EXTENSIONS OF MORPHOLOGICAL GRADIENT FOR HYPERSPECTRAL IMAGES

Supplementary Material

1. DATASETS AND IMPLEMENTATION DETAILS

Table 1: Hyperspectral datasets used in comparative experiments, and their dimensions.

Dataset	Dimensions	#Bands
Indian Pines	145×145	220
Salinas	512×217	224
Salinas-A	83×86	224
Pavia Centre	1096×715	102
Pavia University	610×340	103
KSC	512×614	176
Botswana	1476×256	145

To evaluate the performance of different HSI gradient magnitude calculation algorithms, we utilize seven publicly available hyperspectral remote sensing datasets: Indian Pines, Salinas, Salinas-A, Pavia Centre, Pavia University, KSC, and Botswana[1]. Some of the datasets have corrected versions that exclude water absorption spectral bands. We use original datasets in this experiment. The spatial dimensions and the number of spectral bands of the datasets are presented in Table 1.

In addition to using the raw data, we consider three normalization techniques to preprocess the data before gradient magnitude calculation. The first normalization approach used is min–max normalization, which scales the values to the range $[0, 1]$ with $f_{\text{mm}} = \frac{f - f_{\min}}{f_{\max} - f_{\min}}$. The second approach scales the values so that the maximum value is mapped to 1 using $f_{\text{m}} = \frac{f}{f_{\max}}$. The last normalization technique is z-score normalization, also called standardization. With this approach, data is adjusted to have a zero mean and a standard deviation of one: $f_{\text{z}} = \frac{f - \mu}{\sigma}$. Here, μ and σ are the mean and the standard deviation, respectively.

To make good use of the data complexity, the normalizations are applied in one of two ways: per band or per spectral signature. In further presentation, a subscript of mm, m, or z, denotes min–max, max, or z-score normalization, respectively; a superscript of xy and a superscript of λ refer to per-band and per-spectral-signature normalizations, respectively.

2. COMPARISON USING EDGE DETECTION

Fig. 1 and 2 show the ROC curves and their AUC (%) for the compared algorithms. For each image, we report the one version, out of seven (raw data and six normalized), that results in the highest AUC for a given algorithm. We do not use z-score normalization for MorphDe because the algorithm input should not contain negative values. The results show that the best normalization setup varies with the dataset, highlighting the importance of the imaging conditions and details of the scene.

For all HSI cubes, the top scorer is a morphological algorithm: our MorphL1 for KSC, Pavia University, and Salinas; MGEuc for Botswana and Pavia Centre; MGSum for Indian Pines; CMG for Salinas-A. Additionally, our MorphL1, CMG, MGSum, GGSum, and our MorphArea frequently appear in the top results. Notably, almost all of these algorithms are morphological: marginal MGSum and vectorial MorphL1, CMG, and MorphArea. GGSum is the only algorithm that relies on partial derivative approximations.

The results of the fifteen gradient magnitude algorithms from our benchmark are demonstrated on six publicly available hyperspectral remote sensing datasets—KSC, Salinas-A, Pavia Centre, Pavia University, Salinas, and Botswana—in Fig. 3–8, respectively. Each figure also shows the RGB rendering and the reference edge mask used. Similar results for Indian Pines can be found in the main paper.

3. PARALLEL IMPLEMENTATION OF COMPETITIVE ALGORITHMS

To achieve fast calculation of HSI gradient magnitudes, we have developed parallel GPU implementations, using CUDA, of the most accurate algorithms from the comparative experiment based on edge detection results. These implementations are compared with their sequential C++ alternatives on the CPU to estimate the speedup factors. The execution times on GPU, as well as the average speedup factor (ASF) for GPU implementations, are included in the main paper. Table 2 shows the execution times on CPU for all algorithms.

4. REFERENCES

[1] M Graña, MA Veganzons, and B Ayerdi, "Hyperspectral remote sensing scenes," `https://www.ehu.eus/ccwintco/index.php/Hyperspectral_Remote_Sensing_Scenes`, Accessed: 29 July 2024. 1

Table 2: CPU execution times (in ms) of the different gradient algorithms. The best three performances are in boldface, underlined, and italicized, respectively.

	Algorithm	Indian Pines	Salinas	Salinas-A	Pavia Centre	Pavia University	KSC	Botswana
CPU: i7-13700F	GGSum	**12**	**68**	**4**	**246**	**58**	**156**	**160**
	GGEuc	$\underline{18}$	$\underline{69}$	**4**	496	$\underline{61}$	$\underline{163}$	$\underline{168}$
	DZ	**12**	*81*	**4**	*361*	*74*	199	*205*
	Sa	**12**	*81*	**4**	$\underline{359}$	*74*	*198*	*205*
	MGMax	376	1929	*115*	6637	1772	4461	4583
	MGSum	374	1920	*115*	6634	1775	4468	4573
	MGEuc	405	1932	116	6974	1780	4484	4591
	CMG	802	4469	279	14078	3639	9901	9253
	MorphArea	*30*	184	$\underline{8}$	569	126	421	370
	MorphL1	912	4986	312	15732	4060	11028	10415
	MorphSS	1402	7177	436	19986	5071	15409	14238

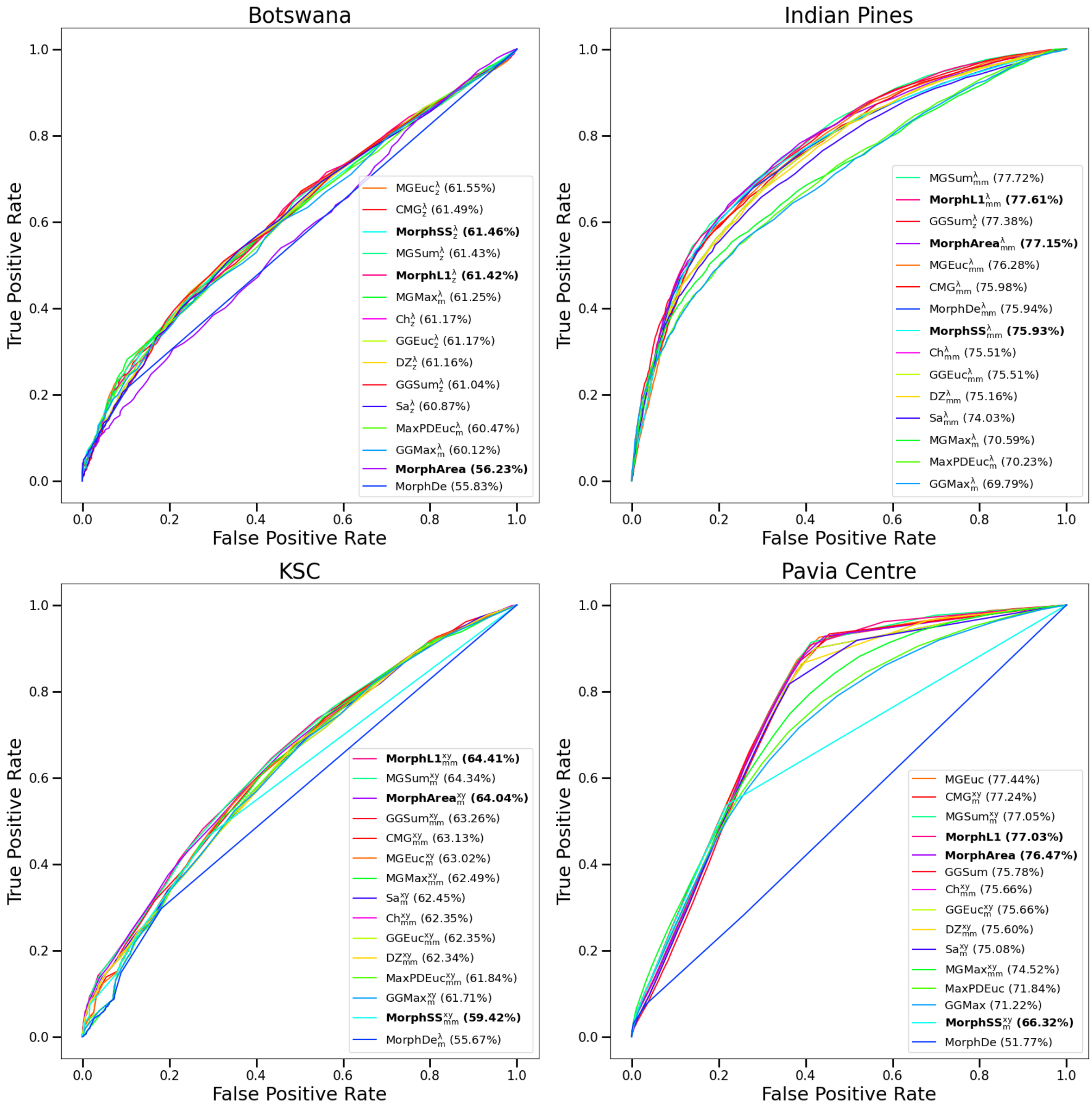


Fig. 1: ROC and AUC (%) for Botswana, Indian Pines, KSC, and Pavia Centre datasets.

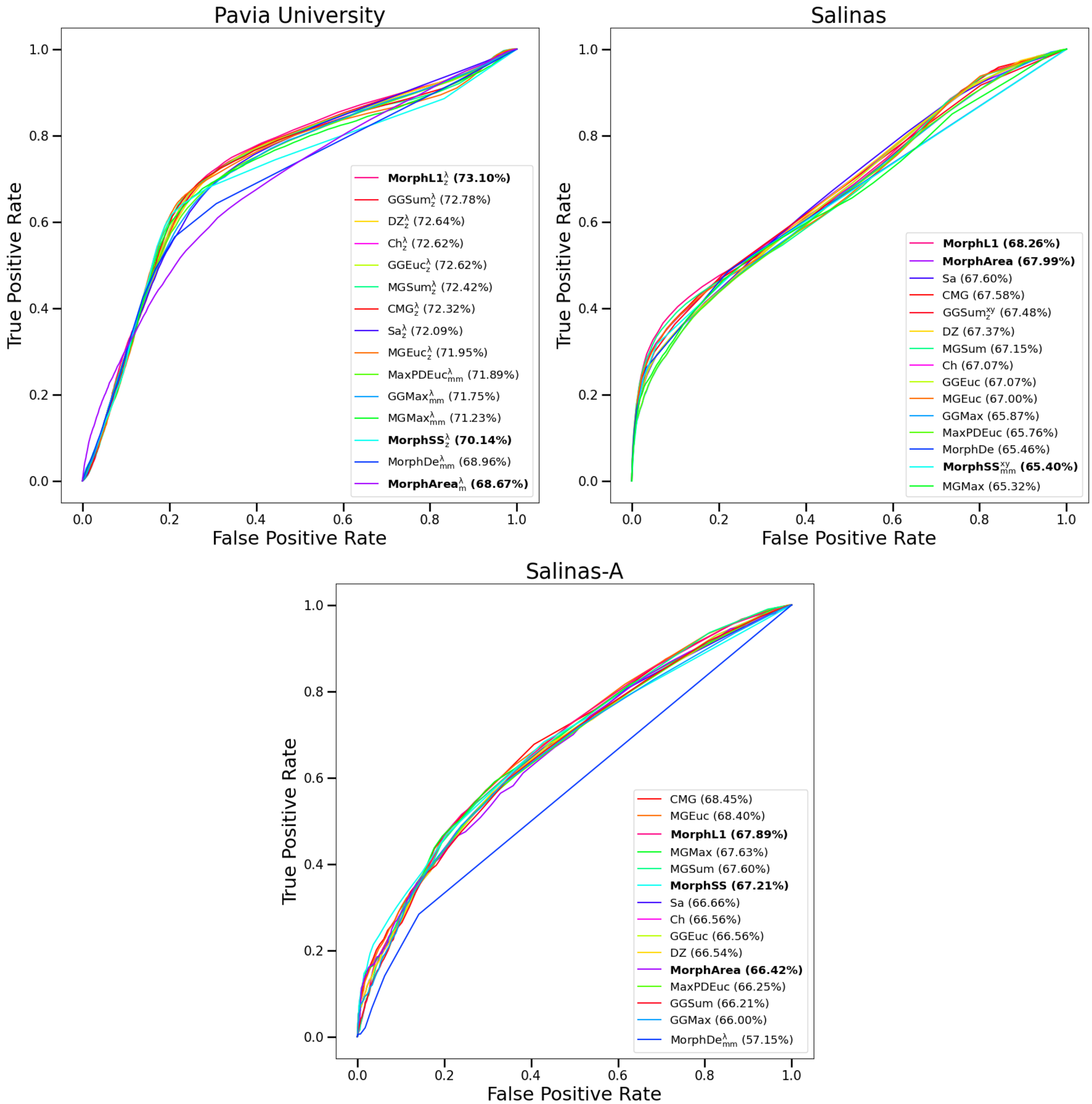
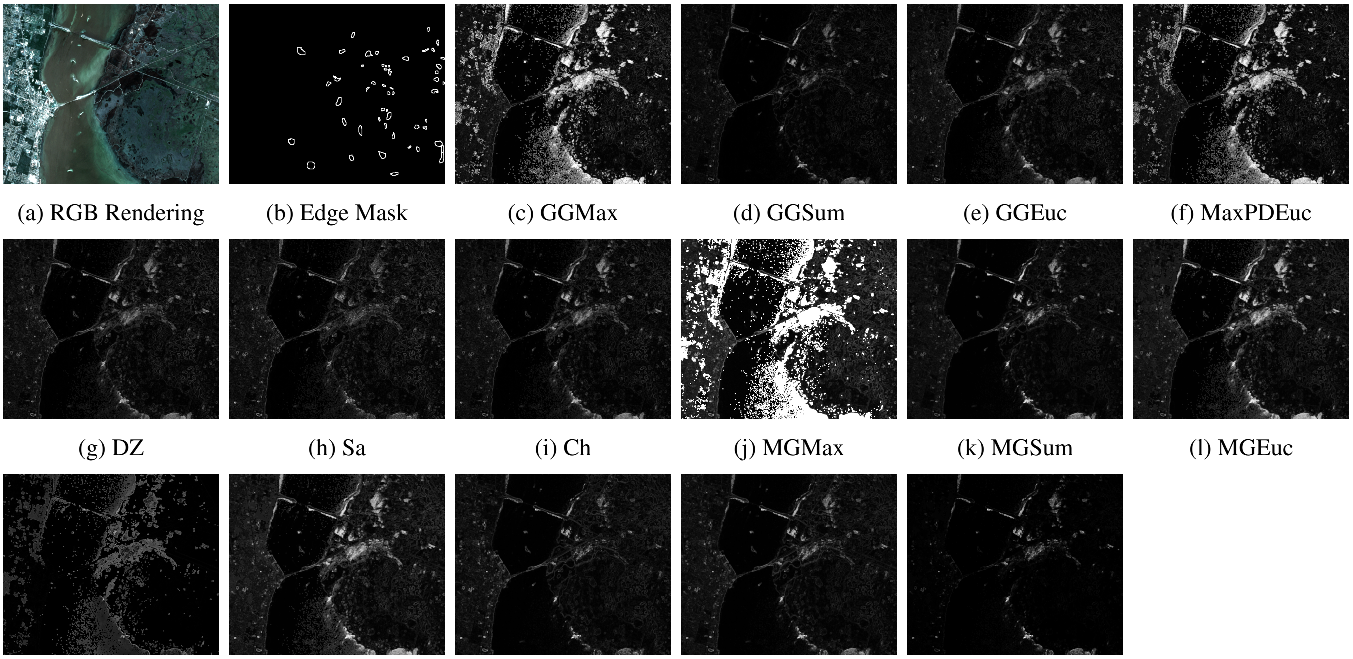


Fig. 2: ROC and AUC (%) for Pavia University, Salinas, and Salinas-A.

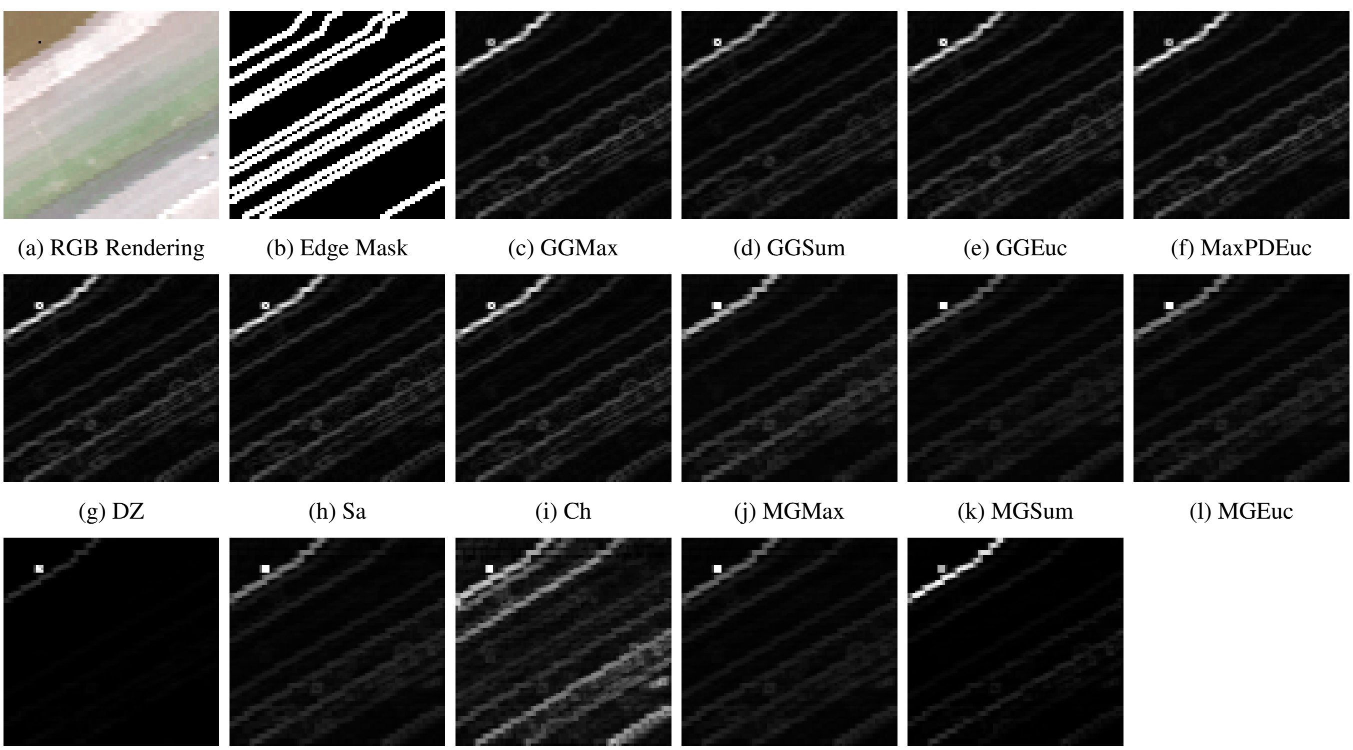


(a) RGB Rendering (b) Edge Mask (c) GGMax (d) GGSum (e) GGEuc (f) MaxPDEuc

(g) DZ (h) Sa (i) Ch (j) MGMax (k) MGSum (l) MGEuc

(m) MorphDe (n) CMG (o) MorphArea (p) MorphL1 (q) MorphSS

Fig. 3: KSC dataset, its edge mask, and corresponding gradient magnitude images.

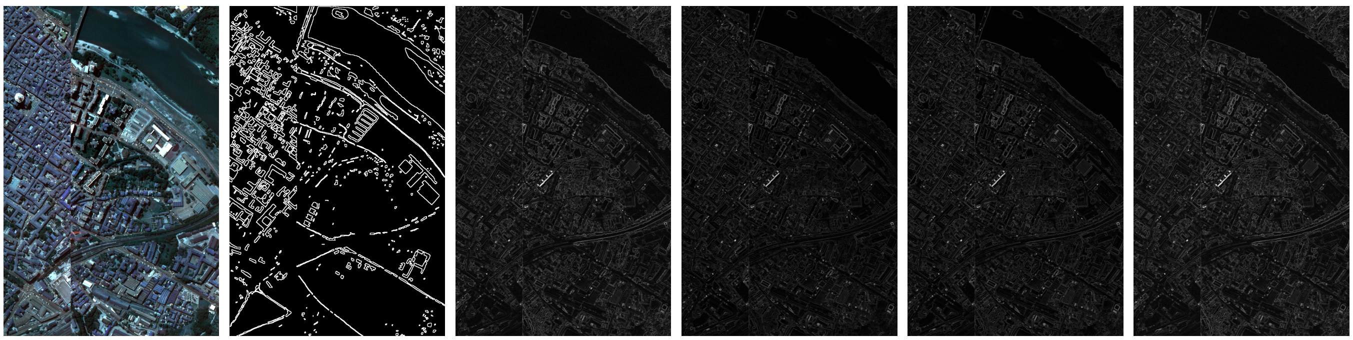


(a) RGB Rendering (b) Edge Mask (c) GGMax (d) GGSum (e) GGEuc (f) MaxPDEuc

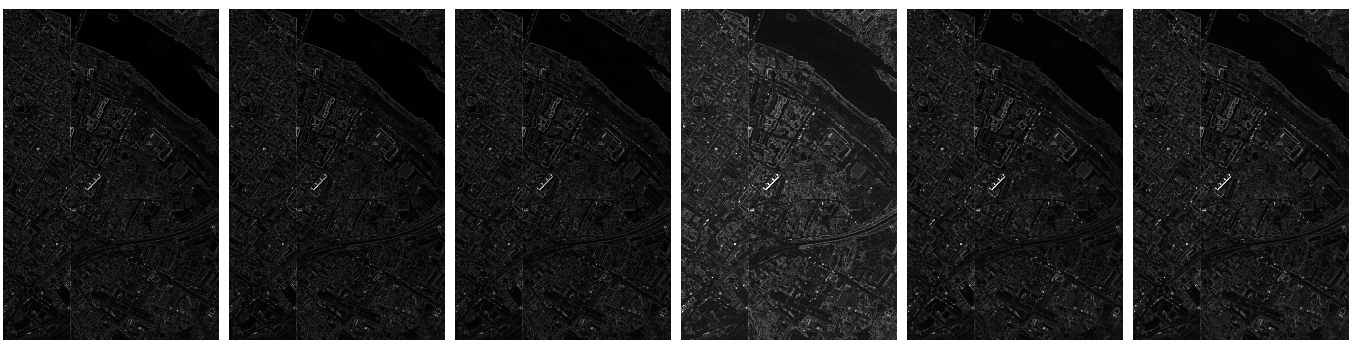
(g) DZ (h) Sa (i) Ch (j) MGMax (k) MGSum (l) MGEuc

(m) MorphDe (n) CMG (o) MorphArea (p) MorphL1 (q) MorphSS

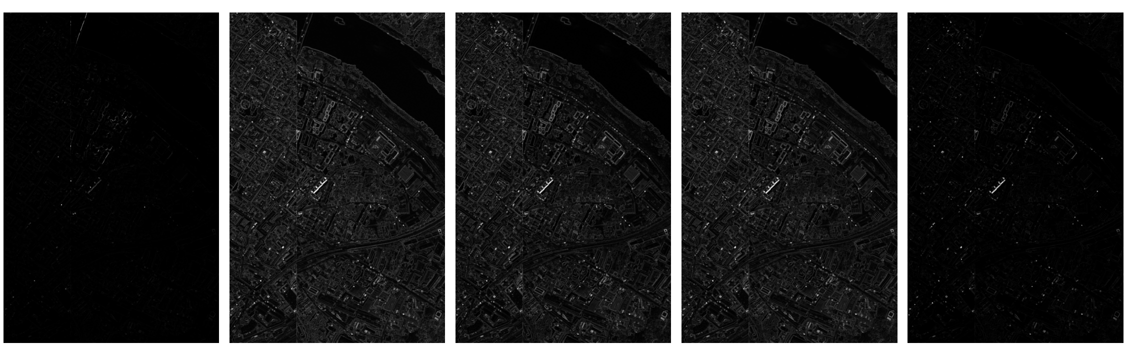
Fig. 4: Salinas-A dataset, its edge mask, and corresponding gradient magnitude images.



(a) RGB Rendering (b) Edge Mask (c) GGMax (d) GGSum (e) GGEuc (f) MaxPDEuc

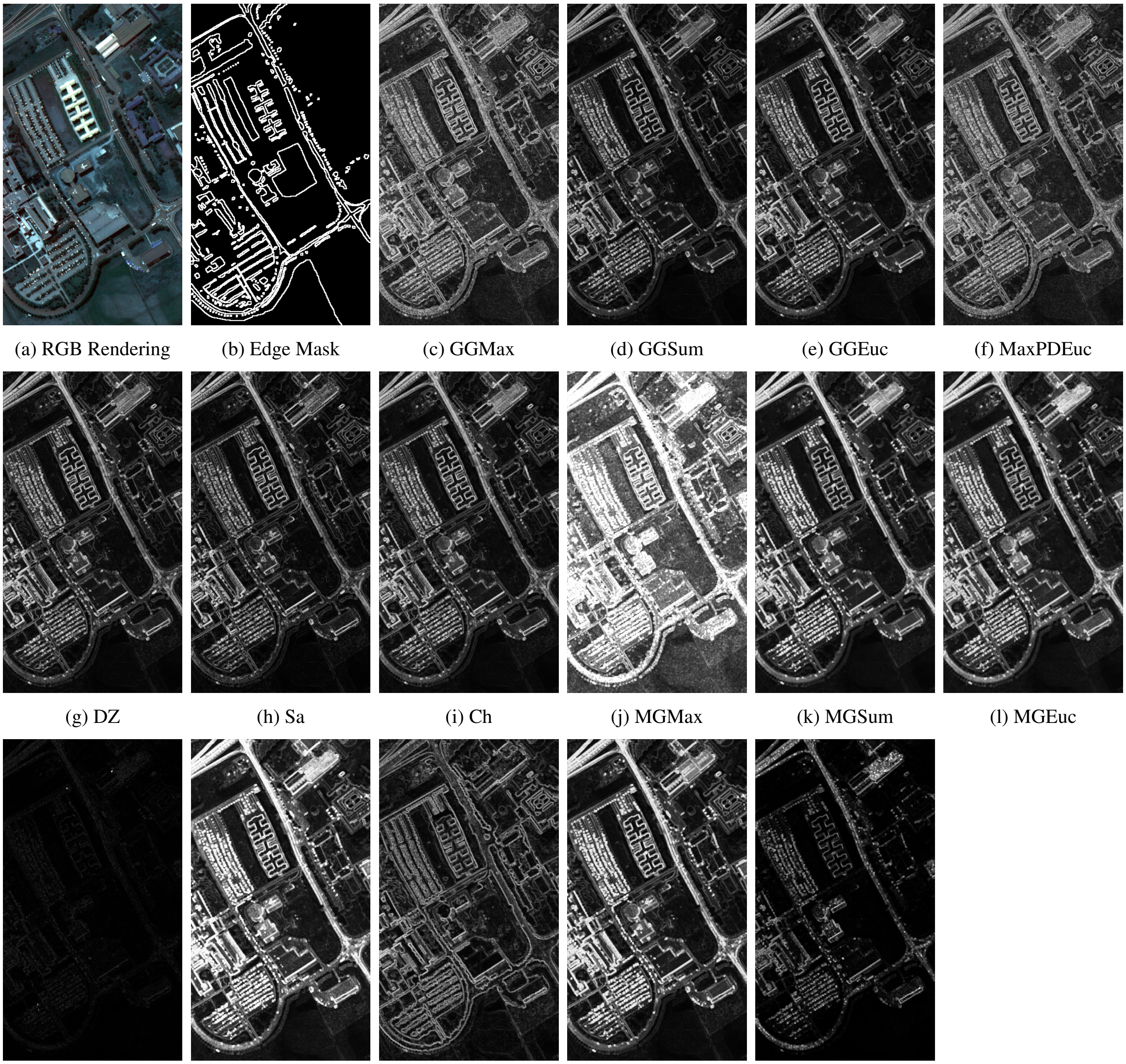


(g) DZ (h) Sa (i) Ch (j) MGMax (k) MGSum (l) MGEuc



(m) MorphDe (n) CMG (o) MorphArea (p) MorphL1 (q) MorphSS

Fig. 5: Pavia Centre dataset, its edge mask, and corresponding gradient magnitude images.

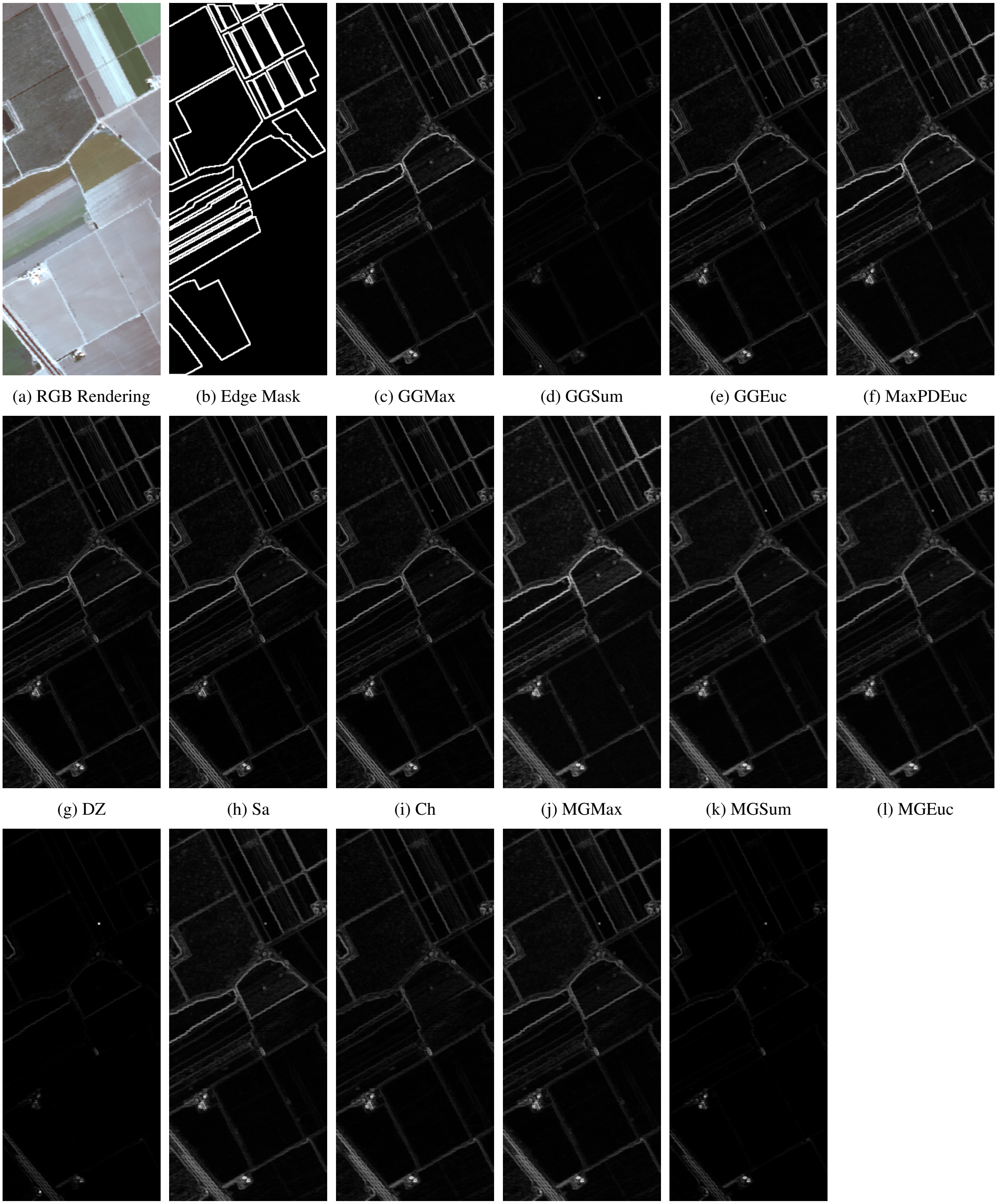


(a) RGB Rendering (b) Edge Mask (c) GGMax (d) GGSum (e) GGEuc (f) MaxPDEuc

(g) DZ (h) Sa (i) Ch (j) MGMax (k) MGSum (l) MGEuc

(m) MorphDe (n) CMG (o) MorphArea (p) MorphL1 (q) MorphSS

Fig. 6: Pavia University dataset, its edge mask, and corresponding gradient magnitude images.

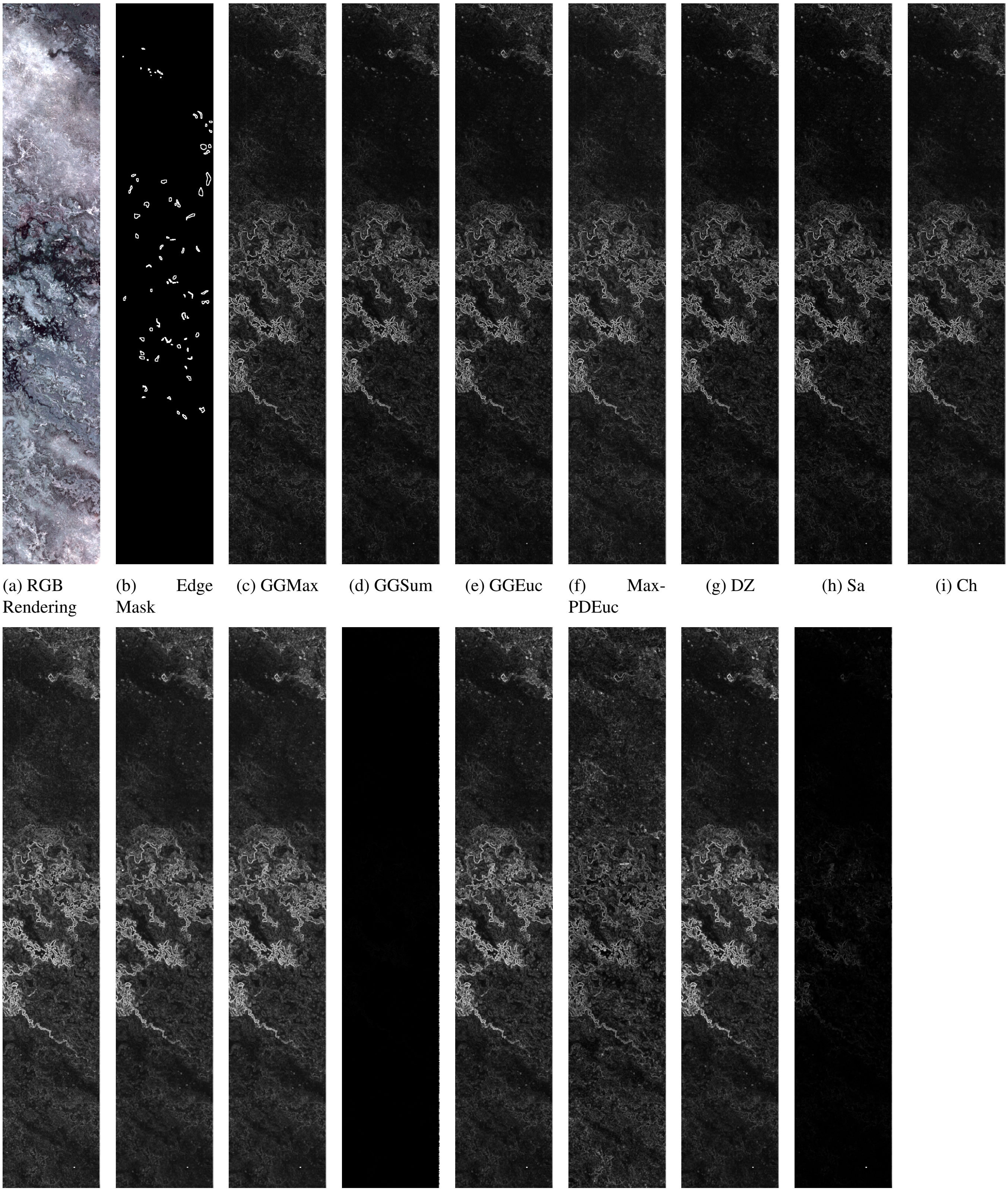


(a) RGB Rendering (b) Edge Mask (c) GGMax (d) GGSum (e) GGEuc (f) MaxPDEuc

(g) DZ (h) Sa (i) Ch (j) MGMax (k) MGSum (l) MGEuc

(m) MorphDe (n) CMG (o) MorphArea (p) MorphL1 (q) MorphSS

Fig. 7: Salinas dataset, its edge mask, and corresponding gradient magnitude images.



(a) RGB Rendering (b) Edge Mask (c) GGMax (d) GGSum (e) GGEuc (f) MaxPDEuc (g) DZ (h) Sa (i) Ch

(j) MGMax (k) MGSum (l) MGEuc (m) MorphDe (n) CMG (o) MorphArea (p) MorphL1 (q) MorphSS

Fig. 8: Botswana dataset, its edge mask, and corresponding gradient magnitude images.