

# SyncLight: Controllable and Consistent Multi-View Relighting

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Fig. 1. Multi-view light editing with SyncLight. From an uncalibrated, multi-view capture of a static scene (top row), a user selects one frame as a “reference” view (top-left) and specifies changes to lighting by clicking on a visible light source (white circle marker) and specifying target light color (intensity and chromaticity). SyncLight relights all input views accordingly. By leveraging a latent bridge matching formulation, each edit requires a *single* feedforward pass performed simultaneously on all views, and generalizes to an arbitrary number of input viewpoints.

We present **SyncLight**, the first method to enable consistent, parametric relighting across multiple uncalibrated views of a static scene. While single-view relighting has advanced significantly, existing generative approaches struggle to maintain the rigorous lighting consistency essential for multi-camera broadcasts, stereoscopic cinema, and virtual production. SyncLight addresses this by enabling precise control over light intensity and color across a multi-view capture of a scene, conditioned on a single reference edit. Our method leverages a multi-view diffusion transformer trained using a latent bridge matching formulation, achieving high-fidelity relighting of the entire image set in a single inference step. To facilitate training, we introduce a large-scale hybrid dataset comprising diverse synthetic environments—curated from existing sources and newly designed scenes—alongside high-fidelity, real-world multi-view captures under calibrated illumination. Surprisingly, though trained only on image pairs, SyncLight generalizes zero-shot to an arbitrary number of viewpoints, effectively propagating lighting changes across all views, without requiring camera pose information. SyncLight enables practical relighting workflows for multi-view capture systems. Project page: [sync-light.github.io](https://sync-light.github.io).

## 1 INTRODUCTION

In photography and cinematography, lighting defines mood, reveals material properties, and directs attention. While neural rendering [Kerbl et al. 2023; Mildenhall et al. 2021] has made capturing high-fidelity 3D geometry increasingly accessible, the ability to *control* illumination after capture remains a significant bottleneck. This challenge is particularly acute for indoor environments, where lighting is complex and multifaceted: multiple light sources with varying colors and intensities, complex interreflections between surfaces, and occlusions create a rich but difficult-to-model illumination landscape. In professional workflows, ranging from stereoscopic cinema and sports broadcasting to virtual production, lighting cannot simply be “plausible”; it must be rigorously consistent. A shadow cast across a face in one camera view must align perfectly with the profile seen from another, preserving the physical logic of the scene.

Relighting is fundamentally an ill-posed problem. From captured images alone, one cannot uniquely decompose the observed appearance into its constituent factors: geometry, material properties (BRDFs), and lighting. Current approaches must therefore force a compromise between visual fidelity and consistency. State-of-the-art generative controllable relighting methods like LightLab [Magar et al. 2025] and ScribbleLight [Choi et al. 2025] have set the standard for single-image editing, achieving photorealism and intuitive interactive control. However, these methods are designed for single images alone. When applied to multi-view scenarios—common in multi-camera cinema and virtual production—they fail to maintain consistency. Because they process each view independently, they hallucinate lighting effects that are plausible locally but contradictory globally. A shadow direction may drift between cameras, or a specular highlight may vanish when the viewpoint shifts—jarring artifacts that destroy the illusion of a unified 3D world. Conversely, inverse rendering and NeRF-based approaches [Jin et al. 2023; Zhao et al. 2024] enforce physical consistency by explicitly estimating geometry and materials. Yet, these methods are often computationally expensive, require long per-scene optimization, and struggle to hallucinate realistic lighting effects in regions where geometric estimates fail—precisely the areas where the ill-posed nature of the problem becomes most apparent.

To resolve this dichotomy, we introduce **SyncLight**, a generative framework designed to bring the flexibility of 2D image editing to multi-view indoor scene relighting. Unlike prior work that relies on explicit geometric reconstruction or intrinsic image decomposition, SyncLight operates as a multi-view diffusion transformer, learning to create consistent relighting effects directly in the image domain. By formulating the task as a conditional generation problem, we sidestep the ill-posed decomposition entirely, instead learning priors for plausible lighting transformations from data. This enables parametric control: a user can adjust light intensity, color, or direction on a single reference image, and SyncLight coherently propagates these changes across all synchronized viewpoints while preserving the complex interplay of shadows, highlights, and indirect illumination characteristic of indoor scenes.

Realizing this system required overcoming two fundamental challenges. **First, data scarcity:** Training requires large-scale datasets, yet no existing resource provides multi-view captures with diverse, calibrated lighting ground truth. We address this by introducing a large hybrid dataset that combines procedurally generated synthetic indoor environments with high-fidelity real-world captures, bridging the domain gap between simulation and reality. **Second, inference latency:** Standard diffusion models are notoriously slow due to iterative sampling. We employ a Latent Bridge Matching (LBM) [Albergo et al. 2025; Chadebec et al. 2025] formulation, which enables direct mapping from input to relit output in a single inference step, bypassing the latency of traditional diffusion sampling.

A key property of SyncLight is its zero-shot scalability to arbitrary view counts. While trained exclusively on image pairs ( $N = 2$ ) to learn local consistency priors, our multi-view attention mechanism generalizes seamlessly to dense camera arrays ( $N > 2$ ) at inference time without retraining. This design effectively decouples training complexity from deployment flexibility. Fig. 1 illustrates multi-view

light editing with SyncLight, where users interactively specify desired lighting by clicking on the reference image to control both intensity and chromaticity.

In summary, we make the following contributions:

- **Consistent multi-view indoor relighting:** We propose the first generative method capable of parametrically relighting synchronized views of scenes with strict spatial and photometric coherence, eliminating the flicker of independent 2D edits.
- **Zero-shot generalization:** We introduce a relighting-aware Multi-View Transformer to induce cross-view feature propagation, enabling it to learn consistency from image pairs while scaling to arbitrary view counts at inference.
- **Efficient one-step inference:** By leveraging a Bridge Matching formulation, SyncLight achieves high-fidelity results in a single forward pass, offering a practical alternative to slow optimization-based baselines.
- **SyncLight dataset:** We release a comprehensive dataset of multi-view indoor scenes under varying illumination, bridging synthetic and real-world domains and providing the community with a new benchmark for multi-view illumination learning.

## 2 RELATED WORK

The paradigm of relighting has recently shifted from physically-based inverse rendering [Gardner et al. 2024, 2019; Karsch et al. 2011, 2014; Li et al. 2021, 2020, 2022, 2023; Zhang et al. 2016; Zhu et al. 2023] to data-driven generative modeling. Rather than explicitly solving the ill-posed decomposition of appearance into geometry, materials, and lighting, modern approaches learn to hallucinate plausible lighting transformations directly in image space [Bhattad et al. 2024; Magar et al. 2025; Xing et al. 2025; Zhang et al. 2024], leveraging the fact that such decompositions can emerge implicitly within generative models [Bhattad et al. 2023; Du et al. 2023].

*Domain-specific methods.* Early generative approaches focused on constrained scenarios with strong priors. For portrait relighting, methods leverage light stage captures [He et al. 2024; Mei et al. 2025; Pandey et al. 2021] to model facial appearance under controlled illumination, achieving photorealistic results but limited to frontal face geometry. Object-centric methods [Alzayer et al. 2025; Bharadwaj et al. 2025; Deng et al. 2024; Fortier-Chouinard et al. 2026; Jin et al. 2024; Zeng et al. 2024b; Zhang et al. 2025a] condition diffusion models on environment/intrinsic maps, spherical harmonics, or shadow masks, enabling compelling material-aware relighting for isolated objects. While effective, these methods lack the generalization required for complex indoor scenes where multiple interacting light sources and global illumination dominate.

*Single-view diffusion for general indoor scenes.* Recent diffusion-based methods have achieved remarkable photorealism by treating relighting as a conditional synthesis task. IC-Light [Zhang et al. 2025b] leverages massive 2D datasets to hallucinate lighting effects based on text or environment maps. LumiNet [Xing et al. 2025] and StyLitGAN [Bhattad et al. 2024] explore unsupervised relighting via latent control [Zhang et al. 2024], though they remain vulnerable to intrinsic ambiguities. IntrinsicEdit [Lyu et al. 2025], IID [Kocsis et al. 2024b], LightIt [Kocsis et al. 2024a], and RGB↔X [Zeng et al. 2024a]

exploit intermediate intrinsic imagery to enable material-aware relighting, though they require explicit intrinsic decomposition or lack fine-grained spatial control over individual light sources.

More recently, ScribbleLight [Choi et al. 2025] allows artists to manipulate illumination via sparse screen-space sketches, while LightLab [Magar et al. 2025] achieves state-of-the-art single-view results through fine-tuned diffusion models conditioned on depth maps and segmentation light masks. While LightLab represents the closest approach to ours, like all single-view methods, it processes each view independently and cannot maintain consistency across synchronized cameras. In contrast, SyncLight introduces explicit multi-view consistency through cross-view attention trained on stereo pairs. Furthermore, while LightLab requires 50+ iterative diffusion steps, we employ Latent Bridge Matching for one-step inference (10–50× speedup). Our conditioning is also simpler: users specify lighting changes on a single reference view, which propagates consistently across all synchronized viewpoints without requiring per-view depth maps or the segmentation light masks.

**3D-consistent approaches.** NeRF- or 3DGS-based methods [Alzayer et al. 2025; Jin et al. 2023; Litman et al. 2025; Poirier-Ginter et al. 2024; Zhao et al. 2024] and inverse rendering approaches enforce consistency through explicit 3D decomposition into geometry, materials, and lighting. While these guarantee geometric coherence, they require per-scene optimization and lack flexibility for rapid editing. More recently, Careaga and Aksoy [2025]; Lin et al. [2025] combine monocular geometry estimation with physically-based rendering to enable CG-like control over light placement in single images or videos. While this achieves physical accuracy, it requires explicit mesh reconstruction per image and does not address multi-view consistency constraints of synchronized camera arrays. SyncLight instead learns consistency priors directly from multi-view data by leveraging generative prior without per-scene 3D reconstruction.

**Multi-view generation and consistency.** Recent work has demonstrated that explicit cross-view attention enforces geometric consistency. MVDream [Shi et al. 2024] introduced multi-view diffusion transformers for text-to-3D object generation, showing that training on multi-view data with shared attention enables consistent generation across viewpoints. We apply this architectural insight to relighting, demonstrating that multi-view transformers trained on stereo pairs generalize zero-shot to larger camera arrays and wide-baseline stereo images never seen during training.

Temporal consistency in video—conceptually analogous to spatial consistency across views—has been explored in recent video relighting work. RelightVid [Fang et al. 2025] and UniRelight [He et al. 2025] address flickering through temporal layers and joint denoising. However, these methods process sequential temporal frames rather than synchronized multi-view captures of the same scene instant, and do not address the rigid geometric coherence constraints of fixed camera arrays.

**Flow matching and efficient sampling.** Our use of Latent Bridge Matching [Chadebec et al. 2025] builds on recent advances in flow-based generative models. Flow Matching [Lipman et al. 2023] introduced simulation-free training of continuous normalizing flows, enabling faster sampling than standard diffusion. Bridge Matching

and Schrödinger Bridge methods [Albergo et al. 2025; Shi et al. 2023] further refine these approaches by optimizing transport between arbitrary distributions by adding stochasticity in the trajectory. We adopt this formulation to enable one-step inference essential for interactive multi-camera relighting workflows.

### 3 SYNCLIGHT METHOD

Our goal is to enable consistent relighting across multiple synchronized views by conditioning on parametric lighting edits applied to a single reference view. We build upon latent diffusion models [Rombach et al. 2022] and extend them to the multi-view setting through two key contributions: (1) a multi-view transformer with cross-view attention that enforces spatial coherence and consistent propagation of lighting edits, and (2) a LBM formulation [Chadebec et al. 2025] that enables one-step inference, avoiding the iterative sampling required by standard diffusion models. Fig. 2 provides an overview of our approach.

**Latent bridge matching.** Traditional latent diffusion models learn to denoise from pure Gaussian noise, which is inefficient for image-to-image translation tasks like relighting, where the source image already contains most of the desired scene content. Flow matching [Lipman et al. 2023] provides a framework for learning continuous transport between arbitrary distributions. We adopt LBM [Chadebec et al. 2025], which constructs flows between a source latent  $\mathbf{z}_{src}$  (encoding an image under source lighting) and a target latent  $\mathbf{z}_{tar}$  (encoding the same scene under target lighting).

We encode an image under source and target lighting  $\{\mathbf{x}_{src}, \mathbf{x}_{tar}\}$  into latent representations using a pretrained VAE encoder,  $\mathbf{z} = \mathcal{E}(\mathbf{x})$ , and define a stochastic interpolation path between them:

$$\mathbf{z}_t = (1 - t)\mathbf{z}_{src} + t\mathbf{z}_{tar} + \sigma\sqrt{t(1 - t)}\epsilon, \quad (1)$$

where  $t \in [0, 1]$ ,  $\epsilon \sim \mathcal{N}(0, I)$ , and  $\sigma$  controls the noise magnitude. Following prior work [Chadebec et al. 2025; Liu et al. 2023; Tan et al. 2025], we use  $\sigma = 0.005$ , resulting in stochastic trajectories.

The model  $\mathbf{v}_\theta$  is trained to predict the velocity field that transports  $\mathbf{z}_{src}$  to  $\mathbf{z}_{tar}$ . The target velocity is:

$$\mathbf{v} = \mathbf{z}_{tar} - \mathbf{z}_{src}, \quad (2)$$

The training objective minimizes the mean squared error between predicted and target velocities:

$$\mathcal{L}_{lmb} = \mathbb{E}_{t, \mathbf{z}_{src}, \mathbf{z}_{tar}} \left[ \left\| \frac{\mathbf{v}_\theta(\mathbf{z}_t, t, c)}{(1 - t)} - (\mathbf{z}_{tar} - \mathbf{z}_{src}) \right\|_2^2 \right], \quad (3)$$

where  $c$  denotes the conditioning information. We limit  $t$  to only 4 equally-spaced timesteps during training.

At inference time, given a source latent  $\mathbf{z}_{src}$  and a conditioning  $c$ , the target latent is directly estimated in a *single* step:

$$\hat{\mathbf{z}}_{tar} = \mathbf{z}_t + \mathbf{v}_\theta(\mathbf{z}_t, t, c). \quad (4)$$

The decoded output  $\hat{\mathbf{x}}_{tar} = \mathcal{D}(\hat{\mathbf{z}}_{tar})$  provides the relit image. Compared to iterative diffusion sampling (50+ steps), this one-step inference is significantly faster while maintaining high visual quality, making it practical for interactive multi-view applications.

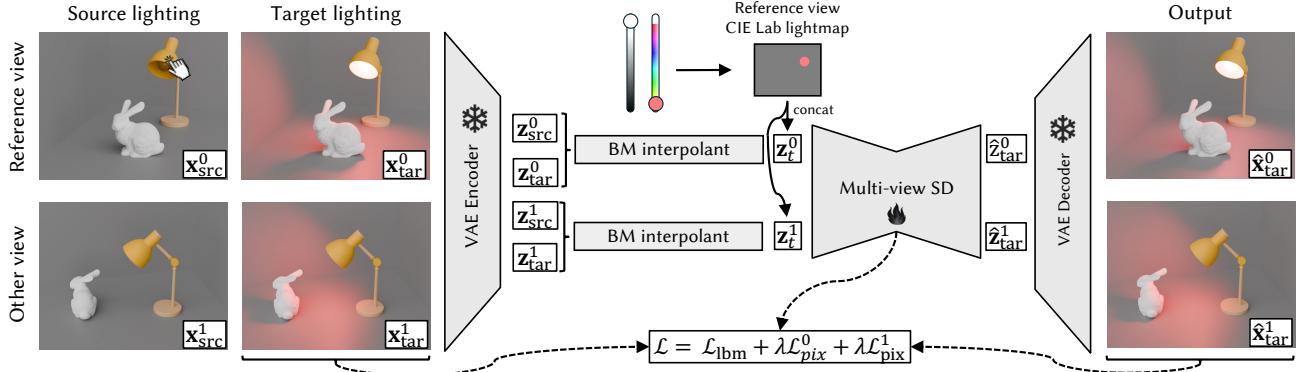


Fig. 2. SyncLight formulates multi-view relighting as a conditional flow matching problem in latent space. (Left) Input scenes under source ( $\mathbf{x}_{src}$ ) and target lighting ground truth ( $\mathbf{x}_{tar}$ ) are encoded into latents ( $\mathbf{z}_{src}$ ,  $\mathbf{z}_{tar}$ ) via a VAE encoder. This done for both the “Reference” (0) and “Other” (1) views. (Middle) During training, we sample a timestep  $t$  and construct a Bridge Matching (BM) interpolant  $\mathbf{z}_t$ . Our backbone, “Multi-View SD”, is conditioned on a user-specified “Lightmap” (encoding color as intensity and chromaticity) derived from the “Reference view”. To enforce consistency, the backbone processes both views simultaneously. (Right) The model predicts the target latents, which are decoded into relit images ( $\hat{\mathbf{x}}_T$ ). The network is optimized using a hybrid objective  $\mathcal{L}$  combining latent flow matching loss ( $\mathcal{L}_{lmb}$ ) with pixel-level reconstruction losses ( $\mathcal{L}_{pix}$ ) for each view to ensure high-fidelity, consistent relighting.

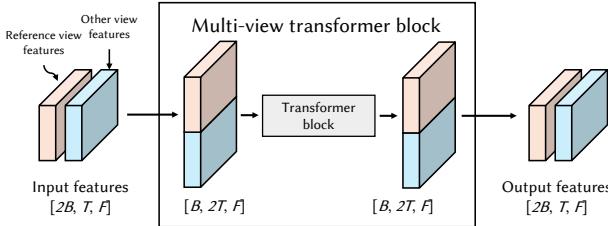


Fig. 3. Multi-view transformer block. To ensure consistent relighting across viewpoints, we modify the standard self-attention mechanism of SDXL. View features are concatenated and reshaped along the sequence dimension, creating a unified representation of shape  $[B, 2T, F]$ . This enables the transformer block to perform global self-attention across all views simultaneously, effectively propagating lighting cues from the reference view to target views. This formulation is *agnostic to the sequence length*: while trained on pairs ( $N = 2$ , as shown here), it supports an arbitrary number of views at inference, enabling zero-shot generalization to  $N > 2$ .

**Multi-view latent bridge matching.** SyncLight takes as input two synchronized, uncalibrated views under source lighting  $\{\mathbf{x}_{src}^0, \mathbf{x}_{src}^1\}$  and a lighting condition  $c^0$  defined on the control view  $\mathbf{x}_{src}^0$ , and predicts both views under target lighting  $\{\hat{\mathbf{x}}_{tar}^0, \hat{\mathbf{x}}_{tar}^1\}$ . Standard diffusion- or flow-based architectures are designed for single-image inputs and do not model cross-view interactions. We therefore use Stable Diffusion XL [Podell et al. 2024] as our velocity field model, adapting it to explicitly reason across multiple views while using its pretrained weights as the model initialization.

Inspired by MVDream [Shi et al. 2024], we replace each transformer block in SDXL with a multi-view transformer block. The key idea is to enable information exchange across  $N$  different views through modified self-attention, see fig. 3 for an illustration with  $N = 2$ . Given a batch of  $N$  view latents, we first process each view’s features independently through the initial convolution layers. Before each transformer block, features from all views are concatenated along the token dimension rather than the batch dimension. This

allows the self-attention mechanism to attend across views, capturing cross-view geometric and photometric consistency. After attention, features are reshaped back to the original per-view layout. Importantly, although we train exclusively on pairs ( $N = 2$ ), the architecture is agnostic to the number of views due to the token-level attention mechanism. At inference, we observe generalization to arbitrary view counts while maintaining consistency (see sec. 5). Formally, the input to the model  $\mathbf{v}_\theta$  is the batch-wise concatenation of all interpolated latent views:  $\mathbf{z}_t = \text{concat}[\mathbf{z}_t^0, \dots, \mathbf{z}_t^{N-1}]$ .

**Lighting control.** We represent target lighting conditions via a 4-channel lightmap  $L \in [-1, 1]^{H \times W \times 4}$  defined on the reference view  $\mathbf{x}_{src}^0$ . Other than the desired light source to be visible, no constraint is imposed on the choice of the reference view. Users specify locations of light sources to modify (via circular markers), and the lightmap encodes: (1) activation state (1 = on, -1 = off), and (2–4) target color in Lab space. All values default to 0, unless the user specifies the activation and color. We use Lab rather than RGB to enable independent control of brightness (L) and chromaticity (ab). The lightmap is resized to latent resolution and concatenated to each interpolated latent  $\mathbf{z}_t^i$ , yielding 8-channel inputs (4 latent + 4 lightmap). Since all latents must have the same dimensions, we simply apply the same lightmap to all views—this works well in practice, likely because providing color and intensity information to other views is helpful, even despite the spatial misalignment.

**Training objective.** In addition to the velocity-matching objective ( $\mathcal{L}_{lmb}$  in eq. (3)), we follow prior work [Chadebec et al. 2025; Yue et al. 2023] and impose reconstruction losses on the decoded images:

$$\mathcal{L} = \mathcal{L}_{lmb} + \lambda \mathcal{L}_{pix}^0 + \lambda \mathcal{L}_{pix}^1, \quad (5)$$

where  $\mathcal{L}_{pix}^i$  denotes the LPIPS loss [Zhang et al. 2018] for view  $i$ .

## 4 SYNCLIGHT DATASET

Training a generative model for consistent multi-view relighting requires data satisfying three strict criteria: (1) diverse, high-fidelity indoor geometry; (2) perfectly synchronized multi-view camera poses;



Fig. 4. Parametric color control, with the lamp relit to different colors. In the original captures (not shown), the lamp is turned off. SyncLight correctly relights both the reference and other views consistently across all colors. Note that the color cast on the wall is also consistent with the light color.

and (3) isolated, controllable light sources for supervision. Existing datasets fail to meet these requirements. The Multi-Illumination dataset [Murmann et al. 2019], while offering real-world lighting variations, does not contain consistent multi-view captures or visible light sources. The dataset used by LightLab [Magar et al. 2025] is single-view only and unavailable. To address this gap, we introduce the **SyncLight Dataset**, comprising nearly one million multi-view image pairs under diverse lighting conditions, designed to enable learning of physically consistent relighting across viewpoints.

Our dataset comprises both synthetic and real captures. Following prior work [Aksoy et al. 2018; Heckbert 1996; Hui et al. 2018; Magar et al. 2025], we employ a One Light At a Time (OLAT) capture scheme. For each scene, we render or photograph each controllable light source independently, plus an ambient capture containing only non-controllable illumination (skylight, bounce light). Crucially, all images are captured in linear color space—HDR for synthetic data and camera RAW for real captures—ensuring the photometric linearity required for accurate light composition.

For each scene, we generate multiple lighting conditions by sampling different color values  $c_i$  (in Lab space, see sec. 3) for each light source. Crucially, we impose the constraint that the lights being modified must be visible in at least one view, designated as the reference view, while the second view may or may not have direct visibility of the modified light sources. To enable controllability, we also generate a lightmap for the reference view: a mask with colored circles placed at the spatial location of each modified light source, where the circle’s RGB values encode the target  $c_i$  values. This design ensures that our model learns to propagate lighting changes across viewpoints, even when the light source itself is not visible in all views, mimicking real-world multi-camera scenarios where some lights may be occluded from certain viewpoints.

Our dataset comprises three sources with complementary objectives: (i) 320 *Infinigen* scenes to help the model leverage pretrained scene geometry priors across views; (ii) 40 *BlenderKit* scenes to provide higher realism, furniture, and light sources; and (iii) *Real* captures from 40 scenes to bridge the domain gap between synthetic and real-world data. In total, our SyncLight Dataset contains nearly one million multi-view training pairs: 920,000 for *Infinigen*, 47,000 for *BlenderKit*, and 18,000 for real images. All three subsets follow the same multi-view OLAT capture protocol described above.

To ensure rigorous testing, we hold out a diverse subset of scenes disjoint from the training set: 10 from *Infinigen*, 3 from *BlenderKit*,

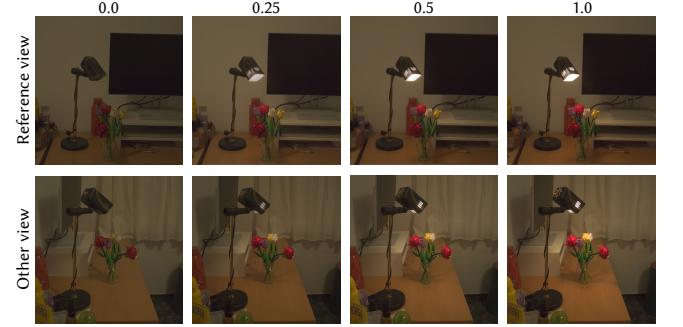


Fig. 5. Parametric intensity control. (left to right) The target lamp intensity is set to increasing levels; SyncLight correctly relights both views consistently. Note how the shadow of the flowers progressively increases in the second view (bottom row), even if the conditioning is provided for the reference view (top row).

and 6 from *Real Captures*. From these unseen scenes, we randomly sample a fixed test set of 135, 45, and 105 pairs, respectively.

## 5 EXPERIMENTS

*Implementation details.* We fine-tune our modified SDXL model [Podell et al. 2024] for 100,000 steps using a learning rate of  $1 \times 10^{-5}$  and a batch size of 6 at a resolution of  $1280 \times 720$ . Training is performed on six NVIDIA A40 GPUs.  $\lambda = 10$  in all experiments.

We evaluate all models on the SyncLight test set. We measure performance using four standard reference metrics: PSNR for pixel-wise fidelity, SSIM [Wang et al. 2004] for structural similarity,  $\Delta E_{00}$  [Sharma et al. 2005] for perceptual color difference in CIE Lab space, and LPIPS [Zhang et al. 2018] for perceptual similarity.

*Results and comparisons.* SyncLight enables parametric control over light intensity and chromaticity. Fig. 4 illustrates how SyncLight turns on a lamp at seven different chromaticity levels, while fig. 5 shows the same operation at three different intensity levels. Note how consistently SyncLight maintains colors across views (fig. 4) and correctly casts shadows across intensity variations (fig. 5).

To the best of our knowledge, SyncLight is the first method to provide parametric control over light sources across multiple views simultaneously. Since no prior work offers this capability directly, we evaluate baseline methods using various adaptations of state-of-the-art methods. For single-view relighting of the reference view, we compare against ScribbleLight [Choi et al. 2025] and a single-view variant of our method (SyncLight-1V). For the former, we use

Table 1. Quantitative multi-view image relighting results on our SyncLight dataset. Each section of the table indicates which view is used to compute metrics: the “Reference view” (where edits are specified), “Other view” (another view in the set), and “Add. views” (all but the reference view). Best results, achieved by SyncLight in all cases, are highlighted. See text for details on baselines. “Inf. time” represents the total inference time. Since SyncLight is always run on more than one image, no inference time is reported for the “Reference view.”

Method	Infinigen				BlenderKit				Real captures					
	PSNR $\uparrow$	SSIM $\uparrow$	$\Delta E_{00}\downarrow$	LPIPS $\downarrow$	PSNR $\uparrow$	SSIM $\uparrow$	$\Delta E_{00}\downarrow$	LPIPS $\downarrow$	PSNR $\uparrow$	SSIM $\uparrow$	$\Delta E_{00}\downarrow$	LPIPS $\downarrow$	Inf. time (s) $\downarrow$	
Reference view	ScribbleLight	10.89	.518	30.67	.382	11.02	.528	29.26	.372	11.78	.483	28.36	.375	58.2 $\pm$ 1.14
	Flux.2-dev	14.23	.672	20.31	.338	16.71	.704	17.22	.291	18.32	.757	14.28	.264	55.6 $\pm$ 1.02
	SyncLight-1V	29.86	.941	3.08	.131	26.38	.907	4.92	.147	28.42	.880	4.61	.199	1.17 $\pm$ 0.02
	SyncLight	31.32	.950	2.47	.119	27.16	.915	4.02	.134	30.34	.895	3.73	.196	-
Other view	ScribbleLight+LumiNet	13.41	.498	19.67	.284	12.72	.507	23.91	.306	14.48	.518	23.77	.318	69.6 $\pm$ 1.82
	Flux.2-dev	12.75	.617	25.82	.386	14.92	.604	20.40	.469	16.35	.685	19.13	.305	111 $\pm$ 2.08
	SyncLight-1V+LumiNet	17.36	.817	7.89	.184	15.92	.863	9.82	.196	20.46	.815	8.46	.279	13.1 $\pm$ 0.68
	SyncLight	31.45	.949	2.45	.119	28.19	.925	3.72	.126	30.23	.897	3.56	.197	1.58 $\pm$ 0.02
Add. views	ScribbleLight+LumiNet	13.36	.494	19.65	.292	12.88	.509	23.47	.299	14.29	.525	23.92	.320	89.7 $\pm$ 1.93
	Flux.2-dev	12.55	.616	26.03	.388	14.90	.606	20.03	.472	16.21	.678	20.42	.328	273 $\pm$ 3.87
	SyncLight-1V+LumiNet	17.22	.808	8.35	.195	16.07	.871	10.43	.185	20.40	.809	8.93	.287	38.5 $\pm$ 0.83
	SyncLight	31.42	.941	2.57	.122	28.01	.929	3.78	.125	30.44	.905	3.57	.194	2.38 $\pm$ 0.03

Marigold [Ke et al. 2024, 2025] to obtain the albedo and depth, while the latter behaves as a generative single-view relighting method and thus serves as a closer comparison to LightLab [Magar et al. 2025], whose code and data are unavailable. For relighting the second view, we adopt LumiNet [Xing et al. 2025], giving as input the second view and as reference the relit version of the reference view.

Additionally, we compare against Flux.2-dev [Labs 2025], a large-scale text-conditioned image editing model. Since Flux.2-dev lacks native multi-view support, we implement a two-stage sequential pipeline. First, we use Qwen-2.5-7B-Instruct [Bai et al. 2023] to generate a text prompt describing the desired lighting change by comparing the source and target lighting conditions on the reference view. We then apply Flux.2-dev to relight the reference view using this prompt. Finally, we relight the second view by providing the relit reference view as visual conditioning and prompting Flux.2-dev to match the lighting of the reference image.

As shown in tab. 1 (“Reference” and “Other view”), our method outperforms previous approaches by a large margin. Several key observations emerge from these results. First, SyncLight improves upon its single-view variant (SyncLight-1V) on the control view, indicating that incorporating a second view enhances performance even for single-view relighting. Second, the results for both views in SyncLight are extremely close, clearly indicating the method’s ability to consistently match the illumination conditions imposed for the first view with those in the second view. Finally, the average inference time across all images in our dataset demonstrates that our method achieves the most efficient relighting for both views.

Fig. 7 demonstrates SyncLight’s performance across synthetic (*Infinigen*, *BlenderKit*) and *Real* indoor scenes. Our method exhibits three key capabilities: (1) Precise light manipulation: The model correctly activates or deactivates individual light sources while preserving other illumination (e.g., *BlenderKit* row 1, where only the table lamp is turned off while the window light remains unchanged). (2) Multi-view consistency: Lighting edits propagate coherently across

viewpoints, including secondary effects such reflections and color casts, even when light sources are occluded in some views (*Infinigen* rows, *BlenderKit* row 2). (3) Indirect effects: The model plausibly synthesizes indirect illumination effects like wall reflections and color bleeding (Real row 1). In contrast, Flux.2-dev struggles with cross-view consistency, producing visually plausible but geometrically inconsistent results—note the differing lamp colors across views in *BlenderKit* row 2. The 1V+LumiNet baseline, while maintaining better consistency through explicit relighting of each view, fails to propagate lighting effects when sources are not directly visible (*BlenderKit* row 2, second view). In contrast, SyncLight uniquely combines the photorealism of generative models with the geometric coherence of multi-view reasoning.

Fig. 8 shows results on images from the RealEstate10K dataset [Google Research 2018], demonstrating the generalization of our method to out-of-domain images with large displacements between cameras. In the first example, we ask the models to turn on the light that is next to the sofa. In the bottom scene, we ask the models to turn off one of the bedside table lamps, while leaving the other untouched. In both cases, SyncLight is the only one that correctly relights both images consistently.

**Zero-shot multi-view generalization.** A crucial property of SyncLight is its ability to generalize zero-shot to an arbitrary number of views, despite being trained exclusively on image pairs ( $N = 2$ ). This capability stems from our multi-view transformer architecture: because cross-view attention operates at the token level rather than being constrained to a fixed number of views, the learned consistency priors naturally extend to larger camera arrays. Fig. 6 presents an example with  $N = 7$  views, demonstrating consistent relighting across all views despite exceeding the training configuration. Notably, the modified light source is occluded in views 2 and 4, yet the model correctly propagates the lighting changes based on geometric



Fig. 6. Relighting a scene with seven different views. Top row: Input images. Bottom row: SyncLight results. Note how all the views are consistently modified. We want to emphasize views 2 and 4, in which the lamp turned on is not visible, yet the effects in the scene match those of the other views.

Table 2. Ablation studies. Average results on the “Other view” of the *Real* split of the SyncLight dataset.

	PSNR	SSIM	$\Delta E_{00}$	LPIPS
w/o <i>Infinigen</i>	26.91	.863	4.59	.281
w/o <i>BlenderKit</i>	27.29	.872	4.42	.247
w/o <i>Real</i>	25.61	.860	4.92	.238
w/o MV-SD	22.47	.833	5.03	.236
SyncLight	30.23	.897	3.56	.197

cues from other views. Our architecture exhibits favorable scalability: at 2K resolution, each additional view requires only 0.01GB VRAM and 1.23 seconds on an NVIDIA A40.

We quantitatively evaluate this generalization capability in tab. 1 (*Add. views*). For each image pair in our test set, we randomly sample additional views, obtaining an average of 4.38 views per scene. Baseline methods require a separate forward pass for each additional view, always using the first view as a reference. In contrast, SyncLight processes all views in a single forward pass. Our method maintains consistent relighting quality across the reference view, second view, and all additional views, demonstrating robust multi-view consistency beyond the training distribution.

*Ablation Studies.* Tab. 2 presents ablation experiments. Dataset splits: Removing any split degrades performance on the real test split, with *Infinigen* (-3.3 dB in PSNR), *BlenderKit* (-2.9 dB in PSNR), and *Real* (-4.6 dB in PSNR). Multi-view transformer: Replacing multi-view blocks with standard single-view processing causes severe degradation on “Other view” (-7.7 dB in PSNR), reducing performance significantly. Without cross-view attention, the model cannot propagate lighting to other views, confirming that feature exchange across views is critical for multi-view consistency.

## 6 APPLICATIONS

*Zero-shot video relighting.* SyncLight can efficiently relight videos while maintaining temporal consistency, even if it is trained only of *image pairs*. Fig. 9a shows five frames from a 142-frame video from the RealEstate10k dataset [Google Research 2018] alongside their relit versions, demonstrating consistent relighting across all frames. Notably, all 142 frames are processed jointly in a single forward pass, requiring only 156 seconds and 27 GB of VRAM.

*Novel view synthesis with radiance fields.* Relighting in radiance field representations (NeRFs, or 3DGS) is inherently challenging since it typically involves complex inverse rendering (e.g., [Jin et al. 2023]). SyncLight’s view-consistent relighting enables an alternative approach: users can relight multiple 2D views and reconstruct the 3D scene, effectively using our method as a proxy for 3D relighting. Fig. 9b shows an example using 3DGS [Kerbl et al. 2023] implementation from NerfStudio [Tancik et al. 2023]. Note that, as opposed to Poirier-Ginter et. al [2024], no multi-view consistency optimization was performed: we simply used vanilla 3DGS directly on the images relit by SyncLight.

## 7 DISCUSSION

We proposed SyncLight, the first method capable of consistently relighting multiple uncalibrated views conditioned on a single reference edit. Our approach demonstrates strong qualitative and quantitative performance. While this work establishes a foundation for multi-view relighting, we observe the following limitations. First, SyncLight may struggle in the presence of rare or unconventional light sources since it only relies on a circular region for light conditioning. Leveraging more precise segmentation masks, as in LightLab [Magar et al. 2025], would increase interaction complexity but might help generalize to more complex light sources. Second, leveraging priors learned by video models (e.g., as in [Liang et al. 2025]) might better generalize to videos. We note however that this approach may not work in the wide baselines typical of sparse multi-view setups. Our results on RealEstate10k demonstrate that SyncLight’s attention mechanism is robust across both wide-baseline pairs (fig. 8) and dense video trajectories (fig. 9a). This suggests that rigorous spatial consistency often suffices as a proxy for temporal stability. However, we believe integrating explicit temporal priors remains a promising direction to further refine coherence in dedicated video-specific applications. Finally, our model’s ability to generalize zero-shot from pairs ( $N = 2$ ) to arbitrary views ( $N > 2$ ) *without requiring explicit camera poses* is an intriguing empirical finding (fig. 6). It suggests that the multi-view attention mechanism successfully learns local consistency priors that scale to global scenes. However, understanding the precise limits of this generalization, particularly in scenes with extreme occlusion or minimal overlap, warrants further investigation. Incorporating explicit 3D priors, such as depth maps or camera poses, could further improve consistency in these challenging geometric scenarios.

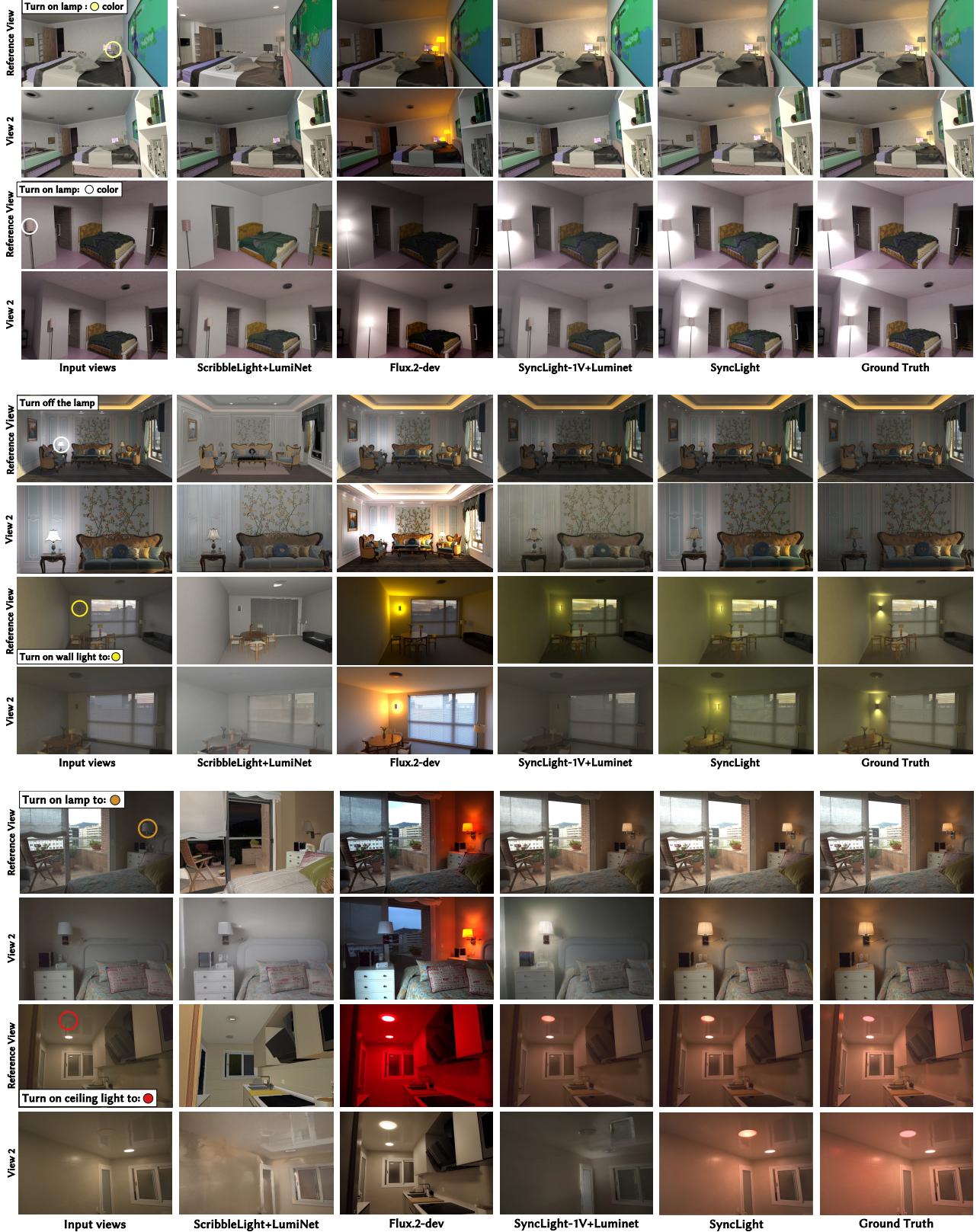
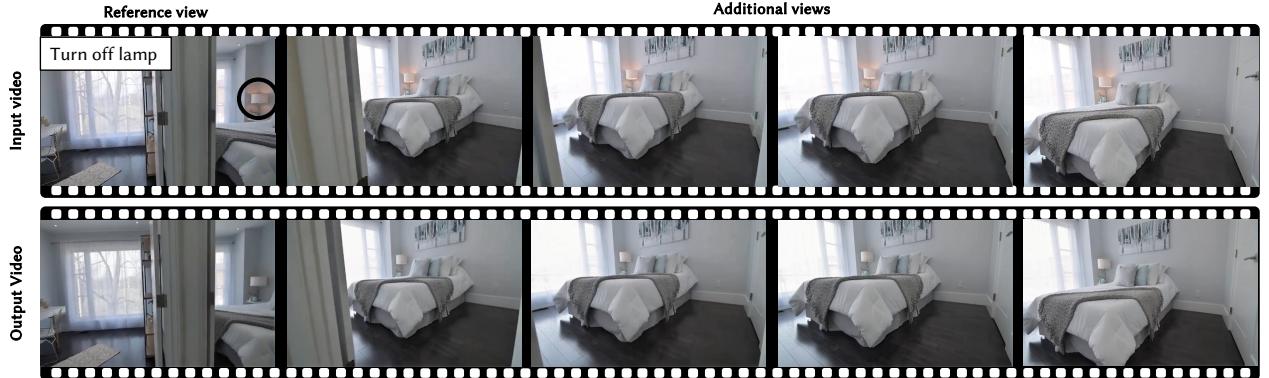
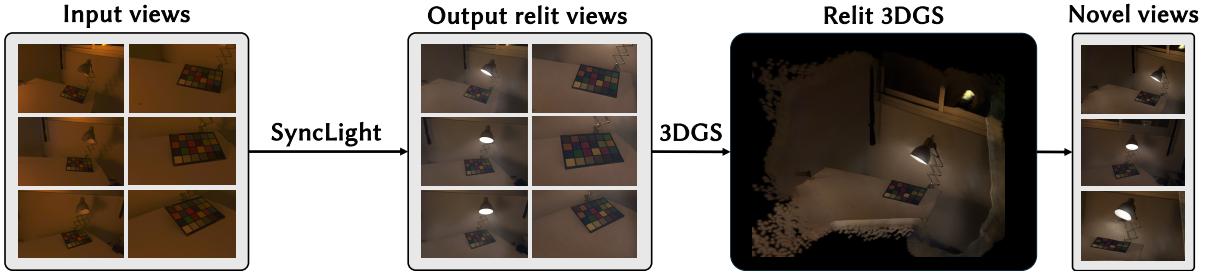
Fig. 7. Qualitative results on the SyncLight dataset. From top to bottom: *Infinigen* (1–2), *BlenderKit* (3–4) and *Real* (5–6) splits.



Fig. 8. Qualitative results on out-of-distribution images from the RealEstate10K dataset [Google Research 2018].



(a) Video relighting. From user inputs in the first frame only, SyncLight automatically relights 142 frames of a video from the RealEstate10k dataset [Google Research 2018].



(b) Novel-view synthesis. 3DGS [Kerbl et al. 2023] is applied to images relit by SyncLight, which achieves out-of-the-box multi-view consistency.

Fig. 9. SyncLight applied to: (a) very wide baseline images, (b) video relighting, and (c) novel-view synthesis with radiance fields.

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