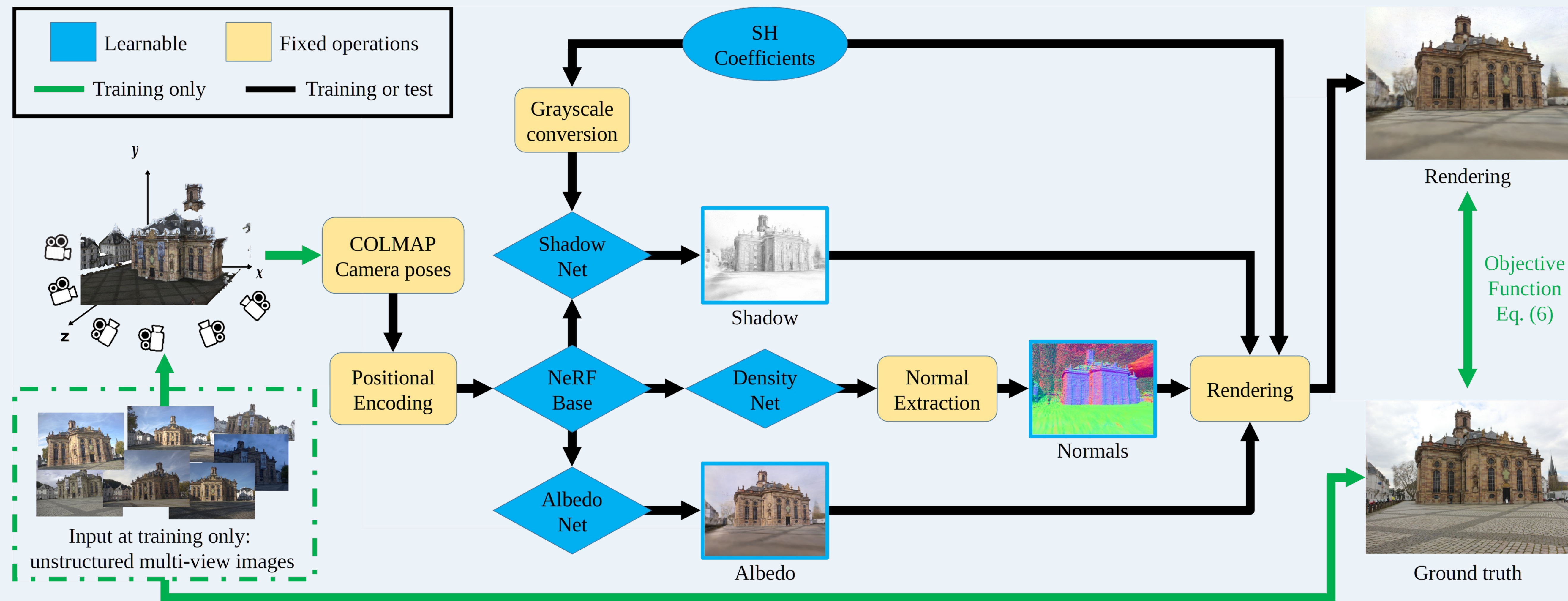


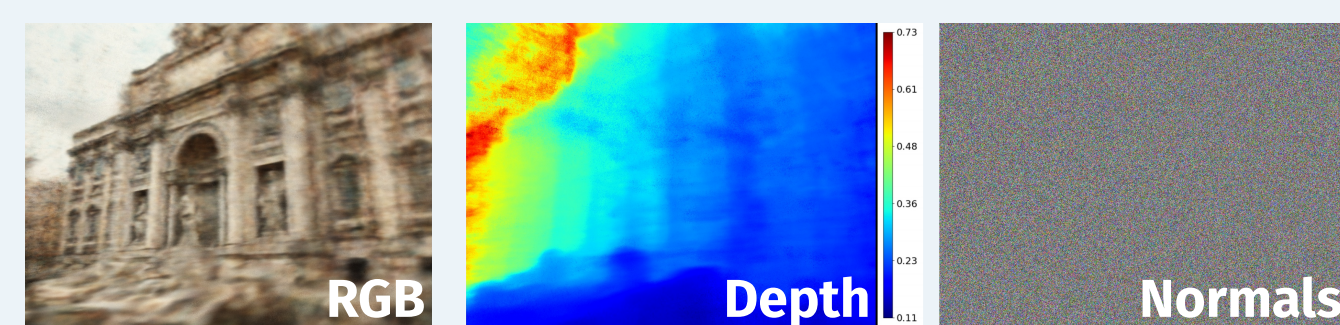
Method



$$L = L_{reconstruction} + L_{shadow}, L_{shadow} = \lambda(1-s)^2,$$

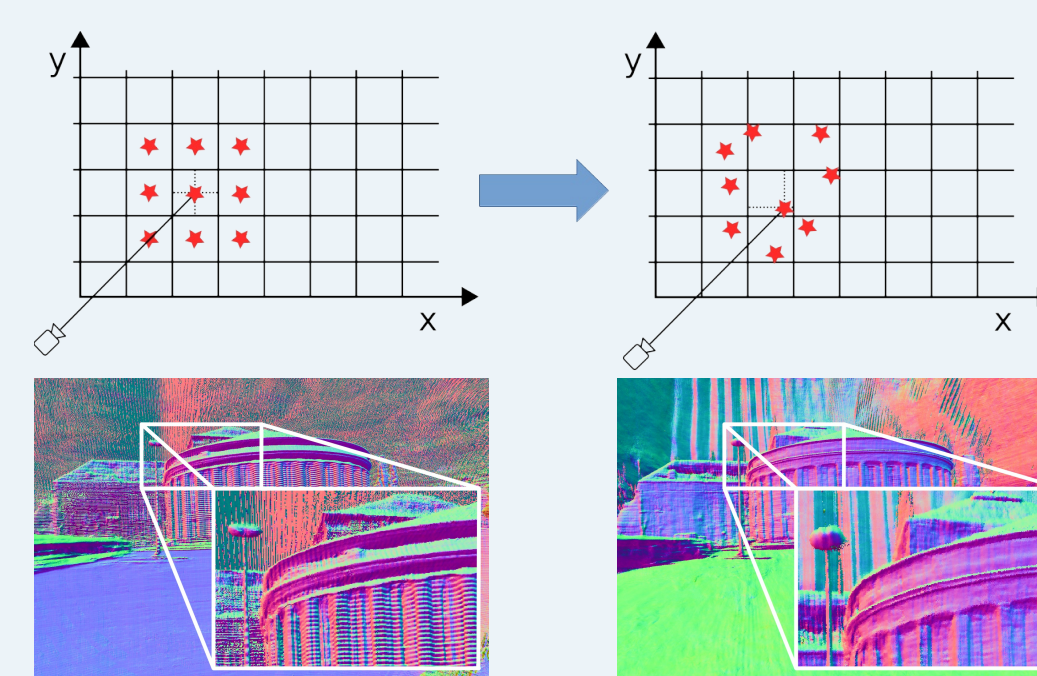
Loss function is the mean-squared error between the reconstructed image and the ground-truth and, in addition, the **shadow regularizer** term.

The latter prevents the shadow network from learning all of the illumination effects which should be learned with the SH illumination components



To prevent the collapse of geometry and normals as in the example above, we apply **frequency annealing** introduced in Park et al.:

$$w_j(\alpha) = \frac{(1 - \cos(\pi \text{clamp}(\alpha - j, 0, 1)))}{2}$$

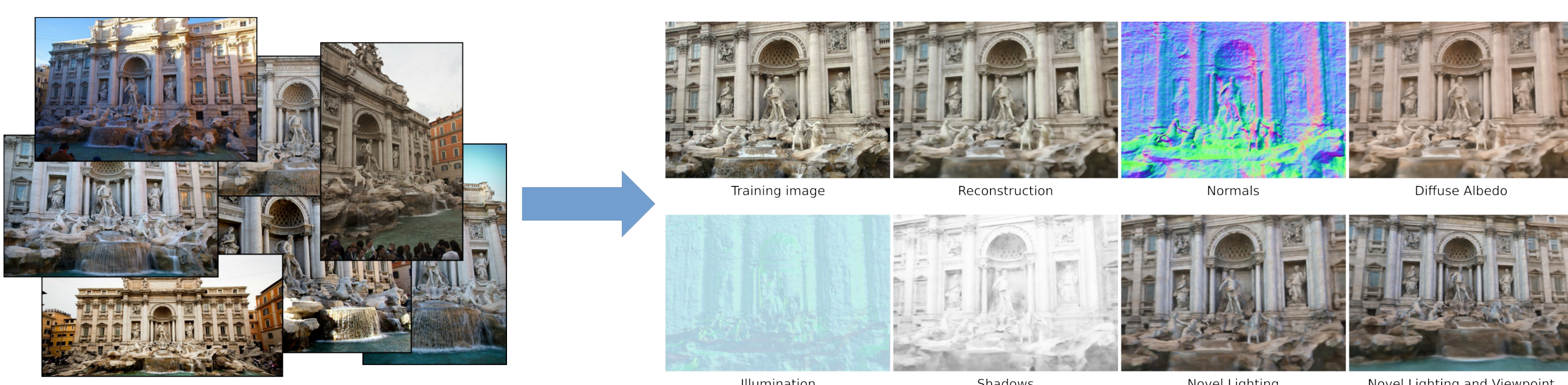


To prevent overfitting of normals we apply **ray direction jitter**



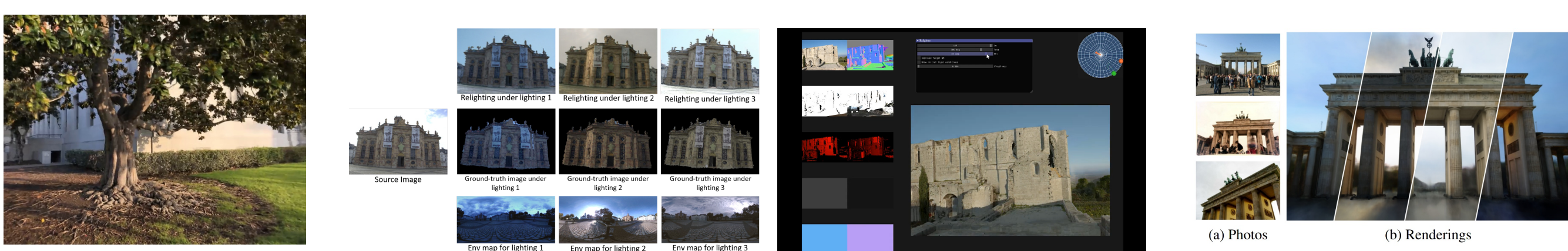
To improve generalisation of the shadow network, we apply a **small noise vector** to its environment map coefficients input

Problem



Novel viewpoint and relighting **at the same time** from 50-300 **in-the-wild** photos

Related work



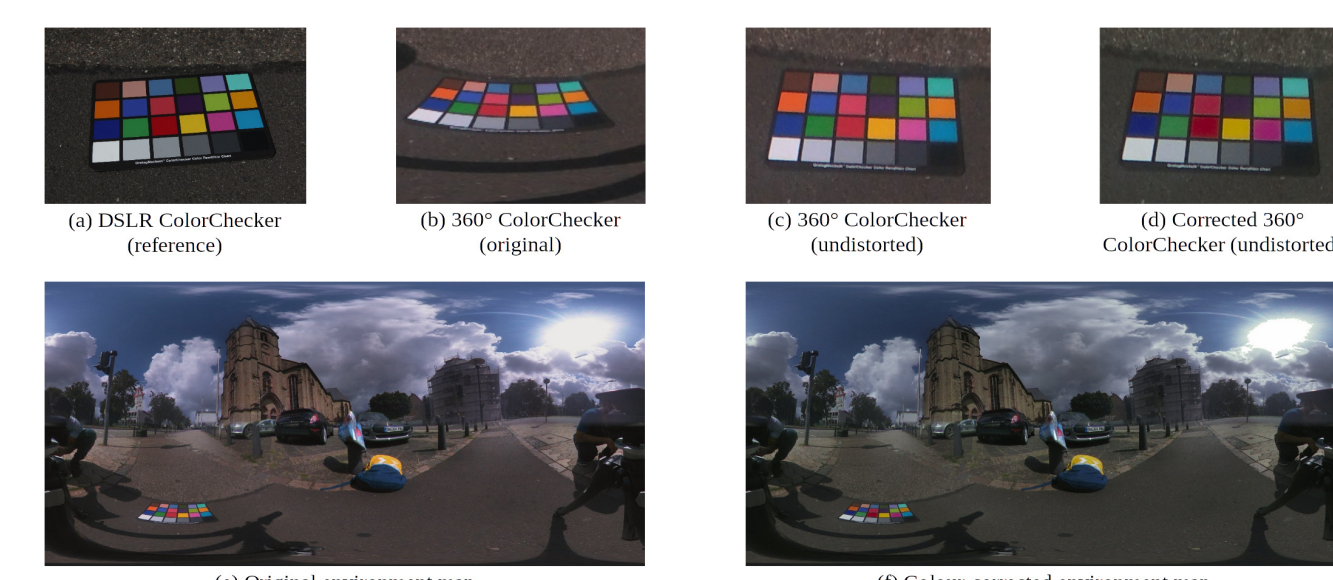
NeRF
(Only novel viewpoint)

Yu et al.
(Only novel lighting)

Philip et al.
(Only novel lighting)

NeRF-W
(No semantic control)

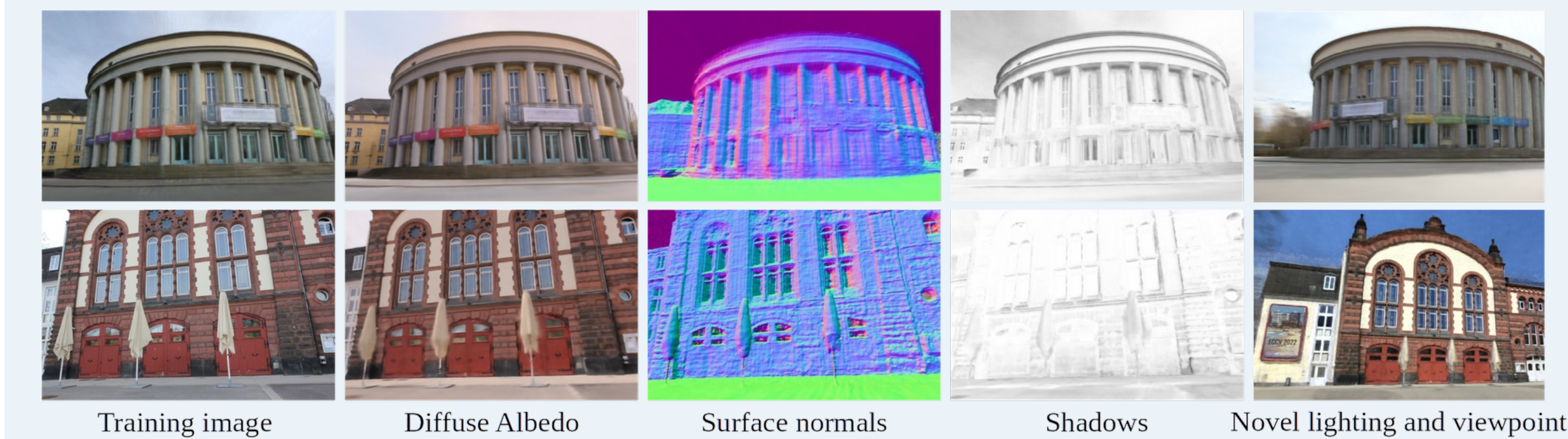
New Dataset with Environment Maps



We colour-correct environment maps using a **GretagMacbeth ColorChecker** captured on both the 360° environment photos and DSLR photos

| | Sessions | Views |
|--------|----------|-------|
| Site 1 | 18 | 373 |
| Site 2 | 17 | 423 |
| Site 3 | 16 | 372 |
| Site 4 | 11 | 401 |
| Site 5 | 13 | 493 |
| Site 6 | 12 | 379 |
| Site 7 | 11 | 468 |
| Site 8 | 12 | 331 |
| Total | 110 | 3240 |

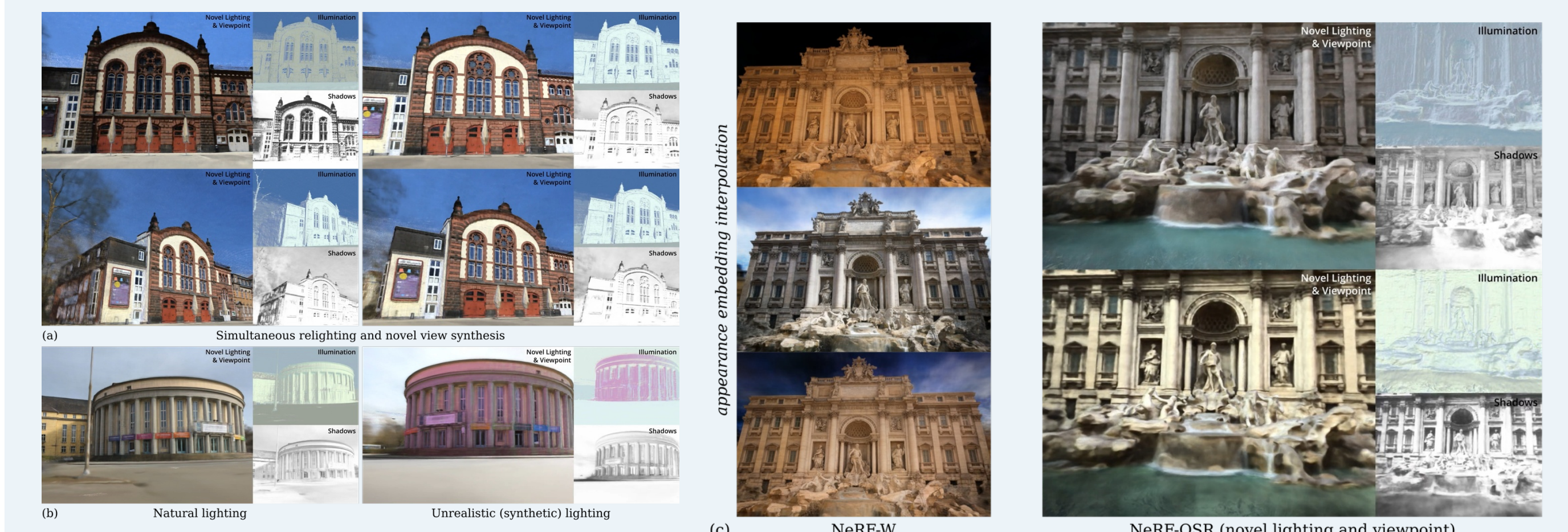
Results



Additional Applications



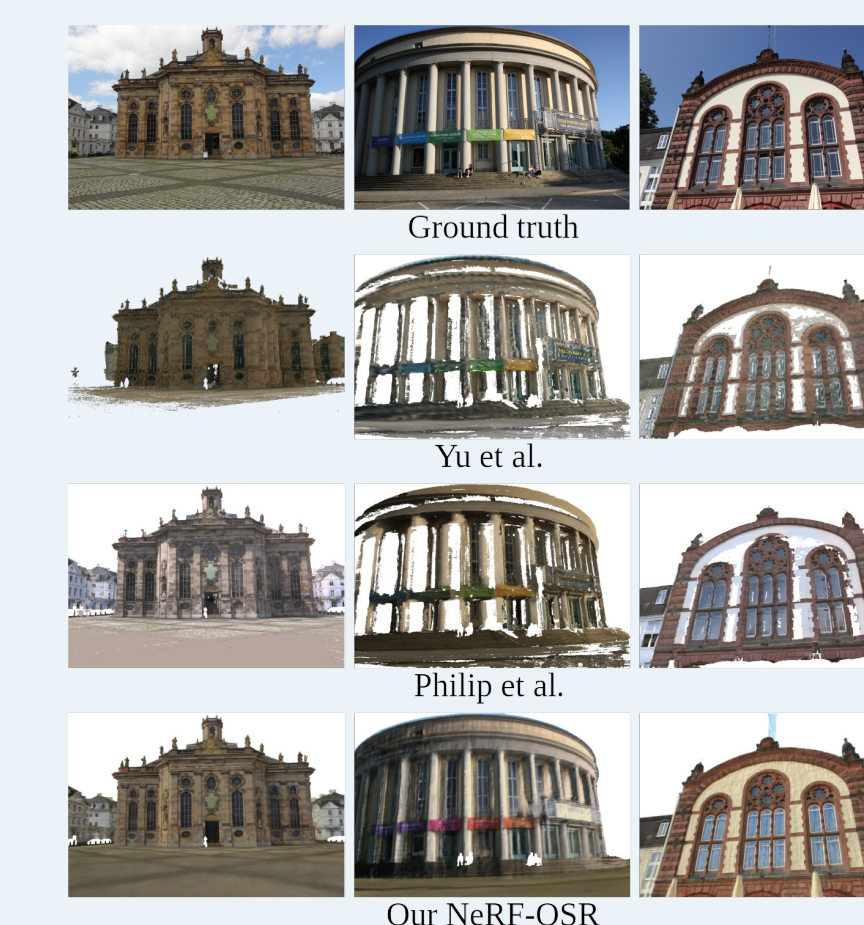
Various Results



Simultaneous relighting and novel view synthesis with our NeRF-OSR, even with **synthetic** lighting conditions, thanks to its **image intrinsic decomposition**

Compared to NeRF-W which can only interpolate between learned illuminations, our NeRF-OSR can synthesise **completely novel lighting conditions** with **full semantic control**

Comparisons to Yu et al. and Philip et al.



| Method | PSNR ↑ | MSE ↓ | MAE ↓ | SSIM ↑ |
|--------------------------|--------------|--------------|-------------|--------------|
| Site 1 | | | | |
| Yu et al. [46] | 18.71 | 0.014 | 0.088 | 0.4 |
| Philip et al. [27] (d/s) | 17.37 | 0.019 | 0.105 | 0.429 |
| Ours (d/s) | 19.86 | 0.011 | 0.08 | 0.626 |
| Yu et al. [46] (u/s) | 17.87 | 0.017 | 0.097 | 0.378 |
| Philip et al. [27] | 16.63 | 0.023 | 0.113 | 0.367 |
| Ours | 18.72 | 0.014 | 0.09 | 0.468 |
| No shadows | 17.82 | 0.017 | 0.101 | 0.418 |
| No annealing | 17.16 | 0.02 | 0.108 | 0.324 |
| No ray jitter | 18.43 | 0.015 | 0.093 | 0.433 |
| No shadow jitter | 18.28 | 0.016 | 0.095 | 0.413 |
| No shadow regulariser | 17.62 | 0.018 | 0.105 | 0.373 |

References: Yu et al. "Self-supervised Outdoor Scene Relighting", ECCV 2020
 Philip et al., "Multi-view Relighting Using a Geometry-Aware Network", SIGGRAPH 2019
 Mildenhall et al., "NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis", ECCV 2020
 Martin-Brualla et al., "NeRF-W: Neural Radiance Fields for Unconstrained Photo Collections", CVPR 2021
Acknowledgements: We thank **Christen Millerdurai** for the help with the dataset recording. This work was supported by the ERC Consolidator Grant 4DReply (770784).