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UAWOS - Unmanned Airborne Water Observing System

Deliverable 4.1:

Technical Report on Rating Curve estimation using UAS hydrometry

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3. Overview and Summary

This document constitutes deliverable D4.1 of the Horizon Europe project “UAWOS – Unmanned Airborne Water Observing System”, contract number 101081783. The document represents the technical report aimed at establishing protocols for the development of rating curves for virtual stations using Unmanned Aerial Systems (UAS) hydrometry.

The document is structured in three main parts: the first focuses on the estimation of rating curves (section 4); the second describes the estimation of river discharge from UAS hydrometry (section 5); the third is focused on the application of rating curves derived from UAS hydrometry at virtual stations (section 6).

The report also includes the evaluation of the expected accuracy and the error budget and the validation of the selected procedure for rating curve and discharge estimation (Section 7 and Section 8, respectively).

4. Introduction: rating curve development

River discharge is a key quantity in hydrology and provides essential information for environmental monitoring, water management and warning systems. Traditionally, the continuous estimate of river discharge at a site is based on transformation of observations of water level (stage) to discharge using a so-called **rating curve.** This is a stage-discharge relationship whose development requires the collection of simultaneous measurements of river stage and discharge at the section of interest over a range of flow conditions. The simplest method for rating curve estimation consists in interpolating with a fair accuracy the observations of stage and discharge, fitting a mathematical function (see Figure 1).

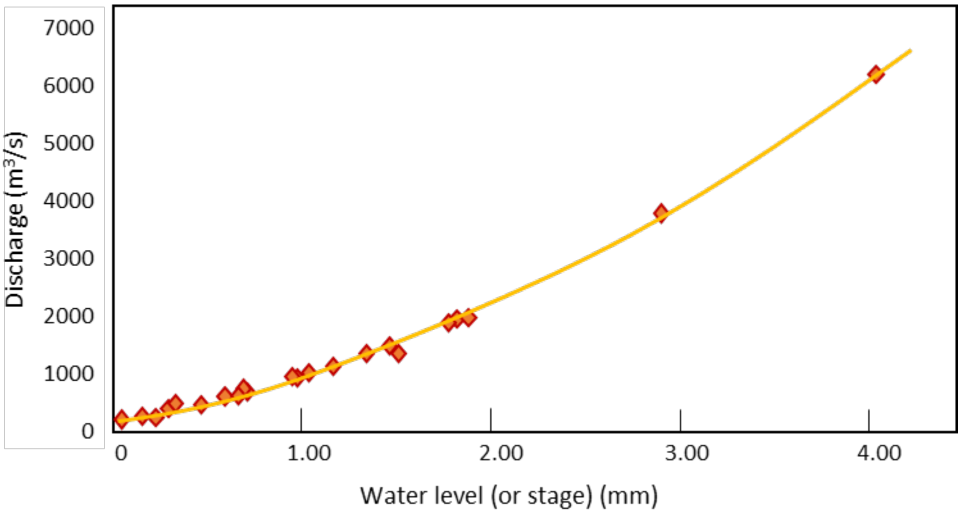

Figure 1. Example of stage-discharge relationship (rating curve).

Different methods for rating curve assessment can be found in the scientific literature, **all based on the availability of contemporaneous measurements of stage and discharge.**

The continuous monitoring of river stage is developed by installing hydrometric sensors at the section of interest. The discharge is estimated indirectly: one of the traditional methods to estimate river discharge is the “velocity-area” method (Herschy, 1993), based on measuring: 1) the velocities at different points across the river section, 2) the depth of flow, and 3) the channel distances between sampled verticals. The velocity field is integrated in the liquid area of the cross section of interest, according to the relationship:

$$Q = \iint_{b \cdot h} \vec{U} \cdot db \cdot dh \qquad (1)$$

where *U* is the local flow velocity, *b* is the width and *h* the water depth.

The flow velocity in rivers is not constant throughout the section but decreases near the banks and bottom due to friction. In addition, because the motion of the flow is turbulent, the local velocity can vary in direction and intensity from point to point in space and time. The river discharge is calculated by dividing the liquid section into several subsections, bounded by a number of verticals. The average velocity along each vertical is estimated by sampling a number of "velocity points" using hydrometric current meters (Herschy, 1985). The total river discharge is then obtained as the sum of the products of the average velocities of each vertical for their respective areas of influence.

The following sections outline the most important rating curve estimation methods.

4.1. Experimental data fitting method

The most straightforward and most widely used method for rating curve estimation consists of interpolating the observations of stage and discharge, using, for instance, a power law fitted to the observations (e.g. Rantz, 1982). In this case the knowledge of the cross-section geometry is not required. However, in practical applications it is common to split the rating curve into several power-law relationships for different segments of the water level range, which thus implicitly take into account how the cross-section geometry impacts the stage-discharge relationship. In general, it is also possible to represent the stage-discharge relationship with a look-up table which allows for more freedom than a simple power-law function. This method provides reliable streamflow values in the range defined by the measured data while it becomes less accurate for higher water levels in case the extrapolation phase is not supported by hydraulic criteria.

Rating curves are required to be extrapolated when the discharge measurements are not available over the entire range of observed stages. In simple cases, the curve may be smoothly extended. This will not be correct if, in the extended range, channel geometry changes, there is flow over flood plain, or the roughness coefficient changes significantly. The extrapolation in high flow ranges should be attempted with utmost caution and based on other methods that take the flood propagation processes into account.

Fitting of a power-law is a straight-forward optimization task that can be made with various tools. There are also more elaborate solutions available for empirical rating curve estimations, some of which also provide uncertainty estimations, eg. the Bayesian BaRatin method (Le Coz et al., 2014; Horner et al., 2018) and Ratingcurve: A Python Package for Fitting Streamflow Rating Curves (Hodson et al, 2024).

4.2. Slope-friction factor method

The classical approach based on the slope-friction factor, α, is derived from the well-known Manning equation for discharge Q estimation (Herschy, 1985):

$$Q(h) = A(h)U_m(h) = \frac{\sqrt{S_f(h)}}{n(h)} A(h)R(h)^{2/3} = \alpha(h)A(h)R(h)^{2/3} \qquad (2)$$

where A is the flow area, h is the water level, U_m is the mean cross section velocity, S_f is the water surface slope, n is the Manning roughness coefficient and R is the hydraulic radius.

In order to obtain the rating curve expression, Q(h), the relationship between the factor α and the stage h, and between the quantity $AR^{2/3}$ and the water level have to be defined. $AR^{2/3}$ has to increase with the stage and it depends on the cross-section geometry. For estimating the relationship α(h) the velocity measurements have to be employed: for each observed stage the factor α is evaluated as ratio between the observed discharge, Q, and the quantity $AR^{2/3}$ value corresponding to the recorded stage, h. Typically, the factor α value increases with stage and this tendency allows to determine an asymptotic value to employ during the rating curve extrapolation phase. If the experimental data range within a limited interval, the asymptotic factor value could be difficult to define and, therefore, the rating curve extrapolation may be affected by a high level of uncertainty. Practical limitations of the slope-friction factor method are linked to: unsteady effects are not considered, extrapolation in presence of hydraulic structures that could affect the flow conditions, the α factor has not a physical meaning. On the other hand, this method is simple and easily applicable and requires the knowledge of the geometry of the section of interest.

4.3. Surface slope method (Conveyance method)

The Manning equation (eq. 1) can be rewritten in terms of water surface slope, S_f, as:

$$Q(h) = \frac{\sqrt{S_f(h)}}{n(h)} A(h)R(h)^{2/3} = K(h)\sqrt{S_f(h)} \qquad (3)$$

The discharge value depends on free-surface slope, S_f. The procedure to be applied consists of the following steps (Fenton, 1999):

1. the slope of the water surface at the gauging station has to be measured, e.g. by installing two measuring devices for stage, and the S_f dependence on h, S_f(h) can be assessed;

2. for different flow conditions, the discharge Q has to be measured and for each measurement, the value of the conveyance, K, can be then assessed by using eq. (3);
3. from all data pairs (h_i, K_i) the functional dependence of K on h, K(h), can be estimated;
4. the rating curve is derived from eq. (3) based on K(h) and S_f(h).

Figure 2 shows an example of the conveyance method application for a gauged section in central Italy; the trend of 1/K(h) quantity against stage is identified and the asymptotic value of 1/K(h) can be adopted for high floods, i.e. for rating curve extrapolation.

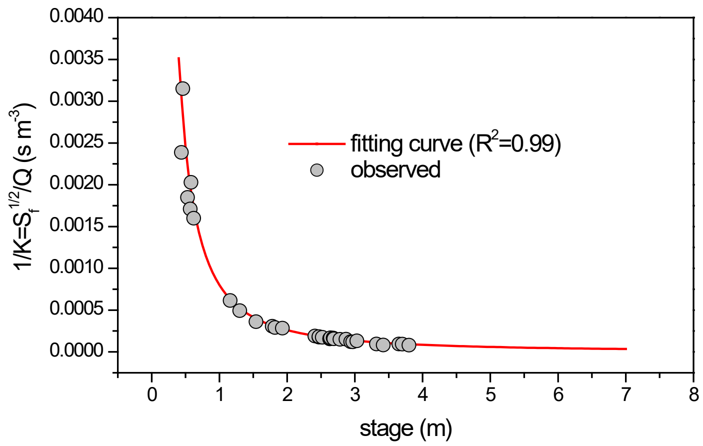

Figure 2. Example of conveyance-stage relationship.

Rantz (1982) recommended the use of the conveyance-slope method. Other methods, such as efficient hydraulic modelling and high-performing data-driven approaches, can be used to derive accurate rating curves.

4.4. Hydraulic modelling

Hydraulic modelling can be employed for rating curve estimation purpose. Different models can be used such as Mike11, developed by the Danish Hydraulic Institute, HEC-RAS of the US Army Corps of Engineers). Alternatively, steady gradually varied flow can be assumed for the river reach of interest (e.g. Mansanarez et al., 2019). The wave routing process along the river reach including the gauged section is described through the well-known Saint Venant equations. The application of hydraulic models requires:

- hydrographic network planimetry and geometry of the hydraulic structures (bridges, weirs. …);
- channel geometrical properties (survey of a sufficient number of cross sections);
- initial conditions (unsteady simulation);
- boundary conditions (input hydrograph; downstream rating curve or downstream water level, etc.);
- channel roughness characteristics.

The hydraulic model application is mostly addressed to identify the roughness characteristic of the channel. To this end, the observed data (discharge and stage) are employed to carry out simulations aimed to calibrate the Manning roughness coefficient typically assumed uniform for the selected river reach. In this way, each observed stage is associated with a coefficient n value and therefore, a relationship n(h) can be defined in order to extrapolate the n value to be employed for simulating the high levels and discharges. Typically, the coefficient decreases when the stage increases identifying an asymptotic value. Obviously, when the measurements range is limited to low discharges the extrapolation phase becomes uncertain. This method is able to account of the unsteady flow effects and is based on the physical based n whose values are reported in literature. It may also be useful to associate the roughness coefficient with the land cover types affecting the river flow at the different stages (e.g. Mansanarez et al, 2019). This can be particularly useful for two-dimensional models and for a-priori approximating of the roughness coefficients outside the main river channel. Land cover types and their physical characteristics can be established with varying degree of accuracy, using detailed field surveys or approximated from UAS or satellite-based remote sensing data.
Furthermore, the setup of a hydraulic model requires the knowledge of the geometry of a river reach including the gauged section. In many regions of the world, land surface elevation data is available with high enough

resolution except for the permanently sub-merged part of the rivers. As shown by Coppo Frias et al., 2023, it is further possible to approximate the elevation of the sub-merged part of river cross-section using certain satellite-based data. Traditionally, hydraulic model applications require expensive topographical surveys to be carried out, and the possibility to make a first approximation based on satellite data has great potential. This is further discussed in the following chapters.

In general, the reliability of the hydraulic model and its calibration of the n value depends on the range of available velocity and stage measurements as well as to what degree the representation (simplifications) of the hydraulic processes in the model are adequate for the specific conditions in the river reach.

Many applications of hydraulic modelling for rating curve estimate can be found in the literature (Lang et al., 2010; Kim et al., 2016; Holmes, 2016; Mansanarez et al., 2019; Pedersen et al., 2019; Westerberg et al., 2020). Revel et al. (2021) even presented a hydraulic model-based framework for global-scale river discharge estimation by assimilating satellite altimetry data.

4.5. Data driven empirical and statistical approaches

The Artificial Neural Networks (ANN) technique is a powerful procedure for non-linear function mapping and can also successfully model a looped rating curve (Jain and Chalisgaonkar, 2000; Goel, 2011; Bakshi and Bhar, 2013; Barkha and Prashant, 2022; Bhandari et al., 2023).

In recent years, data-driven empirical and statistical approaches have been developed to establish the rating curves. Singh et al. (2014) used the entropy theory-based probability distribution method. They created a relation between drainage area and discharge to determine the entropy index, which was used to predict discharge. However, a logarithm relation between stage and discharge was considered, which may not always apply for all basins both spatially and temporally. Chaplot and Birbal (2022) used an ANN for deriving the rating curves. However, ANN, in addition to being data and computationally expensive, may not always be interpretable; as a result, there is less adaptation by the water manager. In addition, machine learning models especially using multi-layer perceptron takes time to train the network and requires specialized knowledge as the machine learning models are prone to overfitting especially in cases where the data points are erroneous. In 2023, Bhandari et al. introduced a data-driven method for automatically generating the stage-discharge rating curve and showed uncertainties using a statistical approach; the technique used time-series information to understand the changes in the floodplain to generalize the rating curve.

4.6. Main issues of rating curves development: potential advantages of UAS hydrometry and satellite data

The different methods for rating curve development require contemporaneous measurements of stage and discharge and their accuracy in the extrapolation interval mainly depends on the availability of measurements carried out for medium-high water levels.

Deriving reliable rating curves using coincident measurements of stage and discharge requires long time series from in-situ stations on a river, to cover the range of stages and discharges occurring at the site. Moreover, it is worth noting that developing river flow measurements during high flow conditions can be difficult and even dangerous for the technical operators. The ground stations maintenance is particularly challenging for water bodies in remote locations, ephemeral rivers and streams, and small catchment areas.

Using alternative methods based on contactless measurements (satellite or UAS) of estimating the key variables, e.g. bathymetry, flow velocity, water surface elevation and hence river discharge, would be the ideal option for overcoming most of the above-mentioned issues for rating curve development and discharge monitoring.

To date radar altimetry is the most widely used technology to estimate river discharge from space. The altimeters provide water surface elevation (WSE) measurements which are used as in the traditional flow monitoring, to derive river discharge through the rating-curve established with multiple simultaneous water level and river discharge pairs. This allows radar elevation measurements to be converted into river discharge at each passage of the satellite over the river at the so-called virtual station. Often, these virtual stations are not located near the ground hydrometric stations, where the river discharge is known. Therefore, establishing a valid and reliable rating curve can be difficult.

Based on these premises, the UAWOS project aims to develop a drone-borne water observation system of river discharge at the virtual stations located at significant distances from ground hydrometric sites. Indeed, a drone system capable of measuring all hydrometric variables necessary for estimating river discharge at the virtual stations represents a valid solution to set up rating curves and convert the satellite water level measurements in river discharge over remote areas where the satellite water level is provided.

In this context, this report describes the estimation of river discharge from UAS hydrometry sensors and delineates the rating curve construction at the virtual stations.

5. Contactless river discharge estimation from UAS hydrometry

This section aims to provide a summary on the estimation of river discharge from Unmanned Aerial Systems (UAS) hydrometric measurements. UASs are a new emerging technique for global environmental monitoring and represent a link between traditional satellite observations and ground-based measurements.

They are low cost and versatile in-flight operations (low altitude and at short notice flight) and flexible in payload design. UASs can mount various no-contact instruments for the estimation of the quantities necessary for the river discharge estimation, i.e. river depth, flow velocity and bed geometry. Indeed, the size and the weight of the payload must meet special requirements and only precisely developed sensors meet these conditions. Despite internationally recognized as significant assets for environmental monitoring, the UASs are only occasionally used in operational water monitoring and often restricted to optical or thermal inspection. Indeed, most of the sensors used in UASs are optical-electronic sensors, including RGB, multispectral, hyperspectral and thermal infrared cameras. Their selection depends on several hydrological applications (Vélez-Nicolás et al., 2021, for a review).

In the following, a high-level classification of the sensors is given based on the variable to be monitored: 1) surface flow velocity; 2) riverbed geometry; 3) water surface elevation.

The river discharge is derived by exploiting the UAS hydrometry quantities (i.e. surface velocity, channel morphology and water depth).

5.1. Surface flow velocity measurement

For water velocity measurements, optical tracking methods based on time-lapse imagery, also known as image-based velocimetry, are the most popular and widely used method (Perks, et al., 2020; Tauro et al., 2016). The technique is based on cross-correlation and feature-based tracking of a series of consecutive images (or video frames) to generate vectors of water velocities across a field of view. Reported approaches based on this methodology include large-scale particle image velocimetry (LSPIV, le Coz et al., 2010), large-scale particle tracking velocimetry (LSPTV, Jolley et al., 2021), and space-time image velocimetry (STIV, Fujita et al., 2007). A comparison of these three image-based methods is carried out by Koutalakis et al. (2019) over the Aggitis River in Greece demonstrating the consistency of the methods in terms of the obtained surface water velocity. Despite the widespread use of these methods, they have several drawbacks in operational settings: First, images must be stabilized to correct for drone movements, which requires stable features within the video/image scene. Second, the flow must exhibit trackable features visible in optical or thermal imagery with the involvement of artificial seeding for successful tracking. Third, the data volumes are considerable and processing effort is significant, requiring careful outlier removal and data filtering routines which cannot be fully automatized.

Alternatively, Doppler radar (Costa et al.; 2006; Alimenti et al., 2020; Zhou et al., 2024) and Doppler Laser (Albrecht et al., 2013; Nezu and Rodi, 1986) can measure contactless water velocity even if, so far, there are only few studies reporting results of UAS Doppler river surveys. Doppler radar and Doppler laser have the advantages of largely automatic data acquisition and processing workflows to obtain a cross-sectional profile of flow velocity. For both techniques, performance is independent of daylight conditions. Differently from the Doppler radar in which it is necessary to have a roughness element of the water's surface, Laser Doppler has the added advantage that data quality is independent of surface roughness and that velocity data can be collected below the water surface (down to several decimeters in depth), which enables more accurate estimates of bulk flow velocity and discharge. Depending on the flight height, Doppler radar measurements have ellipsoidal footprints of several square meters. Thus, Doppler radar is particularly well suited for larger rivers, but cannot resolve small-scale surface velocity variations.

5.2. Bathymetry measurement

Several technologies have been demonstrated to be useful for mapping of riverbed geometry and it is possible to classify them into three categories: Sonar/Echosounder, water penetrating radar and Green Lidar.

Lidar and sonar technologies have been demonstrated for mapping riverbed geometry. Single-beam or multi-beam sonars (SOund NAvigation and Ranging) are fairly common aboard vessels (Bio et al., 2020; Halmai et al., 2020; Specht et al., 2020).Recently some companies have developed systems to place them aboard UAS, while still retaining the constraint that the sensors must remain in contact with the water during the survey (Bandini et al., 2018). Another solution for monitoring inland water bathymetry is represented by Lidar systems. So far, most green Lidar systems are used onboard aircraft and satellites (e.g., ICEsat-2), but there are a few commercial solutions available for UAS (Astralite Edge, TDOT green). The main limitations of commercial Lidar systems lie in their high costs, limited penetration capability (up to 1–1.5 times the Secchi depth), and uncertain performance for low-reflectivity bottom types and dense aquatic vegetation.

Table 1. Advantages and limitations of UAS bathymetry techniques of Sonar, Water Penetrating Radar and Green Lidar.

	Sonar	**Water Penetrating Radar (WPR)**	**Green Lidar**
Cost of payload	ca. 10 kEURO	ca. 20 kEUR	ca. 150 kEUR
Postprocessing effort	medium, can be automatized	high, not fully automatic	Medium-high, Can be automatized
Autonomy/flight height	Tethered and in contact with water	ca. 1-2 m above water	> 30 m above water
Deployment in strong currents	Limited in strong current	yes	yes
Sensitivity to turbidity	none	none	ca 1.5 Secchi depths
Sensitivity to salinity	low, can be corrected for	high, <300 microS/cm	none
Sensitivity to water temperature	high, can be corrected for	none	none
Sensitivity to bottom type / color	medium	high	medium
Sensitivity to aquatic vegetation	high	low/none	high
Depth range	up to 100 m	ca 5 m, dependent on bottom type, salinity	Limited by turbidity ca 1.5 Secchi depths
Resolution	centimeters	centimeters to decimeters, frequency dependent	centimeters
Penetration into bed sediments	no	yes	no

Water penetrating radar (WPR), typically used for frozen water bodies, works well in freshwater environments with low electric conductivity (<300 µS/cm), provided suitable antennas are used (often depending on water depth), and with deployment of floats or boats. Failures are mainly due to higher water conductivities, inappropriate choice of antenna frequency or use of an incorrect boat (Ruffel and Parker, 2021). A first evaluation of performances of an airborne WPR for freshwater bathymetric measurements was carried out by Bandini et al. (2023). They demonstrated that vertical accuracy better than 10 cm can be achieved and that WPR outperforms sonar measurements in waterbodies with medium or high density of aquatic vegetation.
Because it is difficult to find a method for the estimation of bathymetry that works in all situations and rivers, it is convenient to operate with different techniques. Table 1 lists the advantages and the limitations of each

technique demonstrating that, depending on site characteristics, a combination of different techniques is required for the difficult task of monitoring riverbed geometry.

5.3. Water surface elevation (WSE) measurement

WSE retrieval from UAS photogrammetry is based on photogrammetric digital elevation models (DEMs) of the water surface by interpolating WSE information with data points acquired from dry locations ("water-edge") adjacent to inundated areas (Woodget et al. 2015; Westaway et al. 2001). The accuracy of WSE observations in this case depends on the accuracy of the photogrammetric DEM and on “water-edge” identification. The disadvantage lies in the high computing power and time consumption for visual identification of ground control points (GCPs) and "water-edge" points.

Lidar instruments can measure WSE and water surface slope, but they are mainly used in manned aircraft. In case of UAS the study of Mandlburger et al. (2016) demonstrated that the green Lidar was able to measure WSE penetrating the water surface with an error of ca. 4.5 cm. In the study of Bandini et al. (2020), Lidar, photogrammetry and radar altimeter are compared over two small rivers in Denmark. Their analysis showed that the best accuracy in WSE estimates was obtained by radar altimeter compared with photogrammetry and Lidar. Radar also does not require GCP and has lower survey and calculation times. As a disadvantage, it does not have the ability to produce a DEM of the riverbank but can only determine the WSE and water surface slope. In another comparative study, Bandini et al. (2017) tested three different ranging sensors, i.e. radar, sonar and camera-based distance sensor (CLDS), for the measurement of the water surface elevation in 6 rivers in Denmark and Italy. They demonstrated again that the radar showed the best accuracy (0.5% of the range) and longest maximum range (60 m); the sonar is more accurate if UAS flies at a stable and low height; the CLDS is less accurate than the radar, but it is useful in case of narrow field of view of the water surface.

5.4. River discharge estimate

River discharge estimation from UAS follows the same rules as traditional ground measurements in natural channels (Eltner et al., 2020), such as the “velocity-area” method (see section 4).

From UAS, bathymetry measurements can retrieve the cross-sectional area and the water depth with respect to the water surface elevation measurements. However, UASs can only directly measure surface velocity whereas, discharge estimation requires depth-integrated water velocity profile, hence the mean velocity estimation. To derive mean velocity starting from the knowledge of surface velocity, some methods provided in the scientific literature can be used:

Method of coefficient

Welber et al. (2016) estimated discharge from surface velocity radar, SVR, surveys by defining a velocity coefficient α, which represents the ratio of depth-averaged to surface velocity values. Yang et al. (2019) estimated the discharge of the Taklamakan desert river by combining low-altitude UAS and satellite remote sensing technology.

Bandini method

Bandini et al. (2020) proposed a method to estimate the river discharge and the roughness coefficient, based on UAS-borne measurements of water surface slope and water surface velocity, while water depth was measured with in situ surveys. The method relies on two nonlinear equations: i) Manning's equation and ii) the mean-section method for computing discharge from uniform flow. They investigated this joint estimation approach in 27 case studies conducted in various streams with different hydraulic conditions. The estimated discharge using this approach exhibited a mean absolute error of 19.1% compared to in situ measurements. Similarly, the estimated roughness values showed a mean absolute error of 3 $m^{1/3}/s$ when compared to in situ measurements.

Entropy method

Another potential solution is to estimate the bulk velocity using Entropy theory (Bahmanpouri et al., 2022). Some details of the procedure are described in the following.

Chiu (1989) and Moramarco et al. (2004) developed an estimation of cross-sectional velocity distribution, *U(x,y)*, using the entropy probability density function. The approach allows to determine the entropy-based velocity profile along the verticals as follows:

$$U(x_i, y) = \frac{U_{max\,v}(x_i)}{M} ln\left[1 + (e^M - 1)\frac{y}{D(x_i)-h(x_i)} exp\left(1 - \frac{y}{D(x_i)-h(x_i)}\right)\right] \quad i = 1 \dots N_v \tag{4}$$

where U is the time-averaged velocity, $U_{max\ v}(x_i)$ is the maximum value of U along the i^{th} vertical, x_i is the distance of the i^{th} sampled vertical from the left bank, $h(x_i)$ is the dip, i.e., the depth of $U_{max\ v}(x_i)$ below the water surface, $D(x_i)$ the flow depth, y is the distance of the velocity point from the bed, and N_v is the number of verticals sampled across the river section. M can be estimated using the linear entropic relation using the mean and the maximum flow velocity, U_m and U_{max}, measured within the entire cross-section (Chiu, 1989):

$$U_m = \left(\frac{e^M}{e^M-1} - \frac{1}{M}\right) U_{max} = \phi(M)\, U_{max} \tag{5}$$

In general, for a given river site, $\phi(M)$ is assumed to be constant for all flow conditions, while for ungauged sites $\phi(M)$ can be estimated as (Moramarco and Singh, 2010):

$$\phi(M) = \frac{\frac{1}{n}R^{1/6}}{\sqrt{g}\frac{1}{k}\left[ln\left(\frac{y_{max}}{y_o}\right) + \frac{h}{y_{max}} ln\left(\frac{h}{D}\right)\right]} \tag{6}$$

where y_{max} is the location of U_{max} from the bottom and y_o is the datum where the velocity is equal to zero, k is the von Karman constant, R is the hydraulic radius, n is the Manning roughness and D is the maximum flow depth.

Whether at a river site only the surface velocities, $U_{surf}(x_i, D(x_i))$ are available, then $U_{max\ v}(x_i)$ can be estimated as (Fulton and Ostrowski, 2008):

$$U_{max\,v}(x_i) = \frac{U_{surf}(x_i, D(x_i))}{\frac{1}{M} ln\left[1 + (e^M - 1)\delta(x_i) e^{1-\delta(x_i)}\right]} \tag{7}$$

where $\delta(x_i) = D(x_i)/[D(x_i) - h(x_i)]$. Specifically, if $h(x_i) = 0$, it follows that $\delta(x_i) = 1$ and, hence, $U_{maxv}(x_i) = U_{surf}(x_i, D(x_i))$. The magnitude of $\delta(x_i)$ can be obtained based on the iterative procedure proposed by Moramarco et al. (2017). The procedure can be applied for sites with a given $\phi(M)$. The procedure is based on assigning an initial dip, $h(x_{i,p=1})$, where the maximum surface velocity occurs (p is the iteration).

For the current research, according to the initial value of dip, a laboratory distribution law of dip suggested by Yang et al. (2004) is implemented, and the $U_{maxv}(x_{i,p=1})$ is assessed by Eq. (7) for all the considered verticals. $U_{max(p=1)}$ is identified as the maximum of $U_{maxv}(x_{i,p=1})$. Therefore, once $U_{maxv}(x_{i,p=1})$ is replaced in Eq.(5), it enables estimation of the depth-averaged velocities in each cross-section. For the first iteration, the mean flow velocity, $U_{m(p=1)}$, can be estimated using the velocity-area method. As a consequence, $\phi(M_{com,p=1})$ can be computed by Eq.(5), using $U_{m(p=1)}$ and $U_{max(p=1)}$. The iteration continues until the error of $\phi(M_{com,p}) - \phi(M)$ becomes lower than 0.01. For more details, the reader is referred to Moramarco et al. (2017).

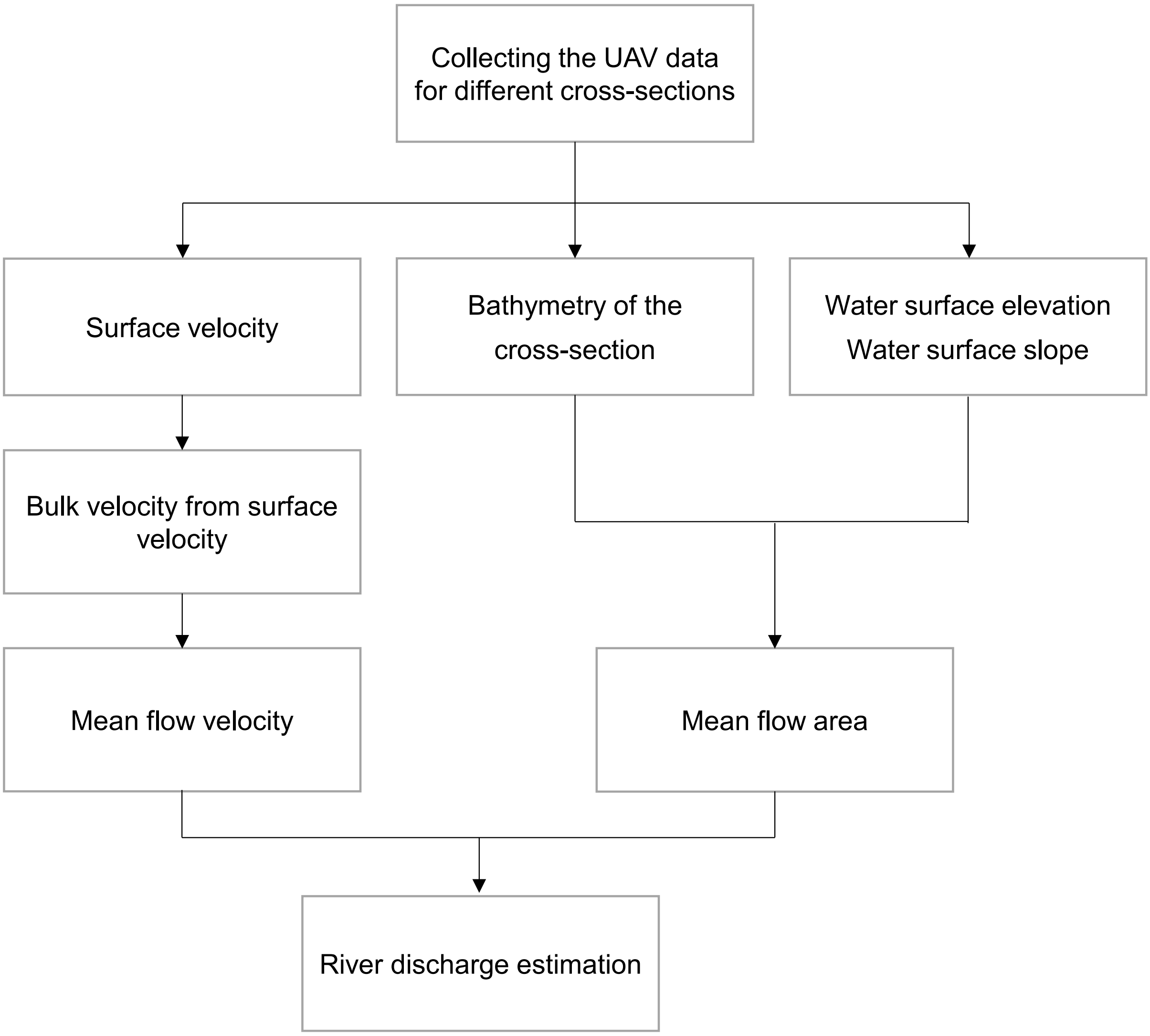

Figure 3. Depicts the flowchart of the process of estimation of river discharge based on UAS data.

6. Rating curve at virtual stations informed with UAS hydrometry

Satellite measurement has emerged as a promising alternative for direct measurement of WSE in rivers since last two decades. For river discharge estimation using the altimeter-derived water level, the conceptualization of the rating curve methods was explored in the literature (Belloni et al., 2021). As already underlined, the development of rating curves always requires the availability of simultaneous measurements of discharge and stage at the river section, but collecting such information to establish the space-based rating curve was daunting task due to the variability of the altimeter passage along the river. In this regard, researchers had also investigated several approaches to derive space-based rating curves and based on development and applicability, those approaches are classified into two specific categories.

Highlighting the first category, when the space-based rating curves were developed at the gauging stations or the altimeter passages were available near to the gauging station, the rating curves were derived using: i) power law (Papa et al., 2010; Birkinshaw et al., 2010; Michailovsky et al., 2012; Zakharova et al., 2020); ii) empirical relationship (Zakharova et al., 2006; Getirana et al., 2010; Rai et al., 2021), and iii) probabilistic approach (Tourian et al., 2013).

The second category refers to the absence of *in situ* gauging stations along the altimeter passage. In this case, the discharge is estimated at an ungauged station using the hydraulic modelling (Leon et al., 2006; Tarpanelli et al., 2013; Domeneghetti et al., 2014; Dhote et al., 2021) and hydrological modelling (Getirana et al., 2009; Pereira-Cardenal et al., 2011; Getirana et al., 2013; Paris et al., 2016) and subsequently, the model simulated discharge was used for the space-based rating curve establishment. Hydraulic modelling has also been shown to be useful in cases with in-situ data for the purpose of reducing the uncertainty when extrapolating the rating-curve outside the range of the available data (Mansanarez et al., 2019; Westerberg et al, 2020). In fact, Mansanarez et al, 2019 showed that rating curves could be generated with their hydraulic model informed of only 3 low-flow discharge measurements with comparable uncertainty as a power-law rating curve based on a wide range of flow conditions.

Due to the large foot-print of the altimeters, the majority of the aforementioned studies were carried out along the large and medium size rivers. The development of the SAR and InSAR altimeters made it amenable for developing the rating curves for small and narrow width rivers which has been demonstrated in many recent studies (Kleinherenbrink et al., 2020; Jiang et al., 2019; Zakhorova et al., 2020; Kittel et al., 2021; Coppo Frias et al., 2023; Nielsen et al., 2022).

In this recent scenario, due to the malfunctioning of gauging stations and their remote locations, river discharge estimation from UAS is an important complementary information for the development of rating curves, exploiting satellite data. Based on the distance between the altimetry track and the location where the UAS survey is carried out, two distinct scenarios can be faced: 1) time-lapse survey; 2) hydraulic modelling. In the following the detail description of the proposed methodologies is provided.

6.1. Time lapse survey

Time lapse survey is the process of acquiring and analysing multiple surveys, repeated at the same site over time, to analyse differences between data sets from different instants. The first step is the identification of points along the river where selected altimetry crossing tracks are available. With respect to the nominal satellite track, sections should be identified at a distance of no more than ±1 km upstream or downstream, also depending on the accessibility to conduct the drone survey. The second step is the choice of time period. Note that the days of drone flight should be prefixed to the days of satellite altimeter passage, so as to obtain coincident observations for the drone and satellite altimeter. At this point, once the discharge from the UAS system and the corresponding WSE of the altimeters are identified, the rating curve is established from a one-to-one relationship.

By retrieving the historical WSE time series of the altimeter observations for those locations, it is possible to subsequently reconstruct the river discharge time series through the rating curve at the site. The main difficulty in constructing rating curves is related to the availability of reliable measurements made over a wide range of hydrometric levels; the typical lack of data in the area of high hydrometric levels makes it difficult to extrapolate the relationship beyond the range of measurements taken.

The flowchart of the sequence is depicted in Figure 4.

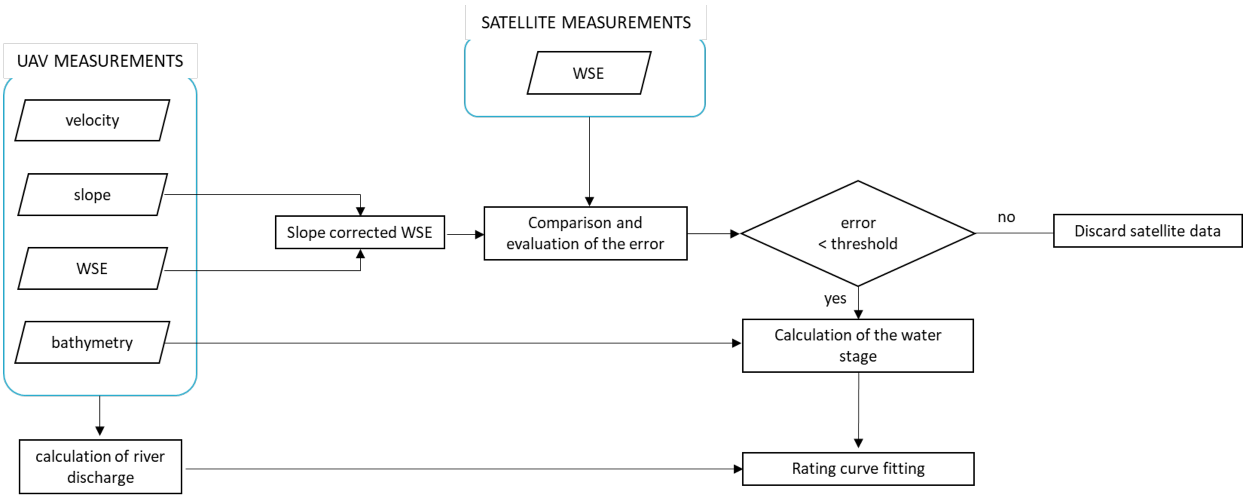

Figure 4. The estimation of the rating curve based on in-situ gauged station data

6.2. Hydraulic modelling

As an alternative, or as a complement to the first case, the stage-discharge relationship can also be approximated by simulations with a hydraulic model informed by the available data. As already described in detail in section 4, the application of hydraulic models requires information on the river geometry, boundary conditions, initial condition for unsteady simulations as well as stage, velocity and/or discharge data for calibration of the Manning roughness coefficients. Once established, the stage-discharge relationship provided by the hydraulic model can be expressed either as a rating-curve table or approximated by a power-law model for the further application in the virtual station.

As for the case of ground measurements, the data (discharge and stage) derived from UAS and satellite can be employed to approximate the cross-section geometries (dry and sub-merged parts), mapping of vegetation cover for a-priori estimation of Manning roughness coefficients, and to carry out simulations aimed to calibrate the Manning roughness coefficient for the selected river reach. If a sufficient number of data is available, a relationship $n(h)$ or n(vegetation types) can be defined to extrapolate the n value to be employed for simulations of the full water stage range.

This method allows to develop baseline rating curves by exploiting existing data from satellites and other data sources, and improved rating curves using UAS (and in-situ) measurements as depicted in the workflow in Figure 5.

As already pointed out, hydraulic modelling requires knowledge of the geometry of a river reach including the gauged section, which for the baseline model can be approximated from existing topographical data and satellite data and will be further improved through the UAS surveys. The reliability of the n value to use for depends on the range of available velocity measurements and will depend on the availability of existing discharge data, or the data provided by the UAS surveys.

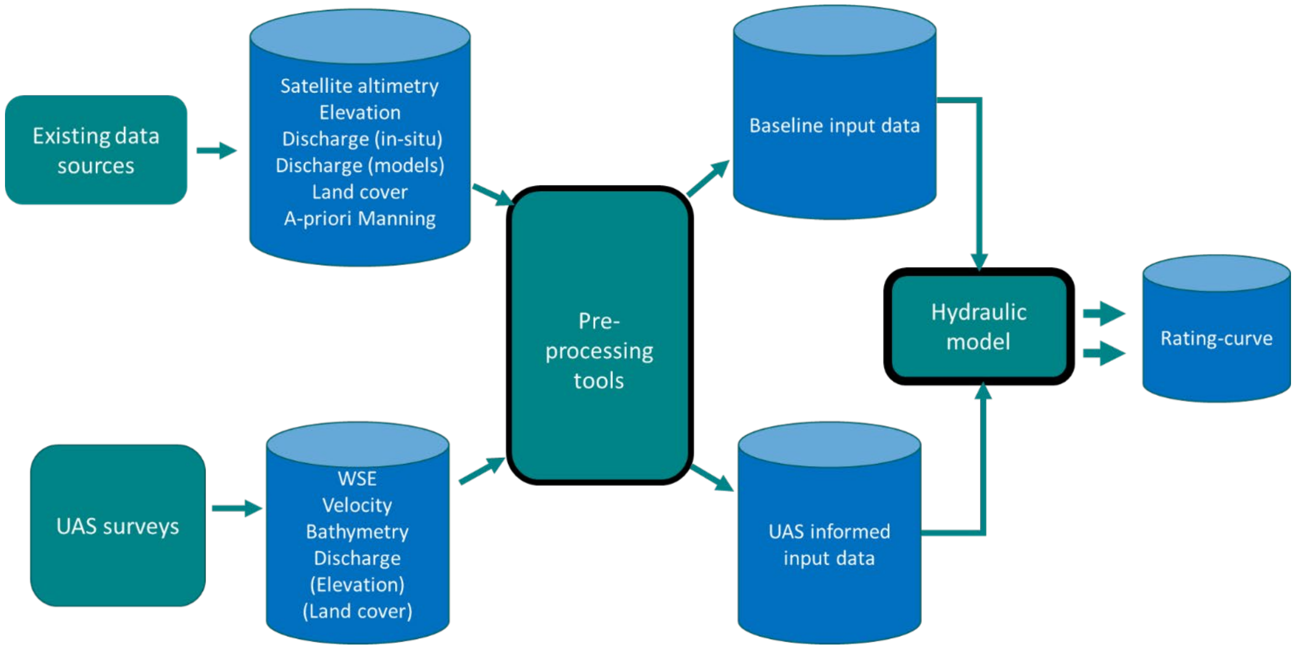

Figure 5. Workflow and data for development of satellite (baseline) and drone-based rating curves as streamflow monitoring tools.

7. Expected accuracy and error budgets in rating curve estimates

The rating curve estimation can be affected by large uncertainty due at least to three types of errors:

- Errors in measurements, including instrumental, environmental and spatial integration errors (Le Coz et al., 2012);
- Errors in time integration caused by potential flow variability during the measurement period, as discussed by Corbett et al. (1943) and Rantz (1982).
- Stage-discharge bias induced by non-reference flow conditions, such as the dynamic hysteresis effect (e.g., Muste et al., 2011). This effect is not a measurement error, but a deviation of the real flow conditions from the normal conditions for which the rating curve is built as a one-to-one relationship.

The error in the measurement may vary depending on the hydraulic and morphological characteristics of the stream. It is suggested that streams could be classified based on their size (large, medium, and small), flow velocity (fast and slow-moving) and bed slope gradient (steep slope or mild slope rivers).

To construct acceptable rating curves for low and high gradient streams, Birgand et al. (2013) demonstrated that 22 was the minimum number of gauging points to be developed. Mansanarez et al. (2019) stated that hydraulically modelled rating curves are a promising alternative to traditional methods as they can be rapidly derived with few concurrent stage-discharge gauges. So that rating curves could be modelled with high confidence (i.e., low uncertainty) using only 3 observations for either low flows or low and medium flows. Further, they demonstrated that the calibration gauges had to cover either low flows or low and medium flows to get good results in other words calibration to only medium- or high-flow gauges gave uncertain or biased results. However, even if a hydraulic model is used, the lack of measurements on high flow is a problem for identifying the roughness value to be used in the extrapolation. Therefore, it is highly suggested to carry out measurements under high flow conditions, if possible.

For the time-lapse approach here proposed, the rating curve uncertainty is quantified as confidence intervals of the power-law parameters that are estimated in the fitting process. Instead of one unique rating curve, the 90% confidence interval of discharge corresponding to each water level is given. The given uncertainty of the satellite water level measurement is then propagated through the probabilistic rating curve to yield the discharge uncertainty. For high-quality satellite water level observations (i.e. accuracy of better than 20 cm), we expect discharge estimates with a relative error better than 20%.

For the hydraulic modeling approach, rating curve uncertainty is a consequence of the total uncertainty of the hydraulic model. This can be quantified using a Bayesian uncertainty framework as shown in Mansanarez et al., 2019, and results again in a probabilistic rating curve expressed, e.g. as the 90% confidence interval of discharge corresponding to each water level. The given uncertainty of the satellite water level measurement is then propagated through the probabilistic rating curve to yield the discharge uncertainty. For high-quality satellite water level observations (i.e. accuracy of better than 20 cm), we expect discharge estimates with a relative error better than 20%, less accurate but not much less accurate than the estimates provided by a rating curve produced from time-lapse surveys.

8. Validation

The validation process to convert satellite water level in river discharge is necessary to demonstrate the reliability and efficiency of the chain from the UAS measurements to the continuous river discharge estimation. The validation is performed through a direct comparison of temporal series in case of both water level and river discharge. Concerning the water level, the ground, the UAS and the satellite measurements are compared each other to compute the typical performance metrics: bias, coefficient of correlation, root mean square error, mean and standard deviation of the error. For the river discharge, the comparison is carried out among the ground and the UAS measurements in terms of Nash-Sutcliffe efficiency and the Kling-Gupta efficiency indices to evaluate the goodness of fit of the simulated discharge.

The activity is carried out in the well-monitored Po River in Northern Italy, where a dense hydrometric monitoring network operates from several years under the management of the Interregional Agency of the Po basin. The abundance of ground measurements, surveys and automatic records available in this area represents an ideal case study to validate the satellite and UAS measurements as well as the rating curve derived from them. In this regard, the choice of location to validate water level and river discharge is based on the availability of in-situ measurements close to the virtual station, at a distance such that the influence of the intermediate drainage area is negligible and no flow disconnections due to tributaries or weirs are present. In case of large distances and steep slope, the water surface slope is evaluated to consider the shift in elevation between the two points. In this specific case study, the Po river is recorded with three gauged stations where rating curves are available and updated (see Table 2) for two stations. In the surrounding area, two other left tributaries flow along the Po monitored each by gauging stations. Two satellite tracks from Sentinel-3A and Sentinel-3B overpass the Po River and the tributaries in the area (Figure 6). Several validation exercises will be carried out both for the water level and river discharge through the use of ground observations.

The Lidar survey for the bathymetry is planned in the area of the Orco River from the confluence up to the Sentinel-3B track as upstream limits, whereas over the Po River, the survey starts from the confluence with the Malone up to San Sebastiano. The UAS measurements will be carried out under the satellite tracks and the validation will be carried out at the gauged station of San Sebastiano. A hydraulic model will be built from Settimo Torinese to downstream San Sebastiano to simulate to build rating curves and to allow estimating the river discharge in correspondence of the two satellite tracks.

Table 2. Overview of the available data over the gauging stations in the Po Area selected for the validation procedure.

River	Station	lon	lat	water level	period	river discharge	period
Orco	San Benigno	7.80611	45.24667	x	01/01/2019 - 31/12/2022	x	01/01/2019 - 31/12/2022
Malone	Brandizzo	7.85191	45.18188	x	01/01/2002 - 31/12/2022	x	01/01/2002 - 31/12/2022
Po	Settimo Torinese	7.78446	45.13046	x	01/01/2003 - 31/12/2022	x	01/01/2003 - 31/12/2022
Po	Chivasso	7.89028	45.18111	x	01/01/2004 - 31/12/2005		
Po	San Sebastiano	7.94306	45.1725	x	28/02/2007 - 31/12/2022	x	28/02/2007 - 31/12/2022

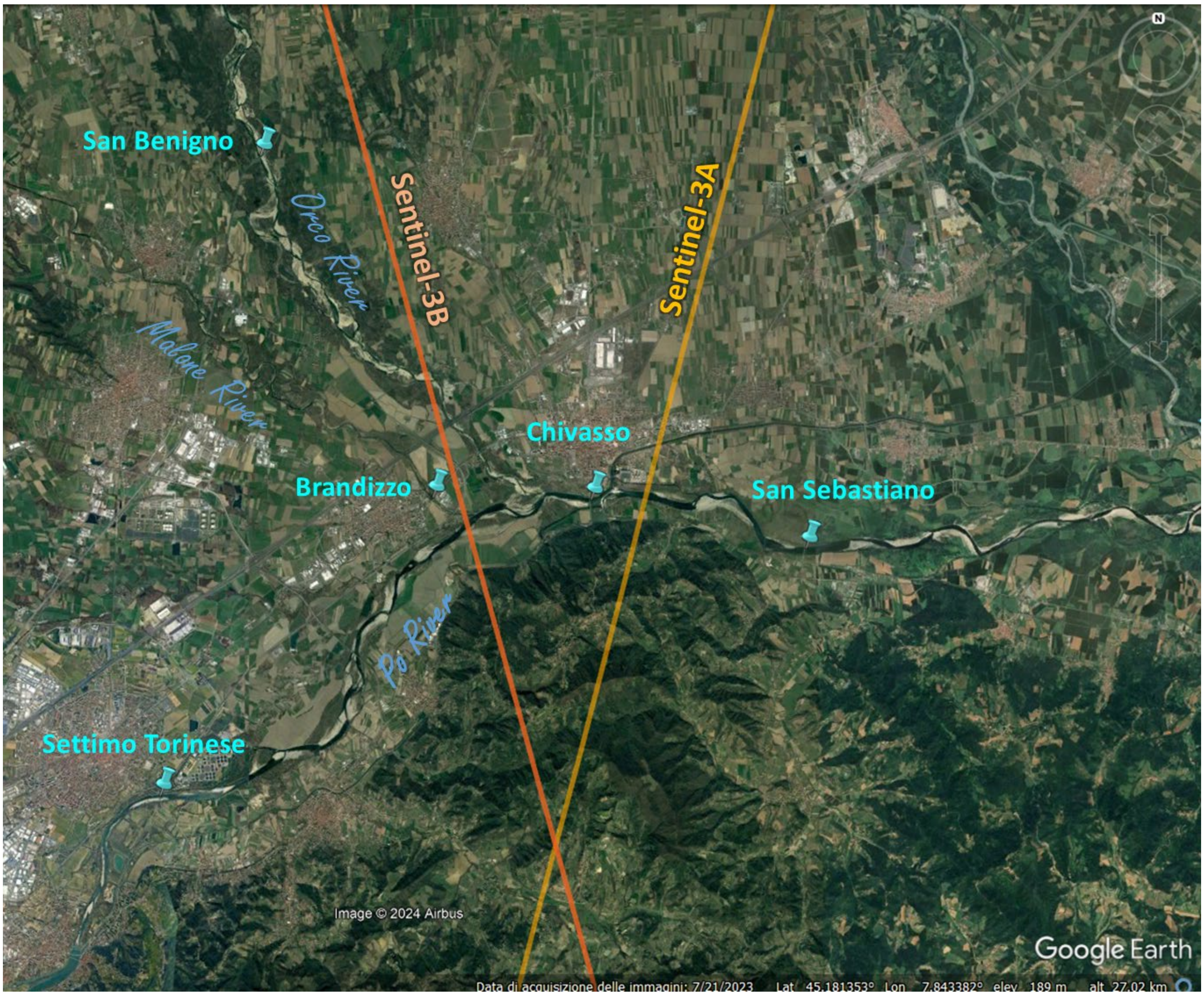

Figure 6: Location of the validation area over the Po River

9. Conclusions

The current report provided a literature review of notable research works conducted on the estimation of rating curve relying on UAS measurements. Considering the previous research work, the method has its own limitations, and the current project aims to find some solution even with new approaches.

In this direction, a protocol for the estimation of rating curves has been identified based on the data collected from UAS data for virtual gauge stations. It is highly suggested to consider different flow conditions i.e. low, medium, and high flow conditions in the development of the rating curve. Further, based on study areas, different cross-sections through different rivers should be considered to cover all parameters that can affect the rating curve estimation.

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