ClimateNeRF: Physically-based Neural Rendering for Extreme Climate Synthesis

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\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Extreme climate synthesis. We fuse NeRF modelling and physical simulation to produce 3D consistent renderings of scenes with simulated physical effects. We apply our method to climate effect simulation: what will it look like if the playground floods? or is covered in snow? Note in particular reflections and ripple effects on water; accumulated snow on horizontal surfaces; trees darkened by wintertime; and consistency of geometry (but not ripples!) across views. Please visit our project page for the interactive illustrations.}
\end{figure}

\section*{Abstract}

Physical simulations produce excellent predictions of weather effects. Neural radiance fields produce SOTA scene models. We describe a novel NeRF-editing procedure that can fuse physical simulations with NeRF models of scenes, producing realistic movies of physical phenomena in those scenes. Our application – Climate NeRF – allows people to visualize what climate change outcomes will do to them.

ClimateNeRF allows us to render realistic weather effects, including smog, snow, and flood. Results can be controlled with physically meaningful variables like water level. Qualitative and quantitative studies show that our simulated results are significantly more realistic than those from SOTA 2D image editing and SOTA 3D NeRF stylization.

\section*{1. Introduction}

This paper describes a novel procedure that fuses physical simulations with NeRF models \cite{53, 55} of scenes to produce realistic movies of physical phenomena in those scenes. We apply our method to produce compelling simulations of possible climate change outcomes – what would the playground look like after a minor flood? a major flood? a blizzard?

Our application – Climate NeRF – is aimed at an important problem. Cumulative small changes are hard to reason about, and most people find it difficult to visualize what climate change outcomes will do to them \cite{9, 25, 29, 41}. Steps to slow CO\textsubscript{2} emissions (say, reducing fossil fuel use) or to moderate outcomes (say, building flood control measures) come with immediate costs and distant benefits. It is hard to support such steps if one can’t visualize their effects.

We show how to merge physical simulations – which pro-
Figure 2. Method Overview. Our method takes multiple posed images, the targeted climate event simulation (e.g., snow), and optionally a user-selected style image as inputs. First, we reconstruct the 3D scene using instant NGP [55] (a variant of NeRF) (Sect. 3.1). The reconstructed radiance fields allow us to synthesize high-quality novel view imagery of the scene efficiently. Second, we optionally finetune the learned instant-NGP model so that it captures the styles of the provided style image (Sect. 3.2). Such 3D consistent stylization is particularly useful for modeling weather effects that are hard to capture via physical simulation. Third, we simulate the climate events by integrating the relevant physical entities (snow, water, smog) to the scene and rendering physically plausible images.

ClimateNeRF allows us to render realistic weather effects, including smog, snow, and flood. These effects are consistent over frames, so that compelling movies result. At a high level, we: adjust scene images to reflect global effects of the physics; build a NeRF model of a scene from those adjusted images; recover an approximate geometric representation; apply the physical simulation in that geometry; then render using a novel ray tracer. Adjusting the images is important. For example, trees tend to have less saturated images in winter. We use a novel style transfer approach in an NGP framework to obtain these global effects without changing scene geometry (Section 3.2). Our ray tracer merges the physical and NeRF models by carefully accounting for ray effects during rendering (Section 3.3). An eye ray could, for example, first encounter a high NeRF density (and so return the usual result); or it could strike an inserted water surface (and so be reflected to query the model again).

We demonstrate the effectiveness of ClimateNeRF in various 3D scenes from the Tanks and Temple, MipNeRF360, and KITTI-360 datasets [3, 37, 44]. We compared to the state-of-the-art 2D image editing methods, such as stable diffusion inpainting [61], ClimateGAN [66]; state-of-the-art 3D NeRF stylization [90]. Both qualitative and quantitative studies show that our simulated results are significantly more realistic than the other competing methods. Furthermore, we also demonstrate the controllability of our physically-inspired approaches, such as changing the water level, wind strength and direction, and thickness of snow and smog.

Our approach results in view consistency (so we can make movies, which is difficult to do with frame-by-frame synthesis); compelling photorealism (because the scene is a NeRF representation); and is controllable (because we can adjust physically meaningful parameters in the simulation). As Fig. 1 illustrates, results are photo-realistic, physically plausible, and temporally consistent.

2. Related Work

Since 1981, the Earth’s temperature has been increasing over 0.32°F (0.18°C) per decade [8], with impacts on health, environment, and economy and disproportionately affecting people in low-income communities and developing countries [30]. Complex scientific figures from statistical analysis and forecasting do not resonate well with everyday people [9, 25, 29, 41], and various 2D image synthesis techniques have been applied to bring climate effects to a captured image.

Climate Simulation: The importance of making climate simulations accessible is well known. [65] collects climate images dataset and performs image editing with Cycle-
GAN [95], [17, 66] leverage depth information to estimate water mask, and perform GAN-based image editing and inpainting. [28] simulate fog and snow. These methods offer realistic effects for a single image, but cannot provide immersive, view-consistent climate simulation. In contrast, ClimateGAN allows the view to move without artifacts.

**Novel View Synthesis:** Neural Radiance Field (NeRF) [2, 3, 53, 76] leverage differentiable rendering for scene reconstruction producing photorealistic novel view synthesis. Training and rendering can be accelerated using multiple smaller MLPs and customized CUDA kernel functions [45, 60]. Sample efficiency can be improved by modeling the light field or calculating ray intersections with explicit geometry, such as voxel grids [48, 60, 82], octrees [87], planes [45, 81], and point cloud [84, 98]. Explicit geometric representations improve efficiencies [24, 50, 70, 84, 92]. We build on Instant-NGP [55] as it offers fast learning and rendering, is more memory efficient than grid-like structures, and accelerates the volume rendering process and fuse the estimated color and density from 1) the original radiance field (by querying the trained instant-NGP model) and 2) the physical entities (by physically based rendering). Our rendering procedure thus maintain the realism while achieving complex, yet physically plausible visual effects.

**Physically-based Simulation of Weather:** Physical simulation of weather in computer graphics has too long a history to allow comprehensive review here. Fournier and Reeves obtain excellent capillary wave simulations with simple Fourier transform reasoning [22] (and we adopt their method), with modifications by [31, 74]; [20] simulates smoke; and [21, 56, 69] simulate snow in wind using metaballs and fluid dynamics. Our method demonstrates how to benefit from such simulations while retaining the excellent scene modeling properties of NeRF style models.

### 3. Method

ClimateNeRF fuses physical simulations with NeRF models of scenes to produce realistic videos of climate change effects. A simple example illustrates how components interact in our approach. Imagine we wish to build a model of a flooded scene in Fall. We acquire images, apply a Fall style (Section 3.2), and build a NeRF from the results (Section 3.1). We then use geometric information in that NeRF to compute a water surface. This is represented using a density field, a color field together with normal and BRDF representations (Section 3.3). Finally, to render we query the model with rays. The details are elaborate (Section 3.4), but the general idea is straightforward: we edit the NeRF’s density and color functions to represent effects like smog;
and we intercept rays to represent specular effects. So if a ray encounters high density in the NeRF first, we use the NeRF integral for that ray; but if the first collision is with the water surface, we reflect that ray in the water surface, then query the NeRF with the reflected ray. Fig. 2 provides an overview of our approach.

3.1. 3D Scene Reconstruction

NeRF builds a parametric scene representation that supports realistic rendering from multiple images of a scene obtained at known poses. The scene is represented by a field

\[(\sigma, c) = F_\theta(x, d),\]  

which accepts position \(x\) and direction \(d\) and predicts density \(\sigma \in \mathbb{R}\) and color \(c \in \mathbb{R}^3\). This function is encoded in a multi-layer perceptron (MLP) with learnable parameters \(\theta\). Rendering is by querying radiance along appropriate choices of ray, computed as a volume integral [34]. This integral is estimated by drawing samples along the ray, evaluating the density and color at those samples, then accumulating values. The rendering process is differentiable, so that NeRF can be trained by minimizing the image reconstruction loss over training views through gradient descent: 

\[
\min_\theta \sum_r \|C(r) - C_{gt}(r)\|_2^2.
\]

There are numerous variants of NeRF. We use instant-NGP [55] to reconstruct the scene. This is an efficient NeRF alternative that explicitly stores multi-resolution features \(\gamma\) for scene representation. During rendering, given an input point, a local feature \(\gamma(x)\) is firstly queried through a spatial hashing function [73] and is then sent to a shallow multi-layer perceptron (MLP) to compute the final density \(\sigma\) and color \(c\): 

\[(\sigma, c) = F_\theta(x, d; \gamma(x)).\]

This explicit feature encoding and spatial partition are particularly suitable for ClimateNeRF because we can edit local features relatively easily.

A physical simulation needs access to the surface normal of any point to compute interactions with snow and water, and it needs access to the point’s semantics (in the sense of semantic segmentation) to transfer style. We expand the NGP and allow it to output both semantic logic \(s\) and surface normal \(n\). There is no semantic or surface normal ground truth during training. We use an off-the-shelf pretrained monocular semantic segmentation network [83] to produce semantic maps for each image. We use density gradients \(\hat{n} = -\frac{\nabla \sigma}{\|\nabla \sigma\|}\) [6, 67] (cf. Ref-NeRF [77]) to guide the predicted surface normals \(n\) with a weighted MSE loss.

To simulate (say) a blizzard, we must add snow to the scene and turn trees dark, but should not change the shape of the house. To keep spatial features intact at the stylization stage, we disentangle instant-NGP’s latent feature (as in [10, 70]). For each voxel in the NGP model, we split the latent feature into geometry features \(\gamma_{geo}\) and appearance features \(\gamma_{app}\). The geometry features are trained to render density. The appearance features are used for rendering color, semantics and normals. We will freeze the geometry feature vector during the stylization stage and change only the appearance feature vector.

Our 3D scene representation model is an improved instance-NGP model which renders density \(\sigma\), color \(c\), semantic log posterior \(s\) and surface normal \(n\), given a query point and ray direction, so

\[
(\sigma, c, s, n) = F_\theta(x, d; \gamma_{geo}, \gamma_{app})
\]

(more details in supplementary).

3.2. Stylization

Deciduous trees drop their leaves in winter, and physical simulation is not an efficient way to capture effects like this. We use FastPhotoStyle [42] to transfer style to rendered images from a pre-trained model \(F_\theta\). We only transfer only to regions ‘terrain’, ‘vegetation’, or ‘sky’ regions to mimic natural weather change phenomena. The resulting images look realistic but are not necessarily view-consistent. Hence, a student instant-NGP model is fixed-tuned to ensure the view consistency of the style-transferred scene. This is trained to minimize the color difference between our student NeRF-rendered results and style-transferred images. We keep the geometry intact and alter only appearance to achieve this goal, so only the appearance feature code \(\gamma_{app}\) is optimized during the style transfer stage:

\[
\min_{\gamma_{app}} \sum_{r \in R} \|C(r) - C_{styled}(r)\|_2^2
\]

where \(C(r)\) is rendered color and \(C_{styled}\) is the style-transferred in the same view. This gives us a new NGP
model \( \langle \sigma, c' \rangle = F'_o(x, d, \ell_i) \) which encodes the style. Fig. 4 demonstrates the visual effects of such NeRF stylization. This optional style transfer step simulates composite effects, such as a flood in Fall, where the original images were captured in Spring.

### 3.3. Representing and Rendering Climate Effects

We want to generate scenes with new physical entities – snow, water, smog – in place. We must determine where they are (the job of physical simulation) and what the resulting image looks like (the job of rendering). How the simulation represents results is important, because results must be accessible to the rendering process. Rendering will always involve computing responses to ray queries, so computing radiance at \( u \) in direction \( v \). We must represent simulation results in terms of densities and we must be able to compute normals and surface reflectance properties. Generally, we write \( O_o(x; F_o): \mathbb{R}^3 \rightarrow \mathbb{R} \) for a density resulting from a physical simulation; \( N_o(x; F_o): \mathbb{R}^3 \rightarrow S^2 \) for normals; and \( B_o(x, \omega_o, \omega_i; F_o): \mathbb{R}^3 \rightarrow \mathcal{S}^2 \) for BRDF. Each depends on the existing scene \( F_o \). Choice of \( B_o \) can simulate various effects, including the atmospheric effect of smog, refraction and reflections on water surfaces, and scattering of accumulated snow. \( \{O_o, N_o, B_o\} \) differs drastically across different physical simulations (details per effect in Sect. 3.4).

Once the physical entities are defined by functions \( O_o, N_o, B_o \), we can render them realistically into the image by modeling the light transport between the physical entities and the scene. Given the query point position \( x \), the simulation framework estimates the density and color of physical entities at position \( x \) through physically based rendering:

\[
\sigma_o = O_o(x; F_o), \\
c_o = \int_{\Omega} L(x, \omega_i) B_o(x, d, \omega_i; F_o)(\omega_i \cdot N_o(x; F_o))d\omega_i,
\]

where entity color \( c_o \) is approximated with physically-based rendering equation [33] with normal \( N_o \) and BRDF \( B_o \). Importantly, we approximate the incident illumination \( L(x, \omega_i) \) with radiance by tracing a ray \( r(t) = x - t\omega_i \) opposite to the incident direction in the learned NeRF, i.e. \( L(x, \omega_i) = C(x) \). Depending on the surface BRDF of physical entities, we use analytical or sampling-based solutions for the integral. Note that multiple bounces can be simulated through sampling.

### Smog Simulation

We assume that smog is formed by tiny absorbing particles, uniformly distributed in empty space. In empty space the NeRF density \( \sigma_o = 0 \). The Beer-Lambert law (originally [4, 40]; in [23]) means we can model smog density in free space by simply adding a non-negative constant to the density. Inside high density regions of the NeRF, adding the constant does not significantly change the integral, so we have

\[
O_o(x; F_o) = \sigma_{smog}
\]

where \( \sigma_o \) is a controllable parameter that decides the density of the smog. Smog particles have a constant color \( c_{smog} \). Both \( c_{smog} \) and \( \sigma_{smog} \) are controllable parameters. Fig. 12 depicts the effects of various smog densities.
Flood Simulation  The water surface of the flooded scene is approximately a horizontal plane: \( \mathbf{n}_w(x - \mathbf{o}_w) = 0 \), where the gravity direction normal \( \mathbf{n}_w \) is estimated with camera poses and vanishing points detection [49], and plane origin \( \mathbf{o}_w = (0, 0, h) \) determines the water height. But there are water ripples, which we implement following [31] with Fast Fourier Transform (FFT) based ripples and waves. The FFT wave takes random spectral coefficients as input and outputs a spatiotemporal surface normal based on wind speed, direction, and spatial and temporal frequencies. As shown in Fig. 8, compared against still water, FFT-based water surface simulation significantly improves the realism of the water surfaces. We simulate opacity and micro-facet ripples that make the water look glossy (details in supplementary). To approximate the integral in Eq. 4, we adopt the sigma-point method [52, 78] and sample 5 rays from \( x \), including reflection direction \( \mathbf{d}_r \) and nearby four rays. ClimateNeRF simulates Fresnel effect, glossy reflection, and wave dynamics.

Snow Simulation  Snow is more likely to be accumulated on surfaces facing upward, and the deeper part of the snow is denser due to gravity. We simulate density distributions over object surfaces using metaballs [36, 56] centered on surfaces and with density \( \sigma_o \) at the center. The density distribution within a metaball can be formulated by kernel function \( K(r; R, \sigma_o) \), which leads to a smooth decrease of density as the distance \( r \) from the metaball’s center grows. We follow [75] and tuned it to create a denser visual effect:

\[
K(r; R, \sigma) = 315 \frac{1}{64 \pi R^3} (1.5^2 - \left( \frac{r}{R} \right)^2)^3 \sigma
\]

For any point \( x \) in the space, we calculate the snow’s density of \( x \) using a parzen window density estimator over \( N \) local nearest neighbors (details in supplementary). The final density of the snow surface is decided accordingly:

\[
O_\phi(x; F') = \frac{1}{1 + e^{-\alpha(x - \sigma_{\text{snow}} - \tau_{\text{snow}})\sigma_{\text{snow}}}},
\]

where \( \tau_{\text{snow}} \) is a controllable surface truncation threshold and \( \alpha \) is a hyper-parameter. This equation implies a point is more likely to be surface boundary if it’s close or larger than the threshold. We use a spatially-varying diffuse color \( c_\phi(x) \) (which is close to pure white multiplied by the average illumination of the scene) to approximate BRDF, and apply a subsurface scattering effect [56] to light the snow’s shadowed part (further detail in supplementary). Surface normal values are still calculated in a gradient based manner. A visualization of snow rendering is shown in Fig. 6.

4. Experiments

We evaluate ClimateNeRF and show simulated results over various scenes across different climate effects. We compare our results with state-of-the-art 2D synthesis and 3D stylization to show the quality and consistency of rendered frames. Experimental results demonstrate that our method is more realistic and faithful than existing 2D synthesis and NeRF model finetuned on stylized images while we also maintain temporal consistency and physical plausibility. We encourage readers to watch supplementary videos for a better demonstration of our method’s quality.

4.1. Experimental Details

Datasets  We conduct experiments on various outdoor scenes: Playground, Family, Horse, Truck, and Train from Tanks and Temples dataset [38], Garden from MipNeRF360 [3] and Seq 00 from KITTI-360 dataset [44]. These testing scenes vary significantly regarding scales, contents, layouts, and viewpoints.
Figure 9. **Snow simulation comparison.** Swapping-Autoencoder [57] captures appearance changes but ignores the geometry of both truck and train. 3D Stylization preserves the geometry of original scene well but doesn’t accumulate snow on horizontal surfaces. In contrast, ClimateNeRF has convincing snow accumulation both on ground and on objects. Note small snow accumulations on the bogies and running board on the train and the boards and bonnet of the truck.

Figure 10. **User Study.** The length of bars indicates the percentage of users voting for higher realism than the opponents. The green bar with the number shows our win rate against each baseline. The video quality of our method significantly outperforms all baselines.

**Baselines** We compare ClimateNeRF to the state-of-the-art 2D image editing methods, such as stable diffusion inpainting [61], ClimateGAN [66], as well as state-of-the-art 3D NeRF stylization [90]. For all 2D synthesis approaches, we first build a NeRF using NGP, render at the target view, and conduct synthesis. For all the 3D methods, we re-use the improved version of NGP-based NeRF. ClimateGAN [66] uses monocular depth to predict masks and use GAN to inpaint the climate-related effects, including smog and flood; ClimateGAN++ is an improved version for flood simulation using our method’s water mask, yielding better geometry consistency; **Swapping Autoencoder** [57] is a photorealistic 2D style transfer method. We use the model pretrained on Flickr Mountains dataset and Flickr Waterfall dataset [57] for snow. **Stable Diffusion** [61] is the state-of-the-art guided image inpainting method based on latent diffusion model. We feed accurate water masks produced by ClimateNeRF and use text prompts of “flooding” for inpainting. **3D Stylization** leverages FastPhotoStyle [42]. To simulate white snow coverings, we stylize regions labeled

road, terrain, vegetation, and sky while keeping the geometry. Please refer to supplementary materials for additional implementation details for all competing methods including ours.

4.2. Experimental Results

Qualitative Results Fig. 7 depicts qualitative results from smog simulation. Our method delivers better realism and physical plausibility (see the different transmission levels across foreground and background). ClimateGAN [66] generates visually reasonable results but fails to provide sharp boundaries. Additionally, video results further show our method is better at view consistency.

We also report flood simulation results in Fig. 8. ClimateGAN++ [66] produces waters with wrong reflection and blurry artifacts. Stable Diffusion [61] provides realistic and diverse colors and reflectance but hallucinates additional
controllable Simulation. The simulation framework is highly controllable by the users. Top: different smog density; middle: different flood levels; bottom: different snow accumulations; all easily adjusted by a user.

contents (e.g., cars, trees) and lacks view consistency. ClimateNeRF renders accurate reflections with Fresnel effects and simulates realistic water ripples thanks to physical simulation. Video results show that our method is view-consistent and can provide fluid dynamics.

We report snow simulation results in Fig. 9. As the figure shows, 3D Stylization changes the floor texture but cannot add physical entities to the scene, limiting its realism. Swapping Autoencoder [57] changes the overall appearance but hallucinates unrealistic textures (e.g., car texture). On the other hand, ClimateNeRF simulates photorealistic winter effects, including accumulated snow and change of sky and tree colors, etc. ClimateNeRF even piles snow on tiny structures like pedals, as shown in the figure.

User Study We perform a user study to validate our approach quantitatively. Users are asked to watch pairs of synthesized images or videos of the same scene and pick the one with higher realism. 37 users participated in the study, and in total, we collected 2664 pairs of comparisons. Results are reported in Fig. 10. ClimateNeRF has consistently been favored among all video simulation comparisons thanks to its high realism and view consistency. Single image comparison does not consider view consistency. In this case, ClimateNeRF still outperforms most baselines except diffusion models on flooding, which also produces realistic water reflectances. Users find diffusion models tend to produce more reflective water surfaces and diverse ripples.

Controllability One unique advantage of ClimateNeRF is its controllability. Fig. 12 depicts the changes in smog density, water height, and snow thickness. We show additional controllability results, such as ripple size, flood color, water reflectance, and smog color in supp materials.

Adverse Weather Simulation for Self-Driving ClimateNeRF is a generic framework and can be applied to any

Figure 12. Controllable Simulation. The simulation framework is highly controllable by the users. Top: different smog density; middle: different flood levels; bottom: different snow accumulations; all easily adjusted by a user.

Figure 13. Simulation on Urban Driving Scenes. ClimateNeRF simulates smog, flood, and snow on a KITTI-360 scene [44]. We anticipate automatically generated severe weather data will enhance the robustness of self-driving to weather conditions.

Figure 14. Limitations. Snow simulation on KITTI-360 [44] dataset fails to cover a shadowed road due to wrong geometry estimations.

We propose a novel NeRF editing framework that applies physical simulation to NeRF models of scenes. Leveraging this framework, we build ClimateNeRF, allowing us to render realistic climate change effects, including smog, flood, and snow. Our synthesized videos are realistic, view-consistent, physically plausible, and highly controllable. We demonstrate the potential of ClimateNeRF to help raise climate change awareness in the community and enhance self-driving robustness to adverse weather conditions.

Limitations ClimateNeRF is dependent on the quality of NeRF reconstruction. Inaccurate geometry leads to non-ideal flood and snow simulation. Fig. 14 depicts a case that the incorrect ground surface results in artifacts in snow simulation. This also shows a future opportunity to automatically spot geometry understanding errors through physical simulation.

5. Conclusion

We propose a novel NeRF editing framework that applies physical simulation to NeRF models of scenes. Leveraging this framework, we build ClimateNeRF, allowing us to render realistic climate change effects, including smog, flood, and snow. Our synthesized videos are realistic, view-consistent, physically plausible, and highly controllable. We demonstrate the potential of ClimateNeRF to help raise climate change awareness in the community and enhance self-driving robustness to adverse weather conditions.
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Supplementary Material

In this supplementary material, we describe implementation details of the simulation framework in Sect. A; and provide ablation study to validate our design choices in Sect. B. ClimateNeRF is highly controllable and is demonstrated in Sect C; and more qualitative and quantitative results are included in Sect. D and Sect. E, respectively. Please also refer to our project page for more interactive demonstrations.

A. Implementation Details

3D Scene Reconstruction  We use spatial hashing grid [55] to represent the 3D scene. The entire space contains a multi-resolution feature grid \{enc(x; \theta^l_i)\}_{l=1}^L, where L is the total number of resolution levels; \theta^l are learnable parameters at each level. For a point x, we index grids by a spatial hash function [73] and fetch feature by interpolation and concatenation: \gamma = \text{cat}\{\text{interp}(x, enc(x; \theta^l_i))\}_{l=1}^L. In order to keep spatial features intact at the stylization stage and separate gradient flows between geometry and color, we develop a disentangled version of instant-NGP inspired by [10, 70]. Each voxel maintains a geometry code \gamma^\gamma and appearance code \gamma^\gamma app contains color, semantic and normal information:

\[
\gamma^\gamma = \text{cat}\{\text{interp}(x, enc(x; \theta^l_i))\}_{l=1}^L, \quad \gamma^\gamma app = \text{cat}\{\text{interp}(x, enc(x; \theta^l app_i))\}_{l=1}^L
\]

where interp stands for linear interpolation, cat denotes concatenation.

We use shallow MLPs to predict densities \sigma, colors c, semantic logits s and surface normal values n respectively from geometry features \gamma^\gamma and appearance features \gamma^\gamma app. We also incorporate appearance embeddings \{\hat{\theta}^a_i\}^N_{i=1} [51] to balance different lighting conditions across images. With hash grids and MLPs, we have the following function to reconstruct the original scene:

\[
(\sigma, c, s, n) = F_\theta(x, d, \hat{\theta}^a_i; \gamma^\gamma, \gamma^\gamma app)
\]  

Following volume rendering and alpha blending [53], we render the color C(r) for ray r and its semantic logit S(r) [94].

\[
C(r) = \sum_{i=1}^N T_i(1 - \exp(-\sigma_i \delta_i)) c_i; \quad S(r) = \sum_{i=1}^N T_i(1 - \exp(-\sigma_i \delta_i)) s_i, \text{where } T_i = \exp \left(-\sum_{j=1}^{i-1} \sigma_j \delta_j \right)
\]  

We apply softmax to semantic logits S(r) to obtain semantic probabilities \{p(r)^s_i\}_{i=1}^N for all labels. During training, we perform MSE loss \(L_C\) and cross-entropy loss \(L_S\) for rendered colors and semantic logits using ground truth color \(C_{gt}\) and 2D semantic logits \{\hat{p}(r)^s_i\}_{i=1}^N predicted by segformer [83] pretrained on cityscape dataset [16]. Moreover, we detach densities \sigma when rendering \(S(r)\) since we leverage pseudo-semantic labels. Like Ref-NeRF [77], we use the density gradient normals \(\hat{n} = -\frac{\nabla \sigma}{\|\nabla \sigma\|}\) [6,67] to guide the predicted surface normals n using a weighted MSE loss.

\[
L_C = \sum_{r \in \mathcal{R}} \|C(r) - C_{gt}(r)\|^2_2
\]  

\[
L_S = -\sum_{r \in \mathcal{R}} \sum_{l \in \mathcal{L}} \hat{p}(r)^s_l \log p(r)^s_l
\]  

\[
L_n = \sum_{r \in \mathcal{R}} \sum_{i=1}^N w_i \|n_i - \hat{n}_i\|^2_2
\]

where \(w_i = T_i(1 - \exp(-\sigma_i \delta_i))\) denotes the detached weight in Eq.10. We also leverage distortion loss \(L_{dist}\) [3,71] to mitigate floaters in the reconstruction results:

\[
L_{dist} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} w_i w_j \left| t_i + t_{i+1} - \frac{1}{2} \left( t_j + t_{j+1} \right) \right| + \frac{1}{3} \sum_{i=0}^{N-1} w_i^2 \left( t_{i+1} - t_i \right)
\]  

However, ngp model tends to create big ‘blobs’ in the sky with distortion loss. We alleviate this by applying a simple penalty \(L_{sky} = \sum_{r \in \mathcal{R}} e^{-D(r)} \cdot \mathbb{1}\{\hat{p}(r) = \hat{p}_{sky}\}\) where \(D(r)\) denotes the depth following Eq. 10 [88] and \(\mathbb{1}\{\cdot\}\) is an indicator function.
Figure 15. **Ablation on monocular dense depth supervision** Normal estimations in (b) shows that leveraging monocular dense depth removes artifacts on the road.

using 2D predicted semantic logits \( \hat{p} \). Moreover, we incorporate opacity loss \( L_O = -\sum_{r \in R} O(r) \log O(r) \) [58] to encourage ray opacity being either 0 or 1 to avoid semi-transparent regions in reconstruction results. During our training time, our model’s total loss is a weighted sum of aforementioned losses:

\[
L = L_C + \lambda S L_S + \lambda n L_n + \lambda_{dist} L_{dist} + \lambda_{sky} L_{sky} + \lambda O L_O
\]

**Transient Object Occlusion** In order to occlude transient objects like pedestrians or vehicles across views in tanks and temples dataset [38], we follow [11] and create per-image learnable masks:

\[
M_i(u, v) = F_\psi(u, v, i, \gamma_M)
\]

where \((u, v) \in \mathbb{R}^2\), \(i\) denotes image coordinate and image index in all training images. \(F_\psi\) denotes a shallow MLP and \(\gamma_M\) is the output of hash grids.

In such case, we change color reconstruction loss [11] following [11]:

\[
L_C = \sum_{r \in R} M(r)\|C(r) - C_{gt}(r)\|^2 + \lambda_M(1 - M(r))
\]

where the second term is used to prevent the mask from predicting everything transient.

**Geometry improvements** As mentioned in the limitation subsection in the main paper, ClimateNeRF strongly relies upon high-quality geometry. To improve geometry estimations for KITTI-360 dataset [44], we further leverage the monocular dense depth \(D_{mono}\) and depth loss:

\[
L_{depth} = \sum_{r \in R} \|((wD(r) + d) - D_{mono}(r))\|^2
\]

where \(w\) and \(d\) are used to align the predicted depth from NeRF \(D(r)\) and monocular depth cue \(D_{mono}(r)\) with a least-square criterion [18, 59, 88]. As can be seen in Fig.15, holes on the ground are “filled” due to supervisions from monocular dense depth.

**Training Details** Our implementations of the hash grids and distortion loss follow [54, 58]. For the scale and resolution of hash grid in our model, we get the inspiration from [70] where appearance features allocate more grids with finer resolutions. Geometry hash grids have 16 levels and \(2^{19}\) entries at most per level while appearance hash grids have 32 levels and \(2^{21}\) entries at most per level. For Tanks and Temples dataset [38] and MipNeRF-360 dataset [3], side length of hash grids is 16. Geometry MLP and appearance MLP both have 128 neurons per layer and 1 hidden layer while semantic MLP and normal predicting MLP has 32 neurons per layer and 1 hidden layer. For more details about network architecture, we recommend readers read supplementary materials. To balance between losses at reconstruction stage, we set the weights of image reconstruction loss and cross-entropy loss to 1 and 4\(^{-2}\) respectively while weights for opacity loss \(\lambda_O\), normal loss \(\lambda_n\), distortion loss \(\lambda_{dist}\) and sky loss \(\lambda_{sky}\) are 2\(^{-4}\), 7\(^{-4}\), 3\(^{-4}\) and 1\(^{-1}\) respectively.

**A.1. Flood Simulation**

Given that water is mostly muddy and non-transparent, we approximate the opacity by simply checking a point above or under the water’s surface:

\[
O_\phi(x; F_\theta') = \begin{cases} 
\infty & \text{if } n_w(x - o_w) = 0 \\
0 & \text{otherwise}
\end{cases}
\]

\[
O_\phi(x; F_\theta') = \begin{cases} 
\infty & \text{if } n_w(x - o_w) = 0 \\
0 & \text{otherwise}
\end{cases}
\]
Water is highly reflective, yet the microfacet ripples sometimes make the water look glossy. To simulate these effects, we leverage a Spherical Gaussian (SG) to approximate the BRDF on the reflective water surface:

$$B_\phi(x, -d, \omega_i, N_\phi(x)) = \exp(\lambda(-\omega_i, d))$$

(20)

where SG lobe axis is $d = d - 2(d \cdot N_\phi(x)) N_\phi(x)$, and $\lambda \in \mathbb{R}_+$ is the lobe sharpness, controlling the glossy effects.

We use sigma point-based sampling for rendering water. Specifically, the camera ray $r(t) = o + td$ is cast from the camera and hits the water surface at position $x$. The observed color is decided by a sampling-based approximation of the rendering equation:

$$c_\phi = (1 - R)c_o + R \sum_{i=1}^5 L(x, \omega_i) e^{\lambda(-\omega_i, d_i)}$$

(21)

where $L(x, \omega_i) = C(r)$ is the NeRF ray color (Eq. 10), representing the incident light color hitting $x$ along direction $\omega_i$, $R \in (0, 1)$ is the reflectance index determined by viewing direction $d$ and normal $N_\phi(x)$, which enables the system to simulate the Fresnel effect on the water. To approximate the integral in rendering equation [33], we adopt the sigma-point method [52,78] and sample 5 rays from $x$, including reflection direction $d_i$ and nearby four rays. In short, ClimateNeRF simulates Fresnel effect, glossy reflection, and wave dynamics.]

**Fresnel Effect** When the light hits the water surface, the amount of reflection and transmission is determined by the incident and normal directions and is described by the Fresnel effect. The angle between normal and incident rays is denoted by $\theta_i$, and the angle between normal and refracted ray in water is $\theta_t$. According to Snell’s Law: $r_i \theta_i = r_t \theta_t$, where $r_i = 1$ is the refraction index of air and $r_t = 1.33$ is the refraction index of water in our experiments, which is also consistent with real-world water properties. Next, the reflectance $R$ in Eq. 21 is computed by:

$$R = \frac{R_s + R_p}{2}, \quad R_s = \frac{\sin(\theta_i - \theta_t)}{\sin(\theta_i + \theta_t)}^2, \quad R_p = \frac{\tan(\theta_i - \theta_t)}{\tan(\theta_i + \theta_t)}^2$$

(22)

where $R_s$ and $R_p$ are the reflectance for s-polarized light and p-polarized light respectively. Modeling the Fresnel effect in our flood simulation pipeline makes the water far from the camera (larger $\theta_i$) have higher $R$ and looks more like a mirror; and the water nearby (smaller $\theta_i$) has lower $R$ and shows watercolor, which enhances the realism of the simulation.

**A.2. Snow Simulation**

For any point $x$ in the space, we calculate the snow’s density of $x$ in a particle-based manner. We first figure out a set of $N$ particles as metaballs’ centers $\{x_{i}^{(p)}\}_{i=1}^{N}$ with densities $\{\sigma_{i}^{(p)}\}_{i=1}^{N}$ and metaball radius $\{R_{i}^{(p)}\}_{i=1}^{N}$ around $x$. Then we sum up the densities calculated by kernel function $K(r, R, \sigma_o)$.

$$\sigma_{\text{snow}}(x) = \sum_{i=1}^{N} \sigma_{K}(x, x_{i}^{(p)}),$$

(23)

where $\sigma_{K}(x, x_{i}^{(p)}) = K(||x - x_{i}^{(p)}||_2, R_{i}^{(p)}, \sigma_{i}^{(p)})$

$\sigma_{i}^{(p)}$ is defined by weights during volume rendering 10 for $\sigma_{\theta}$ of $F_{\theta}^{(p)}$. More details are shown in Section A.3. During rendering, we identify snow surface by a threshold $\tau_{\text{snow}}$ and a hyperparameter $\alpha$:

$$O_{\phi}(x; F_{\theta}^{(p)}) = \frac{1}{1 + e^{-\alpha(x\sigma_{\text{snow}} - \tau_{\text{snow}})}} \sigma_{\text{snow}}$$

(24)

The BRDF of snow particles is set as spatially-varying diffuse color $c_{\phi}(x_{i}^{(p)})$ close to pure white multiplied by the average illumination of the scene. Furthermore, since the snow is semi-transmissive, the subsurface scattering effect [56] will light the snow’s shadowed part. To simulate such effect, we leverage warp lighting function [26] $\Phi(n_K, n_l, \gamma_{\phi})$ based on normalized surface normal $n_K$, light vector $n_l$ and hyperparameter $\gamma_{\phi}$. For an arbitrary point $x$ in space, the color of point $x$ is a weighted sum of $\{c_{i}^{(p)} \in \mathbb{R}^3\}_{i=1}^{N}$ based on kernel function:

$$c_{\phi}(x) = \frac{\sum_{i=1}^{N} \sigma_{K}(x, x_{i}^{(p)}) c_{i}^{(p)} + c_0}{\sum_{i=1}^{N} \sigma_{K}(x, x_{i}^{(p)})} \Phi(n_K(x), n_l, \gamma_{\phi})$$

(25)
where $\Phi(n_K(x), n_i, \gamma \Phi) = \frac{n(x)^{\mu + \gamma \Phi}}{1 + e^{L \gamma \Phi}}$ and $\frac{c^{(p)} + c_0}{1 + e^{L \gamma \Phi}}$ is used to approximate a high albedo for snow and $c_0$ is a hyperparameter. Surface normal values are still calculated in a gradient-based manner.

### A.3. Extensions

#### Bake Editing

When simulating physical entities, especially snow, rendering will be time-consuming if we straightly let snow fall from the sky and do collision detection. Moreover, due to a lack of supervision in a bird’s eye view, depth estimation for rays cast from the sky is not accurate. To mitigate the aforementioned issues, we fit the distribution of metaballs’ densities and albedo color in a new model and fetch them in a particle-based manner. The new model outputs high densities where metaballs collide and colors to surfaces. To identify surfaces where snow accumulates, we incorporate surface normals to figure out metaballs’ density weights: $w_i^{(p)} = \frac{1}{1 + e^{-u(n_i, n_i - \cos(n_i \theta_\theta)}} w_i$ where $\theta_\theta$ is a hyperparameter. We then bake $w_i^{(p)}$ into a new model $G_{\phi_w}$:

$$
\sigma_i^{(p)}(x) = G_{\phi_w}(x)
$$

We also bake the gray scale [68] of $c_\theta$ from $F_\theta$ into a new model $G_{\phi_e}$ to capture an approximation for light intensities and shadows:

$$
\sigma_i^{(p)}(x) = G_{\phi_e}(x)
$$

Then, we leverage the pre-trained $G_{\phi_w}, G_{\phi_e}$ and do voxel sampling to fetch $\{\sigma_i^{(p)}\}_{i=}^{N_i} \text{ and } \{\sigma_i^{(p)}\}_{i=}^{N_i}$ from 8 vertices. Also, to automatically alter metaballs’ radiuses according to the size of the surface, we sample nested grids with different side lengths defined in a geometric progression. Moreover, we define metaballs’ radiuses by grids’ side lengths. Hence, Eq. 23 and Eq. 25 can be rewritten as:

$$
\sigma_{\text{snow}}(x) = \sum_{i=1}^{8N_n} \sigma_k(x, x_i^{(p)}); \quad \sigma_o(x) = \frac{\sum_{i=1}^{8N_n} \sigma_k(x, x_i^{(p)}) c_i^{(p)} + c_0}{\sum_{i=1}^{8N_n} \sigma_k(x, x_i^{(p)}) \Phi(n_k(x), n_i, \gamma \Phi)}
$$

where $N_n$ is the number of nests. We calculate density $\sigma^{(p)}$ and albedo color $c^{(p)}$ for metball centered at $x^{(p)}$ by $\sigma^{(p)} = w_i^{(p)}(x^{(p)}) \sigma_0$ and $c^{(p)} = c_i^{(p)}(x)$ where $\sigma_0$ is a hyperparameter. See Fig. 16 for a visualization of this sampling strategy. If stylization is done on the scene, we leverage the stylized model $F'_\theta$ and finetune the $G_{\phi_e}$ to match new illumination conditions while remaining $G_{\phi_w}$ intact since $F'_\theta$ shares the same spatial information with $F_\theta$.

#### Anti-Aliasing

When rendering with simulation, the high-frequency normal map changes on the physical entity surface would lead to an aliasing effect. To alleviate such artifacts, we can render four times larger images with higher resolution, and perform anti-aliasing downsampling to the original resolution.

### B. Ablation Study

To justify our design choices, we perform an ablation study of flood simulation, and the results are shown in Fig 17. Specifically, we report the simulation results without certain technical components depicted in Sec. A.1 of the main paper.
Fig 17 shows that all components are essential for realism. For example, vanishing point detection [49] makes the water plane follow gravity direction; wave simulation adds ripples to the water surface; the Fresnel effect makes the water reflectance view-dependent and physically plausible; the Glossy effect mimics realistic microfacet water surfaces with ripples; anti-aliasing removes far-away high-frequency noises. In short, all components contribute to the realism of the simulation.

We also perform an ablation study on snow simulation to validate our approximate scattering rendering in Fig. 18. We compare 1) pure white metaballs with spatial variant colors, 2) metaballs in a fully diffuse model, and 3) our full simulation. Results demonstrate that our choice provides a more realistic rendering of accumulated snow.

C. Controllability

We further demonstrate that ClimateNeRF is highly controllable during the simulation process. In Fig. 19, our method simulate different colors of smog and flood, varying spatial frequency of water ripples, and distinct heights of accumulated
snow. The results show that our simulation framework is highly controllable by the users. Consequently, scientists can use this framework to simulate accurate climate conditions depending on the projected climate in the future and visualize the consequences corresponding to different actions taken by policymakers and the general public.

D. Qualitative Results

We demonstrate more qualitative results in Fig. 20, Fig. 21, Fig. 22, and Fig. 23. For smog scene images in Fig. 20, ClimateGAN [66] generates visually plausible results but fails to provide sharp boundaries, and 3D stylization attempts to change the surface texture but makes the images overall darker. Our method simulates realistic visibility reduction effects caused by smog, thanks to the geometry reconstruction.

The flood images are shown in Fig. 21. ClimateGAN++ [66] cannot reconstruct realistic reflection on the water surface, Stable Diffusion [61] synthesize realistic water appearance but also produce random objects (e.g., cars, signs) in the scene, which is not consistent across views. ClimateNeRF simulates realistic reflection and water ripples while being view-consistent. This is better demonstrated in the supp video and website.

We also compare our FastPhotoStyle [42] based stylization method with Artistic Radiance fields [90]. As shown in Fig. 24, we sustain more appearance details from the original scene.

E. Quantitative Results

No automatic quantitative score can holistically evaluate the quality of our weather-simulated movies. In this project, we evaluate the synthesized videos with the state-of-the-art video quality assessment model UVQ [80] and report the results in Table 1. The score ranges between interval (1, 5), where 1 indicates the lowest quality and 5 indicates the highest quality. As the table shows, our smog simulation outperforms all other baselines, while it does not win Stable Diffusion [61] in flood simulation and ClimateGAN [66] in snow simulation. That being said, UVQ prefers sharp videos instead of measuring holistic realism. As shown in Fig. 22, baselines get a better quality score despite providing low-quality snow simulation.
results, suggesting UVQ might not be a good metric for our task. Hence, despite demonstrating UVQ [80] results, we want to emphasize that such metrics mainly focus on measuring the amount of low-level degradation (such as blurriness and noise), which cannot faithfully reproduce human evaluation on realism. Having a good video quality score on simulation remains an open topic.
Figure 21. *Flood simulation comparison.*
Figure 22. Snow simulation comparison.
Figure 23. Simulation on Urban Driving Scenes.

Figure 24. Comparison with Artistic Radiance Fields [90]

Table 1. Video Quality Assessment. We evaluate the video quality with Google’s Universal Video Quality (UVQ) model [80].