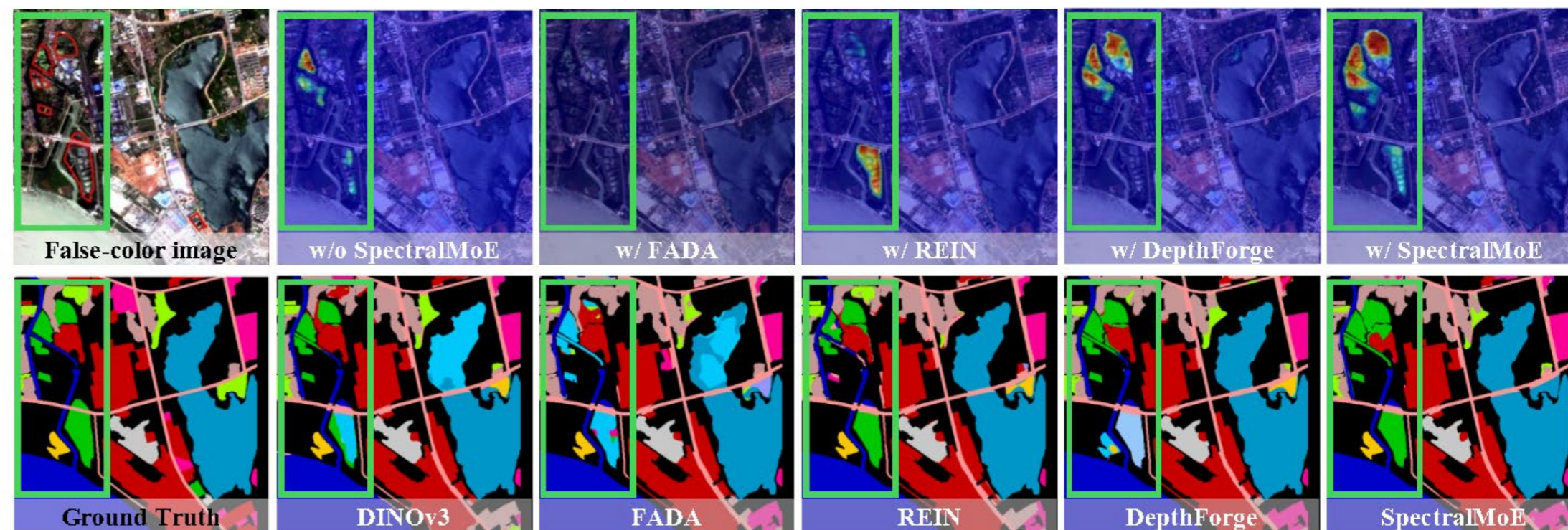
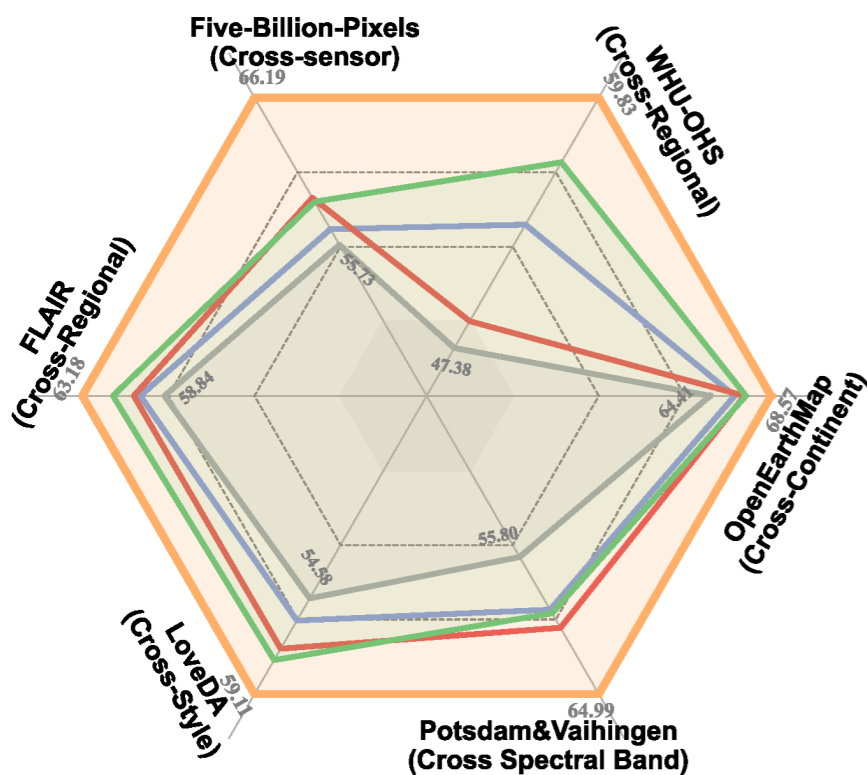
(b)

Most existing fine-tuning approaches rely on global, homogeneous adjustments

Limitation:

- High Spatial Heterogeneity: Remote sensing images are highly heterogeneous (e.g., "paddy fields" and "ponds" are both spectrally similar and spatially adjacent).
- The "Ripple Effect": Global adjustments lack localized control and easily trigger unintended widespread changes, leading to Semantic Confusion.

Our Paradigm Shift: Local Precise Refinement



— SET — FADA — REIN — DepthForge — SpectralMoE (Ours)



## 2. Methodology: SpectralMoE

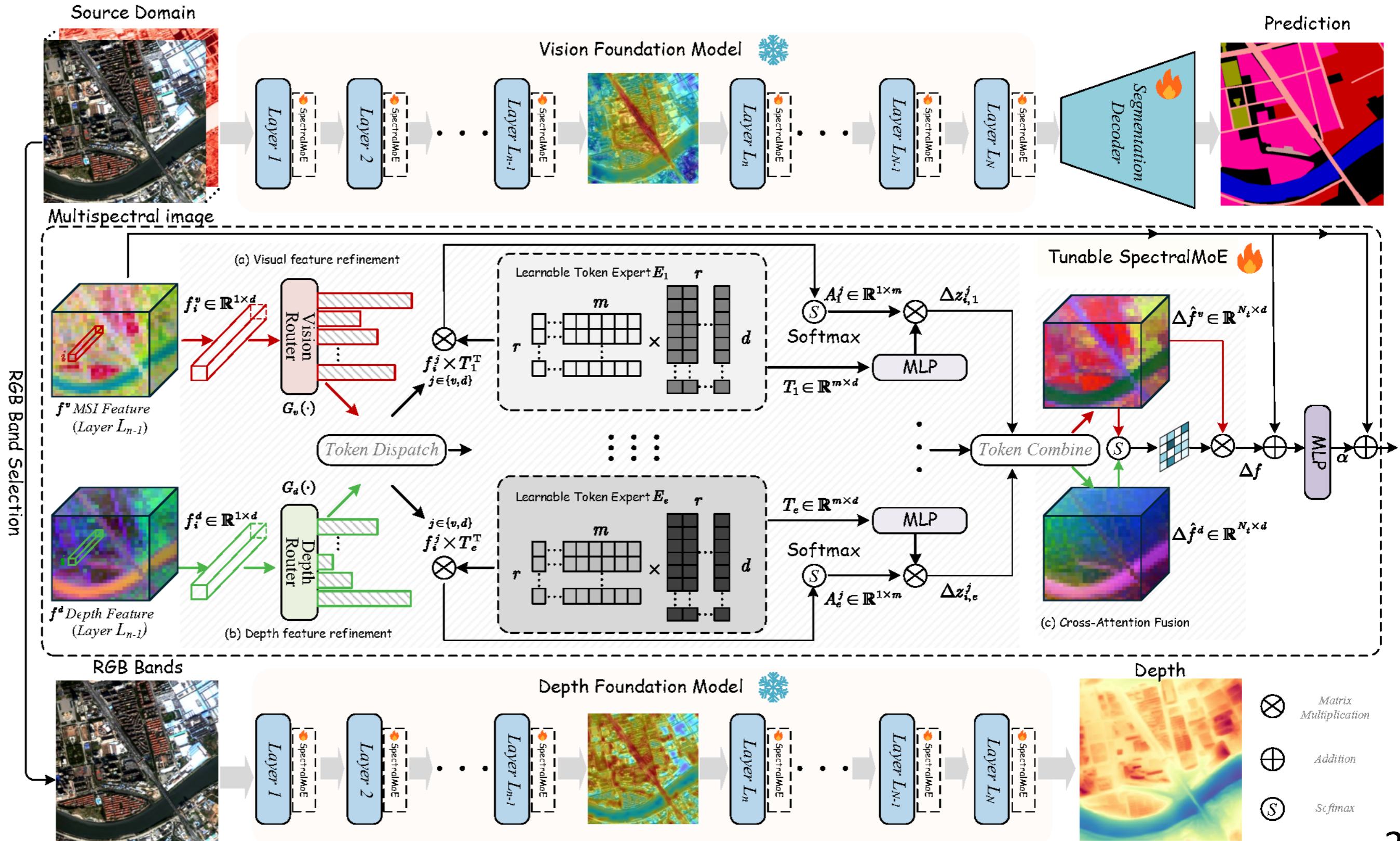
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**SpectralMoE is inserted as a lightweight plugin into each layer of frozen VFMs and DFMs.**

- SpectralMoE, a fine-tuning framework for spectral RS DGSS across hyperspectral, multispectral, and RGB remote sensing imagery.

- A dual-gated MoE that independently routes visual and depth tokens to expert adapters for local precise refinement.

- A cross-attention fusion module that lets visual adjustments query depth-derived structural priors, mitigating semantic ambiguity from spectral similarity.





# 3. Experiments & Results

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□ **Evaluating 7 DGSS Tasks across 3 modalities (Hyperspectral, Multispectral, RGB).**

## Generalization Scenarios: Cross-Sensor, Cross-Region, Cross-Style, etc.

### 1. Hyperspectral Imagery (HSI)

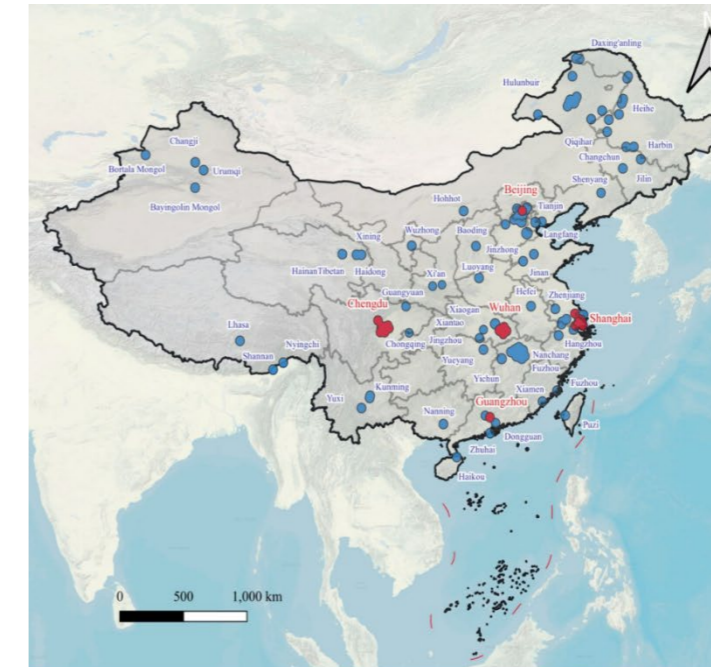
- **Cross-Region: WHU-OHS dataset (covering 40 diverse locations across China).**

### 2. Multispectral Imagery (MSI)

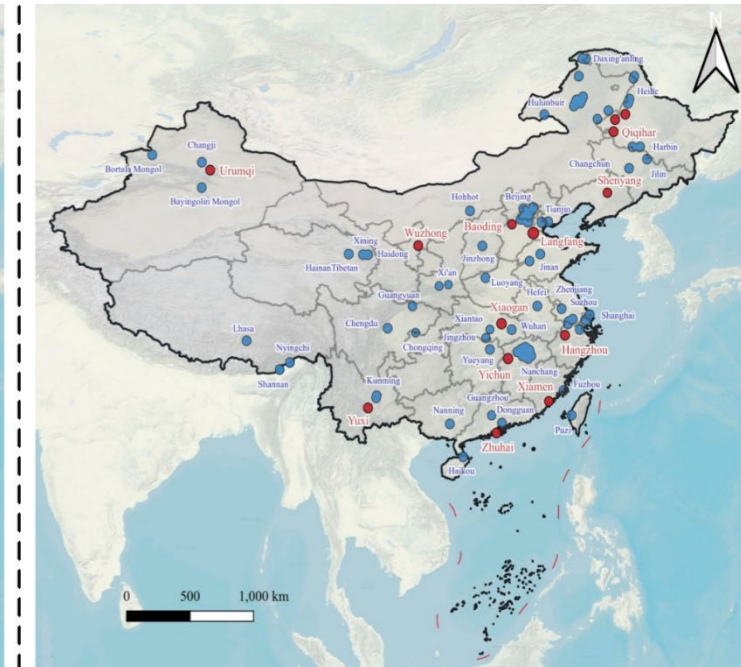
- **Cross-Sensor: Five-Billion-Pixels (Source: GF-2 → Target: PlanetScope / GF-1 / Sentinel-2).**
- **Cross-Region (China): Five-Billion-Pixels (Source: 50 regions → Target: 12 unseen cities).**
- **Cross-Region (Europe): FLAIR (covering 50 distinct spatial domains in France).**

### 3. RGB Imagery

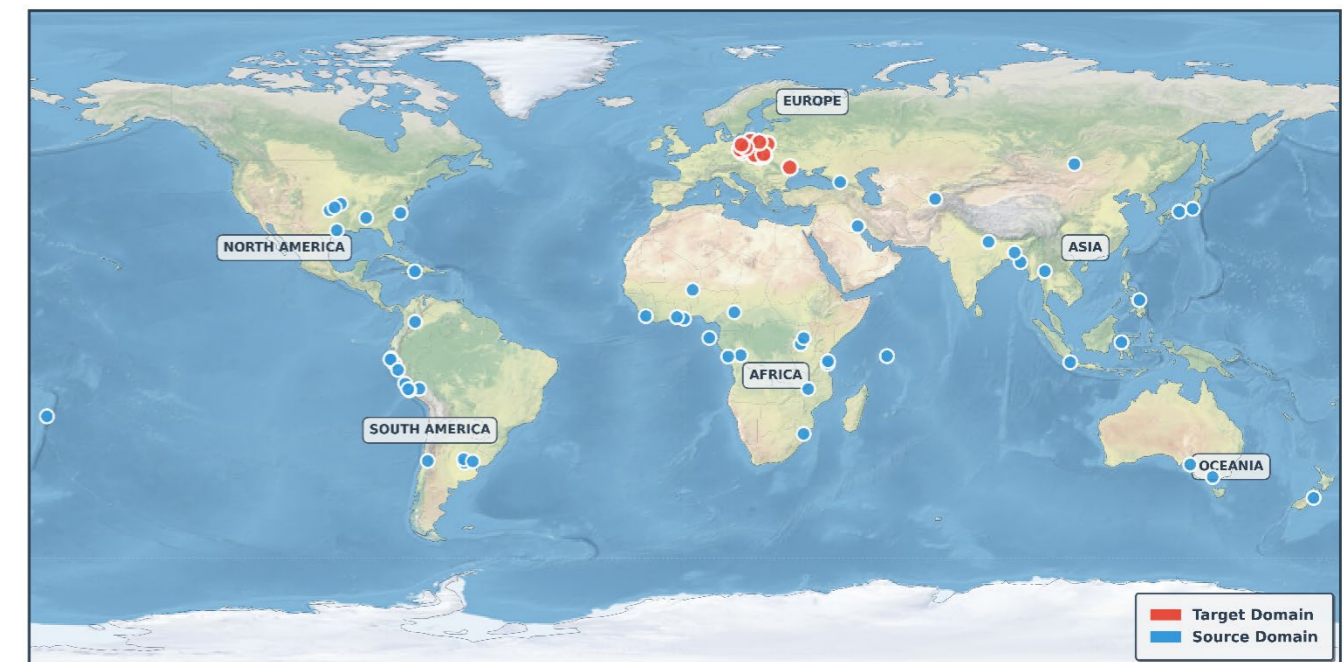
- **Cross-Style (Rural → Urban): LoveDA dataset.**
- **Cross-Spectral-Band: Potsdam (RGB) → Vaihingen (NIR-R-G).**
- **Cross-Continent: OpenEarthMap (Source: 5 Continents → Target: Europe).**



(a) Five-Billion-Pixels (Cross-sensor)



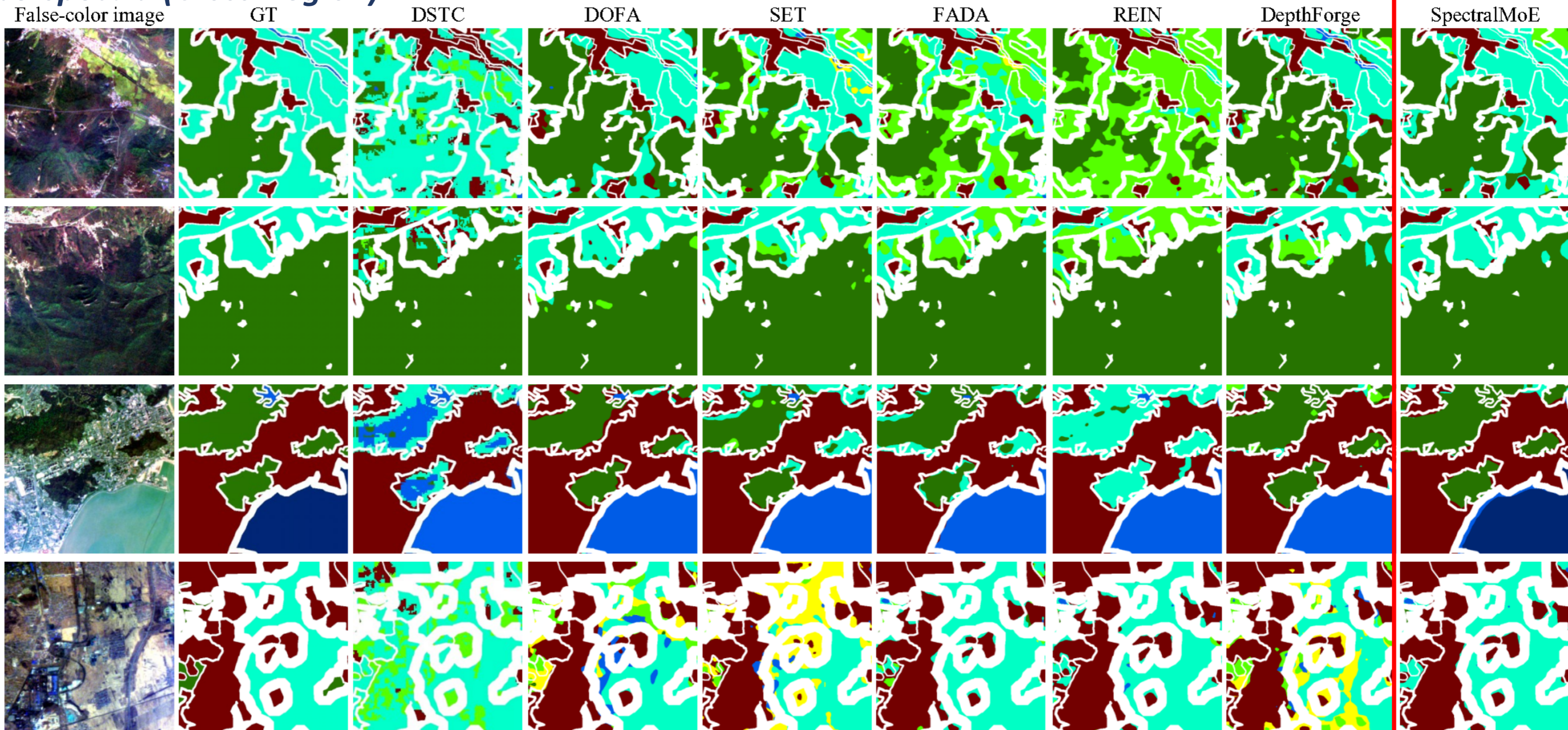
(b) Five-Billion-Pixels (Cross-Regional)



- Boosts mIoU significantly on leading foundation models (DINOv3, DOFA).
- Breakthrough performance on the Five-Billion-Pixels (Cross-Sensor) benchmark.

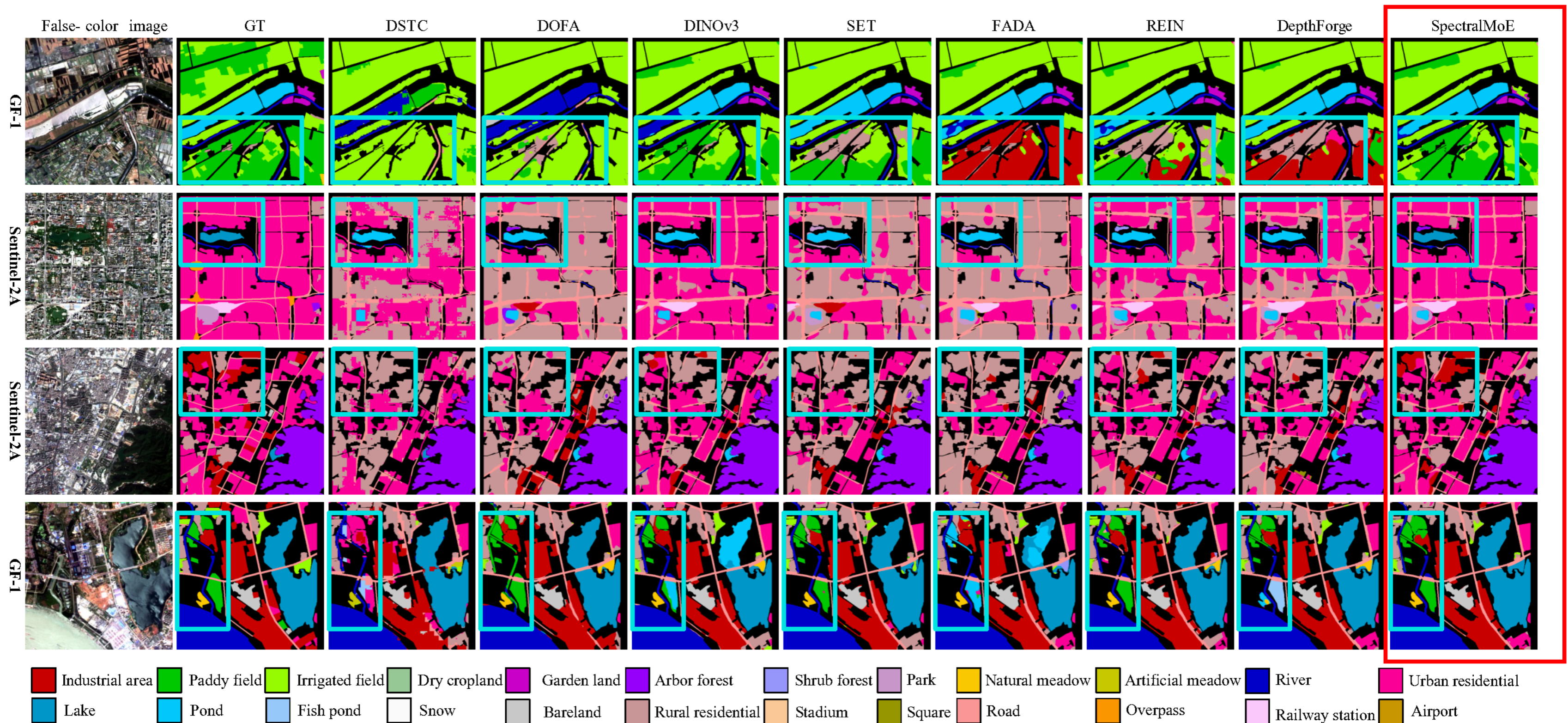
Method	<i>Hyperspectral DGSS Tasks</i>		<i>Multispectral DGSS Tasks</i>				<i>RGB DGSS Tasks</i>							
	WHU-OHS (Cross-Regional)		Five-Billion-Pixels (Cross-sensor)		Five-Billion-Pixels (Cross-Regional)		FLAIR (Cross-Regional)		LoveDA (Cross-Style)		Potsdam&Vaihingen (Cross Spectral Band)		OpenEarthMap (Cross-Continent)	
	mIoU	mAcc	mIoU	mAcc	mIoU	mAcc	mIoU	mAcc	mIoU	mAcc	mIoU	mAcc	mIoU	mAcc
<i>Spectral Remote Sensing Domain Generalized Semantic Segmentation Models</i>														
DSTC [31]	43.09	57.81	29.79	40.61	46.27	59.71	53.42	68.05	47.78	62.90	16.62	32.54	46.49	63.17
<i>Remote Sensing Foundation Models (Freeze Backbone)</i>														
SoftCon [44]	–	–	29.59	40.81	43.24	58.65	53.21	68.27	41.01	54.91	11.27	24.05	39.63	60.15
Galileo [42]	–	–	31.68	43.36	38.54	52.63	52.07	67.58	32.45	45.49	11.69	27.12	35.95	57.12
SenPaMAE [37]	45.76	59.01	32.28	45.50	43.31	58.94	55.48	70.34	38.71	53.10	19.60	34.40	44.13	60.56
Copernicus [45]	42.87	56.83	33.84	42.44	43.56	60.35	56.15	71.84	43.96	58.16	15.91	30.76	48.37	69.16
DOFA [49]	46.03	59.73	44.60	58.66	49.48	67.38	58.25	72.67	52.41	67.54	38.10	58.74	58.49	73.70
<i>Visual Foundation Models (Freeze Backbone)</i>														
CLIP [38]	–	–	46.30	61.59	48.10	64.51	56.81	70.24	51.62	66.95	40.84	64.17	61.93	78.12
SAM [24]	–	–	44.98	59.35	47.14	64.68	56.65	71.92	52.17	66.82	40.48	63.57	56.45	73.32
EVA02 [15, 16]	–	–	45.48	59.11	49.33	62.66	57.52	71.59	53.04	65.70	42.81	65.27	61.83	75.45
DINOv2 [34]	–	–	53.37	69.10	52.48	69.92	58.38	73.03	54.10	68.39	55.39	77.68	64.37	76.79
DINOv3 [39]	–	–	55.54	69.18	54.44	70.71	59.60	73.40	55.75	74.83	58.79	80.27	65.48	77.02
<i>Foundation model-based DGSS Models</i>														
SET [52]	47.38	60.61	55.73	70.24	55.61	70.98	58.84	73.23	54.58	72.38	55.80	78.85	64.41	78.60
FADA [1]	53.51	67.54	56.84	73.44	55.35	71.99	60.12	74.11	55.63	70.85	59.33	80.11	66.08	78.87
REIN [47]	48.71	63.58	59.06	73.44	55.27	71.87	60.46	73.76	56.96	71.37	60.54	81.36	66.76	78.81
DepthForge [5]	56.61	69.76	58.79	75.08	54.92	71.43	61.56	74.14	57.50	71.92	59.57	81.51	66.85	79.70
<i>Ours</i>														
SpectralMoE	<b>59.83</b>	<b>73.13</b>	<b>66.19</b>	<b>77.26</b>	<b>60.32</b>	<b>75.78</b>	<b>63.18</b>	<b>76.52</b>	<b>59.11</b>	<b>75.38</b>	<b>64.99</b>	<b>85.43</b>	<b>68.57</b>	<b>80.17</b>

**Hyperspectral(Cross-Region)**

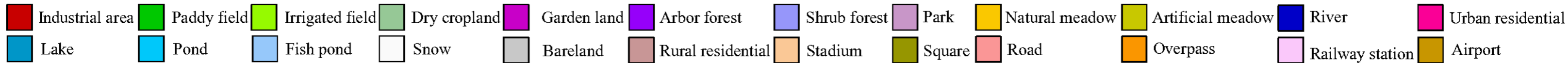
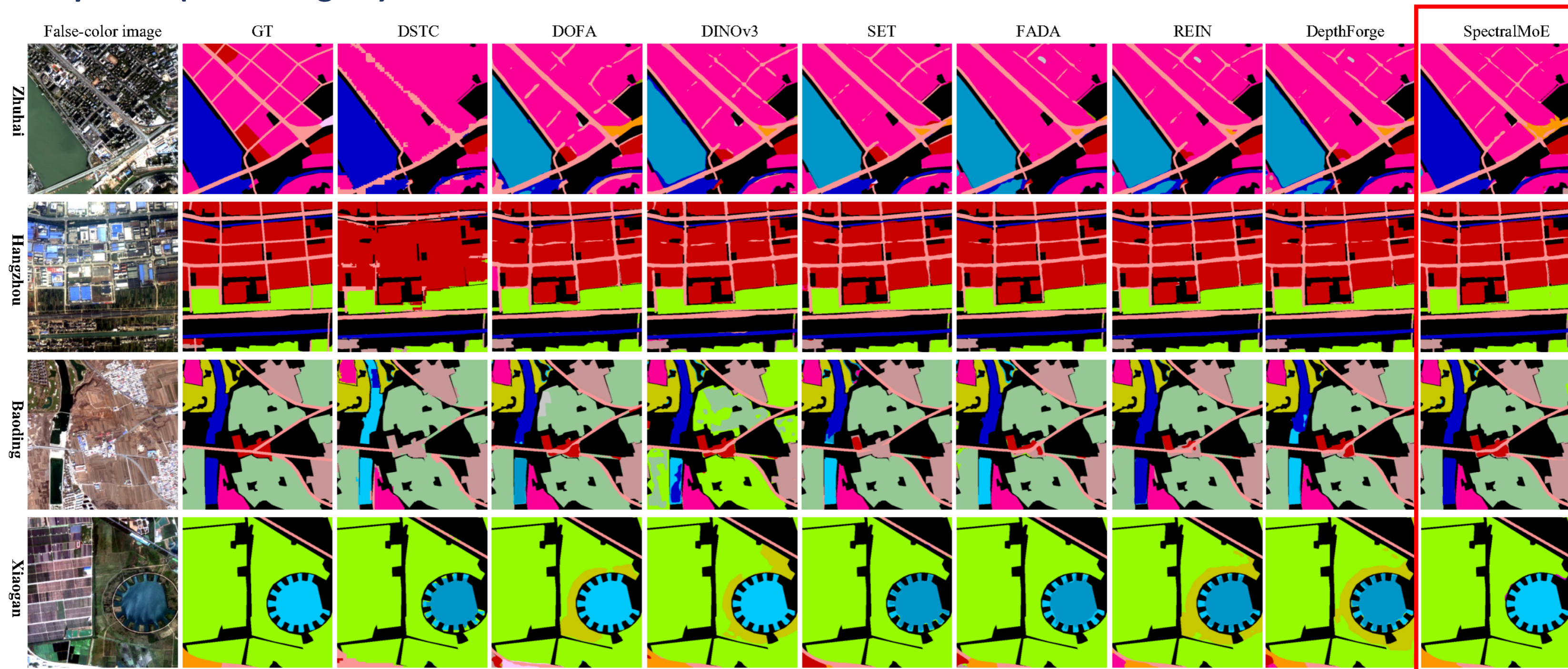


Farmland
  Forest
  Grassland
  Water body
  Built-up land
  Unused land
  Ocean

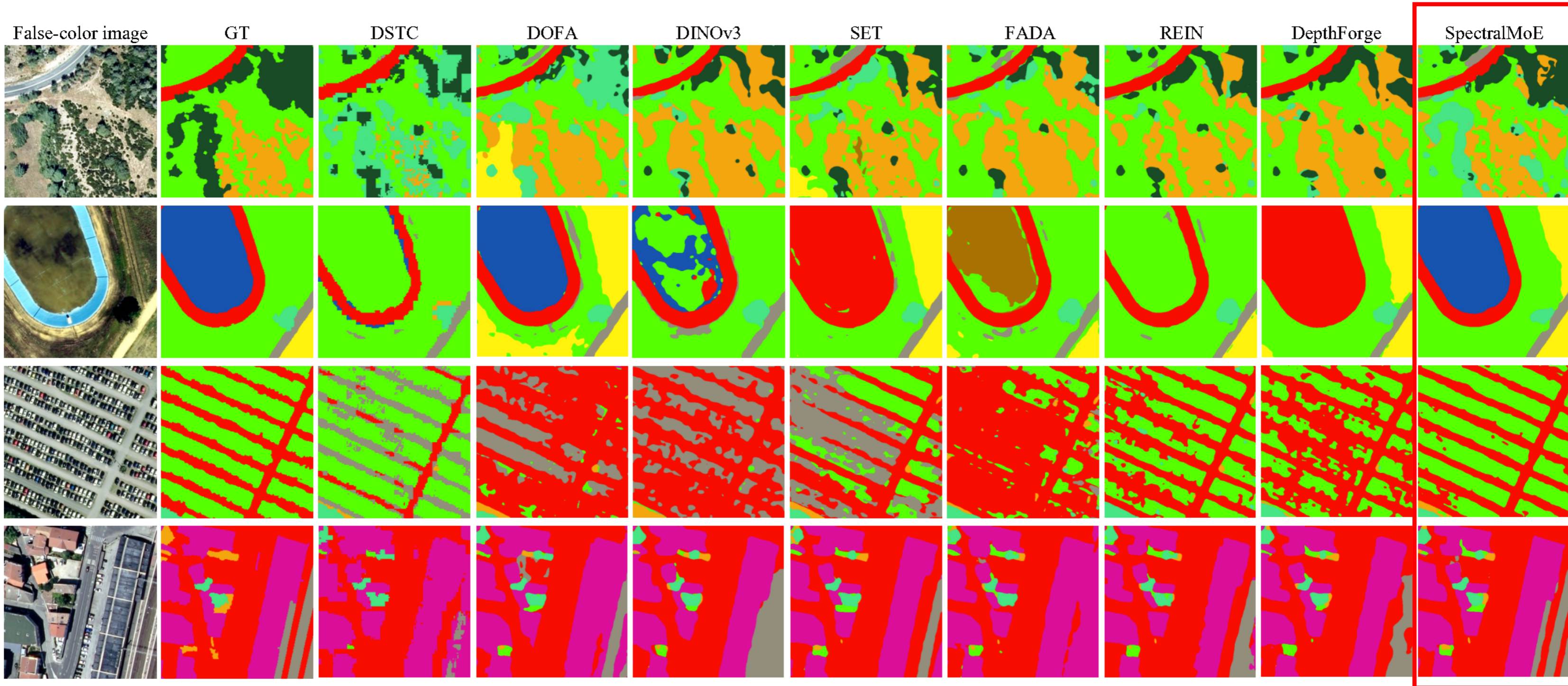
## ▣ Multispectral(Cross-Sensor)



## ▣ Multispectral(Cross-Region)

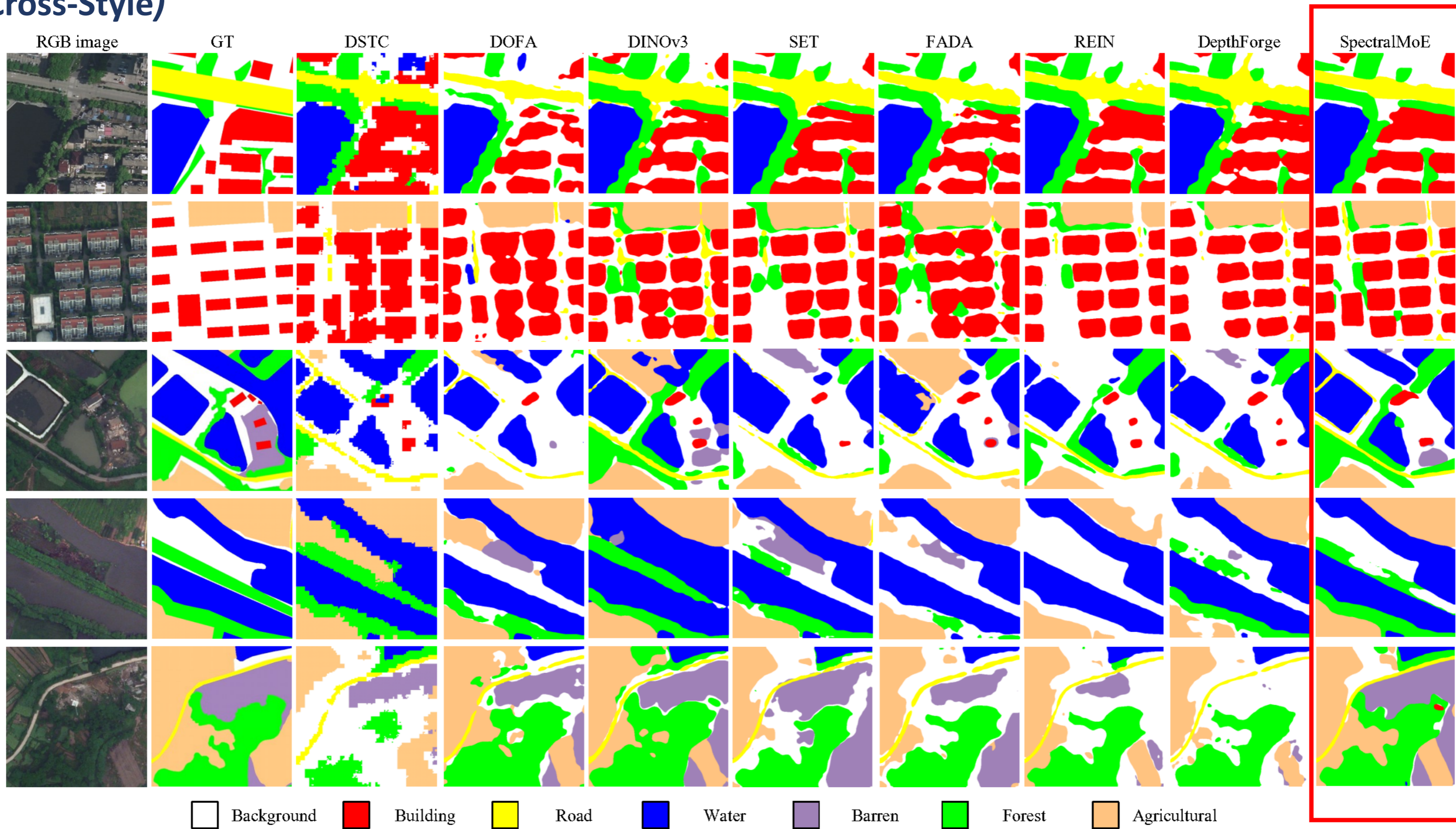


## ▣ Multispectral(Cross-Region)

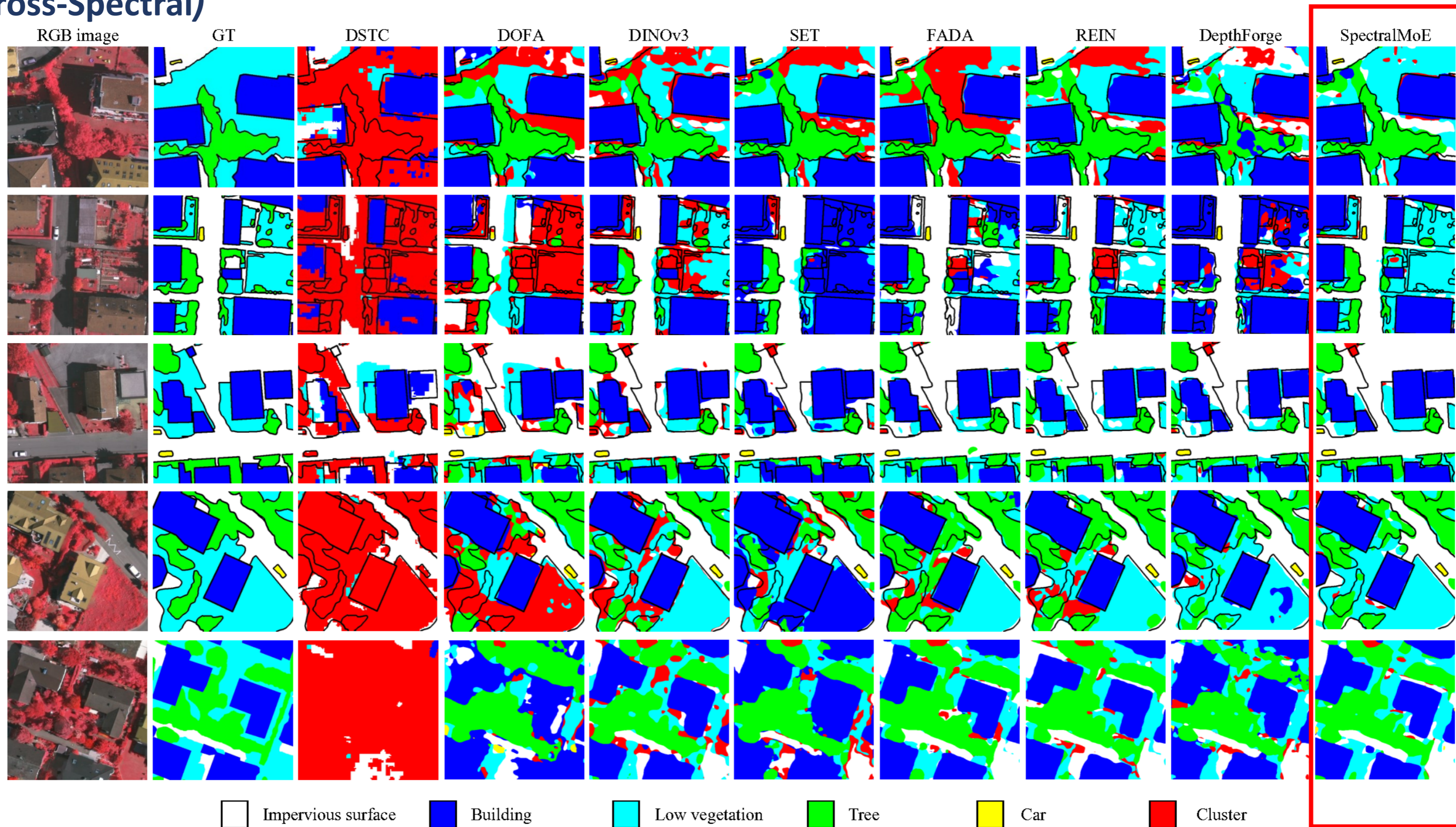


Building
  Pervious surface
  Impervious surface
  Bare soil
  Water
  Coniferous
  Deciduous
  Brushwood
  Vineyard
  Herbaceous vegetation
  Agricultural land
  Plowed land

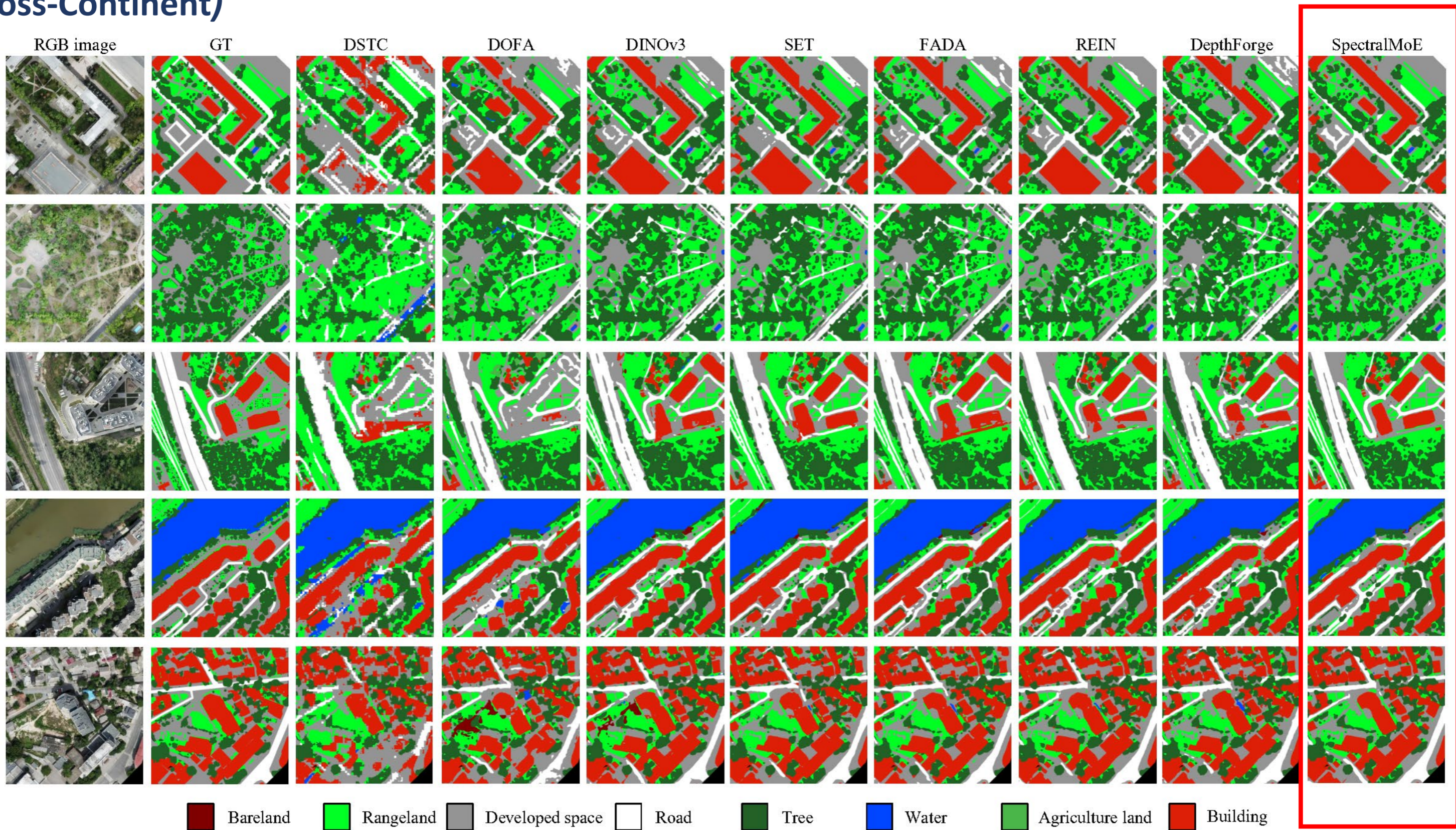
## RGB(Cross-Style)



## RGB(Cross-Spectral)



## RGB(Cross-Continent)





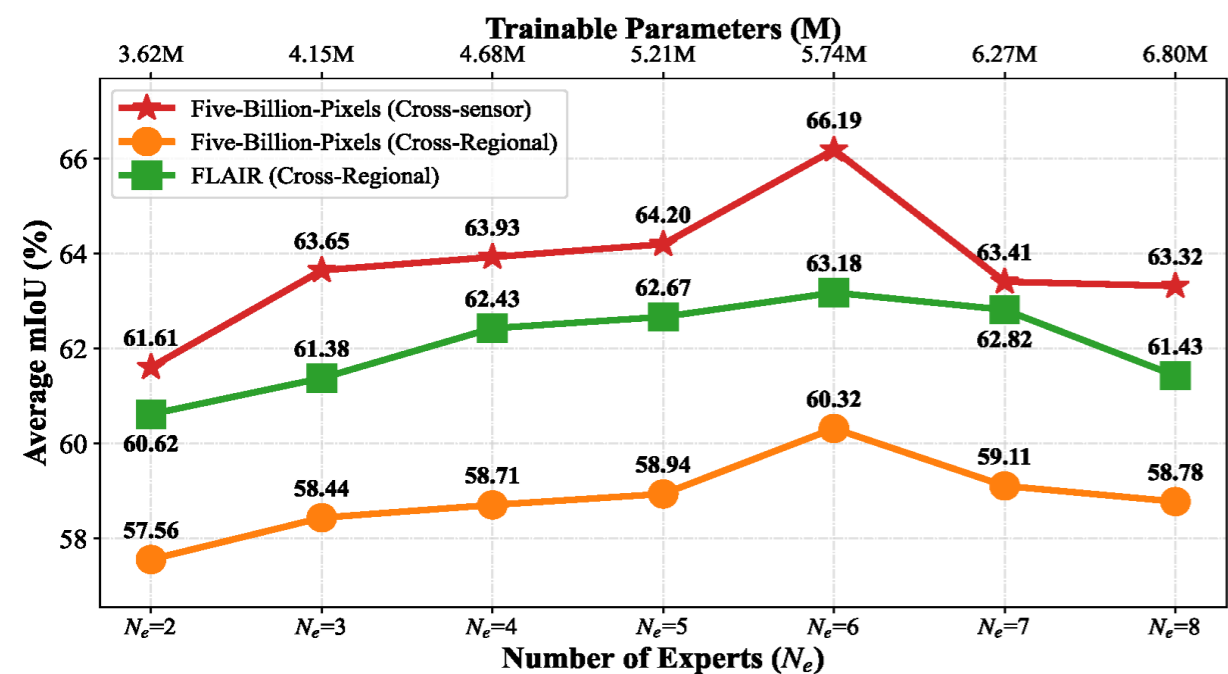
# 4. Ablation Studies

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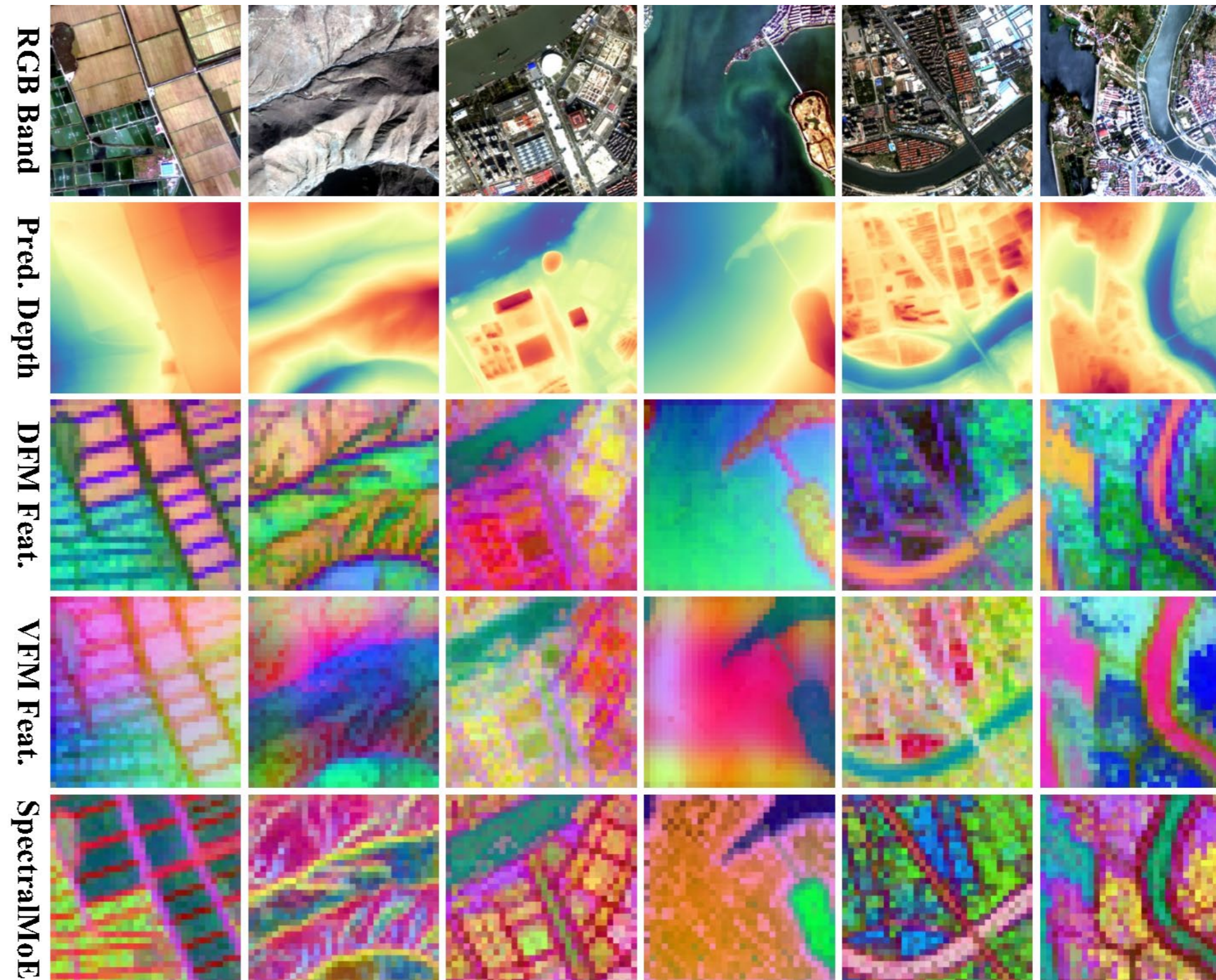
## Effectiveness of Key Modules

Backbone	Configuration	mIoU (%)		
		Five-Billion-Pixels (Cross-Sensor)	Five-Billion-Pixels (Cross-Regional)	FLAIR (Cross-Regional)
<i>VFM</i>	w/o MoE	63.41	59.37	60.82
	w/o Dual Gating	63.44	58.97	61.95
	w/o Depth Feature	63.52	59.01	63.07
DINOv3 (Large) [39]	w/o Cross-Attention	63.48	58.35	61.30
	<b>SpectralMoE (ours)</b>	<b>66.19</b>	<b>60.32</b>	<b>63.18</b>
<i>RSFM</i>	w/o MoE	55.69	54.58	59.94
	w/o Dual Gating	53.66	54.10	60.18
	w/o Depth Feature	54.71	54.44	61.31
DOFA (Large) [49]	w/o Cross-Attention	54.20	53.17	60.10
	<b>SpectralMoE (ours)</b>	<b>57.73</b>	<b>55.41</b>	<b>61.50</b>

## Impact of the Number of Experts



## Superiority of Fine-Tuning Foundation Model Features



## Adaptability Across Foundation Models

VFM	Method	Params (M)	mIoU (%)			
			FBP (CS)	FBP (CR)	FLAIR (CR)	Avg.
CLIP (Large) [38]	Freeze	0.00	46.30	48.10	56.81	50.40
	+ SET [52]	6.13	55.00	52.62	59.88	55.83
	+ FADA [1]	11.65	55.03	51.86	60.52	55.80
	+ REIN [47]	2.99	56.70	53.37	60.97	57.01
	+ DepthForge [5]	2.99	54.77	53.89	61.17	56.61
	+ SpectralMoE	5.74	<b>61.33</b>	<b>54.13</b>	<b>61.47</b>	<b>58.98</b>
SAM (Huge) [24]	Freeze	0.00	44.98	47.14	56.65	49.59
	+ SET [52]	9.21	50.31	52.10	58.17	53.53
	+ FADA [1]	16.59	49.74	50.04	59.38	53.05
	+ REIN [47]	4.51	50.93	50.27	59.36	53.52
	+ DepthForge [5]	4.51	48.15	52.08	59.26	53.16
+ SpectralMoE	10.29	<b>59.16</b>	<b>56.79</b>	<b>59.41</b>	<b>58.45</b>	
EVA02 (Large) [15, 16]	Freeze	0.00	45.48	49.33	57.52	50.78
	+ SET [52]	6.13	46.29	51.57	50.38	49.41
	+ FADA [1]	11.65	46.49	51.27	59.37	52.38
	+ REIN [47]	2.99	50.81	51.33	59.46	53.87
	+ DepthForge [5]	2.99	40.90	47.60	58.81	49.10
+ SpectralMoE	5.74	<b>60.20</b>	<b>56.29</b>	<b>62.09</b>	<b>59.53</b>	
DINOv2 (Large) [34]	Freeze	0.00	53.37	52.48	58.38	54.74
	+ SET [52]	6.13	55.73	55.61	58.84	56.73
	+ FADA [1]	11.65	56.84	55.35	60.12	57.44
	+ REIN [47]	2.99	59.06	55.27	60.46	58.26
	+ DepthForge [5]	2.99	58.79	54.92	61.56	58.42
	+ SpectralMoE	5.74	<b>63.77</b>	<b>57.77</b>	<b>62.62</b>	<b>61.39</b>

## Outperforms State-of-the-Art PEFT Methods

Dataset	Method	Params (M)	DINOv3 Large [39] (VFM)		DOFA Large [49] (RSFM)	
			mIoU	mAcc	mIoU	mAcc
FBP (CS)	Freeze	0.00	53.37	69.10	46.98	62.83
	+ LoRA [21]	0.79	59.64	74.17	49.49	62.12
	+ AdaptFormer [4]	3.22	57.73	73.22	49.88	65.89
	+ VPT [22]	3.69	58.14	72.50	49.70	60.96
	+ SET	6.13	58.02	72.73	49.28	61.51
	+ FADA	11.65	58.27	73.72	53.93	67.32
	+ REIN	2.99	61.79	76.10	52.72	64.50
	+ DepthForge	2.99	62.16	74.91	52.76	65.74
	+ SpectralMoE	5.74	<b>66.19</b>	<b>77.26</b>	<b>57.73</b>	<b>70.37</b>
FBP (CR)	Freeze	0.00	52.48	69.92	49.16	65.41
	+ LoRA [21]	0.79	56.15	73.33	50.60	65.09
	+ AdaptFormer [4]	3.22	55.82	74.89	50.32	64.99
	+ VPT [22]	3.69	56.04	73.75	49.43	68.60
	+ SET	6.13	56.06	72.53	50.11	64.64
	+ FADA	11.65	56.25	72.99	54.20	70.83
	+ REIN	2.99	57.09	74.00	53.74	70.88
	+ DepthForge	2.99	57.54	72.14	53.95	69.33
	+ SpectralMoE	5.74	<b>60.32</b>	<b>75.78</b>	<b>55.41</b>	<b>72.71</b>
FLAIR (CR)	Freeze	0.00	58.38	73.03	58.25	72.67
	+ LoRA [21]	0.79	61.12	75.14	60.31	74.03
	+ AdaptFormer [4]	3.22	60.19	72.76	59.68	74.19
	+ VPT [22]	3.69	60.16	74.11	59.47	73.36
	+ SET	6.13	60.32	72.35	59.93	74.79
	+ FADA	11.65	61.61	76.31	60.15	74.54
	+ REIN	2.99	62.79	76.49	60.94	74.90
	+ DepthForge	2.99	62.47	76.68	60.52	74.57
	+ SpectralMoE	5.74	<b>63.18</b>	<b>76.52</b>	<b>61.50</b>	<b>75.43</b>



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# Thank You for Your Attention!

Xi Chen

[xi\\_chen@nudt.edu.cn](mailto:xi_chen@nudt.edu.cn)

