



River cross-section estimation from lidar altimetry products with lidarcross v1

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Abstract. River cross-sections, i.e. riverbed elevation profiles across the river, are required for hydrodynamic modeling in flood risk assessment and flood forecasting but are expensive and time-consuming to survey in the field. Remotely sensed cross-sections can fill the gap in data-scarce areas, with novel satellite missions enabling increased accuracy compared to previous methods. We present a method for estimating river cross-sections from lidar altimetry products and a discharge time series. The exposed cross-section is delineated using high spatial resolution ICESat-2 or airborne lidar point clouds. The submerged section is then inferred using water surface slope from the lidar products together with a discharge input. Assuming the diffusive wave approximation, the energy slope is taken to be equal to the estimated water surface slope. Manning's equation is subsequently applied to estimate the conveyance at the time of observation. Finally, the full section is defined assuming a roughness parameter and a conceptual submerged shape. The method is implemented in an open-source python package called lidarcross, enabling users to define cross-sections for hydrodynamic models in data-scarce areas. Validation is performed using examples from four surveyed rivers spanning a range of spatial scales. Area and conveyance curves derived from surveyed and lidar-based cross-sections are compared, yielding median WSE differences of approx. 0.5 m. The results demonstrate that the method successfully captures the hydraulic behavior of the channel. Residual errors are primarily attributed to uncertainties in discharge and water surface slope estimates.

1 Introduction

With growing frequency and intensity of extreme weather events (IPCC, 2022), river floods and droughts are increasing in severity, frequency, and impact (Alifu et al., 2022; Li et al., 2023). Hydrodynamic models are essential tools for flood risk assessment and forecasting (Kumar et al., 2023), but their application is often constrained by the limited availability of high-quality input data (Cea et al., 2022). Satellite remote sensing can provide valuable data for modeling efforts (Jaramillo et al., 2024), and the use of global datasets for hydrological-hydraulic modeling in data-scarce regions has become a viable alternative (Mudenda et al., 2025).



However, not all required input parameters are equally observable with remote sensing techniques. Cerbelaud et al. (2025) provides a thorough review of recent efforts to measure hydraulic parameters such as surface water extent [SWE], water surface elevation [WSE] and water surface slope [WSS] via satellite remote sensing of rivers. Yet other parameters, like bathymetry and hydraulic roughness, are not directly observable. River bathymetry is essential for effective hydrodynamic modeling (Dey et al., 2022), as cross-section geometry determines cross-sectional area, wetted perimeter, and the elevation threshold at which rivers overflow banks and levees onto floodplains. While bathymetric data are a necessity for modeling a river or a river system, such datasets are rarely available at the regional scale required in poorly instrumented catchments.

Traditional methods for acquiring bathymetry, such as rods or shipborne sonar, are time-consuming, and restricted by cost or navigability (He et al., 2024). Remote sensing techniques, both airborne and satellite based, have undergone significant development in recent years, with varying sensors and approaches emerging. These methods offer a low-cost alternative, and are the only option in non-navigable rivers. Optical approaches, through-water photogrammetry and spectral depth-inversion based methods can map bathymetry in clear rivers (Kasvi et al., 2019; Dietrich, 2017), but struggle in turbid water or when submerged vegetation is present (He et al., 2024).

UAV-based surveys with tethered sonar (Alvarez et al., 2018; Bandini et al., 2018) or water penetrating radar (Bandini et al., 2023) can provide high resolution measurements, and are effective in turbid or vegetated rivers, but require close contact and do not scale efficiently to regional surveys.

Airplane lidar altimetry surveys provide datasets with high resolution and accuracy over wide areas, but measurements are costly and complex (He et al., 2024). National surveys are usually not publicly distributed and use the near-infrared [NIR] lidar band, which does not provide bathymetric measurements. Bathymetric single-wavelength lidar on both airplanes and UAVs is often green lidar (532 nm) which can penetrate the surface 1-3 secchi depths (Szafarczyk and Toś, 2023). A range of algorithms are available to interpret the full waveform into water surface and bottom elevation (Wang et al., 2015; Xing et al., 2019; Schwarz et al., 2019; Rhomberg-Kauert et al., 2025).

To inform regional or global scale hydrodynamic models, more indirect methods have been applied. Digital Elevation Models [DEMs] have been used for river and flood-plain geometry, but hydrodynamic models based on DEMs are severely limited in accuracy without a sound estimate of depth (Dey et al., 2022).

In hydrodynamic models, river roughness and bathymetry can compensate for each other, leading to multiple equifinal geometry/roughness parameter sets producing the same modeled WSE and WSS (Grimaldi et al., 2018). Garambois et al. (2017) show an example with a braided river modeled in a synthetic single channel, where a high hydraulic roughness at low water levels compensates for the artificially low wetted perimeter in the single-channel model. For Neal et al. (2015), the assumption of rectangular cross-sections drives optimization towards high hydraulic roughness, slowing wave propagation unrealistically. Equifinality limits the estimation of channel geometry from hydraulic observations alone and motivates approaches that target effective hydraulic behavior rather than exact bathymetry.

With its along-track resolution of 0.7 m, the ICESat-2 mission (Neumann et al., 2019) provides terrain and water surface elevation with the opportunity to outline the exposed part of river cross-sections. While some studies have been successful in identifying bathymetry using ICESat-2's 532 nm beams in clear ocean waters (Parrish et al., 2019; Chen et al., 2021; Leng



et al., 2022; Cao et al., 2023), river bathymetry is not reliably observed, and an inference of the submerged part of the cross-section must be made. Coppo Frías et al. (2023) inferred the submerged section by calibrating a steady-state hydraulic model using a conceptual shape proposed by Dingman (2007). As also observed by Neal et al. (2021) and Kittel et al. (2021), inverse modeling is limited by computational requirements, the efficiency of search algorithms, and regularization requirements.

The ATLAS instrument onboard ICESat-2 provides 6 simultaneous tracks of altimetry observations, allowing the calculation of water surface slope either along the satellite track or through multiple crossings (Scherer et al., 2023; Christoffersen et al., 2023). WSS is an important hydraulic parameter, revealing non-uniform flow conditions caused by the backwater effects of confluences, ledges and pools (Bauer-Gottwein et al., 2024a). With the launch of The Surface Water and Ocean Topography [SWOT] mission (Biancamaria et al., 2016; Fu et al., 2024), observations of WSS have become further available for river analysis (Jiang et al., 2025; Ledauphin et al., 2025). But while SWOT provides frequent WSE and WSS observations, the radar interferometer does not provide terrain elevation readily, making it unsuited for cross-section delineation. Efforts to estimate WSE-width relationships, called hypsometric curves, from SWOT provide an inferred bathymetry (Cerbelaud et al., 2026), but only across the active WSE range. While useful for discharge estimation (Durand et al., 2024), SWOT does not capture exposed terrain as easily, despite its relevance in hydrodynamic modeling of flooding scenarios. Rong et al. (2026) train a physics-informed neural network to estimate bed elevation in rectangular cross-sections, informed by WSE from SWOT.

Observing both WSS and WSE at the time of the satellite pass allows the description of the flow using the diffusive wave approximation, where the energy slope is assumed equal to the observed WSS. These developments create new opportunities to constrain river hydraulics from remote sensing observations. This paper builds on the method developed by Coppo Frías et al. (2023) and Musaeus et al. (2024), using terrain elevation, WSE and WSS from ICESat-2 to estimate conveyance in the submerged part of the cross-section. Limited by the equifinality of geometry and roughness parameters, the method does not seek to recreate actual channel geometry, but rather reproduce the relationship between the water surface elevation and the conveyance as represented in 1D hydrodynamic models. Since the same principles can be applied to NIR lidar point clouds from aircraft, the method can ingest airborne lidar datasets where available and rely on ICESat-2 in areas without airborne lidar datasets.

The paper is organized as follows: Section 2 presents the data inputs and study areas. Section 3 presents the method steps including processing, the diffusive wave approximation and the outputs. Section 4 presents four rivers with surveyed cross-sections and comparison metrics followed by validation results. Considerations and limitations are discussed in Section 5, while Section 6 concludes and provides an outlook perspective. The method is implemented in an open-source Python package called lidarcross, enabling reproducible and scalable cross-section definition from both ICESat-2 and airborne lidar datasets while allowing for parameter adjustment. The package contains functions for retrieving ICESat-2 data, and processing both ICESat-2 or airborne lidar point clouds, calculating WSS and producing cross-sections in a preferred format. The package is discharge agnostic, relying on the user to provide the best available discharge input in a simple format. Lidarcross allows hydrologists to interact with remote sensing products and parametrize hydrodynamic models with airborne lidar or ICESat-2 point clouds.



2 Data and Study Area

2.1 Data

2.1.1 ICESat-2 ATL03

The ATLAS instrument aboard ICESat-2 emits photon pulses at a rate of 10 kHz, corresponding to one laser pulse every 0.7 m along the 6 ground tracks (Neumann et al., 2025b). The instrument records an arrival time for the photons it receives, called a photon event. A subset of recorded photon events comes from solar background noise. For each photon event, the travel time is used to estimate the height over the WGS84 ellipsoid along the ground track below the satellite. The instrument emits pulses along 6 tracks, in 3 pairs with a strong beam (right) and weak beam (left), separated by 90 m within pairs and ≈ 3 km between pairs.

The ATL03 data product (Neumann et al., 2025a) consists of individual photon events recorded by the ATLAS instrument. Each event is indexed by time, latitude and longitude, referenced to ITRF2020. The data product contains additional parameters, both per individual photon and grouped by geosegments, nominally 20 m in length. For example, geolocation and geophysical corrections to photon heights are calculated for geosegments, so the corresponding parameters are grouped for photons in respective geosegments. Geophysical corrections consist of atmospheric effects, solid earth tide, ocean tide and geoid. All geophysical corrections are applied to the photon height as part of the ATL03 data processing, except for geoid correction. The geoid correction value in the dataset is derived from the tide-free version of the EGM2008 geoid model (Pavlis et al., 2008), and a separate mean-tide correction is included. The product contains the quality parameters 'quality_ph', 'signal_conf_ph', 'weight_ph', 'signal_class_ph', which are used for later filtering. All parameters and processing steps are described in the Algorithm Theoretical Basis Document (Neumann et al., 2025b). The current version of the ATL03 product is 007.

2.1.2 Airborne Lidar

Accelerating demand on readily available high quality geo-data, climate change, and land-use trade-offs make high-resolution elevation data essential. These Digital Elevation Models [DEM] function as "digital twins" of the land surface, enabling holistic and resilient governance (Hopfstock et al., 2021). To create high-accuracy elevation data, researchers and agencies increasingly favor airborne topographic lidar campaigns.

The European Union (EU) leads this shift. Its "INSPIRE" (2007/2/EC) and "Open Data" (2019/1024) directives mandate that member states provide high-quality topographic lidar data free of charge, among other geospatial data sets. Other high-income countries follow similar policies. In Figure 1 and Table A1, we map and list authoritative, publicly available topographic lidar data globally; Kakoulaki et al. (2021) provides a specific list for the EU. While other nations also conduct (localized) airborne campaigns, they often restrict access, offer sparse coverage, or lack accessible platforms. Consequently, open-access topographic lidar availability remains heavily concentrated in high-income nations. This creates a critical data gap in developing regions characterized by large, ungauged river basins - precisely where high-resolution data would offer the greatest added value for hydrological modeling and flood risk assessment.



High resolution elevation data facilitates regional studies and provides the necessary detail to accurately resolve regional details (e.g., Kim et al. (2026); Köhn et al. (2025); Aristizabal et al. (2024); Ploeg and Stroeven (2025)) forming the basis for better decision making. We anticipate that more countries will adopt open geodata policies in the future.

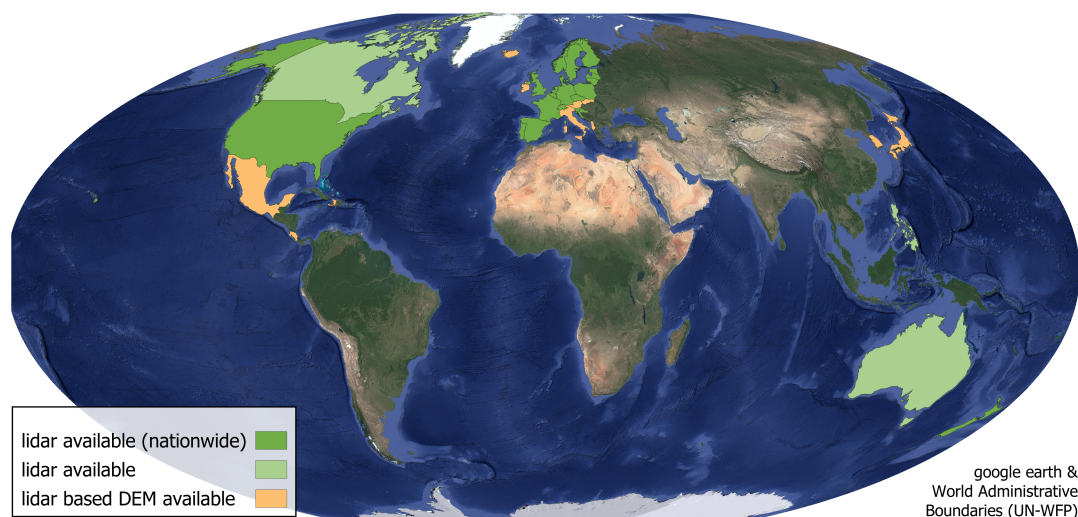


Figure 1. Countries with available comprehensive authoritative topographic lidar data. Refer to Table A1 for the list of countries. Background © Powered by Esri, administrative borders from World Food Programme (2019). Map projection ESRI:53009.

Agencies typically distribute lidar point clouds in .laz format as tiles covering several square kilometers, with point densities ranging from 1 to 40 pts./m². Lidarcross uses per-point metadata, specifically acquisition time and agency-provided classification labels. Using raw lidar data instead of higher-level rasterized DEMs offers unique value, as it allows users to implement custom sampling algorithms and leverage point-specific metadata. However, lidar datasets often employ local horizontal and vertical reference systems and require reprojection. In this work, we use topographic lidar data from Finland (NLS, 2026), Sweden (Lantmäteriet, 2024), and Denmark (KDS, 2020).

2.1.3 Other Inputs

Lidarcross requires additional inputs separate from the lidar sources. First, a **linestring geometry** representing the river centerline is needed to define the chainage and angle of the cross-sections. This linestring must begin at the upstream end of the branch, with chainage increasing downstream. To ensure accurate geometric calculations, this geometry must be provided in a projected, distance-true coordinate reference system [CRS], such as a local UTM CRS and the package returns cross-sections in that same CRS. Second, the user must supply a **discharge time series** in .csv format, with each row containing discharge values (m³s⁻¹) corresponding to specific chainage locations, which serve as column labels. The index must include time or date data for the package to parse, allowing each column to represent a discharge time series at a specific point along the river.



140 If the package is being used to retrieve ICESat-2 data, the user must provide simple **AOI polygons** (in a latitude/longitude CRS) covering the river channels and terrain where the package should retrieve tracks.

If the package is used to process topographic lidar data, the user must define the locations and lengths of all cross-sections. Unlike satellite ground tracks, these can be placed freely. Importantly, agencies that adhere to the `.laz` intrinsic framework do not follow a unified convention for the data. Differences in file naming, acquisition date references, and point classification labels prevent the use of standardized functions. Consequently, the user must prepare a **lidar file lookup** that matches `.laz` files to cross-sections, provide a verified **acquisition date** (either absolute or as a GPS time datum offset), and select the **point classes** for cross-section generation. Finally, since standard lidar wavelengths are not always optimized for water applications, open water returns may be sparse, especially over calm water. Users may therefore provide an *optional secondary data source* for WSS estimation, such as SWOT data.

150 2.2 Study Areas

The described method is demonstrated in locations of varying scale to showcase multiple applications. For a river to serve as a suitable case study, the required input data must be available, along with shareable in situ surveyed cross-sections for validation. Location maps showing river branches and both in situ and lidar-based cross-sections are found in Figure 3 in Section 4. To demonstrate the topographic lidar application, the rivers Torne, Rönne, and Gudenå, located in Finland, Sweden and Denmark, respectively, are used as examples of smaller scale model work, where both the highest resolution lidar and observed discharge data are available. Cross-sections are defined over 46, 10 and 21 km reaches, with observed discharge in the range of 80-3600, 1-90 and 3-75 m^3s^{-1} , respectively (Torne, Rönne and Gudenå).

To demonstrate the method in a major river lacking in situ discharge and topographic lidar observations, as is the case in many major river systems worldwide, the Loire river in France is chosen. Flow can vary between 10 m^3s^{-1} in the summer dry period and 6000 m^3s^{-1} during peak floods (Moatar et al., 2022). The lower 700 km of the river is unregulated by dams. Surveyed cross-sections are available for 140 km of the downstream reach, after which the river flows into the Atlantic Ocean. To simulate a situation where no discharge time series from rating curves are available, routed discharge from the DHI-GHM is used (Murray et al., 2023), which follows the HydroRIVERS network based on runoff generated in hydroBASINS catchments (Lehner and Grill, 2013). This paper uses the hindcast discharge time series from the GHM for 2018-2025.

165 3 Methods

The general steps of the method are shown in Figure 2. Lidar altimetry, a discharge time series and additional inputs are given to the functions. After altimetry data processing and WSS estimation, the cross-sections are defined using Manning's Equation. The cross-sections are then exported as `.xns11` or `.csv` files. Section labels in the flowchart refer to sections of this paper where detailed descriptions can be found.

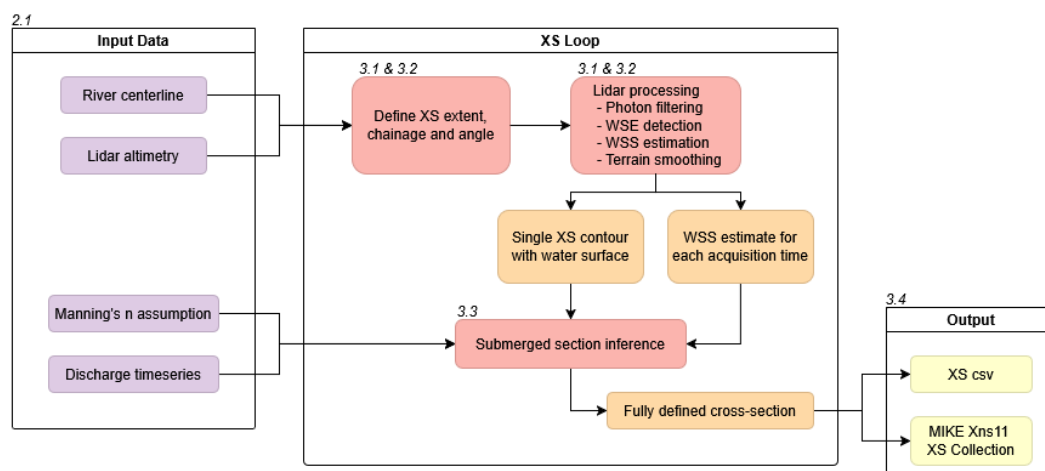


Figure 2. Flowchart of the general operational chain. XS extent definition and lidar processing differs between lidar inputs, with ICESat-2 processing described in Section 3.1 and topographic lidar processing in Section 3.2.

170 3.1 ICESat-2 ATL03 processing

The package includes a function to download ICESat-2 ATL03 data using the python package Sliderule (Shean et al., 2023), an API that allows for extensive filtering and preprocessing on the cloud server, minimizing download sizes. Only photons with 'quality_ph' = 0 (nominal quality) and 'signal_conf_ph' >= 2 (low confidence) are retrieved. While ATL03 provides a confidence class for multiple surface types, Sliderule is configured to filter on the highest confidence attributed to each photon, regardless of surface type. Sliderule also provides the parameter 'x_atc', the along-track distance of photons.

For each AOI provided by the user, all ATL03 tracks are retrieved. An additional filter at this step only processes tracks from a user-defined list of months, to ensure only dry-season tracks are used. Tracks with more than 100 photons are processed further individually. Orthometric height is calculated by subtracting the geoid correction and the free2mean tidal conversion from the ellipsoidal photon heights.

First, downloaded photons are mapped into crossings of the river centerline. Linestring geometries are created along photon tracks, and intersections with the river centerline are identified. Due to river meandering, multiple crossings can occur along the same satellite track. Each crossing is recorded for WSE estimation and possible cross-section definition. Two filters are applied based on user-defined requirements of minimum track length and minimum distance between track end and river centerline. The first filter ensures that the photon coverage is wide enough to capture the entire river width, and the second filter ensures that long tracks, with almost all photons on one side of the river, are discarded.

Each photon cloud at a crossing is trimmed based on its distance to the river centerline, and filtered using the parameters 'weight_ph' and 'signal_class_ph', to retain only the most probable surface photons, excluding most vegetation and noise returns. The water surface is identified by finding peaks in a kernel-smoothed histogram of photon elevations. Because the water surface typically produces a strong and coherent photon return, it appears as a dominant mode in the elevation distribution. The



lowest histogram peak is first considered as the WSE, but since the water surface can cause echo returns to ICESat-2 (Neumann et al., 2025a), the lowest peak will be discarded if a second peak exists within 60 cm above it. Surface water is then identified as clusters of photons with elevations close to the identified WSE. Multiple channels can be identified this way, if multiple water surfaces are found at the same WSE, but a gap filter can be used to exclude water surfaces far from the river centerline.

An initial loop over all crossings is used to estimate WSS for each satellite pass. WSE is calculated for each river intersection in a pass. WSS estimation follows the approach for ICESat-2 river crossing tracks developed and described in (Scherer et al., 2022), where slope is calculated pairwise between all intersection pairs from the same pass, except for intersections with less than 1000 m between them. A weighted average WSS is calculated, where the weight is the inverse sum of variance of the WSE estimates within each pair.

The second loop draws terrain profiles around and between channels. Terrain profiles adjacent to water surfaces are derived from non-water photons using quantile-based sampling within a moving window, followed by smoothing and slope constraints to suppress vegetation and noise artifacts. Finally, a continuous profile is created from the terrain profiles and water surfaces. The angle between the river centerline and the satellite track is identified to project the cross-section to be perpendicular, adjusting x-axis values. Submerged geometry is then inferred using the WSS from the satellite pass, see Section 3.3. The cross-sectional area and conveyance should only be calculated based on the relevant river channel and its flood plain. A function searches outward from the outermost water edges to identify the first local elevation maximum on each side to use as the boundary.

Throughout the processing steps, quality checks ensure that crossings that seem to be incorrectly identified are discarded. All quality check parameters are adjustable in the processing function, allowing the user to balance the amount of cross-sections in the final collection with the strictness of quality parameters. Quality checks include verifying that a sufficient number of high-quality photons are present and that coverage contains no large gaps. Tracks are further discarded if they intersect the river at an oblique angle, if no clear water surface is identified, or if water is only detected at the edge of the profile, indicating that the full river width was not captured. Optionally, cross-sections with a very low estimated WSS can be discarded or assigned a predefined WSS value. A fixed depth or elevation level can also be assigned, bypassing the inference of the submerged section entirely if the WSS falls below a specified threshold.

3.2 Airborne lidar processing

Unlike satellite-based observations, which are constrained by fixed orbital tracks, topographic lidar allows for flexible 2D sampling of the land surface. The package initializes cross-sections perpendicular to points along the river chainage, using either equidistant spacing or user-defined locations. Users may freely define the width on either side of the centerline, provided the cross-section does not intersect the river at multiple chainages (e.g., due to tight meanders). Alternatively, users can manually define a cross-section by specifying two points on opposite sides of the river.

The package manages raw topographic lidar I/O via the `laspy` library. The algorithm identifies and loads all lidar tiles that intersect a given cross-section, clips them to the buffered maximum spatial extent, and concatenates them into a single dataset. To refine this data, the package filters the points—retaining only "ground" and "water" classes based on the provided classi-



fications, and projects them onto the cross-section nodes. Lidar points are aggregated within a specified search radius around
225 each node, and representative elevations are assigned using the median value. During this stage, the package distinguishes data
by both campaign and acquisition date, as a single .laz tile may contain multiple flight dates.

The package calculates the local WSS for each unique campaign and acquisition date. After projecting the point cloud onto
the river nodes and calculating median heights, the algorithm estimates the WSS using a multi-step procedure. The observations
are first filtered using a windowed standard deviation filter, then fitted with a monotonic falling spline, based on which a PCHIP
230 [Piecewise Cubic Hermite Interpolating Polynomial] spline is constructed. Uncertainty in the slope estimate is quantified using
bootstrapping, from which a 95th percentile confidence interval is derived. If the algorithm fails to achieve a reliable fit, a
secondary user-defined method can be applied.

To create a "harmonized cross-section," the package processes the different versions of the cross-section (derived from
various acquisition dates or sources) to identify their respective WSE. The algorithm flattens values near the WSE and integrates
235 the different versions into the harmonized model in ascending order of their WSE. A version is only cast into the harmonized
model if the corresponding position currently lacks a height value. The package fills any remaining gaps in the resulting profile
and applies a smoothing spline.

Finally, the package identifies the acquisition date, slope, and discharge corresponding to the observation with the lowest
WSE. To finalize the geometry, it vertically clips the cross-section at a threshold height or adds a vertical wall up to that
240 threshold. As a last quality control step, the process removes any water occurrences that touch the edges of the cross-section
boundaries.

3.3 Submerged Section Inference

After the lidar point clouds have been processed, a terrain trend line is drawn with a spline, and the river banks are identified.
River widths are calculated based on these banks, and the WSE is estimated during the WSS calculations. Based on the
245 derivation shown in (Musaeus et al., 2024), an estimate of the submerged part of the cross-section can be inferred using
Manning's equation (Manning, 1891):

$$Q = \frac{1}{n} \cdot A \cdot R^{\frac{2}{3}} \cdot S_f^{\frac{1}{2}} \quad (1)$$

Where Q is discharge, n is Manning's n ($\frac{s}{m^{\frac{1}{3}}}$), A is cross-section area, $R = \frac{A}{P}$ is hydraulic radius, P is wetted perimeter,
and S_f is friction slope.

250 Assuming the diffusive wave approximation of the 1D de Saint Venant equations (Saint Venant, 1871), where inertia terms
are neglected, the friction slope can be set as equal to WSS. This approximation accurately describes flow in river stretches
with uniform flow or gradually varied flow, but not stretches with acceleration or deceleration, such as whitewater rapids.

Since this method is used to create cross-sections for 1D hydrodynamic models, the objective is not to reconstruct the exact
channel geometry, but to reproduce the relationship between WSE and conveyance that governs flow. The conveyance, K ,



255 collects the roughness and geometry terms of the flow equation:

$$K = \frac{1}{n} \cdot A \cdot R^{\frac{2}{3}} \quad (2)$$

These individual terms are not observable remotely, which is why it is necessary to directly estimate the conveyance that reflects several physical parameters.

260 Using a conceptual shape presented by Dingman (2007), the conveyance can be estimated in the submerged section based on the derived width W :

$$z(x) = d \cdot \left(\frac{2}{W} \right) \cdot x^r, \quad 0 \leq x \leq \frac{W}{2} \quad (3)$$

Where $z(x)$ is height above deepest point in the channel, d and W are maximum depth and width of the submerged section, and x is the horizontal distance from the center of the submerged section. Now, the area and wetted perimeter becomes functions of W , r and d :

$$265 \quad A(d) = d \cdot W - 2 \cdot \int_0^{\frac{W}{2}} z(x) dx = d \cdot W - 2 \cdot d \cdot \left(\frac{2}{W} \right)^r \cdot \frac{\left(\frac{W}{2} \right)^{r+1}}{r+1} = \frac{d \cdot W \cdot r}{r+1} \quad (4)$$

$$P(d) = 2 \cdot \int_0^{\frac{W}{2}} \sqrt{1 + \left(\frac{dz}{dx} \right)^2} dx = 2 \cdot \int_0^{\frac{W}{2}} \sqrt{1 + \frac{d^2 \left(\left(\frac{2}{W} \right)^r \right)^2 (x^r)^2 r^2}{x^2}} dx \quad (5)$$

We can now collect the expressions for $A(d)$ and $P(d)$ into the conveyance term in Manning's Eq. (1), and introduce the estimated WSS instead of friction slope:

$$Q = K(d) \cdot WSS^{\frac{1}{2}} \quad (6)$$

270 Given discharge from a time series, width derived from altimetry observations and an assumed shape parameter, we can solve the equation for depth of the submerged section such that the computed discharge equals the discharge input at the time of the altimetry observation. The conceptual shape then allows for an estimate of conveyance down through the submerged part, while conveyance in the exposed part is calculated from the altimetry observations.

275 The roughness parameter n is not observable and equifinality prevents a unique estimate. Instead, a roughness parameter must be assumed and later calibrated through hydrodynamic modeling using the defined cross-sections.

3.4 Output

The python package can output cross-sections in two formats: MIKE's .xns11 format, with cross-sections labeled by the provided branch name and chainage or as csv files, containing (x, z) geometry pairs. The Xns11 collection can be opened



with MIKE software or the mikeio1d python package, and can be used to calculate hydraulic properties such as flow area and
 280 conveyance from the specified geometry and hydraulic roughness. The csv file on the other hand contains only the geometry
 of the fully defined cross-section, including the assumed shape of the submerged part.

4 Results

To evaluate our method, cross-sections are defined along four rivers where both the necessary input data and in situ cross-
 sections for validation are available. Figure 3 maps comparison pairs along the four rivers. When comparing cross-sections,
 285 agreement is quantified as the difference in WSE at fixed values of flow area and conveyance between the compared cross-
 sections. This metric directly reflects differences in hydraulic behavior rather than geometric differences alone. We define
 a representative range of flow area and conveyance for each river and compute the WSE difference at 20 equidistant sample
 points in the defined range. Table 1 lists the median Root Mean Square Error [RMSE] and bias for both the area and conveyance
 estimates across all rivers. Figure 4 shows slope estimates from ICESat-2, and Figure 5 shows example cross-sections as well
 290 as error distributions. Performance is similar across lidar data sources, although topographic lidar based cross-sections exhibit
 more similar bias in smaller rivers. We analyse the results from each lidar source separately in the sections below.

Table 1. Cross-section flow area and conveyance accuracy metrics, when comparing in situ and lidar-based cross-sections. WSE difference
 at fixed values of area and conveyance was used as accuracy metric.

Data Source	Site	N(XS) [1]	median RMSE [cm]		median bias [cm]	
			Area	Conveyance	Area	Conveyance
Topographic lidar	Torne	9	32.98	49.09	−29.63	−43.13
	Rönne	4	20.62	16.19	17.58	12.11
	Gudenå	21	50.68	67.11	38.17	61.62
ICESat-2	Loire	31	47.08	46.71	3.70	−6.58

4.1 Topographic lidar cross-sections in Torne, Rönne and Gudenå

The cross-sections for the topographic lidar were placed to overlap with the available in situ cross-section for Torne (Zhou
 et al., 2025), Rönne (Bauer-Gottwein et al., 2024b), and Gudenå (Bandini et al., 2021). We initially quality-controlled the
 295 cross-sections to ensure sensible placement in the data and obvious misplacements are rejected. Additionally, we also rejected
 those with relative slope errors exceeding 50 % based on the 95 % confidence interval. The comparison pairs are shown in
 Figure 3 c,d,e for Torne, Rönne, and Gudenå, respectively. Both data sources use the same local reference frames.

Figure 5 contains an example cross-section geometry for Torne (a) as well as area and conveyance profiles for increasing
 WSE (b,c) in the same cross-section. Subplots d and e show WSE differences at fixed values of area and conveyance for all
 300 compared pairs on Torne. As seen in the example geometry, the exact bottom level is not identified, leading to negative Δ WSE
 at very low area and conveyance levels. This is a general trend in the cross-sections, seen in subplots d and e. While WSE

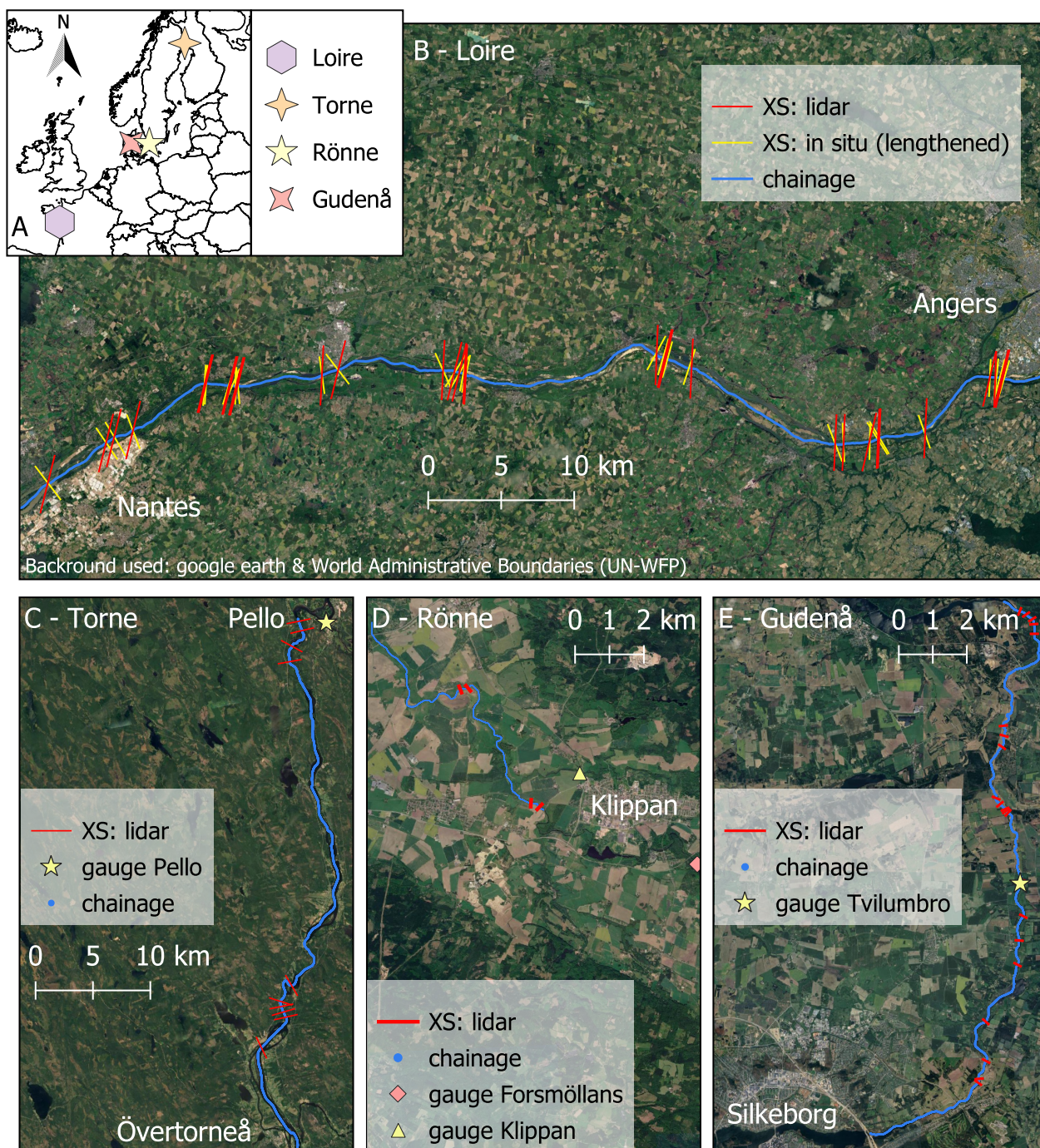


Figure 3. Study areas with compared cross-section pairs. The overview map (A) shows geographical locations. Background ©2026 Google, administrative borders from World Food Programme (2019). In situ cross-section lines in the Loire (B) have had lengths extended 1 km in each direction as a visual aid. The sites of topographic lidar on Torne, Rönne, and Gudenå (C-E) do not show the in situ location as the cross-section overlay. Map projection EPSG:3035.

ICESat-2 based cross-sections were created for the main branch of the Loire river, based on ATL03 datasets acquired during the dry season (May to September) over the period 2018-2025. For the 700 km course considered, 1000 cross-sections were generated and passed the default quality checks. In the 140 km span where in situ cross-section are available, 300 ICESat-2 based cross-sections were created with the package. The WSS estimates in Figure 4 clearly show that WSS generally decreases as the river approaches the ocean, as expected. Given the 10 cm elevation accuracy of ICESat-2 photons, and the maximum track spacing of approx. 6 km, the WSS becomes effectively undetectable as it approaches 0. Scherer et al. (2022) find a median absolute error of 2.3 cm km^{-1} for ICESat-2 derived slope estimates. Consequently, we recommend against using ICESat-2 lidar to define cross-sections in regions where the WSS is below 5 cm km^{-1} . Following this principle, we do not consider comparison pairs after chainage 75 km, where the WSS is very low. Some higher slope estimates are found in this section, but they represent misidentified water surfaces, not true hydraulic conditions, and are discarded as outliers.

Figure 4. Water surface slope estimates from defined cross-sections in the downstream end of the Loire. WSS estimates generally decrease as the river approaches the ocean. Following the principle of not using the method in areas with WSS trends of 5 cm km^{-1} , we do not consider cross-sections after Chainage 75 km.



In situ cross-sections for the Loire were re-referenced from NGF-IGN69, the official geoid model for mainland France, to EGM2008, the global geoid model (Pavlis et al., 2008) used for ICESat-2. Since ICESat-2 cross-sections are restrained to fixed satellite paths, exact matches for the in situ cross-sections cannot be created. Instead, suitable comparison pairs are selected based on spatial proximity and similarity in river conditions, with all chainage differences limited to less than 200 m. While lidarcross strives to create a single cross-section for braided parts of the river, the in situ cross-sections are split between channels in braided sections. For this reason, comparison pairs are only chosen in sections with a single major channel. However, at low flow conditions, braiding occurs within the main channel, which is visible in both the lidar-based and in situ cross-section example in Figure 5 (h). The comparison pairs are mapped in Figure 3 B. The different angles relative to the river between in situ and lidar based cross-sections are notable, with ICESat-2 based cross-sections only occurring at two specific angles, due to the satellite path around a spinning earth.

Figure 5 contains an example cross-section geometry (h) as well as the area and conveyance profiles for increasing WSE (i-j) in the same cross-section. Subplots k and l show WSE differences at fixed values of area and conveyance for all compared pairs. As seen in the example geometry, the exact bottom level is generally not identified, leading to large negative Δ WSE at very low area and conveyance levels. As also seen in the topographic lidar case, this behavior is consistent across sites, highlighting the difficulty of resolving the exact channel bed bottom level from surface-based observations. The geometry shows another compromise of the method, where the calculation assumes the same depth in all submerged parts of a multichannel cross-section. This is not observed in the in situ survey, leading to an overestimation of area and conveyance when WSE exceeds 2.5 m. This compensates for the shallow bottom elevation. The curves increase in parallel above this WSE.

This cross-section further illustrate a potential issue from misalignment between compared tracks, through the presence of a small islet in the right channel in the in situ cross-section that is not captured beneath the satellite track. This affects the area and conveyance curves for the quantitative comparison, but is a necessary compromise when finding comparison pairs between two fixed sets of cross-sections.

340 5 Discussion

This paper presents a rapid and scalable method of estimating full-flow cross-sections for hydrodynamic modeling from lidar altimetry datasets. Combined with a best-available discharge input, conveyance at the time of the lidar survey is balanced with a WSS estimate under the diffusive wave assumption. Here, we discuss insights and limitations that must be considered when using the presented python package.

345 5.1 Validation and Equifinality

Since lidarcross can be used with global products as input, application is possible in most watersheds and at both small and large scale, with a likely lower limit of 20-30 m river width for ICESat-2 cross-sections. However, as the method is intended for application in data-scarce areas, in situ cross-sections are unlikely to be available. This inhibits the validation of 'effective' hydraulic geometry in the form of area and conveyance curves, but the hydraulic validity of the derived cross-sections can

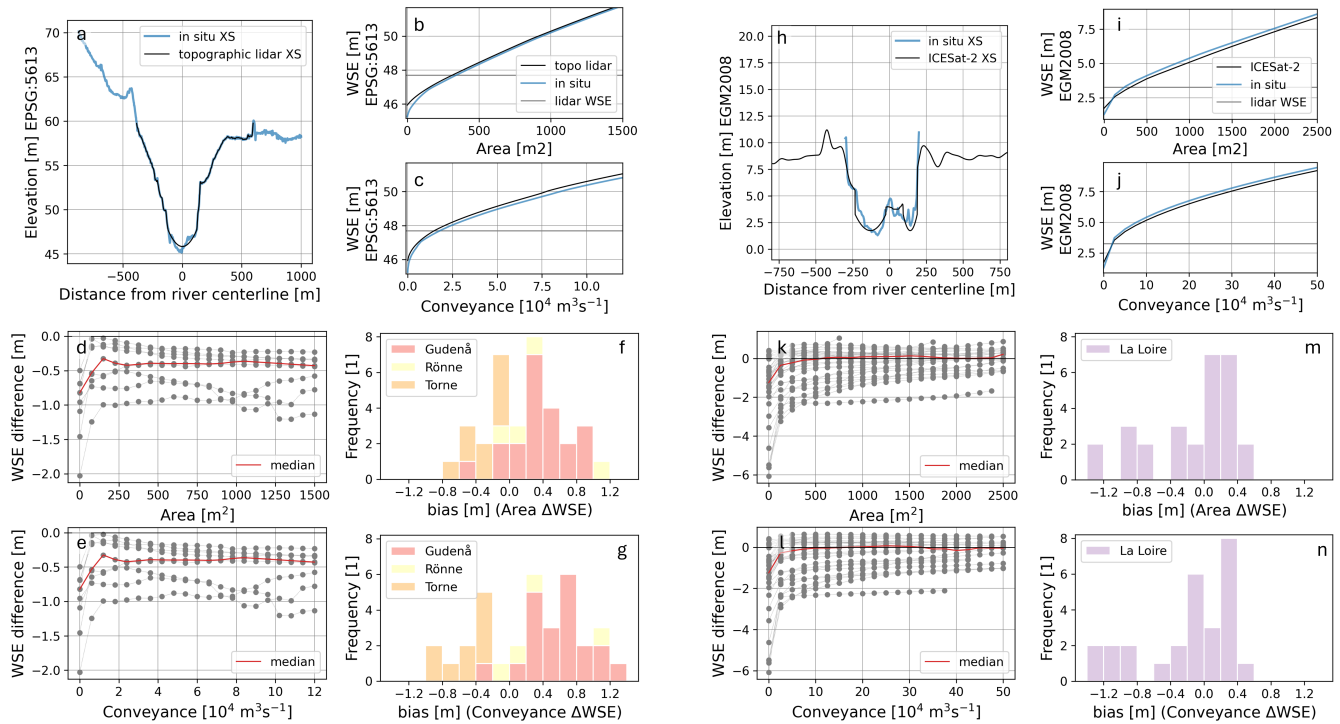


Figure 5. Comparisons between in situ and lidar-based cross-sections. Topographic lidar in Torne (a-e) and Torne, Rönne, and Gudenå (f,g); ICESat-2 in la Loire (h-n). Examples comparisons of (a,h) geometry, (b-c, i-j) area and conveyance. (d-e, k-l) WSE differences between all cross-section pairs, with median Δ WSE for compared values of area and conveyance. (f-g, m-n) histograms of Δ WSE bias.

350 still be assessed through hydrodynamic model performance, evaluated against observations of WSE from either in situ gauges or altimetry missions like SWOT. The SWOT data product is an entirely independent validation data source not used in the cross-section definition, since the radar instrument does not reliably provide terrain elevation, but its high spatial and temporal resolution makes it ideal for hydrodynamic model validation.

The issue of equifinality is unavoidable as multiple combinations of shape, roughness and depth can reproduce the observed
 355 discharge, however, the roughness and shape parameters can be adjusted to better reproduce the dynamics observed in the modeled river. Because the exposed part of the cross-section is less dependent on the shape and depth, the assumed hydraulic roughness will be the most significant parameter for model WSE amplitude, and roughness can be adjusted based on observed WSE amplitude. Dry-season satellite passes are selected to minimize the extent of the submerged area, thereby reducing the impact of depth estimation uncertainties on model performance.

360 5.2 The ICESat-2 altimetry product

While the method described in Musaeus et al. (2024) relied on the ATL13 water surface product from ICESat-2 for WSE estimation, lidarcross calculates WSE directly from ATL03. Since ATL13 is only provided in areas classified as water based on



an internal water mask, small or ephemeral rivers are excluded from the dataset. Identifying the main channel water surface for WSS estimation is an important processing step, as errors in WSS estimation directly propagate into the inferred submerged geometry. Neighboring off-channel water surfaces, like lakes or irrigation trenches, can be misidentified as the main river channel, skewing the WSS estimate.

To process multiple cross-sections rapidly, lidarcross relies on the automatic identification of river surfaces and banks within the altimetry products. While the package does take advantage of built-in labels in the lidar products, automatic detection should be verified by the user, to ensure that reasonable water surfaces and banks have been identified. Validation of simulated results will also provide insights into the accuracy of the defined cross-sections. Musaeus et al. (2024) provides examples of how model performance can inform spatially varying channel roughness and identify dynamically evolving river reaches, where additional cross-sections can significantly improve model performance. An iterative approach can improve the final model performance without requiring extensive visual inspection of every cross-section.

With the number of ICESat-2 passes increasing over time, quality checks that ensure that terrain and water surfaces are correctly identified can become more strict. If few tracks are available, tracks have to be widely accepted to ensure adequate cross-section coverage for hydrodynamic modeling - but with more available passes, the focus of ICESat-2 data processing shifts from identifying every potential cross-section candidate to ensuring only high quality cross-sections are retained. When choosing a cross-section set based on available candidates, cross-sections should not be too close in proximity to ensure model stability, and filters could be implemented to ensure that width and slope estimates fall within expected ranges.

Another limitation of ICESat-2 based cross-sections is the anchoring to defined satellite ground tracks. The satellite's polar orbit causes the satellite tracks to be north-south aligned, with a slight angle caused by the earth's spin, dependent on the ascending or descending phase. Cross-sections for north-south aligned rivers can still be produced due to natural meandering and the angle correction, but there will be fewer opportunities for perpendicular tracks, and the wider flood-plain is most likely inadequately captured. While this limits use-cases, the hydraulic models informed with these cross sections will still be useful for flood risk assessment and forecasting as intended, providing insights in timing and positioning of bank overflow occurrences.

5.3 The topographic lidar product

Governmental authoritative topographic lidar missions' main objective is to produce high accuracy DEMs of the land surface. Signal return over water may be poor or even non-existent, depending on the lidar wavelength chosen by the conducting agency. This will yield highly accurate geometry of the river's exposed section. On the other hand, an accurate WSS estimate from topographic lidar alone is harder to obtain. The inference of the submerged section depends on an accurate WSS measurement. This was especially apparent on Gudenå, since the Danish topographic lidar data retains no water points. The issue is addressed through the secondary data interface for slope estimation.

In this paper, we rely on the respective agencies' lidar point classification. This could pose potential challenges if the classification quality is insufficient. In our analysis, we did not observe any quality issues with the data used. Additionally, while some topographic lidar products have an intrinsic water class, it is not sufficient to define the river's extent. The algorithm



we employed in this paper usually works reliably, but may produce minor errors in the river width estimates. The effect is negligible in wider rivers like the Torne, but could degrade results in narrower rivers like the Gudenå. This could explain the relatively large median RMSE reported for Gudenå in Table 1.

400 **5.4 Discharge inputs**

While the method is intended for use in data-scarce regions, it relies on discharge as an input, which remains notoriously difficult to estimate remotely. Since discharge forcing is required for hydrodynamic modeling regardless of cross-section source, the package does not introduce an additional dependency and is discharge agnostic. Efforts to estimate discharge from SWOT are ongoing (Bjerklie et al., 2023; Durand et al., 2023; Eggleston et al., 2024; Andreadis et al., 2025; Cerbelaud et al., 2025; 405 Larnier et al., 2025), however such methods rely on estimating or assuming cross-sectional shape, and as such would not bring new information to our purposes. Instead, the method in this paper synergizes well with global or regional discharge products based on other inputs, like global hydrological models [GHMs]. Models like GLOFAS (Emerton et al., 2018) or DHI-GHM (Murray et al., 2023) provide modeled discharge globally, and can be used as input for this package. Improvements to GHMs, such as increasing resolution (van Jaarsveld et al., 2025), should also improve cross-section definition.

410 **5.5 1D modeling limitations**

As the method represents channel geometry in an effective hydraulic sense, it remains subject to the limitations of 1D modeling assumptions. Braided rivers are not simplified into a single channel when estimating geometry, but flow is not separated in the 1D model. 1D modeling is not always valid in braided rivers, exemplified for the Brahmaputra by Franze et al. (2025). A 1D hydrodynamic model assumes identical water level in all channels, which is not always observed. Extensive validation of 415 model results is required to ensure that 1D modeling effectively simulates observed water levels.

6 Conclusions

This paper presents a scalable and transferable method for estimating river cross-sections from lidar altimetry products combined with discharge information, designed specifically for application in data-scarce environments. By combining altimetry from ICESat-2 or airborne lidar, including water surface elevation [WSE] and water surface slope [WSS] estimation with 420 best-available discharge, the method enables the definition of full-flow cross-sections suitable for hydrodynamic modeling. Rather than attempting to resolve the exact bathymetry – an inherently under-determined problem – the method focuses on reproducing the effective hydraulic behavior of the channel through conveyance–stage relationships, aligning with the needs of 1D hydrodynamic models.

Validation across four rivers spanning local to regional scale demonstrates that the method can reproduce key hydraulic 425 properties with reasonable accuracy. Comparisons against surveyed cross-sections show median WSE differences of approximately 0.5 m when evaluated at fixed values of flow area and conveyance, indicating that the defined cross-sections mimic the hydrodynamic relationships of the surveyed cross-sections. As expected, the largest discrepancies occur at low flow con-



ditions, where the inferred submerged section has the most influence. While these errors can propagate to higher flow levels, their relative importance diminishes in flood-related applications, where the exposed part of the cross-section and near-bank geometry are more influential.

A central strength of the method lies in its ability to exploit WSS observations, an increasingly available variable with missions such as ICESat-2 and SWOT. By invoking the diffusive wave approximation and combining WSS with discharge, the method provides a physically grounded estimate of conveyance in the submerged part of the cross-section. This represents a shift from inverse approaches toward a framework where remotely sensed hydraulic observations directly constrain channel properties. As global altimetry datasets expand in spatial and temporal coverage, the applicability and robustness of this approach are expected to improve.

The method is implemented as an open-source Python package, enabling rapid and standardized cross-section generation from either satellite or airborne lidar data. This facilitates practical adoption in hydrodynamic modeling, where cross-sectional data are often a limiting factor. The package is particularly valuable as a first-order solution: it provides a consistent, physics-informed baseline geometry that can be used to initialize models, identify areas of high uncertainty, and guide targeted field surveys. In this context, it supports efficient allocation of field resources by prioritizing locations where improvements in geometry are most impactful.

At the same time, several limitations must be acknowledged. The method depends on the availability and accuracy of discharge data, which remain challenging to estimate remotely. However, this dependency is consistent with the requirements of hydrodynamic modeling more broadly, and lidarcross is well aligned with global hydrological models and discharge products. Uncertainty in WSS estimation, particularly in low-slope stretches or where water surfaces are difficult to identify, can also significantly influence results, as slope directly impacts the estimated conveyance. Additionally, assumptions regarding channel shape and hydraulic roughness mitigate issues of equifinality, but assumed parameter values must be further refined when validating hydrodynamic model results.

The method's deterministic formulation, with limited reliance on calibration, distinguishes it from traditional inverse modeling approaches that require extensive parameter optimization. Instead, it supports an iterative workflow in which cross-sections can be refined based on hydrodynamic model performance and independent observations of WSE. Such an approach allows users to progressively improve model fidelity without the computational burden of large-scale optimization, while maintaining transparency in how cross-sections are generated. Finally, the method does not overcome the intrinsic limitations of 1D hydrodynamic modeling, particularly in complex or highly braided systems where flow cannot be adequately represented by a single stage across the cross-section. Nevertheless, it preserves multi-channel structure within the defined geometry and provides a pragmatic representation suitable for large-scale flood modeling applications, where 1D approaches remain widely used.

Code and data availability. The Python package will be published on PyPI under an MIT license, with a Github repository. An archived version is available for peer-review at <https://doi.org/10.5281/zenodo.21220013> (Musaeus et al., 2026), along with the scripts and cross-section sets created for this paper, and the corresponding surveyed cross-sections, if not already published (Zhou et al., 2025; Bauer-Gottwein et al.,



2024b). ICESat-2 datasets (Neumann et al., 2025a) are not provided, but can be downloaded using the scripts in the archive. Topographic lidar data is also not provided but can be accessed at the respective agencies data distribution (KDS, 2020; Lantmäteriet, 2024; NLS, 2026). Furthermore, a matching of lidar tile to cross-section is thus also not provided.



Appendix A: Comprehensive national topographic lidar missions

Table A1. List of countries with a comprehensive authoritative topographic lidar campaign. †: in progress, *: potentially regional. **: including Lichtenstein. ***: mainland only. ****: currently on a by state basis, by end 2026 federal under digital twin Germany.

Country	nationwide	laz available	Publicly Accessible	Region	Resource
Albania	Yes	No	DEM only	Europe	link
Australia	No	Yes	Yes	Oceania	link
Austria	Yes	No	DEM only	Europe	link
Belgium	Yes	Yes	Yes	Europe	link & link
Canada	No	Yes	Yes	Americas	link
Costa Rica	Yes	No	DEM only	Americas	link
Croatia	Yes	Yes	Yes	Europe	link
Czechia	Yes	Yes	Yes	Europe	link
Denmark	Yes	Yes	Yes	Europe	link
Estonia	Yes	Yes	Yes	Europe	link
Finland	Yes	Yes	Yes	Europe	link
France	Yes †	Yes	Yes	Europe	link
Germany	Yes †	Yes	Yes	Europe	****
Haiti	yes	No	DEM only	Americas	link
Iceland	Yes	No	DEM only	Europe	link
Ireland	No	No	DEM only	Europe	link
Italy	Yes	No	DEM only	Europe	link
Japan	Yes	No*	DEM only	Asia	link
Latvia	Yes	Yes	Yes	Europe	link
Lithuania	Yes	Yes	Yes	Europe	link
Luxembourg	Yes	Yes	Yes	Europe	link
Malta	Yes	Yes	Yes	Europe	link
Mexico	Yes †	No	DEM only	Americas	link
Netherlands	Yes	Yes	Yes	Europe	link
New Zealand	Yes	Yes	Yes	Oceania	link
Norway	Yes	Yes	Yes	Europe	link
Philippines	No	Yes	Yes	Asia	link
Poland	Yes	Yes	Yes	Europe	link
Portugal	Yes***	Yes	Yes	Europe	link
Slovakia	Yes	No	DEM only	Europe	link
Slovenia	Yes	Yes	Yes	Europe	link
South Korea	No	No	DEM only (low res)	Asia	link
Spain	Yes	Yes	Yes	Europe	link
Sweden	Yes	Yes	Yes	Europe	link
Switzerland**	Yes	Yes	Yes	Europe	link
Trinidad & Tobago	Yes	No	DEM only	Americas	link
UK (England)	Yes	Yes	Yes	Europe	link
USA	Yes †	Yes	Yes	Americas	link



PBG and CMMK: Conceptualization, project administration, supervision, review and editing.

JL and KN: Conceptualization, resources, review and editing.

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