The paper is very interesting and presents an application of camera-based flood monitoring. I do not fully agree with some of the terminology used to describe existing approaches, particularly the use of the term “traditional,” but this does not significantly affect the main message of the paper. Given the rapid improvement in machine learning methods, camera quality, and the continuously decreasing costs of imaging systems, I see strong potential for camera-based approaches in the near future. The proposed methodology is timely and well aligned with these developments. Overall, I think the paper can be considered for publication after the authors address the comments listed below and other reviewers’ comments.

We thank the reviewer for their thoughtful comments on our manuscript. We answer any questions and describe any changes made to the text below each comment below.

1- The statement that traditional fluvial monitoring infrastructure (e.g., stream gauges and water level sensors) is not suited to detect spatially disconnected pluvial flood patches appears overstated. The manuscript should acknowledge that recent advances in dense sensor networks, smart drainage monitoring, and urban hydrometric instrumentation partially address these limitations. The authors are encouraged to moderate the claim and more clearly delineate the *specific contexts* (e.g., highly localized, shallow, short-duration inundation) in which conventional monitoring remains insufficient.

2- Lines ~(75–90): The manuscript currently frames alternative approaches in a way that may be interpreted as dismissive of prior work. It is not necessary to portray existing methods as fundamentally inadequate to justify the proposed approach. A more balanced framing that highlights complementary strengths and weaknesses particularly regarding accuracy, spatial resolution, temporal resolution, and operational constraints would strengthen the motivation and credibility of the study.

We thank the reviewer for these comments. We have added additional context on other state of the art monitoring techniques to better highlight the specific applications where camera-based monitoring has advantages, both in terms of flooding process, and implementation/operational considerations (Mydlarz et al. 2024; Silverman et al. 2024; Gold et al 2023). We have also modified the language to avoid appearing dismissive of other approaches, but still highlight where camera-based approaches can build new capacity.

> ***Lines 81-86: “****Both contact sensors (e.g., pressure transducers) and non-contact sensors (e.g., radar, ultrasonic), have proven effective for monitoring distributed urban flooding (Mydlarz et al. 2024; Gold et al. 2023). However, they can face operational challenges for small-scale flooding in urban settings, including limited installation locations and sensitivity to local disturbances (Song et al., 2024). For example, the radar based FloodNet system was limited at many sites to placement over sidewalks, limiting observation of early road flooding (Mydlarz et al. 2024). “*

> ***Lines: 798-821: “****Cameras offer a flexible, low-cost, and highly informative option for distributed monitoring in settings where flooding dynamics are poorly understood. However, even under ideal conditions image-based water level estimates are unlikely to reach the absolute accuracy of pressure-based*

sensors, and the sensitivity of image quality to environmental conditions make them less well suited for contexts where the consistency of measurement in paramount. Particularly when more direct public sector cooperation is possible, storm drain installed pressure sensors have proven highly valuable for realtime distributed flood monitoring (Gold et al. 2024; Silverman et al. 2024). However, even in these cases, cameras can serve as important complement to non-visual sensors. Gold et al. 2024 used co-located cameras and storm-drain pressure sensors, with images helping to identify cases where storm drain based measurements may be impaired. Another major advantage of semi-permanent cameras compared to other sources of flood images, such as public webcams, security cameras, or crowdsourced photos, is the flexibility to adapt the network while otherwise maintaining stability in observations (Helmrich et al., 2021). While camera sensors themselves are highly available, the requirement of high-resolution topographic data can still be a barrier to broader application of our methods. However, advancements such as smartphone mounted lidar, and national scale datasets like 3DEP have reduced this. Future research could leverage this framework to optimize camera network configuration, balancing the number and placement of ground-based cameras to maximize spatial coverage and the ability to observe flood connectivity (Negri et al., 2025; Zhao et al., 2025)."

3- The challenge of translating two-dimensional image-based flood fractions into real-world water depth should be explained more rigorously. In heterogeneous urban environments, flooded pixel fraction does not scale linearly with water depth because inundation often occurs in shallow, spatially discontinuous depressions controlled by microtopography, curbs, and drainage infrastructure. Small vertical changes in water level can produce large apparent changes in flooded area (or vice versa), leading to ambiguity when inferring depth or volume from image coverage alone. Explicitly linking this limitation to urban surface complexity would clarify why image-only approaches are insufficient for depth estimation.

In the revised discussion we draw more explicit contrast between the image-only SOFI characterization of flooding, and the 3D-2D projection-based approach. Inundated area shows a nonlinear increase in the presence of depressions (Figure 7), with further bias in image coverage produced by camera scene geometry (SI Figure 3). While still subject to inherent resolution and visibility limitations, 3D-2D projection can overcome this limitation by explicitly accounting for the relative geometry of flood extents to the camera:

Lines 258-262: *"This ratio is referred to as the Static Observer Flooding Index (SOFI), following the approach of Vitry et al. (2019), providing a simple proxy for flood intensity as seen from a fixed observation point. SOFI has been shown to correlate strongly with changes in water level for a given location (Moy de Vitry et al. 2019). The shape and magnitude of SOFI response depend strongly on the geometry of a camera relative flooding, and as such values cannot be directly compared between study sites."*

Lines 563-566: *"Accordingly, SOFI should be interpreted primarily as a scene-specific indicator of relative change in water levels over time, rather than a measure of absolute flood magnitude or spatial extent."*

4-Use of the term “traditional” The repeated use of the term *traditional* to describe existing monitoring and modeling approaches is potentially misleading. Many of these methods are actively evolving and increasingly integrated with high-resolution data and advanced numerical schemes. The authors may consider replacing this term with more precise language to avoid implying obsolescence.

In revision we will remove use of the term ‘traditional’ throughout and instead refer to either specific technologies or specific distinguishing features, such as between contact/point-based and non-contact/continuous methods.

5-Is this method having a lower cost in compare with existing approaches? this argument is weakened by reliance on aerial LiDAR and high-density terrestrial LiDAR. Why the authors should not explicitly discuss the cost, accessibility, and transferability of these datasets, particularly for low-income or data-scarce regions. A comparative table summarising data requirements, costs, spatial/temporal resolution, and uncertainties across camera-based methods, LiDAR-dependent approaches, and conventional monitoring would provide a transparent and unbiased comparison.

We have moderated the language to instead discuss cameras as one member of a suite of distributed, low-cost monitoring tools. However, we emphasize that the aim of this study is not a ready-made analysis package or hardware platform and feel that a specific cost-breakdown comparison of our deployment may not be representative of camera monitoring as a whole. And given the significant project and site-specific factors involved in sensor network cost feel that explicit cost comparison would be a diversion from the main goal of demonstrating our methodology. We have however added discussion of tradeoffs between resolution, accuracy and cost/flexibility between methods. We recognize that there are still material and data barriers to applying some of our methods. However, we note that most elements of our workflow could be replicated in less intensive ways, albeit with scale and accuracy tradeoffs. For example, at the scale of an individual camera recent studies have leveraged smartphone integrated lidar and photogrammetry for water level prediction (Erfani et al. 2023), while the aerial lidar was freely obtained from the USGS 3DEP program. (Refer to Lines 726-739 in our reply to Questions 1 & 2)

6-The workflow for estimating floodwater elevation is central to the contribution of this paper, yet it is difficult to fully evaluate due to incomplete access to it (the Zenodo link could not be accessed, at least I could not).

The current repository is still in ‘draft’ mode to facilitate any material additions or changes prompted by the review process. The sharing link in the Code Availability section (reproduced below) should give access and we are happy to generate and share a new link if needed.

https://zenodo.org/records/16414887?preview=1&token=eyJhbGciOiJIUzUxMiJ9.eyJpZCI6IjAzM2MxZjBhLTJjNWEtNDI1MS04ZWE1LTRlODJlZTkzMjEyNCIsImRhdGEiOnt9LCJyYW5kb20iOiJhNmVlNDQ0Y2Y0Njc3MTFiZDQ0MzAzMGI5ZDFmYmNkOSJ9.fNd50BKqMzWA7NBgVwrWqpGVKyLTJFSjcn_yawfLlnX3YDGyoL1NwX4-qnnuGKgT6coHGLrntXJGKay-RhatKw

7-The Discussion and Conclusions section is lengthy and combines interpretation with summary statements. I recommend separating this into a concise Discussion section focused on interpretation and limitations, followed by a distinct Conclusions section that succinctly highlights the main contributions, findings, and implications.

We will add subheadings to the discussion and separate the conclusions into a separate and final section.

8-I understand the study is not centred on HEC-RAS, modelling, however, providing a brief description of the HEC-RAS setup, assumptions, and any calibration or validation strategy (ideally in supplementary material) would strengthen the credibility of the comparison without disrupting the narrative flow of the main manuscript.

We have migrated details regarding HEC-RAS model design and execution from the code supplement into the main text and supplement (See Supplementary Text 1). We have also added additional explanation of the motivation, and limitations of the current model comparison:

> ***Lines 372-375:*** *"Because the model itself is only qualitatively calibrated, its output is not treated as a direct validation for absolute water levels estimated from images. Instead, it characterizes similarity or divergence in flood behavior predicted by each method, based. This is quantified both in terms of the relative agreement in predicted flood extent, and spatial flood connectivity, between the two methods."*
>
> ***Lines 707-715: "****Despite these challenges, our results demonstrate how empirically-derived WSEs can complement and strengthen traditional hydraulic modeling workflows. Our method provides continuous, high-resolution estimates of water level and extent that are directly tied to real flood behavior, capturing sub-decimeter changes in WSE and floodwater connectivity that would otherwise be missed by point-based flood monitoring and modeling approaches. While further validation of camera-derived extents would be necessary for confident direct calibration, this level of precision is valuable for the initial validation of uncalibrated models, an important tool for preliminary flood-risk analysis in settings with no gauges or rapidly changing infrastructure performance. As stormwater systems become increasingly strained by climate extremes, integrating data-driven camera networks with physically-based modeling frameworks offers a promising pathway for improving urban flood forecasting, response, and planning. "*

9-The manuscript would benefit from a brief discussion of how segmentation uncertainty propagates into water surface elevation estimates, particularly under challenging conditions such as specular reflections, shadows, low-light conditions, and partial occlusions by vegetation or vehicles. (At least raise them)

This point is well taken and an important aspect of the broader viability of these methods. This is partly included in the discussion of trade-offs of camera-based monitoring in our response to question two. We will also add discussion of both random and systematic segmentation error, noting the ways that our interpolation approach partly reduces their influence:

Lines 709-723:

"4.4 Accuracy and error propagation

Elements of our method including the spatial aggregation of flood boundaries, and the calculation of multiple water level thresholds effectively limit these uncertainties to a magnitude sufficient for urban flood characterization. Water level estimates are robust to both minor random and systematic error in flood mask segmentation. For the severe event at Site A, water levels calculated separately for the half of the scene with a parked park car partly obscuring the water line, differed by a mean of less than 2 cm from water levels. For the same event, introducing random jitter of 10 to 20 pixels to the flood boundary similarly resulted in a mean water level difference of less than 2 cm. More severe errors in flood segmentation or camera pose that are not mitigated are detectable in artifacts such as large re-projection errors, asymmetry in the projected flood extents, or exaggerated ranges between WSE_{90} and WSE_{95}. Additionally, the visual context provided by images allows for qualitative evaluation of agreement with visual flood markers such as road over-topping. In addition to water level uncertainty, flood extent estimates are influenced by the quality of topographic data. Even with robust georeferencing, both physical landscape change between data collections, and artifacts from differences in point density will produce localized elevation differences. In flood extents propagated on the aerial lidar are biased towards over-prediction, due to limited representation of fine scale topographic structure. Both water level estimation and flood extent propagation are more sensitive at lower water levels. As such, interpretations of discreet changes in flood connectivity from small water level increases should be qualified. Future work should further explore the propagation of error between these sources."

Reply Citations:

Hong, Y., Kessler, J., Titze, D., Yang, Q., Shen, X., & Anderson, E. J. (2024). Towards efficient coastal flood modeling: A comparative assessment of bathtub, extended hydrodynamic, and total water level approaches. Ocean Dynamics, 74(5), 391-405.

Gallien, T. W., Sanders, B. F., & Flick, R. E. (2014). Urban coastal flood prediction: Integrating wave overtopping, flood defenses and drainage. Coastal Engineering, 91, 18-28.

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Silverman, A. I., Brain, T., Branco, B., sai venkat Challagonda, P., Choi, P., Fischman, R., … & Toledo-Crow, R. (2022). Making waves: Uses of real-time, hyperlocal flood sensor data for emergency management, resiliency planning, and flood impact mitigation. *Water Research*, *220*, 118648.

Gold, A., Anarde, K., Grimley, L., Neve, R., Srebnik, E. R., Thelen, T., ... & Hino, M. (2023). Data from the drain: A sensor framework that captures multiple drivers of chronic coastal floods. Water Resources Research, 59(4), e2022WR032392.

Negri, R., Ceferino, L., & Cremen, G. (2025). Prioritizing urban areas for the deployment of hyperlocal flood sensors using stakeholder elicitation and risk analysis. Natural Hazards Review, 26(3), 04025020.

Zhao, Z., Liang, Y., Wang, K., Ding, X., Zhang, Y., & Hu, C. (2025). Collaborative sensing optimization layout model of heterogeneous sensors under urban flooding environment. Journal of Hydrology, 650, 132528.