IntrinsicEdit: Precise generative image manipulation in intrinsic space Supplemental document

LINJIE LYU, Max-Planck-Institute for Informatics, Saarland Informatics Campus, Germany and Adobe Research, UK
VALENTIN DESCHAINTRE, Adobe Research, UK
YANNICK HOLD-GEOFFROY, Adobe Research, Canada
MILOŠ HAŠAN, Adobe Research, USA
JAE SHIN YOON, Adobe Research, USA
THOMAS LEIMKÜHLER, Max-Planck-Institute for Informatics, Saarland Informatics Campus, Germany
CHRISTIAN THEOBALT, Max-Planck-Institute for Informatics, Saarland Informatics Campus, Germany
ILIYAN GEORGIEV, Adobe Research, UK

Fig. 1. **Normal and roughness editing.** We demonstrate several variants of material editing using our method. The top row shows different normal edits; note that we drop the albedo channel due to the conflicts with the changing geometry. Our method still delivers a plausible appearance on the floor. In the bottom row, we gradually increase the floor roughness from left to right.

In this supplemental document, we show qualitative results on material editing, object removal and insertion, and relighting, expanding the set presented in the main paper. We also include additional examples from our quantitative evaluation.

Authors' Contact Information: Linjie Lyu, Max-Planck-Institute for Informatics, Saarland Informatics Campus, Saarbrücken, Germany and Adobe Research, London, UK, llyu@mpi-inf.mpg.de; Valentin Deschaintre, Adobe Research, London, UK, deschain@adobe.com; Yannick Hold-Geoffroy, Adobe Research, Quebec, Canada, holdgeof@adobe.com; Miloš Hašan, Adobe Research, San Jose, USA, mihasan@adobe.com; Jae Shin Yoon, Adobe Research, San Jose, USA, jaeyoon@adobe.com; Thomas Leimkühler, Max-Planck-Institute for Informatics, Saarland Informatics Campus, Saarbrücken, Germany, thomas.leimkuehler@mpi-inf.mpg.de; Christian Theobalt, Max-Planck-Institute for Informatics, Saarland Informatics Campus, Saarbrücken, Germany, theobalt@mpi-inf.mpg.de; Iliyan Georgiev, Adobe Research, London, UK, igeorgiev@adobe.com.

ACM 1557-7368/2025/8-ART
https://doi.org/10.1145/3731173

References

Adobe Inc. 2024. *Adobe Photoshop.* https://www.adobe.com/products/photoshop.html

Chris Careaga, S Mahdi H Miangoleh, and Yağız Aksoy. 2023. Intrinsic Harmonization for Illumination-Aware Compositing Supplementary Material. (2023).

Xi Chen, Lianghua Huang, Yu Liu, Yujun Shen, Deli Zhao, and Hengshuang Zhao. 2023. Anydoor: Zero-shot object-level image customization. *arXiv preprint arXiv:2307.09481* (2023).

Peter Kocsis, Vincent Sitzmann, and Matthias Nießner. 2024. Intrinsic Image Diffusion for Indoor Single-view Material Estimation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 5198–5208.

Patrick Pérez, Michel Gangnet, and Andrew Blake. 2003. Poisson image editing. In *ACM SIGGRAPH 2003 Papers.* 313–318.

Stability AI. 2023. Stable Diffusion XL Inpainting. https://huggingface.co/diffusers/stable-diffusion-xl-1.0-inpainting-0.1.

Zheng Zeng, Valentin Deschaintre, Iliyan Georgiev, Yannick Hold-Geoffroy, Yiwei Hu, Fujun Luan, Ling-Qi Yan, and Miloš Hašan. 2024. Rgb↔ x: Image decomposition and synthesis using material-and lighting-aware diffusion models. In *ACM SIGGRAPH 2024 Conference Papers.* 1–11.

Zitian Zhang, Frédéric Fortier-Chouinard, Mathieu Garon, Anand Bhattad, and Jean-François Lalonde. 2024. Zerocomp: Zero-shot object compositing from image intrinsics via diffusion. *arXiv preprint arXiv:2410.08168* (2024).

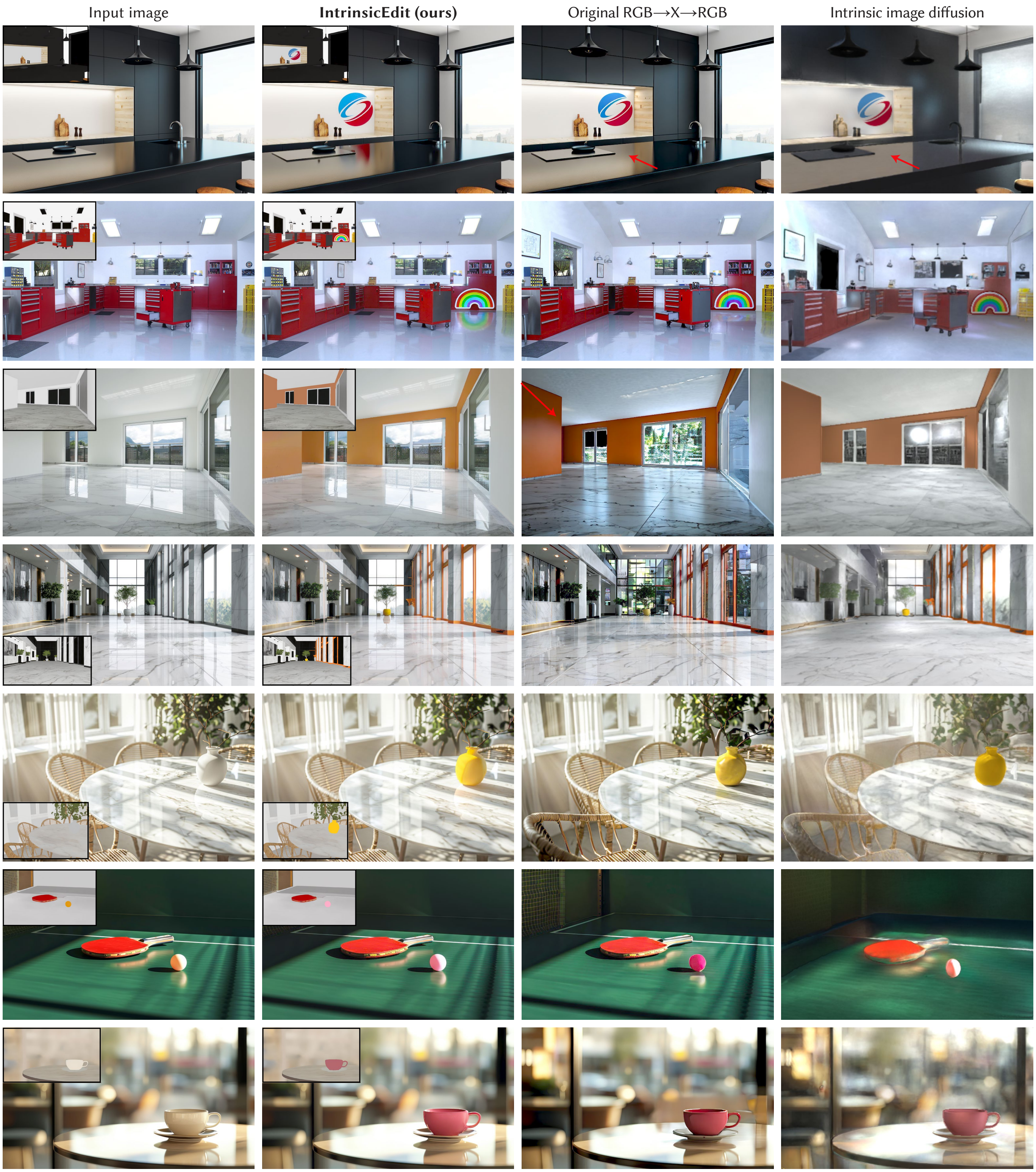

Fig. 2. **Color editing A.** We compare against two intrinsic-image methods: original RGB⟶X⟶RGB [Zeng et al. 2024] and intrinsic image diffusion [Kocsis et al. 2024]. Our method enables precise manipulation of individual material properties while preserving identity and achieving seamless illumination harmonization.

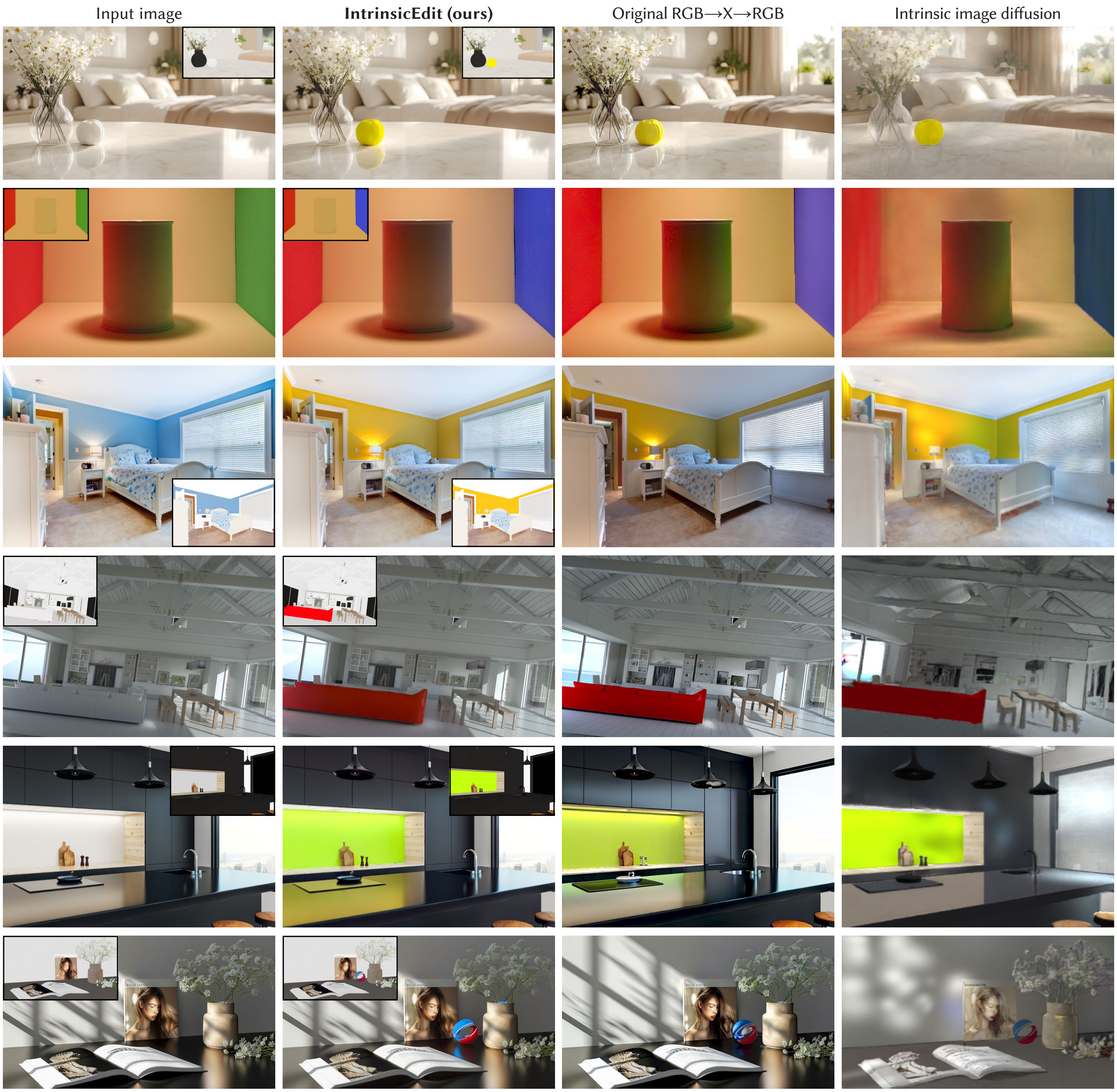

Fig. 3. **Color editing B.** We compare against two intrinsic-image methods: original RGB⟶X⟶RGB [Zeng et al. 2024] and intrinsic image diffusion [Kocsis et al. 2024]. Our method enables precise manipulation of individual material properties while preserving identity and achieving seamless illumination harmonization. In the botom row, we observe that if the texture edit does not align with an existing object, our model interprets the edit as object insertion and harmonizes accordingly.

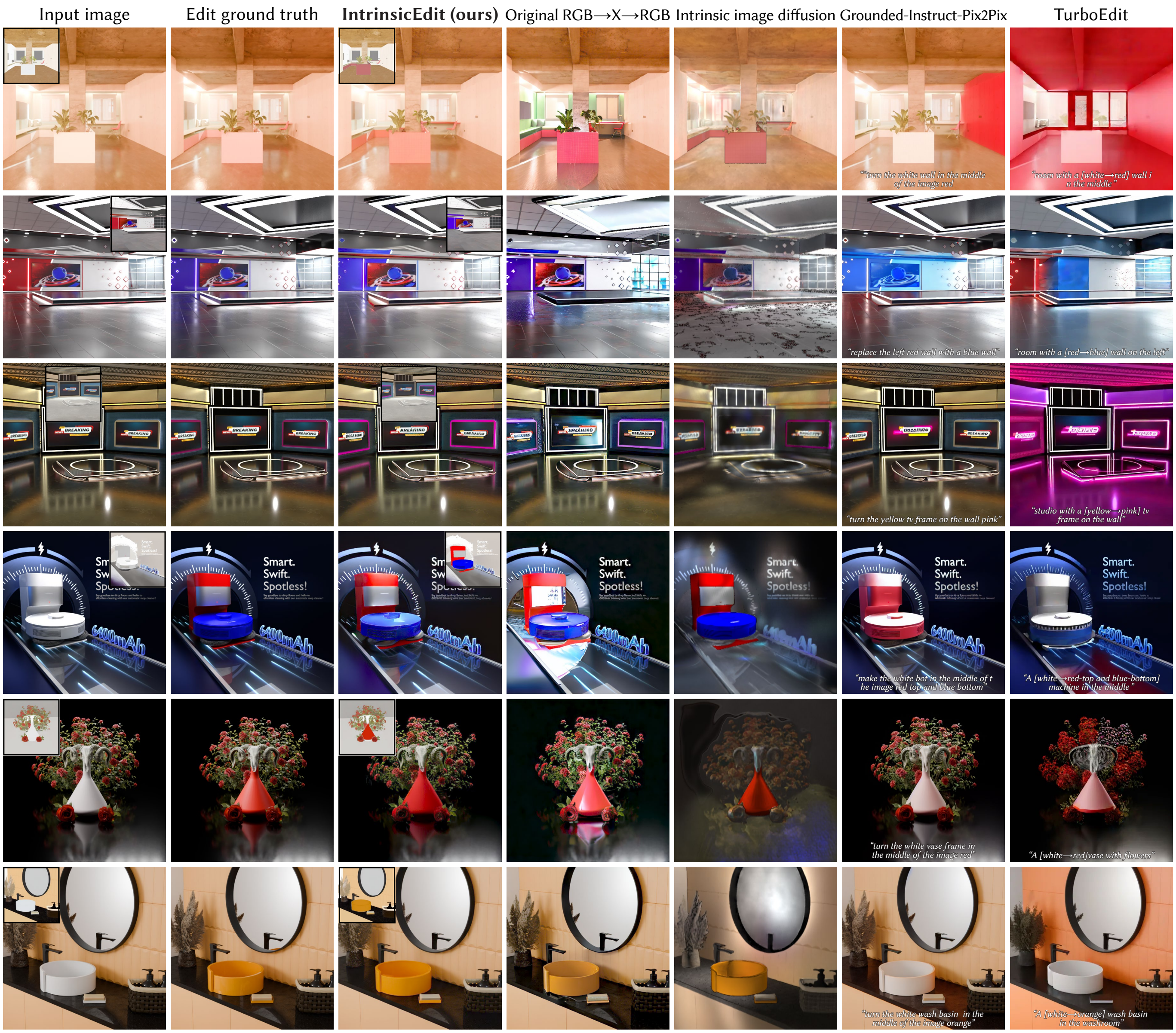

Fig. 4. **Synthetic color editing.** We include additional results used in the quantitative evaluation on a synthetic dataset in the paper.

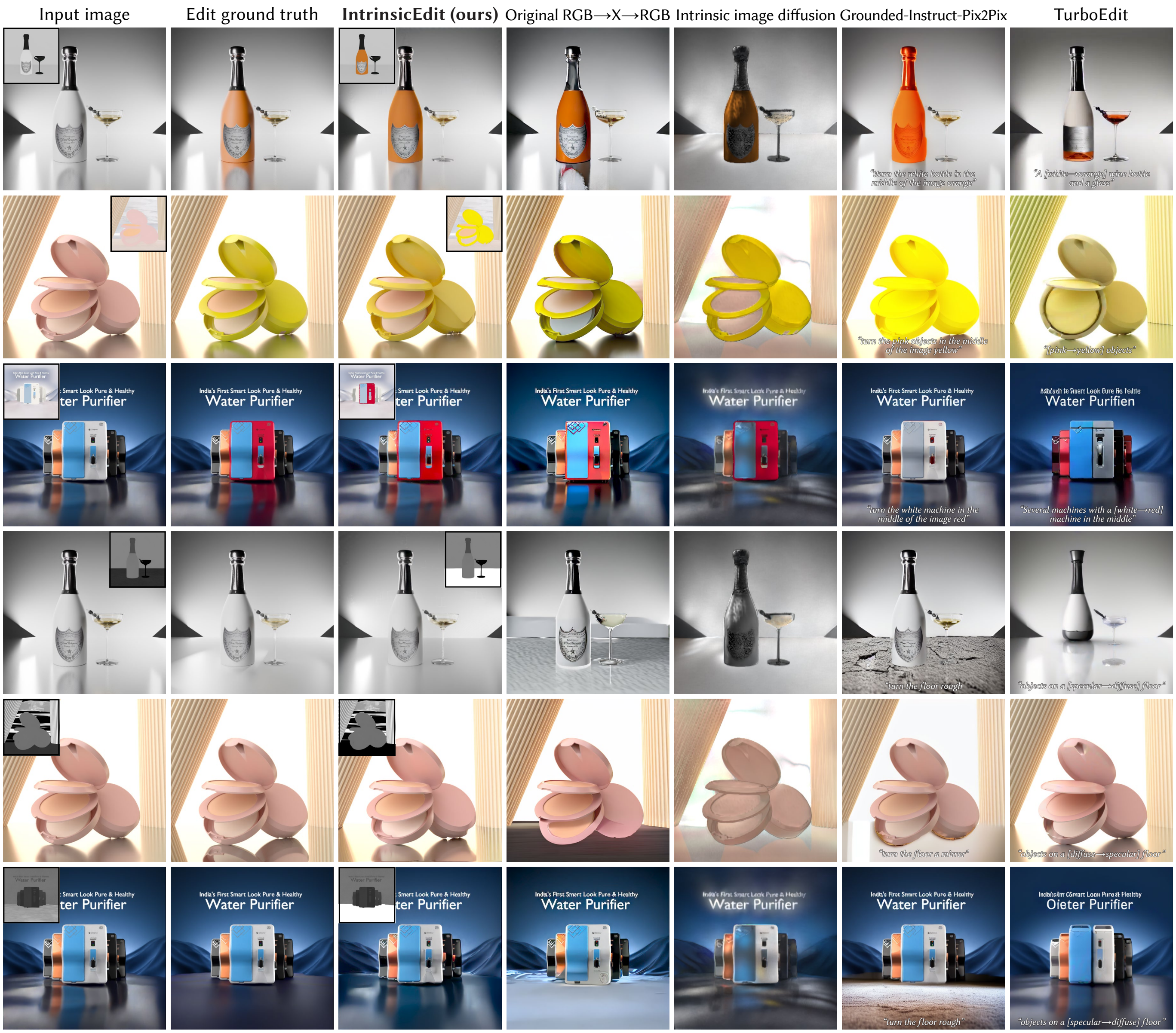

Fig. 5. **Synthetic color and roughness editing.** We include additional results used in the quantitative evaluation on a synthetic dataset in the paper. The top three rows show color editing, the bottom three rows show roughness editing.

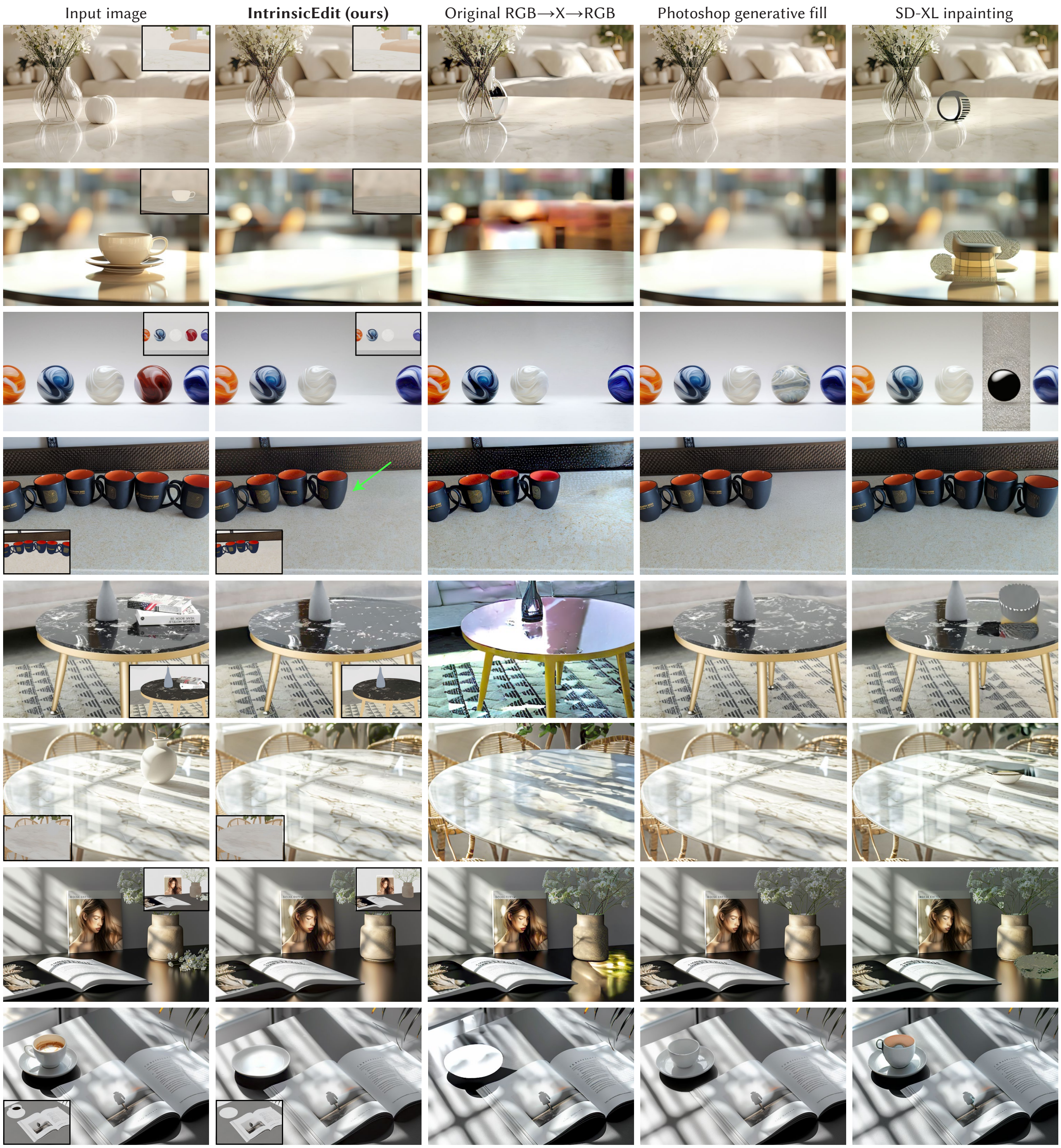

Fig. 6. **Object removal A.** We compare against original RGB⟶X⟶RGB [Zeng et al. 2024], Photoshop generative fill [Adobe Inc. 2024], and Stable Diffusion XL inpainting [Stability AI 2023]. Without being specialized for this task, our method performs on par with or better than prior work. It demonstrates a capability to automatically remove shadows and reflections in alignment with the object. Notably, in the third row, it successfully removes the shadow cast on the nearby cup.

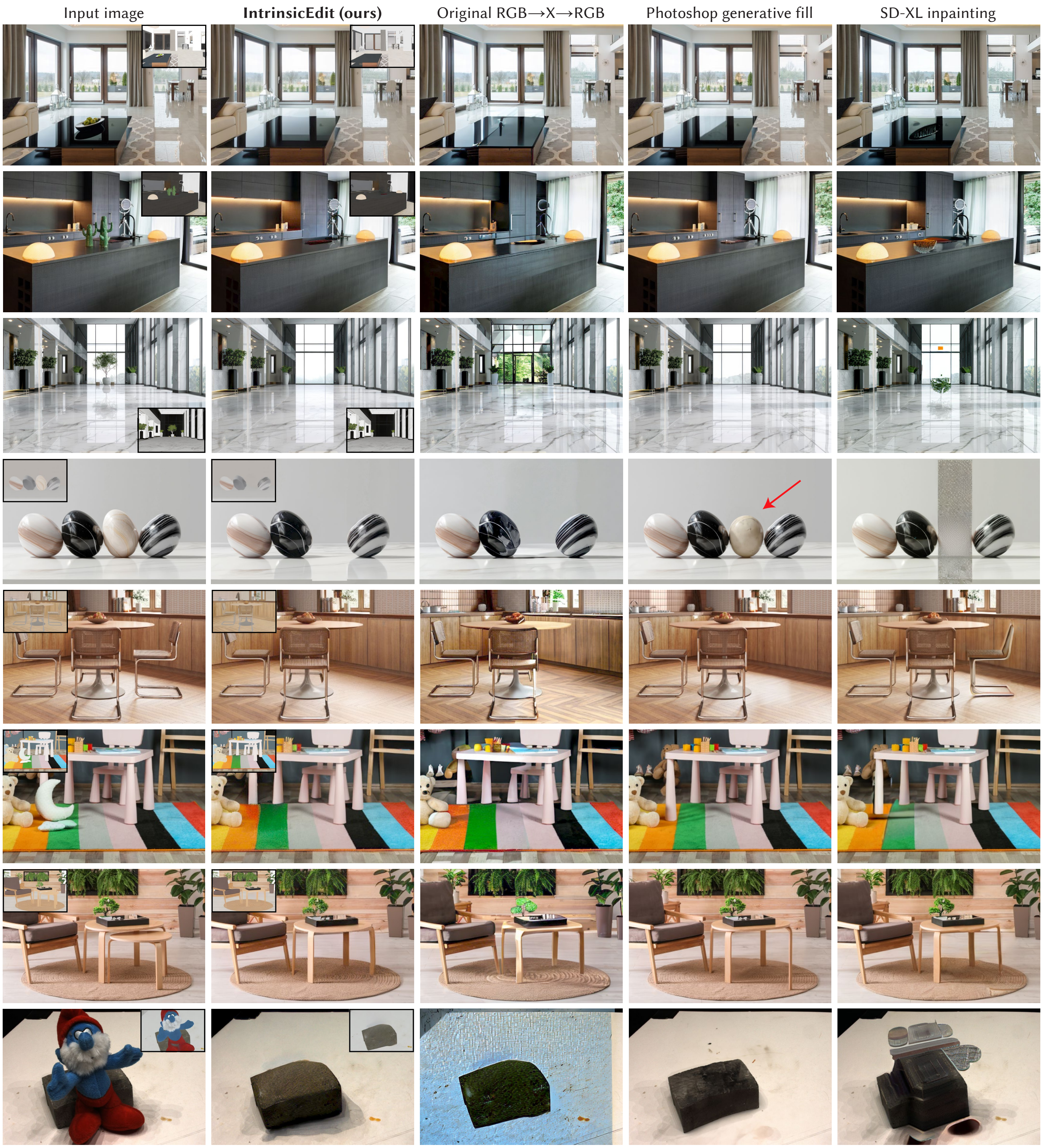

Fig. 7. **Object removal B.** We compare against original RGB⟶X⟶RGB [Zeng et al. 2024], Photoshop generative fill [Adobe Inc. 2024], and Stable Diffusion XL inpainting [Stability AI 2023]. Without being specialized for this task, our method performs on par with or better than prior work. It demonstrates a capability to automatically remove shadows and reflections in alignment with the object. Particularly, in the challenging case in the last row, our method still resolves multiple shadows after removal while previous methods fail.

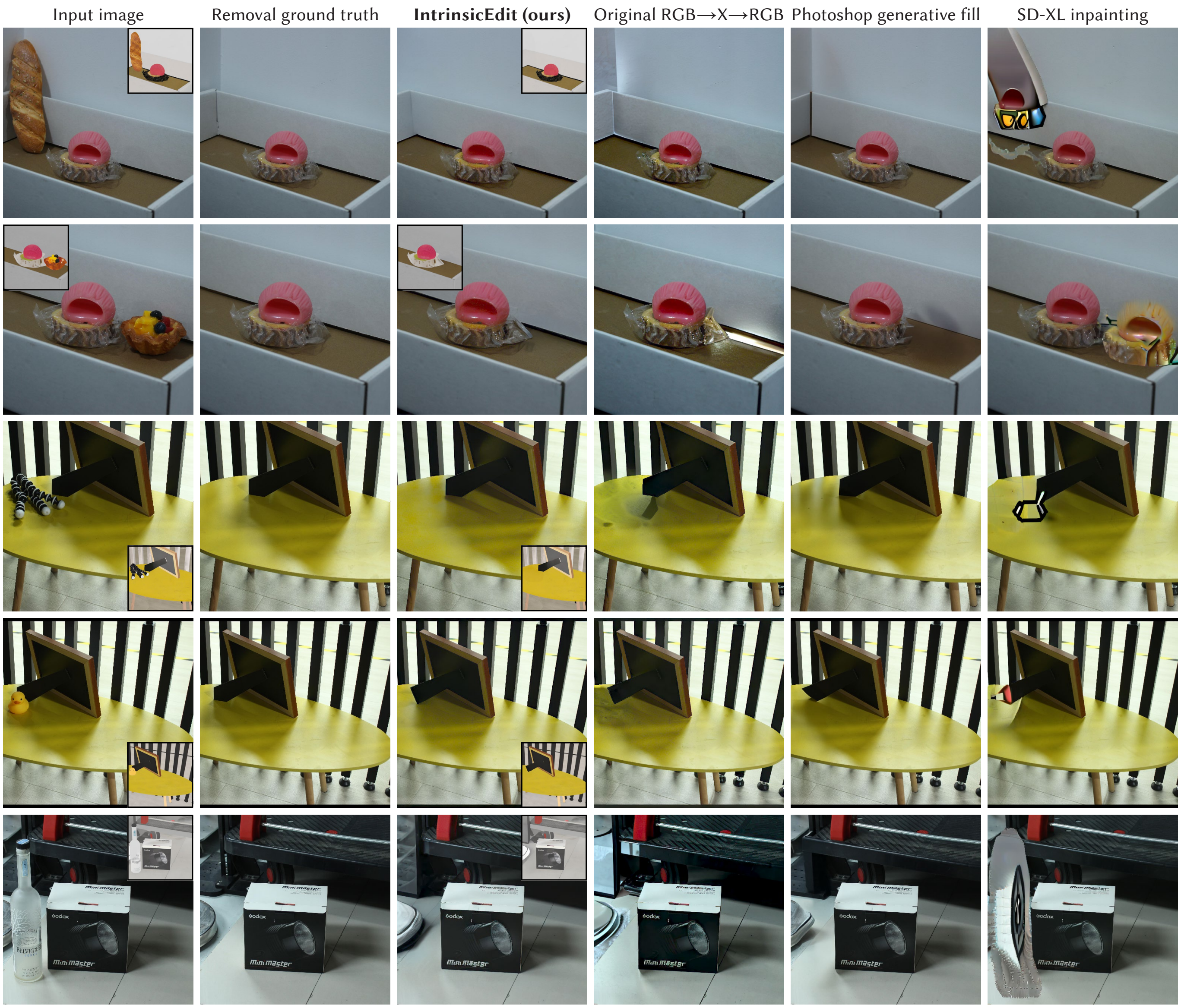

Fig. 8. **Real-world object removal A.** We include more results for the quantitative evaluation in the main paper of object removal on a real dataset.

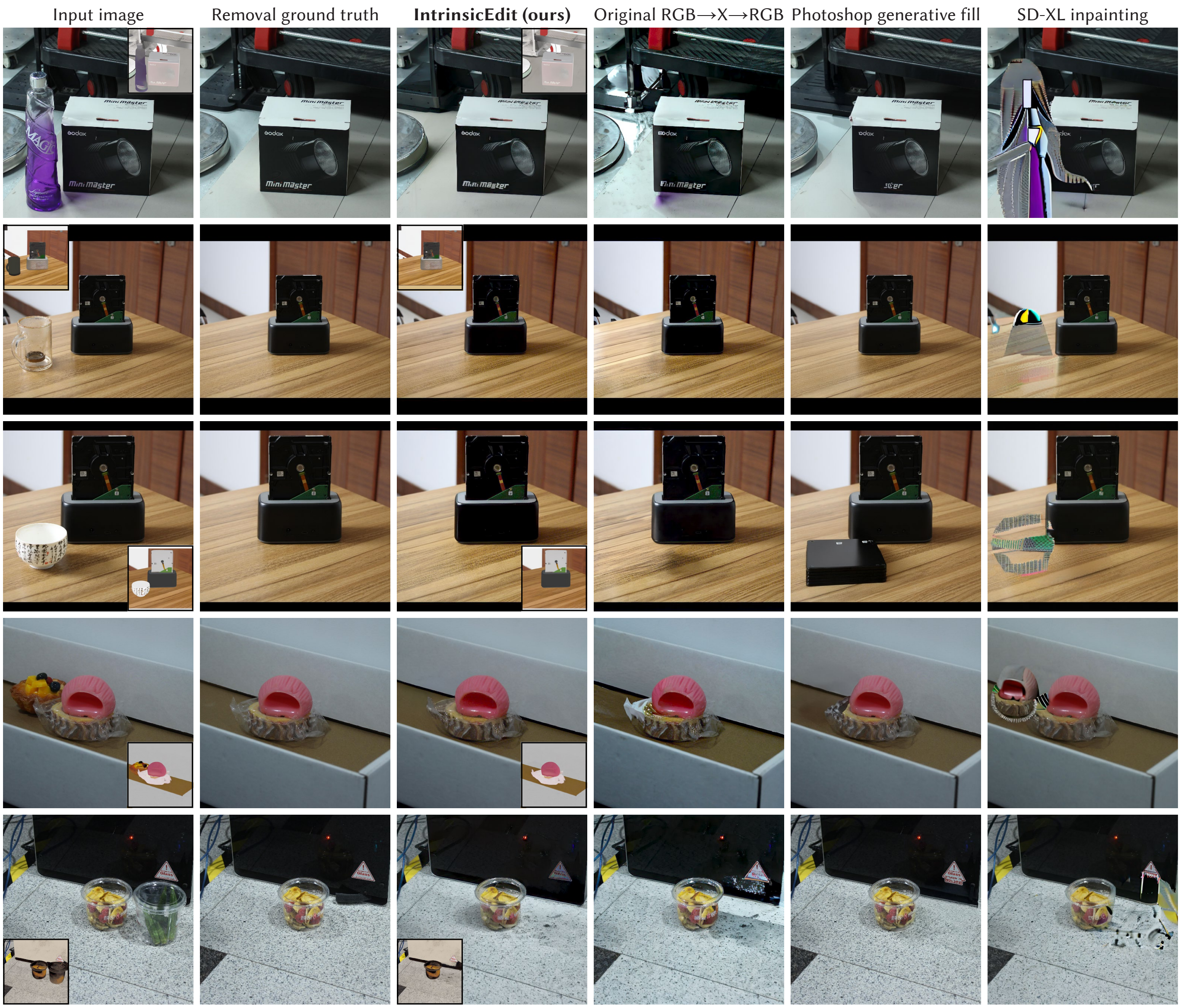

Fig. 9. **Real-world object removal B.** We include more results for the quantitative evaluation in the main paper of object removal on a real dataset.

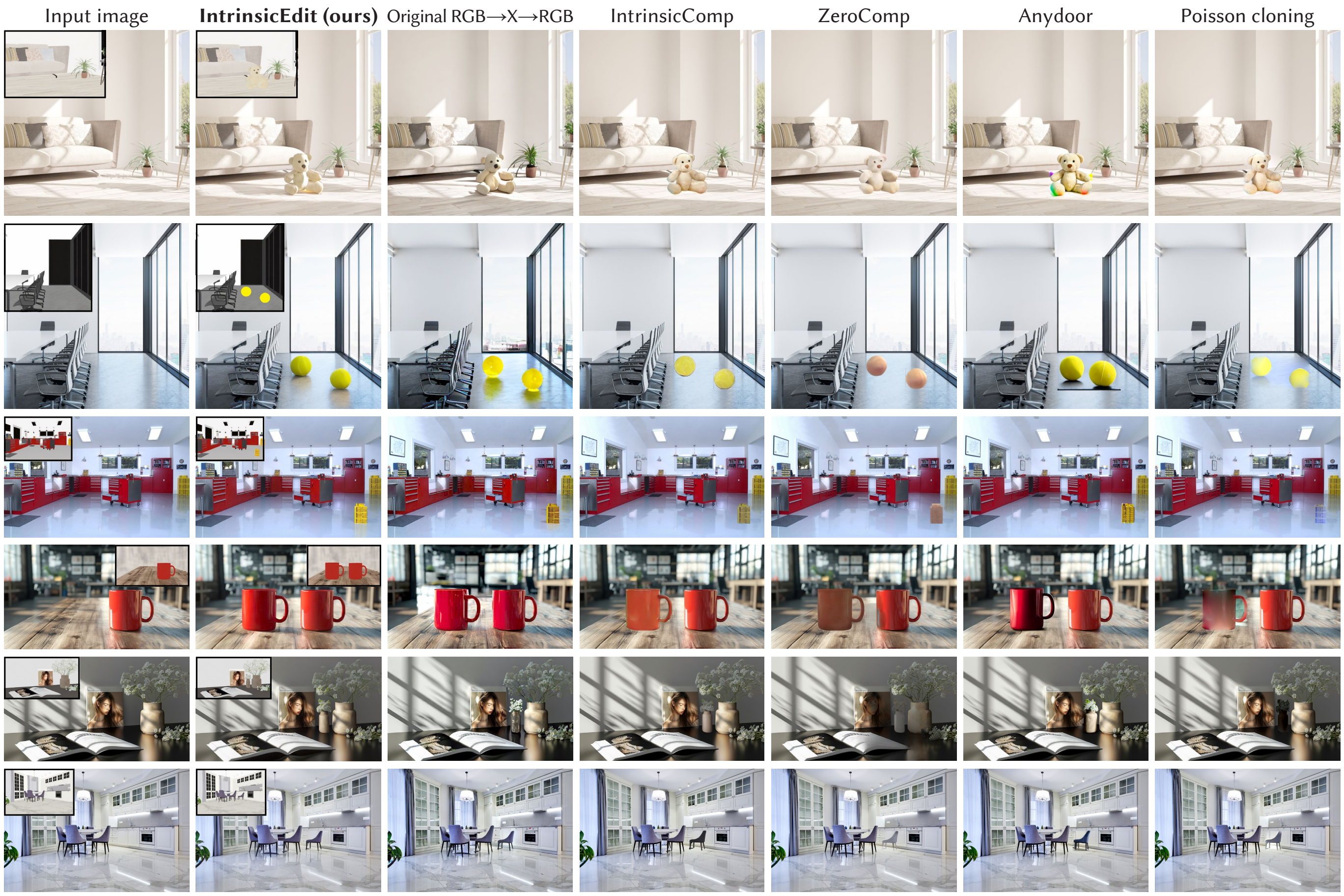

Fig. 10. **Object insertion A.** We compare against original RGB⟶X⟶RGB [Zeng et al. 2024] and existing object-insertion and intrinsic-based methods: IntrinsicComp [Careaga et al. 2023], ZeroComp [Zhang et al. 2024], Anydoor [Chen et al. 2023], and Poisson cloning [Pérez et al. 2003]. For intrinsic-based methods, we insert the object into the albedo channel. Despite not being specialized for this task, our approach better harmonizes the inserted object with the rest of the scene.

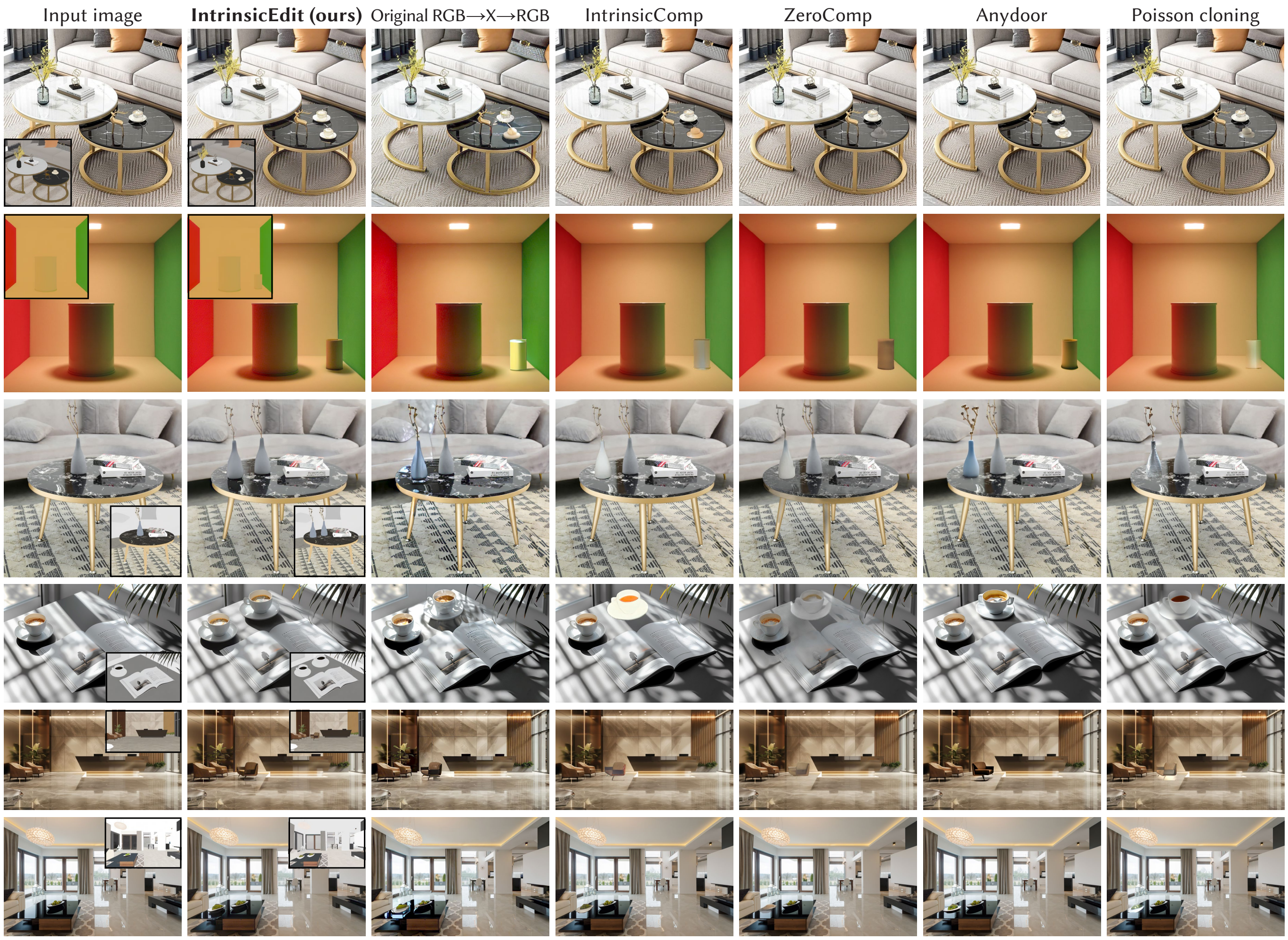

Fig. 11. **Object insertion B.** We compare against original RGB→X→RGB [Zeng et al. 2024] and existing object-insertion and intrinsic-based methods: IntrinsicComp [Careaga et al. 2023], ZeroComp [Zhang et al. 2024], Anydoor [Chen et al. 2023], and Poisson cloning [Pérez et al. 2003]. For intrinsic-based methods, we insert the object into the albedo channel. Despite not being specialized for this task, our approach better harmonizes the inserted object with the rest of the scene.

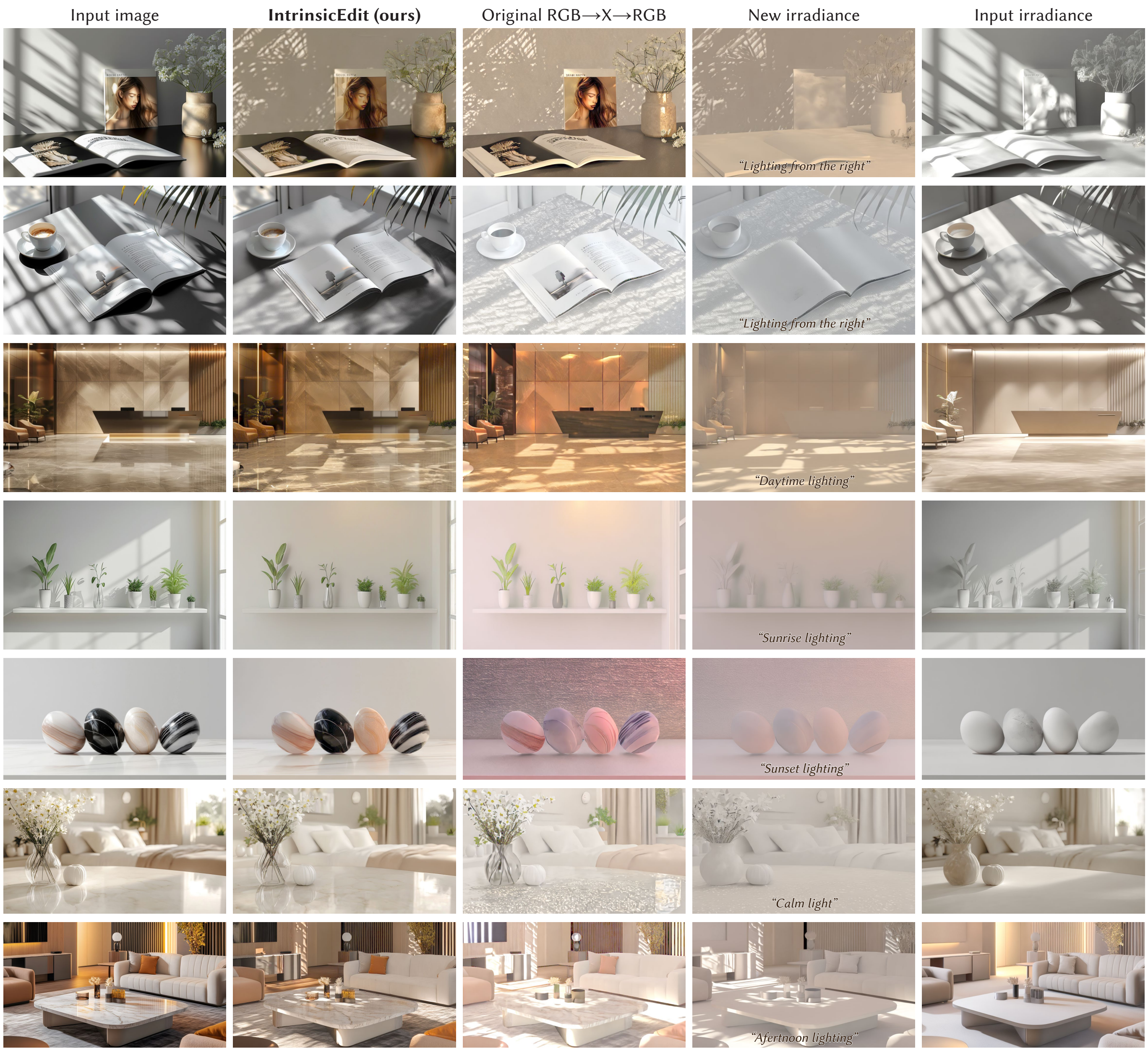

Fig. 12. **Relighting A.** We compare against original RGB⟶X⟶RGB [Zeng et al. 2024] relighting by changing the input irradiance. Our relighting handles the new lighting condition more naturally and better preserves the identity of the scene content.

Fig. 13. **Relighting B.** We compare against original RGB⟶X⟶RGB [Zeng et al. 2024] relighting by changing the input irradiance. Our relighting handles the new lighting condition more naturally and better preserves the identity of the scene content.