THE ROBUSTNESS OF NATURAL IMAGE PRIORS IN REMOTE SENSING: A ZERO-SHOT VAE STUDY

Zhenyuan Chen
Zhejiang University
School of Earth Sciences
bili_sakura@zju.edu.cn

Feng Zhang
Zhejiang University
School of Earth Sciences
zfcarnation@zju.edu.cn

ABSTRACT

This paper explores the robustness of variational autoencoders (VAEs) pre-trained on natural image data, such as ImageNet, when applied to the remote sensing domain in a zero-shot manner. We investigate whether these natural image priors embedded in standard VAEs can serve as effective compressors and reconstructors for satellite images, even when applied in a different manner across various settings compared to natural cases. Our study evaluates several state-of-the-art VAE architectures across multiple remote sensing categories and reconstruction metrics to demonstrate their potential. See code at https://github.com/Bili-Sakura/VAEs4RS.

1 INTRODUCTION

The rapid development of visual foundation models has transformed the landscape of generative AI, with milestone architectures like GANs (Goodfellow et al., 2014; Karras et al., 2018; Brock et al., 2019; Karras et al., 2020; Sauer et al., 2022) and diffusion models (Ho et al., 2020; Song et al., 2020; 2021; Dhariwal & Nichol, 2021; Karras et al., 2022; Lu et al., 2022; Rombach et al., 2022) setting new standards for high-fidelity image synthesis in the general domain. This momentum has recently extended to the remote sensing (RS) domain, where specialized models such as Text2Earth (Liu et al., 2025), DiffusionSat (Khanna et al., 2024), and other Earth observation foundation models (Lu et al., 2025; Tuia et al., 2025) have been developed to capture complex geospatial distributions, alongside other RS generative models (Yellapragada et al., 2025; Yu et al., 2025; Pang et al., 2026; Sastry et al., 2024; Pan et al., 2025; Sebaq & ElHelw, 2024). Despite these advancements, RS imagery presents unique challenges compared to natural images, including distinct viewing geometries, multi-spectral bands, and varying spatial resolutions, as highlighted in several position papers (Rolf et al., 2024). A common practice remains the use of standard VAEs pre-trained on natural image priors (e.g., ImageNet) without domain-specific adaptation. In this work, we investigate the robustness of these zero-shot VAEs in the RS context, focusing on their effectiveness as compressors and reconstructors for satellite data.

2 VARIATIONAL AUTOENCODERS

Variational Autoencoders (VAEs) (Kingma & Welling, 2014) learn to map input x to latent representation z via encoder $q_\phi(z|x)$ and reconstruct via decoder $p_\theta(x|z)$. The objective maximizes the Evidence Lower Bound (ELBO):

$$\mathcal{L}(\theta, \phi; x) = \mathbb{E}_{z\sim q_\phi(z|x)}[\log p_\theta(x|z)] - D_{KL}(q_\phi(z|x)||p_\lambda(z)) \tag{1}$$

where the first term represents the reconstruction likelihood and the second term is the Kullback-Leibler (KL) divergence regularizing the latent space against a prior distribution $p_\lambda(z)$, typically a standard Gaussian $\mathcal{N}(0, I)$. Modern VAEs often employ advanced architectures such as VQ-GAN (Esser et al., 2021) or flow-matching based decoders to improve reconstruction fidelity. In the context of large-scale generative models, these VAEs serve as essential components by compressing high-dimensional pixel data into a manageable latent space for downstream diffusion or transformer-based modeling.

3 EXPERIMENTS

In this study, we evaluate several state-of-the-art VAE architectures in a zero-shot manner on remote sensing data. We include models from the Stable Diffusion family (SD21-VAE, SDXL-VAE, SD35-VAE) (Rombach et al., 2022; Podell et al., 2024), the FLUX family (FLUX.1-VAE, FLUX.2-VAE) (Black Forest Labs, 2025b;a), and other efficient architectures such as SANA-VAE (Xie et al., 2025) and Qwen-VAE (Wu et al., 2025). These models were primarily pre-trained on natural image datasets like ImageNet and LAION, and we test their direct applicability to RS benchmarks without any fine-tuning.

Model	GFLOPs	Spatial Comp. Ratio	Latent Ch.	PSNR↑		SSIM↑		LPIPS↓		FID↓	
				RESISC45	AID	RESISC45	AID	RESISC45	AID	RESISC45	AID
SANA-VAE	846.76	32	32	23.36	24.72	0.558	0.606	0.124	0.123	8.69	5.01
SD21-VAE	894.91	8	4	25.71	26.66	0.672	0.709	0.095	0.094	4.13	3.08
SDXL-VAE	894.91			25.83	26.80	0.692	0.726	0.098	0.098	4.98	3.11
SD35-VAE	895.25		16	29.71	30.72	0.862	0.876	0.035	0.037	1.11	0.69
FLUX1-VAE	895.25			33.30	33.63	0.923	0.918	0.022	0.025	**0.38**	**0.26**
Qwen-VAE	1143.88			30.38	31.46	0.874	0.889	0.080	0.077	9.51	0.42
FLUX2-VAE	895.71		32	**33.42**	**34.46**	**0.925**	**0.926**	**0.021**	**0.022**	0.46	0.37

Table 1: VAE model statistics and zero-shot performance on the full RESISC45 (31.5K images, 45 classes, 20cm–30m/px GSD) and AID (10K images, 30 classes, 600×600px) datasets, evaluated at their original image sizes (RESISC45: 256×256; AID: 600×600). Spatial comp. ratio denotes the per-dimension spatial downsampling factor (input:latent), and latent ch. denotes the number of latent channels.

Model	GFLOPs	Spatial Comp. Ratio	Latent Ch.	PSNR↑	SSIM↑	LPIPS↓	FID↓	CMMD↓
SANA-VAE	846.76	32	32	22.33	0.564	0.112	28.64	0.0002
SD21-VAE	894.91	8	4	25.81	0.688	0.082	16.43	0.0172
SDXL-VAE	894.91			25.92	0.705	0.084	15.97	0.0203
SD35-VAE	895.25		16	30.06	0.858	0.030	6.85	0.0001
FLUX1-VAE	895.25			31.73	0.899	0.020	**5.19**	0.0010
Qwen-VAE	1143.88			30.76	0.873	0.064	15.83	0.0106
FLUX2-VAE	895.71		32	**32.16**	**0.901**	**0.019**	4.23	**0.0001**

Table 2: Zero-shot performance on the UCMerced dataset (2.1K images, 21 classes, 256×256px), evaluated at original image size.

4 EXPERIMENTAL RESULTS

We evaluate the performance of various VAE architectures on multiple benchmark remote sensing datasets: NWPU-RESISC45 (Cheng et al., 2017), AID (Xia et al., 2017), and UCMerced (Yang & Newsam, 2010). Our evaluation focuses on zero-shot reconstruction quality across diverse aerial scene categories, using the full datasets at their original image sizes (RESISC45: 256×256; AID: 600×600; UCMerced: 256×256).

4.1 METRICS AND MAIN RESULTS

Reconstruction quality is assessed using standard metrics: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM) (Wang et al., 2004), Learned Perceptual Image Patch Similarity (LPIPS) (Zhang et al., 2018), and reconstruction Fréchet Inception Distance (FID) (Heusel et al., 2017). Table 1 summarizes the quantitative performance across the RESISC45 and AID datasets, while Table 2 presents results on the UCMerced dataset. See Appendix A for experiments on the MACIV-T-2025 dataset.

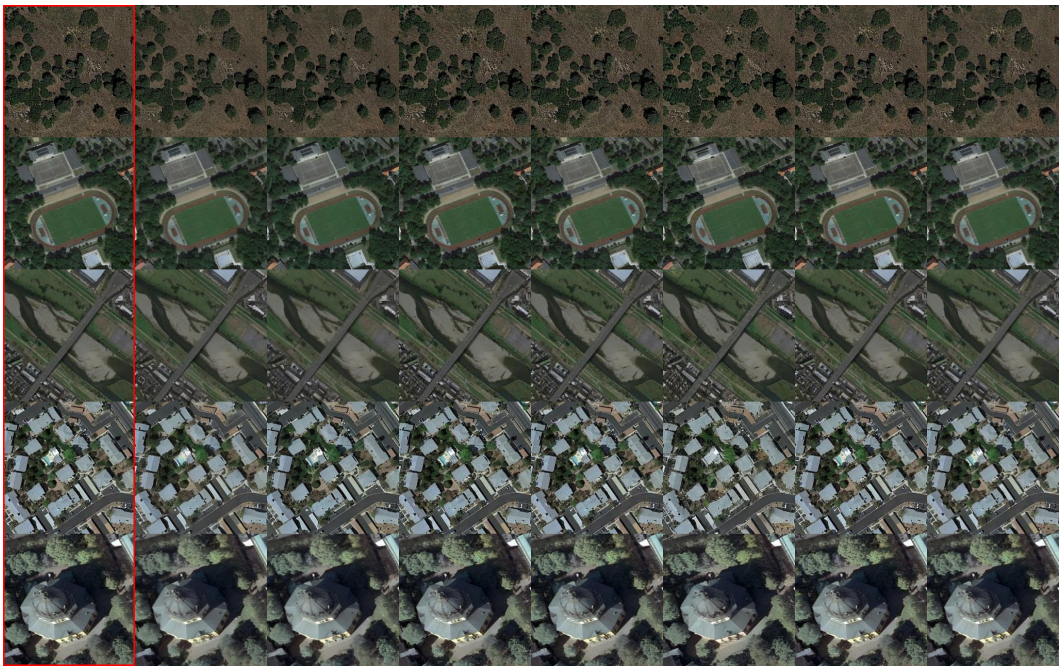

Figure 1: Qualitative reconstructions from 5 random RESISC45 samples. Each column shows (left to right): Original, SD21-VAE, SDXL-VAE, SD35-VAE, FLUX1-VAE, SANA-VAE, FLUX2-VAE, and Qwen-VAE. No significant visual difference appears.

5 Insights

Based on our extensive experiments, we highlight several key insights regarding the application of natural image VAEs to the remote sensing domain:

Insight 1

We find that VAEs reconstruct remote sensing images remarkably well, with reconstructions appearing visually nearly identical to the input. We argue that VAEs may have the potential to implicitly deblur and denoise input images, where the reconstructed image serves as a better data source for model training (e.g., representation learning) with possibly improved statistics.

Insight 2

As the compression appears effectively lossless, we argue for directly storing latent representations instead of original images as datasets to reduce storage requirements.

6 Conclusion

In this work, we explored the robustness of natural image priors in VAEs for remote sensing. Our findings indicate that these models, when used zero-shot, can provide significant utility in data compression across various categories. We will release the reconstructed images along with their corresponding latents for community exploration and further research (`https://huggingface.co/datasets/BiliSakura/RS-Dataset-Latents`).

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A EXPERIMENTS ON MACIV-T-2025

We additionally evaluate reconstruction quality on the MACIV-T-2025 dataset[1], derived from the 4th Multi-modal Aerial View Image Challenge Translation Track (PBVS 2026), which spans multiple modalities including SAR, infrared, and optical imagery. Results across modalities are shown in Figures 2–4.

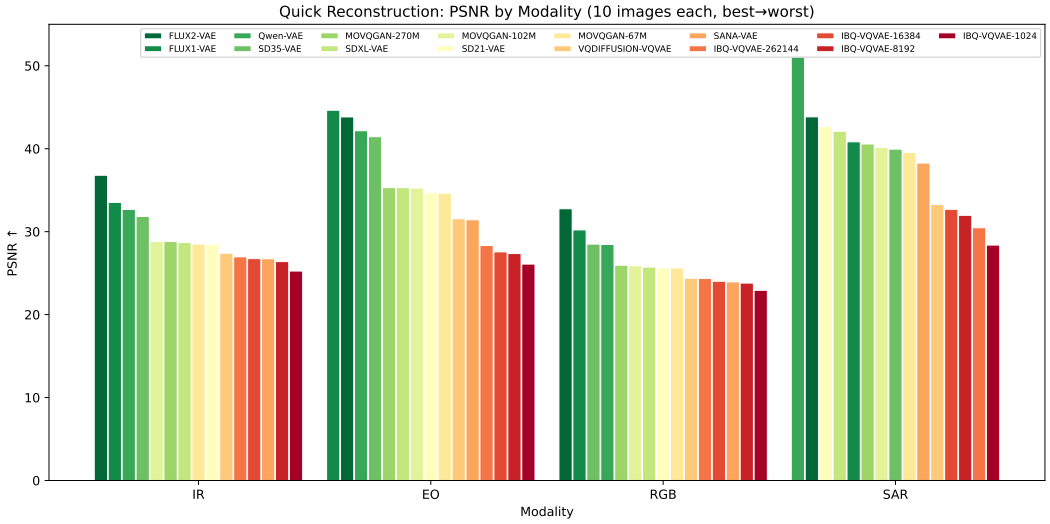

Figure 2: Reconstruction PSNR by modality on the MACIV-T-2025 dataset (4th Multi-modal Aerial View Image Challenge Translation Track, PBVS 2026). VAEs ordered by average rank; color indicates relative performance.

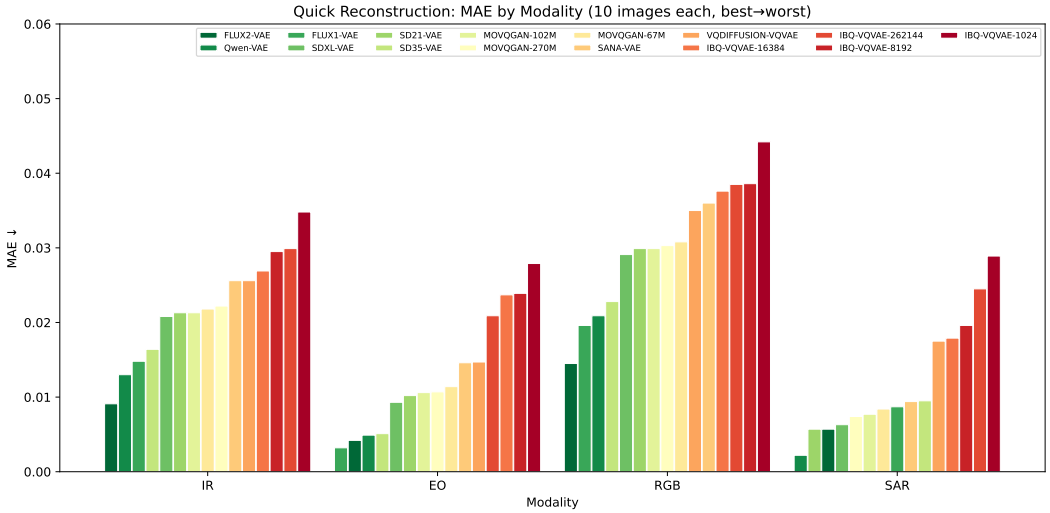

Figure 3: Reconstruction MAE by modality on the MACIV-T-2025 dataset (4th Multi-modal Aerial View Image Challenge Translation Track, PBVS 2026). VAEs ordered by average rank; color indicates relative performance.

[1]Dataset: `https://huggingface.co/datasets/BiliSakura/MACIV-T-2025`. Challenge: `https://www.codabench.org/competitions/12566/`.

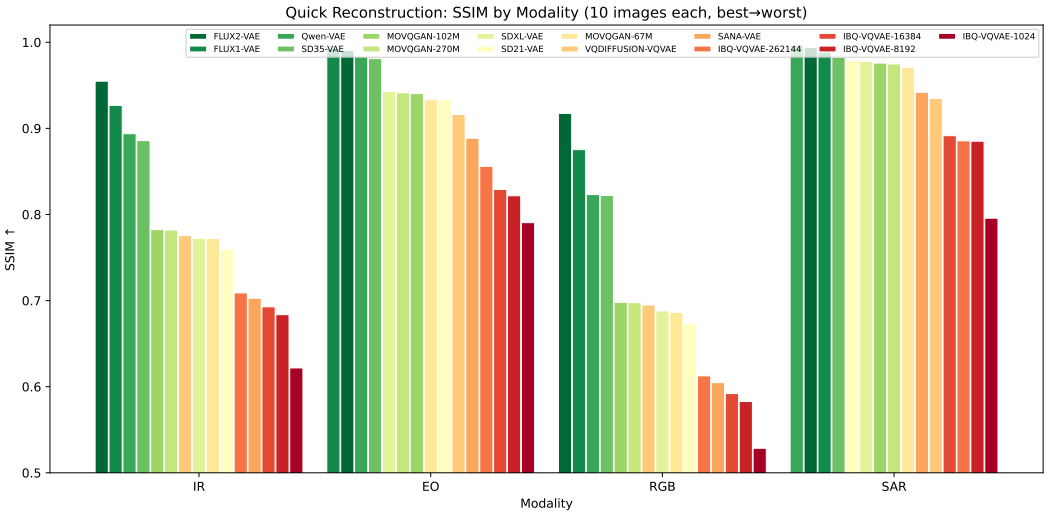

Figure 4: Reconstruction SSIM by modality on the MACIV-T-2025 dataset (4th Multi-modal Aerial View Image Challenge Translation Track, PBVS 2026). VAEs ordered by average rank; color indicates relative performance.