Responses to the comments of Reviewer 3:

► Overall Comment

The authors propose a K-nearest-neighbor-based approach for estimating river cross-section from point cloud data gathered from UAV. It seems this is the second time that the authors have tried to submit their manuscript to GMD. The first submission in 2021, which can be found at https://gmd.copernicus.org/preprints/gmd-2021-309/, was rejected since the authors didn't address the comments provided by the referees. In this submission, the authors made some improvements, but, in my opinion, they still haven't addressed some of the major comments given in the first revision. Moreover, I agree with the comments provided by the two other referees in this submission. In addition to the comments given so far, I have some additional notes.

Response ◄

The authors appreciate this reviewer insightful comment. The authors believe that they tried their best to improve the quality of the manuscript following the provided comments. We informed that the current manuscript is the resubmission in the letter. In addition, we also tried the measurement data that penetrates the water surface. However, the dataset was not related with the point cloud. Hope this limitation can be acceptable to this reviewer.

► Major Comment1

The introduction focuses too much on UAVs instead of point cloud data analysis and river cross-section estimation methods. I recommend the authors give a more in-depth literature review on river bathymetry estimation methods, their implications, and applications. Currently, the introduction does not present the novelty of the manuscript sufficiently.

Response ◄

The authors appreciate this comment and tried to improve the introduction focusing more on in-depth literature review on river bathymetry as the following. Hope this modification is satisfactory to this reviewer.

There have been some studies related with river bathymetry measures riverbed elevation generally using watercraft with multibeam sonar or remotely sensed data of digital elevation models (DEMs). The demarcation of the cross-section in a river has been mainly made with a DEM in the literature (Gichamo et al., 2012; Petikas et al., 2020a, b; Pilotti, 2016; Sanders, 2007). Tarekegn et al. (2010)

employed Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) to generate 15m resolution DEM for 2D hydrodynamic flood modeling and Matgen et al. (2011) presented an automatic delineation of flooded areas with Synthetic Aperture Radar (SAR) images. Azizian and Brocca (2020) performed a comprehensive evaluation of remotely sensed DEMs for flood inundation mapping including the recently available Advanced Land Observing Satellite (ALOS) DEM. Biswal et al. (2023) suggested a Multi-DEM approach using machine learning techniques to demarcate cross-sections adopting the medium resolution DEMs such as Shuttle Radar Topography Mission (SRTM) and ASTER. Petikas et al. (2020b) proposed a novel method to automatically extract river cross-sections from a DEM along with a parametric cross-section extraction algorithm.

Most of the existing studies were focused on drawing sections with low resolution DEMs and improving accuracy. Sanders (2007) tested several on-line public domain DEMs to parametrize 2D hydrodynamic models and concluded that those DEMs contains high vertical and horizontal biases. Gichamo et al. (2012) proposed an approach that simulates river cross-sections from ASTER Global DEM and discussed that the low resolution and the inadequate vertical accuracy could be improved by preprocessing the DEM. Channel widths of small and medium-sized rivers are too small to use DEM-based methods since the resolution of available DEMs are much coarse to draw cross-sections.

Meanwhile, UAV aerial surveying has been easily available and become very economic methods to acquire 2D data. A cross-sectional algorithm for the cloud point dataset of UAV aerial surveying has not been much tested in depth especially for deriving river cross-sections, since the characteristics of the point cloud dataset are far different from the DEM in that a study area for UAV aerial surveying is commonly smaller and many more points can be acquired from UAV aerial surveying.

► Major Comment 2

One of the major hurdles in river bathymetry estimation from data gathered by instruments that do not penetrate water has been estimating the "wet" part underwater surface during the survey. Although this manuscript mentions it as a limitation of their methodology, this shortcoming significantly limits the applicability and novelty of their methodology, for river cross-section applications.

Response ◄

The author totally agree that ‘wet’ part underwater surface was not able to measure UAV in recent technology. However, there are a number of cases that wet perimeter might not be problematic in small and medium size rivers except some perennial rivers. Also, the current model can be applicable, as we wish, whenever useful techniques that penetrates water to river beds is available and those techniques are in developing stage with special equipment as multispectral and hyperspectral camera (Lee et al., 2022; Mandlburger et al., 2021) . Those techniques are not applied in the current manuscript due to technical difficulty and expensive equipment affordability. Hope this reviewer understands this circumstance.

► Major Comment 3

When comparing with observation, I think a comparison with existing DEM data can be informative as well, so we can measure the improvements over using DEMs.

Response ◄

The authors appreciate this valuable comments. The authors downloaded DEM data from the public website. However, its resolution was too coarse to draw the cross-section lines since the applied rivers were relatively small and medium-size river. Often only one or two cells covered the rivers. Hope this can be understandable to this reviewer. Instead, the authors consider that the DEM will be made with all the datapoints without smoothing feature. Therefore, the output from DEM can be produced by the KNN method with k=1. This case was demonstrated with the case study of a trapezoid shape in Figure 5(b) and discussed in the manuscript.

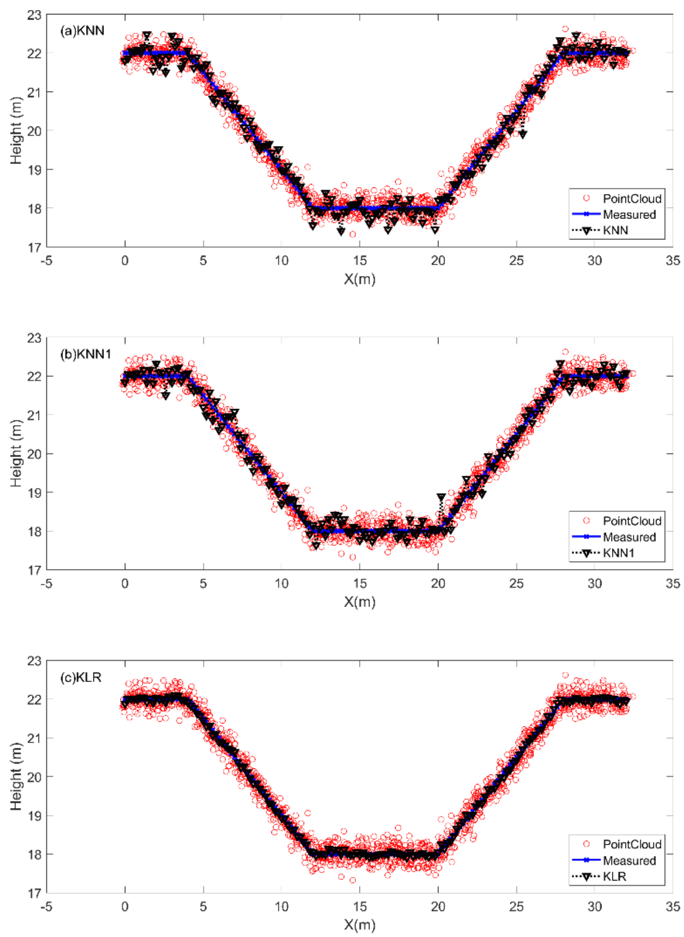

Figure 5. Different KNN-based methods to estimate the synthetic trapezoidal channel as (a)KNN, (b)KNN1, and (c)KLR models. Note that (1) the KNN model was reproduced from the original paper of Lall and Sharma (1996); and (2) the KNN1 model (i.e. k=1) indicates that the closet point was used to demarcate the channel.

► Major Comment 4

Regarding reproducibility, maybe I am missing something, but I couldn't find the point cloud data that the authors generated using WebODM. If the data is public, providing the point cloud data is necessary for running the scripts.

Response ◄

The authors did not upload the point cloud dataset since they were too large to upload them. Following this comment, the point cloud data was uploaded as asked at the Mendeley Data and new location is updated in the manuscript.