A. Appendix

A.1. Results for 8× Super-Resolution

Table 4 reports quantitative results at $8\times$ super-resolution (SR) for Tanks & Temples [15]. We downsample the original 1920×1080 images by $16\times$ and upsample by $8\times$ to half the native resolution. Our method achieves the best SSIM, PSNR, LPIPS, FID, and DreamSim scores. 3DGS (LR) attains higher MUSIQ and NIQE scores, consistent with the behavior discussed in Section 6. Our CMMD score ranks fourth among the compared methods. Prior work [12] shows that CMMD is sensitive to high-frequency distortions introduced by noise in the embedding space. We hypothesize that sharpening effects like mild aliasing or overly crisp edges at high upsampling factors may be interpreted as distortions by CMMD, even when they improve perceptual quality and are reflected positively by other metrics. As no single metric fully characterizes visual fidelity, we report a broad suite of metrics for a more complete evaluation.

Table 5 presents the $8\times$ SR results for Deep Blending [8] and Mip-NeRF 360 [1]. For Deep Blending, we downsample the original images by $8\times$ ($\sim$125$\times$125) and upsample by $8\times$ back to the native resolution ($\sim$1K$\times$1K). For Mip-NeRF 360, we downsample the original images by $16\times$ ($\sim$250$\times$188) and upsample by $8\times$ to half the native resolution ($\sim$2K$\times$1.5K). SplatSuRe achieves the best results across all metrics on Deep Blending and nearly all metrics on Mip-NeRF 360, slightly trailing only Mip-Splatting [33] on SSIM while outperforming SRGS [6]. In these settings, the LR images contain limited high-frequency information due to their lower resolutions, requiring SR to hallucinate substantially more detail. This contrasts with the $4\times$ setting in Section 6, where the higher-resolution inputs in Mip-NeRF 360 reduce the need for SR and favor anti-aliasing approaches such as Mip-Splatting. These results emphasize that our selective SR method yields higher image quality than uniform application, even in settings with highly generative, view-inconsistent SR.

A.2. Unified Training Pipeline

Table 6 evaluates a unified training pipeline that merges the LR initialization and SR refinement stages to avoid the training time overhead introduced by the two-stage pipeline in Section 4. The model is trained with LR images for the first 5K iterations to obtain stable geometry, after which the Gaussian fidelity scores and SR weight maps are computed and training continues with SR supervision for the remaining 25K iterations. The total budget of 30K iterations matches that used by baseline methods using a single-stage pipeline. This unified approach achieves performance comparable to the original two-stage formulation reported in Tables 1 and 2, indicating that our SplatSuRe objective remains effective as a single continuous training schedule.

A.3. Additional Ratio Threshold Analysis

Different scenes exhibit distinct behaviors as the ratio threshold and corresponding amount of super-resolution (SR) information increase. Most scenes benefit from a moderate amount of SR but experience a sharp drop in image quality when it is excessively applied, while others plateau or continue improving with diminishing returns. We visualize these trends by plotting PSNR and LPIPS across ratio thresholds for three representative scenes in each category.

Figure 7 illustrates scenes that benefit from an optimal amount of SR. Image quality initially improves with moderate SR but decreases sharply when it is excessively applied. Our method identifies the most poorly sampled regions and selectively applies SR to them, yielding a substantial initial quality boost. However, applying excessive SR introduces multi-view inconsistencies that rapidly degrade image quality. This behavior appears consistently across most scenes, supporting our hypothesis that selectively applying SR is more beneficial than applying it uniformly.

Figure 8 presents scenes that plateau in image quality or continue improving slightly as the amount of SR is increased. Our selective SR method produces sharp early quality gains at lower ratio thresholds, after which applying additional SR yields diminishing returns or no improvement. In particular, this occurs in scenes where the input images already contain substantial high-frequency detail and SR produces simpler sharpening or edge enhancement effects rather than hallucinating new structure, making uniform application less harmful and sometimes marginally beneficial. This behavior is especially common in outdoor scenes in Mip-NeRF 360 [1], where the downsampled $\sim 500 \times 375$ images remain relatively high-resolution and therefore do not exhibit the multi-view inconsistencies that typically arise when excessive SR is applied.

A.4. Additional Visualizations

Figures 9 and 10 present additional qualitative results on Tanks & Temples [15]. Consistent with the examples in Figures 1 and 5 discussed in Section 6, SplatSuRe produces sharper reconstructions than competing methods while reducing artifacts and preserving smoothness in uniformly textured regions.

A.5. Per-Scene Metrics

Tables 7, 8, 9, 10, 11, 12, 13, and 14 report per-scene SSIM, PSNR, LPIPS, FID, CMMD, DreamSim, MUSIQ, and NIQE results on Tanks & Temples [15], Deep Blending [8], and Mip-NeRF 360 [1] for all methods evaluated in Section 5. Across individual scenes, we observe the same trends as in the averaged results presented by Tables 1 and 2 in Section 6: SplatSuRe achieves the strongest performance on Tanks & Temples and Deep Blending and outperforms SRGS on Mip-NeRF 360.

Table 4. **Quantitative results on Tanks & Temples [15] at 8× super-resolution.** Experiments are performed using ratio threshold τ=1.1. The best , second best and third best entries are highlighted. Our SplatSuRe method achieves the strongest results on most metrics.

Method	Tanks & Temples [15]							
	SSIM ↑	PSNR ↑	LPIPS ↓	FID ↓	CMMD ↓	DreamSim ↓	MUSIQ ↑	NIQE ↓
3DGS (LR) [14]	0.537	16.40	0.473	172.44	3.795	0.2427	46.870	3.976
3DGS [14] + StableSR [27]	0.664	21.49	0.406	99.80	1.878	0.1100	38.929	6.293
Mip-Splatting [33]	0.661	21.53	0.428	109.01	1.941	0.1183	32.417	6.645
SRGS [6] + StableSR [27]	0.674	21.97	0.399	92.91	1.891	0.0981	38.322	6.138
Ours + StableSR [27]	0.692	22.48	0.378	77.17	2.007	0.0774	44.428	5.341

Table 5. **Quantitative results on Deep Blending [8] and Mip-NeRF 360 [1] at 8× super-resolution.** Experiments are performed using ratio threshold τ=1.1. Our SplatSuRe method achieves the strongest results on almost all metrics.

Method	Deep Blending [8]					Mip-NeRF 360 [1]				
	SSIM ↑	PSNR ↑	LPIPS ↓	CMMD ↓	DreamSim ↓	SSIM ↑	PSNR ↑	LPIPS ↓	CMMD ↓	DreamSim ↓
3DGS (LR) [14]	0.783	24.50	0.404	2.051	0.1280	0.509	18.17	0.491	2.395	0.1337
3DGS [14] + StableSR [27]	0.821	26.68	0.383	1.159	0.0705	0.630	24.23	0.445	1.096	0.0546
Mip-Splatting [33]	0.831	27.24	0.391	1.127	0.0689	0.656	24.80	0.420	0.610	0.0243
SRGS [6] + StableSR [27]	0.830	27.35	0.377	1.079	0.0622	0.648	24.88	0.422	0.665	0.0320
Ours + StableSR [27]	0.843	28.03	0.357	0.879	0.0489	0.655	25.08	0.406	0.546	0.0231

Table 6. **Quantitative comparison of our unified and two-stage pipelines at 4× SR across Tanks & Temples [15], Deep Blending [8], and Mip-NeRF 360 [1].** Experiments are performed using ratio threshold $\tau = 1.1$. The best entry is **bolded**. The unified pipeline achieves similar performance to the two-stage approach while requiring less training time.

Dataset	Method	SSIM ↑	PSNR ↑	LPIPS ↓	FID ↓	CMMD ↓	DreamSim ↓	MUSIQ ↑	NIQE ↓
Tanks & Temples [15]	Two-Stage	**0.784**	**23.81**	0.272	37.72	1.040	0.0413	58.332	3.928
	Unified	0.781	23.70	**0.271**	**36.02**	**1.006**	**0.0400**	**59.701**	**3.705**
Deep Blending [8]	Two-Stage	**0.872**	**29.01**	0.306	44.14	0.496	0.0330	**53.019**	5.411
	Unified	0.871	28.96	**0.304**	**41.70**	**0.483**	**0.0326**	52.983	**5.286**
Mip-NeRF 360 [1]	Two-Stage	0.740	26.34	0.323	**27.56**	0.339	0.0179	54.366	3.934
	Unified	**0.758**	**26.69**	**0.304**	26.18	**0.271**	**0.0164**	**56.773**	**3.715**

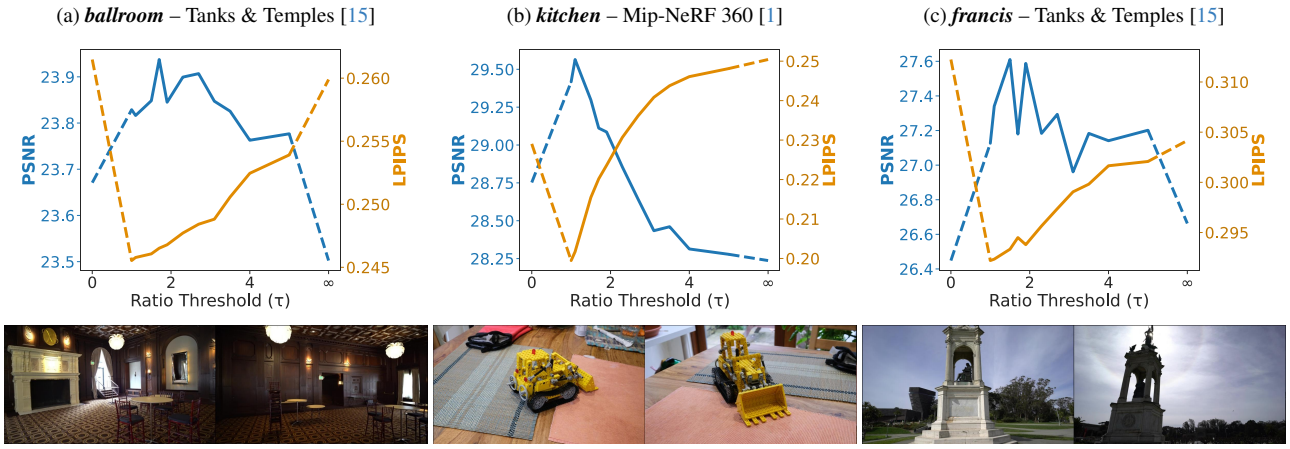

Figure 7. **Representative scenes that benefit from an optimal amount of super-resolution.** Top: Image quality vs. ratio threshold plots. Bottom: ground truth images illustrating scene structure for (a) *ballroom* from Tanks & Temples [15], (b) *kitchen* from Mip-NeRF 360 [1] and (c) *francis* from Tanks & Temples. Applying SR to the most poorly sampled regions yields large gains in image quality, whereas excessive SR introduces multi-view inconsistencies that sharply degrade quality. Most scenes exhibit this behavior, supporting our hypothesis that selectively applying SR is more beneficial than applying it uniformly.

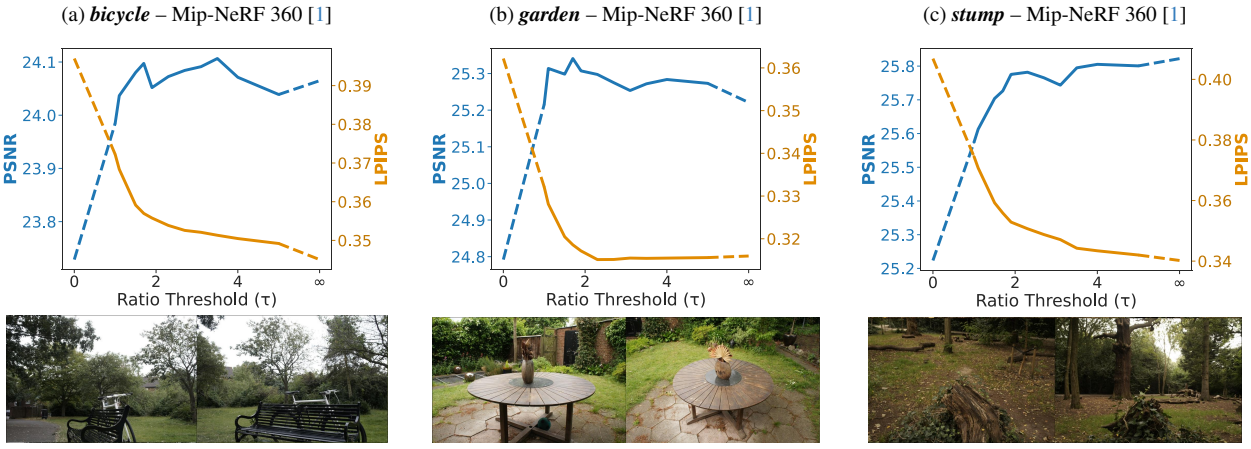

Figure 8. **Representative scenes that plateau in image quality or continue to benefit from increased amounts of super-resolution.** Top: Image quality vs. ratio threshold plots. Bottom: ground truth images illustrating scene structure for (a) *bicycle*, (b) *garden*, and (c) *stump* from Mip-NeRF 360 [1]. Applying SR to the most poorly sampled regions yields large gains in image quality, while further increasing SR yields diminishing returns or no improvement. In particular, this occurs in scenes where the input images already contain substantial high-frequency detail and SR produces simpler sharpening or edge-enhancement effects rather than hallucinating new structure, making uniform application less harmful and sometimes marginally beneficial.

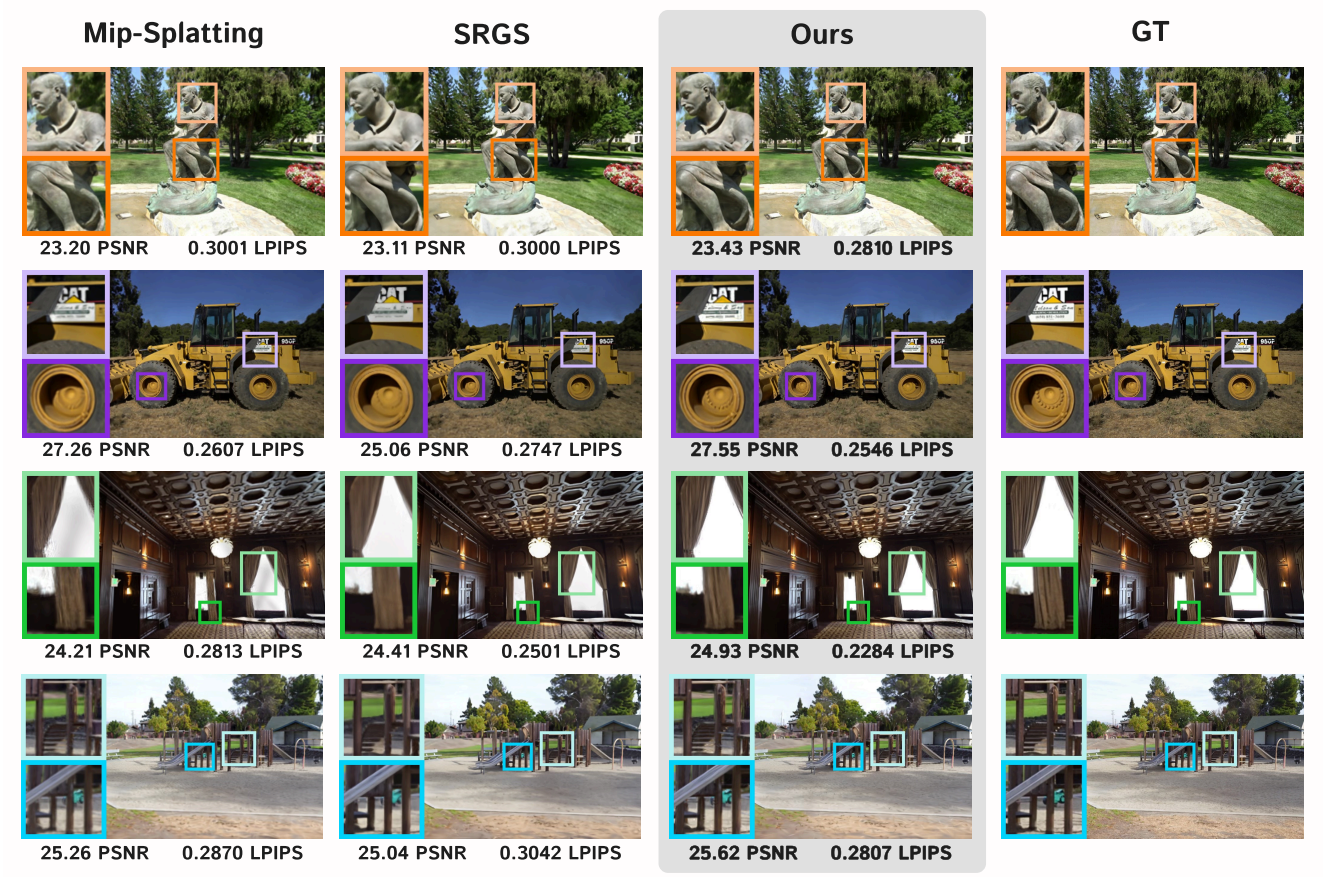

Figure 9. **Additional qualitative results on Tanks & Temples [15].** Experiments are performed at $4\times$ super-resolution with ratio threshold τ=1.1. Compared to Mip-Splatting [33] and SRGS [6], our method produces sharper, more faithful reconstructions that better align with ground truth while maintaining cross-view consistency. It preserves high-frequency patterns (orange boxes on statue), fine details in text (purple box on vehicle), and reduces artifacts while preserving sharpness (green boxes on curtains, blue boxes in playground).

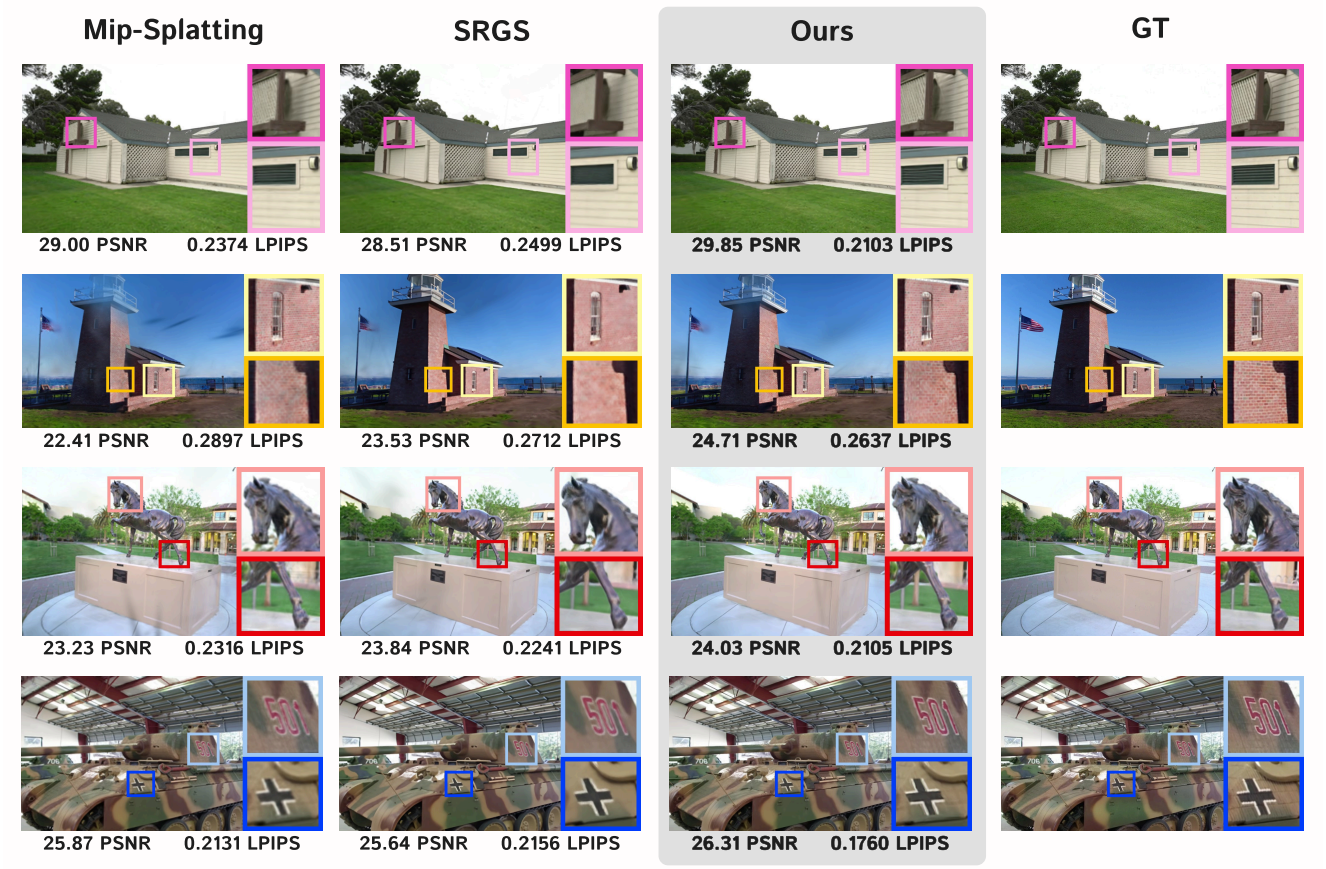

Figure 10. **Additional qualitative results on Tanks & Temples [15].** Experiments are performed at $4\times$ super-resolution with ratio threshold τ=1.1. Compared to Mip-Splatting [33] and SRGS [6], our method produces sharper, more faithful reconstructions that better align with the ground truth while maintaining cross-view consistency. It preserves high-frequency geometry (pink boxes on barn) and retains sharp texture (yellow boxes on lighthouse, red boxes on horse statue, blue boxes on tank).

Table 7. **SSIM ↑ on each scene in Tanks & Temples [15], Deep Blending [8], and Mip-NeRF 360 [1].** Experiments are performed at 4× super-resolution using ratio threshold τ=1.1. The best, second best and third best entries are highlighted.

Method	Tanks & Temples [15]																	
	auditorium	*ignatius*	*palace*	*ballroom*	*panther*	*barn*	*lighthouse*	*playground*	*courtroom*	*m60*	*temple*	*caterpillar*	*family*	*train*	*francis*	*truck*	*church*	*horse*	*museum*
3DGS (LR) [14]	0.807	0.527	0.666	0.578	0.752	0.729	0.742	0.628	0.647	0.735	0.715	0.602	0.566	0.648	0.779	0.649	0.682	0.675	0.579
3DGS [14] + StableSR [27]	0.849	0.646	0.709	0.702	0.819	0.771	0.777	0.720	0.725	0.810	0.761	0.686	0.753	0.705	0.845	0.759	0.744	0.811	0.683
Mip-Splatting [33]	0.838	0.681	0.687	0.729	0.847	0.790	0.789	0.746	0.730	0.836	0.762	0.704	0.788	0.733	0.855	0.786	0.753	0.827	0.689
SRGS [6] + StableSR [27]	0.861	0.671	0.713	0.734	0.846	0.794	0.789	0.742	0.746	0.835	0.773	0.703	0.780	0.729	0.857	0.784	0.761	0.829	0.704
Ours + StableSR [27]	0.859	0.694	0.717	0.746	0.859	0.808	0.807	0.764	0.752	0.846	0.786	0.714	0.795	0.743	0.866	0.798	0.781	0.835	0.716

Method	Deep Blending [8]		Mip-NeRF 360 [1]								
	drjohnson	*playroom*	*bicycle*	*bonsai*	*counter*	*flowers*	*garden*	*kitchen*	*room*	*stump*	*treehill*
3DGS (LR) [14]	0.828	0.843	0.527	0.776	0.772	0.429	0.559	0.719	0.836	0.581	0.516
3DGS [14] + StableSR [27]	0.837	0.854	0.604	0.848	0.833	0.497	0.654	0.751	0.858	0.669	0.571
Mip-Splatting [33]	0.855	0.874	0.676	0.917	0.872	0.544	0.719	0.870	0.897	0.740	0.596
SRGS [6] + StableSR [27]	0.851	0.870	0.653	0.896	0.863	0.533	0.692	0.825	0.888	0.671	0.590
Ours + StableSR [27]	0.867	0.877	0.646	0.906	0.867	0.503	0.690	0.869	0.896	0.706	0.582

Table 8. **PSNR ↑ on each scene in Tanks & Temples [15], Deep Blending [8], and Mip-NeRF 360 [1].**

Method	Tanks & Temples [15]																	
	auditorium	*ignatius*	*palace*	*ballroom*	*panther*	*barn*	*lighthouse*	*playground*	*courtroom*	*m60*	*temple*	*caterpillar*	*family*	*train*	*francis*	*truck*	*church*	*horse*	*museum*
3DGS (LR) [14]	22.14	17.13	18.35	18.23	22.49	22.97	20.47	19.85	19.53	21.72	18.99	19.36	15.09	18.80	22.47	17.38	20.00	16.30	17.44
3DGS [14] + StableSR [27]	23.62	20.52	19.68	22.20	25.23	25.18	21.65	23.24	21.75	24.72	20.24	22.44	22.54	20.55	25.97	22.86	22.02	22.72	19.76
Mip-Splatting [33]	23.46	21.22	18.24	23.15	27.11	26.85	21.29	24.13	22.26	26.16	20.31	22.99	24.09	21.33	26.62	23.94	21.99	23.48	20.28
SRGS [6] + StableSR [27]	24.23	21.26	19.69	23.44	26.98	26.83	21.74	24.12	22.74	26.17	20.49	22.98	23.82	21.28	26.55	23.87	22.54	23.72	20.63
Ours + StableSR [27]	24.66	21.61	20.24	23.82	27.38	27.33	22.82	25.12	22.99	26.63	21.39	23.34	24.00	21.79	27.34	24.11	23.18	23.94	20.77

Method	Deep Blending [8]		Mip-NeRF 360 [1]								
	drjohnson	*playroom*	*bicycle*	*bonsai*	*counter*	*flowers*	*garden*	*kitchen*	*room*	*stump*	*treehill*
3DGS (LR) [14]	26.29	27.15	18.50	22.75	23.27	17.60	18.64	19.55	25.93	20.34	19.44
3DGS [14] + StableSR [27]	26.60	27.71	22.87	26.48	26.44	19.92	23.80	24.80	28.32	24.24	21.64
Mip-Splatting [33]	27.54	29.33	24.28	30.65	28.28	21.05	25.63	29.48	30.69	26.20	22.08
SRGS [6] + StableSR [27]	27.38	29.08	24.05	29.81	28.11	20.91	25.20	28.26	30.42	24.58	21.97
Ours + StableSR [27]	28.46	29.57	24.04	30.54	28.39	20.55	25.31	29.56	31.05	25.61	22.02

Table 9. **LPIPS ↓ on each scene in Tanks & Temples [15], Deep Blending [8], and Mip-NeRF 360 [1].**

Method	Tanks & Temples [15]																	
	auditorium	*ignatius*	*palace*	*ballroom*	*panther*	*barn*	*lighthouse*	*playground*	*courtroom*	*m60*	*temple*	*caterpillar*	*family*	*train*	*francis*	*truck*	*church*	*horse*	*museum*
3DGS (LR) [14]	0.301	0.411	0.380	0.337	0.309	0.317	0.303	0.371	0.376	0.302	0.335	0.385	0.408	0.346	0.352	0.345	0.343	0.322	0.400
3DGS [14] + StableSR [27]	0.247	0.357	0.364	0.283	0.275	0.295	0.283	0.333	0.294	0.266	0.302	0.340	0.289	0.305	0.316	0.298	0.306	0.234	0.317
Mip-Splatting [33]	0.275	0.331	0.408	0.288	0.260	0.293	0.296	0.316	0.323	0.250	0.325	0.325	0.281	0.298	0.316	0.284	0.313	0.237	0.345
SRGS [6] + StableSR [27]	0.242	0.328	0.367	0.266	0.251	0.277	0.276	0.311	0.292	0.242	0.299	0.321	0.271	0.289	0.304	0.274	0.294	0.221	0.315
Ours + StableSR [27]	0.248	0.310	0.355	0.246	0.228	0.262	0.259	0.284	0.285	0.225	0.290	0.313	0.257	0.281	0.292	0.253	0.272	0.211	0.300

Method	Deep Blending [8]		Mip-NeRF 360 [1]								
	drjohnson	*playroom*	*bicycle*	*bonsai*	*counter*	*flowers*	*garden*	*kitchen*	*room*	*stump*	*treehill*
3DGS (LR) [14]	0.332	0.339	0.424	0.328	0.306	0.477	0.400	0.312	0.293	0.436	0.482
3DGS [14] + StableSR [27]	0.315	0.335	0.407	0.256	0.258	0.461	0.356	0.301	0.267	0.394	0.460
Mip-Splatting [33]	0.334	0.321	0.318	0.212	0.242	0.397	0.292	0.205	0.245	0.314	0.403
SRGS [6] + StableSR [27]	0.311	0.323	0.349	0.232	0.239	0.420	0.315	0.249	0.250	0.368	0.428
Ours + StableSR [27]	0.300	0.312	0.368	0.238	0.241	0.454	0.328	0.202	0.253	0.371	0.452

Table 10. **FID ↓ on each scene in Tanks & Temples [15], Deep Blending [8], and Mip-NeRF 360 [1].**

Method	Tanks & Temples [15]																	
	auditorium	*ignatius*	*palace*	*ballroom*	*panther*	*barn*	*lighthouse*	*playground*	*courtroom*	*m60*	*temple*	*caterpillar*	*family*	*train*	*francis*	*truck*	*church*	*horse*	*museum*
3DGS (LR) [14]	86.75	85.58	83.25	73.89	40.93	40.48	84.46	82.51	99.19	53.16	81.79	29.93	113.45	43.80	29.64	35.69	58.24	148.48	88.82
3DGS [14] + StableSR [27]	68.24	114.03	83.65	49.37	38.50	48.11	72.12	66.81	64.95	40.68	78.22	25.98	68.88	35.61	31.14	32.99	54.69	97.74	54.73
Mip-Splatting [33]	78.68	52.74	138.29	40.43	24.78	36.49	67.71	59.20	69.94	25.38	82.25	20.50	38.03	30.99	20.36	20.20	48.50	81.54	60.69
SRGS [6] + StableSR [27]	58.94	79.04	97.00	37.35	26.97	36.74	66.75	54.86	59.58	27.03	75.46	20.10	43.93	29.88	23.64	22.37	45.17	77.02	51.28
Ours + StableSR [27]	60.48	46.33	70.53	27.26	20.96	27.20	57.93	35.69	54.34	19.79	63.87	16.42	28.28	22.83	16.72	14.82	32.61	58.61	41.93

Method	Deep Blending [8]		Mip-NeRF 360 [1]								
	drjohnson	*playroom*	*bicycle*	*bonsai*	*counter*	*flowers*	*garden*	*kitchen*	*room*	*stump*	*treehill*
3DGS (LR) [14]	60.62	72.04	30.50	72.93	79.04	77.01	47.98	59.89	41.92	89.83	42.08
3DGS [14] + StableSR [27]	51.64	67.41	23.55	54.42	64.89	73.04	19.38	49.64	37.09	105.27	40.16
Mip-Splatting [33]	53.90	50.26	10.21	20.19	36.29	22.76	9.05	12.04	17.57	37.03	20.21
SRGS [6] + StableSR [27]	47.05	51.10	11.37	26.41	41.87	46.01	10.46	15.43	21.62	42.73	26.52
Ours + StableSR [27]	43.19	45.09	11.79	22.40	38.03	58.56	10.63	8.47	17.69	50.63	29.83

Table 11. **CMMD ↓ on each scene in Tanks & Temples [15], Deep Blending [8], and Mip-NeRF 360 [1].**

Method	Tanks & Temples [15]																	
	auditorium	*ignatius*	*palace*	*ballroom*	*panther*	*barn*	*lighthouse*	*playground*	*courtroom*	*m60*	*temple*	*caterpillar*	*family*	*train*	*francis*	*truck*	*church*	*horse*	*museum*
3DGS (LR) [14]	1.770	2.234	2.361	1.602	0.718	1.699	1.540	1.925	1.616	1.202	2.522	1.897	3.038	2.153	2.758	2.140	1.705	3.211	2.165
3DGS [14] + StableSR [27]	1.093	1.032	1.491	1.073	0.791	1.068	1.092	1.139	0.987	0.907	1.597	1.464	0.647	1.330	1.401	1.143	1.163	0.779	1.142
Mip-Splatting [33]	1.246	1.046	1.624	0.787	0.633	1.140	0.994	1.151	1.024	0.579	1.853	1.243	0.863	1.384	1.286	1.080	1.029	1.105	1.528
SRGS [6] + StableSR [27]	1.066	0.931	1.582	0.787	0.516	0.942	0.978	0.998	0.943	0.523	1.795	1.261	0.557	1.383	1.408	1.140	1.049	0.658	1.400
Ours + StableSR [27]	0.993	1.121	1.568	0.643	0.351	1.134	0.901	1.025	0.951	0.443	1.699	1.330	0.521	1.529	1.355	1.061	0.944	0.897	1.286

Method	Deep Blending [8]		Mip-NeRF 360 [1]								
	drjohnson	*playroom*	*bicycle*	*bonsai*	*counter*	*flowers*	*garden*	*kitchen*	*room*	*stump*	*treehill*
3DGS (LR) [14]	1.003	0.733	0.392	1.011	0.319	1.354	0.242	0.346	0.261	0.926	0.956
3DGS [14] + StableSR [27]	0.807	0.714	0.621	0.934	0.440	1.409	0.310	0.441	0.578	0.767	1.023
Mip-Splatting [33]	0.828	0.552	0.099	0.346	0.195	0.215	0.036	0.191	0.187	0.125	0.257
SRGS [6] + StableSR [27]	0.715	0.546	0.138	0.417	0.279	0.782	0.081	0.228	0.378	0.261	0.486
Ours + StableSR [27]	0.558	0.434	0.159	0.266	0.139	1.108	0.065	0.119	0.184	0.406	0.610

Table 12. **DreamSim ↓ on each scene in Tanks & Temples [15], Deep Blending [8], and Mip-NeRF 360 [1].**

Method	Tanks & Temples [15]																	
	auditorium	*ignatius*	*palace*	*ballroom*	*panther*	*barn*	*lighthouse*	*playground*	*courtroom*	*m60*	*temple*	*caterpillar*	*family*	*train*	*francis*	*truck*	*church*	*horse*	*museum*
3DGS (LR) [14]	0.0969	0.0884	0.1548	0.0881	0.0399	0.0549	0.1154	0.0806	0.1074	0.0552	0.1156	0.0595	0.1215	0.0747	0.0710	0.0620	0.0795	0.1142	0.1207
3DGS [14] + StableSR [27]	0.0634	0.0703	0.1497	0.0438	0.0443	0.0613	0.0909	0.0759	0.0566	0.0591	0.0955	0.0516	0.0565	0.0652	0.0555	0.0590	0.0558	0.0505	0.0627
Mip-Splatting [33]	0.0739	0.0465	0.2459	0.0312	0.0216	0.0392	0.0887	0.0541	0.0592	0.0266	0.1001	0.0392	0.0278	0.0479	0.0341	0.0293	0.0541	0.0438	0.0703
SRGS [6] + StableSR [27]	0.0500	0.0511	0.1603	0.0271	0.0264	0.0399	0.0792	0.0564	0.0466	0.0369	0.0936	0.0416	0.0359	0.0504	0.0402	0.0402	0.0459	0.0390	0.0567
Ours + StableSR [27]	0.0490	0.0381	0.1272	0.0202	0.0187	0.0314	0.0625	0.0369	0.0422	0.0239	0.0720	0.0315	0.0229	0.0410	0.0309	0.0268	0.0331	0.0279	0.0486

Method	Deep Blending [8]		Mip-NeRF 360 [1]								
	drjohnson	*playroom*	*bicycle*	*bonsai*	*counter*	*flowers*	*garden*	*kitchen*	*room*	*stump*	*treehill*
3DGS (LR) [14]	0.0613	0.0534	0.0624	0.0659	0.0453	0.0562	0.0452	0.0454	0.0322	0.0586	0.0558
3DGS [14] + StableSR [27]	0.0499	0.0510	0.0348	0.0320	0.0377	0.0598	0.0170	0.0240	0.0345	0.0536	0.0553
Mip-Splatting [33]	0.0451	0.0345	0.0126	0.0122	0.0166	0.0124	0.0070	0.0046	0.0163	0.0117	0.0252
SRGS [6] + StableSR [27]	0.0439	0.0378	0.0150	0.0160	0.0226	0.0331	0.0079	0.0066	0.0212	0.0178	0.0345
Ours + StableSR [27]	0.0332	0.0327	0.0151	0.0123	0.0177	0.0380	0.0071	0.0037	0.0144	0.0168	0.0364

Table 13. **MUSIQ ↑ on each scene in Tanks & Temples [15], Deep Blending [8], and Mip-NeRF 360 [1].**

Method	Tanks & Temples [15]																	
	auditorium	*ignatius*	*palace*	*ballroom*	*panther*	*barn*	*lighthouse*	*playground*	*courtroom*	*m60*	*temple*	*caterpillar*	*family*	*train*	*francis*	*truck*	*church*	*horse*	*museum*
3DGS (LR) [14]	55.443	64.965	51.161	56.309	54.610	60.048	48.785	54.510	55.349	53.631	57.565	59.116	65.987	60.573	59.605	61.675	57.991	57.572	62.845
3DGS [14] + StableSR [27]	58.573	58.466	49.326	56.501	57.051	60.822	46.028	53.817	55.209	54.985	54.748	60.520	62.883	60.841	55.264	60.637	55.297	54.926	62.311
Mip-Splatting [33]	51.773	48.745	42.653	50.651	46.800	49.040	33.568	41.815	45.084	47.621	46.236	51.797	49.461	51.300	40.700	47.208	47.433	39.068	53.893
SRGS [6] + StableSR [27]	57.276	57.690	48.339	54.321	54.969	58.305	44.228	52.796	54.435	53.662	52.762	58.732	61.687	58.721	54.220	57.781	54.378	53.369	61.291
Ours + StableSR [27]	58.504	60.078	50.762	59.501	56.915	61.660	47.882	58.036	57.351	55.500	55.978	60.757	65.967	60.214	57.281	62.616	57.574	58.244	63.491

Method	Deep Blending [8]		Mip-NeRF 360 [1]								
	drjohnson	*playroom*	*bicycle*	*bonsai*	*counter*	*flowers*	*garden*	*kitchen*	*room*	*stump*	*treehill*
3DGS (LR) [14]	47.916	49.425	54.239	56.108	55.829	58.968	58.961	63.552	50.931	52.085	41.783
3DGS [14] + StableSR [27]	52.919	53.324	55.767	59.725	57.965	52.194	54.576	59.952	58.135	44.337	38.276
Mip-Splatting [33]	38.800	44.105	38.243	44.656	42.445	35.728	44.342	50.600	41.878	35.866	35.112
SRGS [6] + StableSR [27]	50.849	52.035	54.818	56.237	55.391	53.542	54.318	58.321	55.637	44.039	37.260
Ours + StableSR [27]	50.594	55.444	57.923	58.501	57.752	51.206	56.236	64.952	55.154	49.551	38.014

Table 14. **NIQE ↓ on each scene in Tanks & Temples [15], Deep Blending [8], and Mip-NeRF 360 [1].**

Method	Tanks & Temples [15]																	
	auditorium	*ignatius*	*palace*	*ballroom*	*panther*	*barn*	*lighthouse*	*playground*	*courtroom*	*m60*	*temple*	*caterpillar*	*family*	*train*	*francis*	*truck*	*church*	*horse*	*museum*
3DGS (LR) [14]	4.718	2.628	4.293	2.791	3.884	3.944	4.097	2.744	3.385	3.625	4.081	2.873	2.605	2.994	4.269	2.784	3.169	3.011	2.926
3DGS [14] + StableSR [27]	6.531	4.545	5.820	4.335	5.239	5.229	5.415	4.991	4.830	5.022	4.844	4.690	4.214	4.363	5.611	4.361	5.005	4.564	4.356
Mip-Splatting [33]	5.482	4.693	6.567	4.013	5.614	5.302	5.482	5.086	4.569	4.955	5.039	4.632	5.077	4.449	5.982	5.022	4.653	5.027	4.179
SRGS [6] + StableSR [27]	6.128	4.187	5.629	3.978	4.904	4.988	5.025	4.537	4.562	4.716	4.573	4.323	4.026	4.137	5.234	4.096	4.644	4.280	4.050
Ours + StableSR [27]	5.330	3.440	4.720	3.318	3.997	4.657	4.309	3.644	4.029	3.765	4.167	3.340	3.435	3.498	4.559	3.416	3.785	3.632	3.582

Method	Deep Blending [8]		Mip-NeRF 360 [1]								
	drjohnson	*playroom*	*bicycle*	*bonsai*	*counter*	*flowers*	*garden*	*kitchen*	*room*	*stump*	*treehill*
3DGS (LR) [14]	4.760	5.329	2.808	3.964	3.535	2.915	2.741	2.986	4.210	3.137	2.744
3DGS [14] + StableSR [27]	5.231	6.225	4.333	5.452	5.533	4.938	5.516	5.633	6.013	4.919	5.105
Mip-Splatting [33]	6.097	6.426	5.665	6.458	5.730	5.965	6.155	5.600	5.885	5.623	5.462
SRGS [6] + StableSR [27]	5.208	6.188	4.131	5.228	5.214	4.521	5.074	5.546	5.840	4.846	4.381
Ours + StableSR [27]	5.054	5.768	3.378	4.309	3.828	3.825	3.949	3.828	4.531	4.052	3.702