Spatio-temporally Varying Manning Roughness in Rivers and Streams: A calibration approach using in-situ water level and UAS altimetry

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Spatio-temporally Varying Manning Roughness in Rivers and Streams: A calibration approach using in-situ water level and UAS altimetry

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Abstract
Hydraulic roughness (expressed in terms of e.g. Manning's roughness coefficient) is an important input to hydraulic and hydrodynamic simulation models. One way to estimate roughness parameters is by hydraulic inversion, using observed water surface elevation (WSE) collected from gauging stations, satellite platforms or UAS (Unmanned Aerial System) -based altimeters. Specifically, UAS altimetry provides close to instantaneous observations of longitudinal profiles and seasonal variations of WSE for various river types, which are useful for calibrating roughness parameters. However, it is computationally expensive to run high-resolution hydrodynamic models for long simulation periods (e.g. multiple years), and thus global optimization of spatially and temporally distributed parameter sets for such models, e.g., spatio-temporally varying river roughness, is still challenging.

This study presented an efficient calibration approach for hydraulic models, using a simplified steady-state hydraulic solver, UAS altimetry datasets, and in-situ observations. The calibration approach minimized the weighted sum of a misfit term, spatial smoothness penalty, and a sinusoidal a priori temporal variation constraint. The approach was first demonstrated for several synthetic calibration experiments and the results indicated that the global search algorithm accurately recovered the Manning–Strickler coefficients M for short river reaches in different seasons, and M varied significantly in time (due to the seasonal growth cycle of the aquatic vegetation) and space (due to, e.g. spatially variable vegetation density). Subsequently, the calibration approach was demonstrated for a real WSE dataset collected at a Danish test site, i.e., Vejle Å. Results indicated that spatio-temporal variation in M was required to accurately fit in-situ and UAS altimetry WSE observations. This study illustrated how UAS altimetry and hydraulic modeling can be combined to achieve improved understanding and better parameterization of small and medium-sized rivers, where conveyance is controlled by vegetation growth and other spatio-temporally variable factors.
1. Introduction

Improving the management of floods and significantly reducing their influence on public health, economic activities, and the environment is one of the Sustainable Development Goals (Lee et al., 2020). Climate variability and change and the increased pressure from anthropogenic activities have impacted the frequency and severity of floods on regional and global scales, which are extremely difficult to predict accurately (Blöschl et al., 2020; Knox, 1993; Sauer et al., 2021). Hydrodynamic/hydraulic models are valuable tools to estimate variations of flows and water levels along river courses; widely used modeling tools include MIKE Hydro River, LISFLOOD, and HEC-RAS, which are purposeful for developing flood simulation and early-warning systems (Rokaya et al., 2020; Shi et al., 2015). However, it is computationally expensive to run these models on a seasonal time scale, and to estimate spatiotemporally variable parameter fields because of high computational load, large numbers of unknown parameters, and input data requirements (Hunter et al., 2007).

Empirical estimation and calibration of unobserved parameters, such as river roughness and bed geometry (which may only be available for a few points along the river), is a central task in the development of real-world hydraulic and hydrodynamic models. River roughness is an effective parameter representing friction effects in the shallow water equations. It is a critical controlling parameter for conveyance estimation and thus water levels in rivers and streams. The parameter is influenced by many factors, such as the type of the bed and bank materials, aquatic vegetation, surface irregularity, shape and size of the channel cross-section, the meandering character of the river channel, and state of flow motion (Cowan, 1956). Some studies have emphasized the identification of spatially distributed roughness parameters (Attari et al., 2021; Attari and Hosseini, 2019; Jiang et al., 2020; Mtamba et al., 2015; Werner et al., 2005; Ye et al., 2018). Li et al. (1992) developed a predictive model for mean flow in irregular natural rivers, and the results indicated that the effective resistance was strongly influenced by river cross-sectional nonuniformity, and the authors pointed out that sampling density for geometric parameters should depend on the degree of stream irregularity. Tuozzolo et al. (2019) further analyzed the impact of reach averaging Manning’s equation and showed that roughness varied significantly even in a 6.5 km river stretch.

Meanwhile, seasonal variations in discharge and aquatic vegetation (type, height, and density) also profoundly impact the flow resistance, especially for many lowland vegetated river channels (Marjoribanks et al., 2014). The seasonal growth of aquatic macrophytes can significantly increase bed resistance, which leads to a decrease of river channel conveyance and consequently may increase flood risk. Aquatic vegetation in rivers is therefore regularly monitored and managed in some regions, such as Denmark. Jiang et al. (2020) found that
the Gauckler–Strickler coefficient $K_s$ ($K_s = 1/n$) increased significantly after vegetation was cut. However, simultaneously calibrating roughness parameters in both spatial and temporal scales is seldom reported.

The calibration of spatiotemporally varying river roughness requires dense sampling of the water surface elevation (WSE) in both time and space. Gauging stations and satellite altimetry are two widely used methods to retrieve WSE observations. Gauged WSE is only available at discretely distributed points in space, although the measurements are approximately continuous in time. Satellite altimeters, especially geodetic missions, such as CryoSat-2, have high spatial resolution but low temporal resolution and generally deliver high data quality only over large rivers (minimum width ca. 100 m). Considering the limitations of space-borne missions in monitoring small rivers, Unmanned Aerial Systems (UAS) have also been used for fluvial environments monitoring in recent years. The advantages of UAS for river systems monitoring comprise retrieval of data with a very high spatial resolution and accuracy, surveying inaccessible or cost-prohibitive areas, low-altitude flight, low-cost and flexible payload design (Vélez-Nicolás et al., 2021). Bandini et al. (2020) developed a radar altimetry system onboard lightweight UAS, measuring the range between sensors and water surface. WSE was calculated by subtracting the range from sensor height, retrieved by the GNSS receiver. The radar altimetry system was further applied in small vegetated streams (1-2 m wide), and the accuracy of WSE measurements outperformed LiDAR and photogrammetry methods by one order of magnitude (Bandini et al., 2020). WSE measurements from UAS radar altimetry, were further used for spatial river roughness calibration by Jiang et al. (2020).

Automatic calibration of unobserved or unobservable parameters proceeds by changing model parameters until the value of simulated variables matches the observed truth or the residual drops into an acceptable range, presuming that the resulting parameters are optimal values. Previous hydraulic inversion studies mainly used local search algorithms such as Levenberg-Marquardt (Jiang et al., 2020, 2019), for calibrating parameters of hydrodynamic models due to the high computational cost of the forward simulation models. However, such algorithms cannot guarantee a global optimum and may perform poorly in highly parameterized and non-linear inverse problems. Global optimization methods are more suitable and have a high probability of successfully finding the optimal parameter set (Duan et al., 1992, 1993). Still, global search algorithms require more runs of the forward simulation model (Kittel et al., 2021).

This study proposed the estimation of optimal spatiotemporally varying Manning–Strickler coefficients using station data and UAS altimetry. Considering station data characterized by high-temporal resolution (daily or sub-daily) but coarse and discrete distribution in space, and UAS altimetry with high-spatial resolution and accuracy (centimeter level) but sporadic coverage in time, the present study explored the value of simultaneously using both in-situ and UAS observations of WSE for Manning–Strickler coefficients calibration. The methodology was first evaluated using different synthetic calibration experiments, considering data availability and uncertainty in a medium-sized stream. Subsequently, high spatial-temporally distributed

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References:

- Bandini, M., Vélez-Nicolás, C., Puletti, F., et al. (2020). "A radar altimetry system onboard UAS for the retrieval of water surface elevation in small rivers." *Hydrology and Earth System Sciences*, 24(4), 1789-1798.
- Duan, Q., Sorooshian, S., Gupta, V. K. (1992). "Effective and efficient global optimization through simulated annealing following a successful run." *Water Resources Research*, 28(4), 1097-1106.
- Duan, Q., Sorooshian, S., Gupta, V. K. (1993). "Optimization of water resources systems using global search evolutionary algorithms." *Water Resources Research*, 29(12), 3457-3472.
roughness parameters for the stream was calibrated and validated using real-world WSE data collected from gauging stations and UAS.

2. Materials and methods

2.1. Calibration approach

Forward simulation models, observations, and search algorithms are critical elements for calibrating unknown parameters in hydraulic and hydrodynamic models. In this study, we aimed to calibrate spatiotemporally variable roughness parameters, which involved hundreds of individual parameter values. A simplified hydraulic model, a global search algorithm and appropriate regularization terms were used to guarantee an efficient and effective parameter estimation.

We assumed that the effective roughness in each small river stretch $x$ was constant, and the roughness parameters were also stable over a short time interval $t$, e.g., a month in this study. Thus, we had a spatiotemporally varying-parameter $M(x, t)$, the symbol $M$ is the Manning–Strickler coefficient; $M = 1/n$, $n$ being Manning's roughness coefficient. Considering that a large number of parameters needs to be calibrated, the objective function for the optimization algorithm should be regularized. Here, the objective function comprised a misfit term and two regularization terms. The misfit term was set to measure the weighted squared difference between the simulated WSE and the observed truth. The regularization terms were used to constrain the variations of the parameters. The objective function ($\emptyset$) was presented as:

$$\emptyset = w \cdot \text{misfit} + (1 - w) \cdot \text{regularization}$$

Where $w$ was the weight between misfit, and regularization.

The misfit is the difference between the model simulations ($WSE_{sim}$) and the observations ($WSE_{obs}$) at all the time steps ($N_t$) and chainage points ($N_x$). The observations included in-situ WSE and UAS altimetry, with different uncertainties ($\sigma_m$). The misfit was calculated by the following equation:

$$\text{misfit} = \sum_{t=1}^{N_t} \sum_{x=1}^{N_x} \frac{(WSE_{sim}(x, t) - WSE_{obs}(x, t))^2}{\sigma_m}$$

Regularization terms included a spatial smoothness and an a priori sinusoidal:

$$\text{regularization} = \lambda \cdot \text{smoothness} + (1 - \lambda) \cdot \text{apriori}$$

Where $\lambda$ is the weight between smoothness and a priori term.

The smoothness term was based on the fact that the river channel conditions (e.g., size and type of the bed and bank materials, shape of the cross section, and longitudinal variation in cross-sectional shapes) change.
continuously in space and the roughness parameters along the river channel was expected to change smoothly. The smoothness term was expressed using a standard first-order roughening term, i.e.

\[
\text{Smoothness} = \sum_{x=1}^{N_x} \left( \frac{M(x) - M_{\text{neighbor}}(x-1)}{\sigma_{\text{smooth}}} \right)^2
\]  

Where the $\sigma_{\text{smooth}}$ is a typical variation between neighbors in space.

Considering that the inter-annual and seasonal variations of the discharge and vegetation growth periods, we assumed that the temporal variations of river roughness have a sinusoidal regular pattern. For example, the Manning–Strickler coefficient in Danish rivers has a large seasonal variation with the minimum value in the summer season and maximum value in the winter season. Thus, we assumed an a priori sinusoidal seasonal variation of M:

\[
M_{\text{apriori}}(x, t) = M_0(x) + A_0(x) \sin(\omega t + \phi)
\]  

The parameters in the sinusoidal equation are unknown and are estimated by regression for each candidate parameter set. A corresponding a-priori constraint is introduced in the objective function to stabilize temporal variations of the estimated parameters:

\[
\text{Apriori} = \sum_{t=1}^{N_t} \left( \frac{M(x, t) - M_{\text{apriori}}(x, t)}{\sigma_{\text{apriori}}} \right)^2
\]  

Where $\sigma_{\text{apriori}}$ is a typical deviation from the a priori sinusoidal seasonal model.

2.2. Optimization algorithms

A global search algorithm, the Shuffled Complex Evolution algorithm of the University of Arizona (SCE-UA), was used to calibrate the Manning–Strickler coefficients M in the present study. The algorithm has been widely used for different search problems. It includes features such as the combination of random and deterministic approaches, an implicit clustering strategy, and a systematic complex evolution strategy. More detail about this optimization method can be found in Duan et al. (1992, 1993). SCE-UA has been integrated into the open-source python package, Statistical Parameter Optimization Tool (Houska et al., 2015). To determine how many iterations are required to get reliable information about the bulk of parameters, the number of iterations is calculated by the methods provided by Henkel et al. (2012).

2.3. Forward simulation model

2.3.1. Steady-state hydraulic solver

An efficient forward simulation model is critical for the global optimization. Though the shallow-water equations are simplified one-dimensional forward model, solutions at seasonal time scales are still time consuming. Considering the number of parameters and the required repetitions of the forward solver in the
present study, improvements of the efficiency of the forward simulation model will greatly save calibration time.

Thus, an efficient steady-state hydraulic solver was used.

The simplified hydraulic solver is based on the Saint-Venant equations, assuming that the water flow is in the condition of steady-state, i.e., all quantities are invariable in time. The development of the solver is described fully in Kittel et al. (2021). Only the main formulas of the solver therefore are presented here.

The momentum balance equation under steady-state is presented as:

$$\frac{\partial}{\partial x} \left( \frac{Q^2}{A} \right) + gA \frac{dh}{dx} - gA(S_0 - S_f) = 0 \tag{8}$$

Where $A$ is flow cross-sectional area, $Q$ is volumetric discharge, $x$ is the chainage, $g$ is the gravitational constant, $h$ is flow depth, $S_0$ is the bed slope, $S_f$ is the friction slope. The general form of the equation was organized by taking the partial derivative of the area relative to the chainage and width, and isolating the change in depth over the chainage:

$$\frac{dh}{dx} = \frac{\left( \frac{Q^2}{gA^2} \frac{\partial A}{\partial x} + S_0 - S_f + \frac{2Q \times q}{gA^2} \right)}{\left( 1 - \frac{Q^2}{gA^2} \frac{\partial A}{\partial h} \right)} \tag{9}$$

Where $S_0$ is calculated using river bed elevation ($z$) and chainage as $(-dz/dx)$, $S_f$ is the river channel friction and can be calculated using Manning’s equation:

$$Q = MAR^{\frac{2}{3}}S_f^{\frac{1}{2}} \tag{10}$$

$R$ is the hydraulic radius. Equation (9) was solved explicitly. We used a grid spacing of $\Delta x = 20$ m, and the hydraulic parameters, i.e., area, depth, bed elevation, were interpolated for each calculation grid point from neighboring cross sections.

2.3.2. MIKE HYDRO River

MIKE Hydro River was used to create synthetic WSE observations and validate the calibrated spatio-temporal Manning–Strickler coefficients $M$. MIKE HYDRO River is a one-dimensional (1D) computational engine for modeling fully unsteady flows in river networks, pipe networks, and estuaries. The modeling system is dependent on an implicit, finite difference numerical solution of the shallow water equations, which are transformed into a set of implicit finite difference equations on a computational staggered grid consisting of alternating $q$- and $h$-grid points, i.e. points where the discharge, $q$, and water level $h$, respectively. The computational grid is generated automatically based on the user requirements, but the lower value of the grid spacing needs more calculations.

2.4. Case study site
Vejle Å (Vejle River) is a natural stream located in Vejle Municipality, Denmark, which is a typical lowland river with mild slopes and meandering character. It originates from Engelsholm Sø and empties into Vejle Fjord, with an approximate length of 36.7 km (Fig. 1). The stream flows through woods, farmland, bush, grassland, and urban regions, with the riverbank densely covered with shrubs, trees, and weeds. The dense vegetation in the Vejle Å increases friction in the river channel and raises the water level. It is necessary to cut the submerged vegetation in the river during the flooding season to improve river channel conveyance.

Some downstream areas, e.g., Haraldskær, Vejle city, have been plagued by flooding almost every year, following cloudbursts, extreme precipitation events, and storm surges. Thus, river management and flood prediction are vital in this area. The calibration approach was tested in the 23.90 km long river reach between Refsgårdslund and Vejle Harbor. Seven hydrological stations are located in this reach. Water level and discharge data were available every 15 minutes, and rating curves interpolated the corresponding discharge data.

Figure 1. Field site and channel views. The upper left map showing the study area (Vejle river basin colored in red) in the southeastern part of Jutland, Denmark. The lower right figure shows the studied reach of Vejle Å, including river channel, cross section, in-situ stations and UAS routes.

2.5. In-situ data availability
2.5.1. Discharge

Discharge data were obtained from two hydrological stations, Refsgårdslund and Haraldskær, in the period of 01/08/2018 and 26/08/2020. Fig. A1 shows the flow regime of the Vejle River. The discharge is unevenly distributed during the year, and the discharge is low in the warm season and high in the cold season. The annual average discharge in Refsgårdslund and Haraldskær were 3.03 m$^3$/s and 4.19 m$^3$/s, respectively. The
maximum daily discharge during the period is 10.68 m$^3$/s and 16.13 m$^3$/s. There are no influential tributaries in the chainage interval between Refsgårdslund and Haraldskær, and, therefore, we assumed that the lateral inflow is uniformly distributed between stations Refsgårdslund and Haraldskær.

2.5.2. Water surface elevation

Water surface elevation data was collected from five hydrological stations, i.e., Tørskind (14.77 km), Ravning (18.92 km), Vingsted (21.29 km), Rosborg (33.56 km), and Vejle Havn (36.57 km), and the data are displayed in Fig. A2. The time resolution of the WSE data is 15 minutes. The river surface has an average slope of 5.8 ‰ between upstream Refsgårdslund and the outlet to the sea. WSE of Vejle Havn was used as the downstream boundary of the hydraulic and hydrodynamic models while the other stations were used for calibration.

2.5.3. Cross sections

The cross-section information was obtained from the national information system run by WSP Denmark, and 130 cross-sections were included from Refsgårdslund to Vejle harbor. The raw cross-section data includes the distance from the left levee and the corresponding depth. The raw data were then put into MIKE Zero software for further processing. The processed cross-sections contain hydraulic parameters including width, hydraulic radius, bed elevation, submerged cross-sectional area, and the depth at a specific WSE. The basic information of all bank-full cross-sections is shown in appendix (Fig. A3). The river channel is narrow and deep in the upstream area, wide and shallow in the downstream area. The bank-full submerged area does not increase from upstream to downstream, which is a likely cause of increased flood risk, e.g., the cross-sectional area near Haraldskær located at chainage of 28.13 km is reduced and this area suffered from frequent floods. The river has a width of up to 20.84 m for bank-full depth in Refsgårdslund to 49.87 m in Vejle Havn. The maximum depth is 4.36 m in the upstream and 2.34 m in Vejle Havn.

2.6. UAS altimetry data collection and processing

The UAS-borne WSE measurement system used in this study was developed by Bandini et al. (2020). This system can measure accurate and distributed high-resolution WSE for small-size and vegetation-covered streams. The system uses a lightweight hexacopter drone equipped with a dual-frequency differential Global Navigation Satellite System (GNSS) and a 77 GHz radar chip with full waveform analysis to measure WSE (Bandini et al., 2020).

Several field campaigns were implemented from 2018 to 2020 by DTU Environment and Drone Systems (https://dronesystems.dk). Two long-distance UAS surveys were carried out in February and June 2020, which covered a river reach with a total length over 20 km (Fig. 2). The weather conditions and power supply infrastructure are the main constraining factors for the drone survey, and a one-kilometer-long river stretch can be measured in approximately 15 minutes. UAS altimetry data processing included post-processed kinematic (PPK) processing of the drone position, full-waveform analysis of the radar returns and data filtering. The
processed data was further filtered by a river mask to guarantee that the radar observations were captured above river water surface. The water mask was generated by buffering the river center line by 5 meters in each side. Detailed information of the UAS radar altimetry post-processing can be found in Bandini et al. (2020).

UAS altimetry shows great potential in delivering high-resolution WSE observations, as illustrated in Fig. 2. The water surface slope is clearly shown, which would not be obtainable from discrete gauging stations. UAS altimetry WSE matches in-situ measurement very well with mean square error lower than 0.03 m. There was no significant difference of data accuracy between the different surveys, although some deviations occurred between UAS altimetry and nearby in-situ stations.

![Figure 2. Longitudinal profile plots of WSE derived from UAS campaigns and in-situ measurements. The shaded area indicates the channel bed, which is represented by the deepest point in each cross-section.](image)

2.7. Synthetic calibration experiments

The objective of synthetic studies is to conduct experiments in a controlled environment and allow the results to be compared with a synthetic truth. The synthetic truth for WSE was created by running the MIKE HYDRO River in fully dynamic mode to approximate the real situation. The standard boundary conditions for MIKE HYDRO River include upstream discharge from Refsgårdslund, lateral inflow interpolated between Refsgårdslund and Haraldskær, as well as downstream WSE from Vejle harbor. The overall control settings for model simulations were first initialized, including the simulation period was 2019-8-1 to 2020-8-1, time step length was one minute, computational grid spacing was 20 m, the branch started from chainage 12.8 km to 36.6 km, raw data of 130 cross-sections, and the simulated results have a storing frequency of one day. The synthetic Manning–Strickler coefficients M is created with seasonal sinusoidal variation (Fig. 3).
Figure 3. Synthetic truth creation, including the (a) synthetic Manning–Strickler coefficients (M), and (b) the synthetic truth for water surface elevation with the vertical lines showing the temporal WSE data and the horizontal lines showing the spatial UAS altimetry fully (in dosh) and partially (in solid) covered the stretch of river.

Several synthetic calibration scenarios were created to verify the value of UAS altimetry and in-situ observations for varying M calibration under different situations of data availability. In the description of each scenario for synthetic studies, the UAS altimetry referred to the longitudinal profiles of WSE (horizontal lines in Figure 3b). In-situ data referred to the time series of water level (vertical lines in Figure 3b). The settings for the three scenarios are as follows:

Scenario 1: Calibration of spatially varying M using UAS altimetry on different days. This scenario corresponded to the situations when we collected UAS altimetry covering a long river stretch on a particular day, e.g., February 24, 2020, and June 02, 2020. We want to answer two questions in this scenario: (ⅰ) whether UAS altimetry with full and partial coverage can be successfully used for spatially distributed M calibration; (ⅱ) how the uncertainty of UAS altimetry affects the calibration. Although the real-world drone survey in June was carried out over two different days, we assumed instantaneous data collection on a single day in the synthetic experiment. 02/24/2020, and 06/02/2020 with full and partial coverage of UAS altimetry were selected to conduct the calibration. Three different sets of noise (1 cm, 3 cm, and 10 cm) are assigned to the synthetic truth of WSE. The steady-state hydraulic solver and SCE-UA global optimization were used to calibrate M for each day separately and thus, no a-priori constraint on the temporal variation was applied.

Scenario 2: Calibration of spatiotemporally varying M using adequate UAS altimetry; this scenario ideally assumed that UAS altimetry datasets were available on multiple days, evenly distributed in time. Additionally, the UAS altimetry was collected on days when flow in the river are approximately steady-state. We selected additional suitable steady-state days, approximately evenly distributed throughout the period of interest (1-2 days per month or so). The varying Gauckler–Strickler coefficient, i.e., M(x, t), was calibrated using the steady-state model as forward simulator and the global optimization as the searching engine.
Scenario 3: Calibration of spatiotemporally varying M utilizing a selection of in-situ data and UAS altimetry. This scenario approximated reality when we only have UAS altimetry for limited days and discretely distributed station data. Besides, the UAS altimetry does only partially cover the reach of interest, as shown in Figure 3. Because of the computational constraints, we still selected one day per month. Among the chosen dates, two dates were covered by partial UAS altimetry, i.e., 02/24/2020 and 06/02/2020, and the remaining dates only have WSE from 4 stations. UAS altimetry has a dense sampling compared to the in-situ data, and an appropriate weight must be chosen to balance the contributions of UAS and in-situ datasets to the total misfit term. The steady-state solver and global optimization were used for M calibration in this scenario.

Scenario 4: Real-world calibration of the spatiotemporally varying M. The configuration of the Steady-State solver and objective functions were the same as Scenario 3 but with the real WSE from in-situ observations and UAS altimetry.

3. Results

3.1. Synthetic experiment

The calibrated Manning–Strickler coefficients M in Scenario 1 approximated the synthetic truth, as shown in Fig. 4. The assumed uncertainty of the synthetic dense WSE significantly affected the calibrated M, which was illustrated by three different cases. With the increase of the uncertainty of UAS altimetry, the weight of the smoothness term in the objective function increased and the calibrated M tended to be smoother. When the uncertainty of UAS altimetry derived WSE increased from 1 cm, to 3 cm and 5 cm, the RMSE of the calibrated M changed from 0.7 to 1.06 and 1.93 m$^{1/3}$/s in the high-flow date, i.e., 02/24/2021 (Table 1) and the RMSE of the calibrated M increased from 0.39, 1.46 to 2.07 m$^{1/3}$/s in the low-flow date, i.e., 06/02/2020. Some deviations remained between the calibrated M and the synthetic M partly depended on the balance between the misfit and the smoothness in the objective function, which was determined by trial-and-error.

The calibrated M using partial-coverage WSE showed promising results in the river stretch where synthetic WSE exists. For detail, the UAS altimetry was concentrated in the chainage of 20 – 30 km and the calibrated M agreed well with synthetic truth. Besides, the regularization term of smoothness in the objective function constrained the spatial variations of the M in the chainage where UAS altimetry were missing.

The calibration was implemented by the global search algorithm, which required tens of thousands of forward model evaluations, e.g. the total iterations of each simulations in Scenario 1 is 16500, which clearly illustrated why an efficient forward model is needed.
Figure 4. Calibration results of Manning–Strickler coefficients $M$ on 02/24/2020 by using synthetic truth of WSE fully (a) and partially (b) covered the river stretch. (c) and (d) are the same but for date 06/02/2020. The gray areas are river stretch covered by UAS altimetry.

Spatiotemporally distributed $M$ was calibrated by the steady-state solver under the assumptions of Scenarios 2 and 3, and the results are displayed in Fig. 5. Generally, the pattern of the $M$ variation was successfully retrieved by the calibration algorithm. The RMSE between the calibrated $M$ and the synthetic truth is 0.46 m$^{1/3}$/s for Scenario 2 with sufficient WSE. However, the WSE was over fitted by Scenario 2 (Table 1), which may indicate that a larger weight for the regularization terms may be appropriate. The RMSE of calibrated $M$ is 2.53 m$^{1/3}$/s for Scenario 3, which is inferior to the calibration results of Scenario 2 due to the limited amount of available WSE. The values of $M$ lower than 20 m$^{1/3}$/s were significantly overestimated because the available WSE observations are insufficient for adequately constraining the parameter.

The evaluation results of the simulated WSE against synthetic truth in temporal and spatial scale showed that the accuracy of the simulated WSE is high in both time and space under Scenario 2 and Scenario 3. In Scenario 2, even though the RMSE shows some spatial (red columns in Fig 5e) and temporal (gray columns in the Fig 5f) difference, the overall RMSE is low. The RMSE of the simulated WSE is high in Scenario 3, which indicates that the available WSE is insufficient to constrain the variations of $M$. The RMSE is high in low-flow seasons, e.g., July to December, but the RMSE is low in high-flow seasons, i.e., January to May. Along the
chainage, the simulate WSE is less accurate for chainage 20 - 30 km, because M was overestimated compared to the synthetic truth in this chainage interval.

Figure 5. Calibration results of Manning–Strickler coefficients M for Scenario 2 (a, b) and Scenario 3 (c, d). The calibrated spatial-temporally varying M for each scenario is in left columns, and the simulated M against synthetic truth is in the right columns. The accuracy of simulated WSE against synthetic truth displayed in (e) for Scenario 2 and (f) for Scenario 3. The red columns represent the accuracy of simulated WSE time series in particular chainage grid. The gray columns represent accuracy of simulated longitudinal profile of WSE in each day.
Table 1. Settings for the calibration under different scenarios, together with the efficiency of the calibration algorithms and the calibrated accuracy of WSE, Manning–Strickler coefficients M, three regularization terms and the final objective functions.

| Scenario | UAS altimetry | Noise (cm) | Weight (w) | Weight (λ) | σ (misfit) | σ (smoothness) | σ (a priori) | Day(s) | Repetitions | WSE (cm) | M (m<sup>1/3</sup>/s) | Misfit | Regularization (smoothness) | Regularization (a priori) | Objective function |
|----------|----------------|------------|------------|------------|------------|----------------|--------------|--------|--------------|----------|-----------------|--------|--------------------------|----------------------|-----------------|
| scenario 1 | full | 1.0 | 0.09 | 0.01 | 0.05 | 0.50 | 1 day (24/02/2020) | 16500 | 2.00 | 0.70 | 5029.52 | 227.95 | 25.69 |
|         | full | 3.0 | 0.05 | 0.03 | 0.05 | 0.50 | 1 day (24/02/2020) | 16500 | 3.20 | 1.06 | 1424.30 | 81.73 | 12.20 |
|         | full | 5.0 | 0.02 | 1.0 | 0.01 | 0.50 | 1 day (24/02/2020) | 16500 | 5.67 | 1.93 | 1610.09 | 24.21 | 7.48 |
|         | partial | 1.0 | 0.07 | 0.03 | 0.03 | 0.50 | 1 day (24/02/2020) | 16500 | 1.97 | 1.27 | 2159.79 | 148.64 | 17.01 |
|         | partial | 3.0 | 0.07 | 0.03 | 0.03 | 0.50 | 1 day (24/02/2020) | 16500 | 3.14 | 1.47 | 607.41 | 82.32 | 10.91 |
|         | partial | 5.0 | 0.06 | 0.05 | 0.05 | 0.50 | 1 day (24/02/2020) | 16500 | 5.43 | 1.93 | 656.83 | 36.58 | 8.5907 |
| scenario 1 | full | 1.0 | 0.02 | 0.01 | 0.05 | 0.50 | 1 day (2/6/2020) | 16500 | 1.18 | 0.39 | 1746.55 | 126.90 | 12.72 |
|         | full | 3.0 | 0.02 | 0.03 | 0.05 | 0.50 | 1 day (2/6/2020) | 16500 | 3.36 | 1.46 | 1570.95 | 43.44 | 8.60 |
|         | full | 5.0 | 0.02 | 1.0 | 0.01 | 0.50 | 1 day (2/6/2020) | 16500 | 5.19 | 2.07 | 1351.27 | 19.12 | 6.56 |
|         | partial | 1.0 | 0.04 | 0.03 | 0.03 | 0.50 | 1 day (2/6/2020) | 16500 | 1.12 | 0.59 | 744.24 | 138.00 | 12.74 |
|         | partial | 3.0 | 0.06 | 0.03 | 0.03 | 0.50 | 1 day (2/6/2020) | 16500 | 3.12 | 1.13 | 638.83 | 62.72 | 9.86 |
|         | partial | 5.0 | 0.04 | 0.03 | 0.03 | 0.50 | 1 day (2/6/2020) | 16500 | 5.51 | 1.92 | 717.11 | 24.68 | 7.24 |
| Scenario 2 | full | 3.00 | 0.07 | 0.10 | 0.50 | 0.50 | 12 days | 2627010 | 1.01 | 0.46 | 16823.06 | 2600.39 | 18.71 |
|         | partial | 3.00 | 0.70 | 0.10 | 0.50 | 0.50 | 12 days | 2627010 | 5.38 | 2.53 | 5403.77 | 1406.80 | 16.70 |
| Scenario 3 | partial | 3.00 | 0.70 | 0.10 | 0.50 | 0.50 | 12 days | 2627010 | 5.38 | 2.53 | 5403.77 | 1406.80 | 16.70 | 61.88 |
3.2. Real-world calibration for specific dates

The synthetic studies demonstrated the ability of the calibration approach to fit spatiotemporally distributed Manning–Strickler coefficients $M$ in general. This section used real-world WSE observations, including observations from gauging stations and UAS altimetry, to calibrate $M$ for Vejle Å. The calibration was first implemented for two days, i.e., February 24 and June 02 in 2020, using UAS altimetry, and the results are displayed in Fig. 6. $M$ changed significantly from upstream to downstream on the two different days. $M$ declined from $36 \text{ m}^{1/3}/\text{s}$ to $24 \text{ m}^{1/3}/\text{s}$ on 02/24/2020 from chainage 20 km to 30 km, and the value decreased from 30 to $20 \text{ m}^{1/3}/\text{s}$ on 06/02/2020 in the same area. The landscape shows that dense trees cover the riverbank in this river stretch compared to the upstream area where the river flows through farmland and no forests grow along the riverbank.

The calibration settings and results are displayed in Table 2. The RMSE of the simulated WSE is 8.48 cm against the UAS altimetry on 02/24/2020 and the value is 6.99 cm on 06/02/2020. The calibrated results are not comparable to synthetic study because of the incomplete coverage of UAS altimetry and the structural model deficiencies (unsteady-state in reality). The drone surveys were conducted during a day, but the flow conditions could have changed especially in high-flow days, e.g., 02/24/2020. Moreover, we merged the UAS altimetry in June which we collected in two different dates. Even though we compared the characteristics of the flow regime on 06/02/2020 and 06/07/2020 and there are no significant differences, which causes additional model uncertainty.

![Figure 6. Calibration results of Manning–Strickler coefficients $M$ and the comparison between simulated and UAS altimetry derived WSE for two single dates: (a) 2020-Feb and (b) 2020-Jun.](image)

3.3. Real-world calibration for multiple dates

In the real-world calibration of spatial-temporally distributed Manning–Strickler coefficients $M$, considering the availability of UAS altimetry data, August 2019 to July 2020 was selected as the calibration
period and the validation period was from August 2018 to July 2019, with UAS altimetry data only available in
November and partially covered the river chainage. Steady-state solver and global optimization were used to
search optimal M. Then the calibrated M was used to parameterize the Mike Hydro River model to simulate
continuous time series for each calculation grid.

The calibration results of the M and the comparison between simulated and observed WSE are displayed
in Figure 7. The spatio-temporal variation of M is distinctive, high in the cold season (December to April) and
low in the warm season, relatively high upstream of the river and low downstream. In the upstream Vejle Å (12
– 24 km), the bed elevation shows undulating terrain, and the bankfull width and area are changeable in this
area compared to the downstream (Fig.A3). Thus, the complex bathymetry coupled with seasonal growth of
vegetation, resulted in significant changes of M in different seasons in this area. The calibrated M was more
inconsistent in cold season due to the high-flow but relatively stable in warm-season with low-flow. UAS
altimetry and in-situ observations of WSE were used for the steady-state solver calibration, and the RMSE of
the simulated WSE is 7.67 cm (table 2). While a significant bias between simulated WSE and UAS altimetry is
visible, as shown in Fig. 7b. Because a weight between drone data and stations data was used to balance their
 corresponding misfit in the objective function. The results indicate that the weight of in-situ data is too large.

Figure 7. (a) Calibration results of the spatiotemporally distributed Manning–Strickler coefficients M, and (b)
the difference between simulated WSE and observations along the chainage in Vejle å.
Table 2. Settings and results of the calibration with real-world data.

| Date  | Weight (w) | Weight (λ) | σ (misfit) | σ (smoothness) | σ (a priori) | Repetitions | WSE (cm) | Regularization (misfit) | Regularization (smoothness) | Regularization (a priori) | Objective function |
|-------|------------|------------|------------|----------------|--------------|-------------|----------|------------------------|-----------------------------|------------------------|-------------------|
| 2/24/2020 | 0.55 | 0.00 | 0.03 | 0.50 | 0.50 | 16500 | 8.48 | 5287.50 | 1288.69 | 0.00 | 59.06 |
| 6/2/2020 | 0.07 | 0.1 | | 0.50 | 0.50 | | 2132820 | 7.67 | 27689.15 | 3489.22 | 311.31 | 149.26 |
The comparison results between the simulated WSE against in-situ observations of four hydrological stations are displayed in Figure 8. Generally, the simulated WSE agreed well with in-situ observations in the high-flow period, and the simulated WSE is clearly less accurate in the low-flow seasons, which is similar to the synthetic study. The overestimation of WSE in low-flow seasons indicated an overestimated of M. Considering the UAS altimetry data we used for calibration in different seasons, the WSE on 02/24/2020 used sufficiently for constraining the M.

Validation results indicated that the calibrated M were not representative for the validation period, especially at Vingsted station (Fig. 8). Spatial patterns and dynamics of vegetation growth may change from year to year in which case a longer calibration period is required to obtain more robust parameter estimates.
Figure 8. Comparison results of the simulated WSE (by MIKE HYDRO River with steady-state solver calibrated Manning–Strickler coefficients $M$) against gauging WSE in four hydrological stations: (a) Tørskind, (b) Ravning, (c) Vingsted, and (d) Rosborg. The blue vertical lines divide the simulation period into validation period (Aug-2018 to Aug-2019) and calibration period. The gray dash vertical lines indicate the WSE was used for steady-state calibration.

Figure 9 shows the comparison results of longitudinal profiles of WSE depicted by UAS altimetry and simulations. The simulated WSE profiles during the validation period, i.e., 11/01/2018 and 11/02/2018, were underestimated. The simulated WSE is parallel to UAS altimetry observed WSE on 11/1/2018, but the simulated WSE is underestimated by approximately 0.3 m indicating the estimated $M$ is too large. The simulated profile of WSE on 11/02/2018 is lower than observations, and the water surface shows a different slope. The changing slope in this river stretch is caused by the spatial variation of $M$ and the bathymetry (Fig. 9b). The simulated WSE agreed well with the UAS altimetry in the calibration period but was slightly overestimated (Figure 9f).
Figure 9. Comparison results of simulated WSE against UAS altimetry on: (a) 11/01/2018, (b) 11/02/2018, (c) 02/24/2020, (d) 06/02/2020 (upstream), (e) 06/02/2020 (downstream), and (f) 06/07/2020.

4. Discussion

4.1. Impact of density/coverage of WSE observations for calibrating hydraulic models

In this study, we used a radar altimetry payload on a UAS to measure the WSE of Vejle Å. The altimetry data was smoothed with an interval of 20 m, equivalent to the grid resolution of the steady-state hydraulic solver, ensuring that at least one WSE observation fell on each calculation node. The results indicated that the parameters were well constrained by dense WSE datasets and the uncertainty had significant effects on the calibration results, as illustrated by the synthetic experiments. Potentially, we could further increase the grid resolution to 1 m or even less, considering the spatial sampling resolution of WSE by UAS. However, calculation efficiency will be decreasing as the number of grid points increased.
The advantages of using UAS altimetry data along the chainage were also demonstrated by comparison to the calibration experiments in which temporally continuous in-situ observations and the MIKE Hydro River model were used. The calibrated results improved slightly after including UAS altimetry (Fig. B1). Additionally, UAS altimetry data can be used to calibrate highly resolved Manning–Strickler coefficients \( M \) for a particular period of interest, for example a flooding period, which was not possible when using in-situ station data only.

Additionally, the coverage of the UAS altimetry is essential when spatially variable roughness parameters are calibrated. As shown by Scenario 1, the calibration results of \( M \) in 06/02/2020 outperformed 02/24/2020. Available UAS altimetry were more continuous in 02/24/2020; even though the spatial variations of \( M \) were constrained, the fitted roughness coefficient was far away from the truth in the chainage where the UAS altimetry was missing. In contrast, the available UAS altimetry was more scattered on 06/02/2020. Although UAS altimetry was missing for short intermittent reaches, \( M \) can be estimated in those reaches thanks to the smoothness regularization term. However, \( M \) was not well-constrained for longer reaches without available UAS altimetry data example can be seen in the results for 06/02/2020. We can thus conclude that for spatio-temporal calibration of the \( M \), long and continues UAS altimetry surveys distributed over the seasonal vegetation growth cycle are critical.

4.2. Spatiotemporally varying Manning–Strickler coefficients \( M \)

\( M \) is affected by various factors and changes in space and time. The calibrated results in this study showed that \( M \) of Vejle Å, a stream with high vegetation density, varied from 10 m\(^{1/3}\)/s to 30 m\(^{1/3}\)/s in both space and time and changed significantly along the river channel, especially in the human disturbed river segments. Previous studies have emphasized the spatial variability of \( M \) and pointed out the insufficient representation achieved with uniform \( M \) for long river reaches (Attari et al., 2021; Attari and Hosseini, 2019; Jiang et al., 2020; Pappenberger et al., 2007; Werner et al., 2005). Jiang et al.(2020) displayed promising evidence of using spatially varying \( M \) to predict WSE everywhere along the reach.

The growth and cleaning of vegetation and the seasonal variations of discharge affect the variability of \( M \) in time. Vegetation cutting is an important measure to increase cross-sectional conveyance and decrease floods risks. The \( M \) increased significantly after vegetation cutting, as shown by Jiang et al. (2020). Vegetation management interventions are not included in the modeling approach presented here, which leads to increased model uncertainty in the real-world calibration scenarios.

The calibration approach for spatial-temporally varying \( M \) can also be used for the rivers with complex topography and changeable hydraulic conditions. For instance, \( M \) may vary significantly at high stage for braided and terraced river. Meanwhile, river resistance will be significantly increased by river ice-jams that cause severe floods in some middle and high latitude rivers, e.g., Yellow River. Thus, a varying \( M \) might increase the performance of hydrodynamic simulations in such situations.

4.3. Potential and limitations of the calibration approach
The steady-state solver is efficient and effective for calibrating the M as shown in the present study. It took millisecond for the Steady-state solver to simulate WSE in Vejle Å with a resolution of 20 m. Compared to the hydrodynamic MIKE HYDRO River, the steady-state solver is computationally efficient. To go a step further, we can use global optimization to fit M by using this solver. The global optimization is independent of initial value and capable of avoiding local optima. To calibrate the spatiotemporally distributed M, the number of parameters increased significantly. The high resolution of the parameters in space and time increases the computational requirements for streams or large rivers (Kittel et al., 2021). Moreover, calibration results will be significantly affected by the chosen regularization strategy.

The present calibration algorithm for spatio-temporally distributed M has several drawbacks. In the hydraulic model, we used the cross-sectional information to delineate the river channel, and the cross-sections were linearly interpolated for each calculation node from the limited in-situ data. Thus, the accuracy, representation and density of the surveyed bathymetry is critical for the calculation. The 1-D steady-state hydraulic solver is based on the Saint-Venant equation, and it is insufficient to simulate overbank water flow. For such situations, a 1D-2D hydraulic model would be required. That is a reason for the relatively high error of the simulated water level in February in Vejle Å. For the regularization term, we assumed that M of natural rivers was characterized by spatial continuity and changes smoothly. However, most of the natural rivers have been affected by human activities, for example, the construction of reservoirs and dams, vegetation management, etc., which will often result in abrupt changes of hydraulic properties. Additionally, we introduced different weights for regularization terms which are determined by trial-and-error method. A more comprehensive method to select optimal weights for the regularization terms is the L-curve approach, which aims to compromise data misfit and the regularization terms (Hansen and O’Leary, 1993). However, implementation of such methods requires a large amount of computational resources.

5. Conclusion

This study presented a calibration approach for spatiotemporally distributed Manning–Strickler coefficients M by combining UAS altimetry and in-situ stations. Several synthetic experiments under different assumptions were evaluated and used to demonstrate the feasibility and efficiency of the scheme. We then applied the approach in a real-world case study, an approximately 20 km river stretch of Vejle Å, to calibrate and validate the M.

The synthetic study shows that M could be well-calibrated by the dense sampling of WSE in both spatial and temporal scale. The synthetic calibration experiments showed that standard errors of ca. 3 cm on the WSE, as achieved with our current UAS radar altimetry system, are sufficient to constrain spatio-temporal variations of hydraulic roughness. Meanwhile, the steady-state solver is efficient and effective in simulating the WSE along the river course, which is a requirement for the implementation of global search algorithms for highly parameterized inverse problems.
The calibration algorithm was further applied on a real-world dataset to fit the optimal sets of M with limited gauging data and UAS altimetry. The calibration results indicated that the M of Vejle Å changed significantly in space and time. The simulated WSE has a RMSE of 8.48 cm on a high-flow day and 6.99 cm on a low-flow day compared to highly resolved UAS altimetry. The simulated time series of WSE at four hydrological stations have an average RMSE of 10 cm after we transferred the M calibrated by the steady-state solver to the hydrodynamic model.

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Appendix

Appendix A. In-situ observations of discharge, water surface elevation and bathymetric information in Vejle Å.

Figure A1. Discharge monitored by two hydrological stations (Refsgårdslund and Haraldskær) in the period of Jan 2018 to Aug 2020.
Figure A2. Water surface elevation monitored by five hydrological stations (Tørskind, Ravning, Vingsted, Rosborg, Vejle Haven) in the period of Jan 2018 to Aug 2020.

Figure A3. Basic information of the 130 cross sections, including (a) bed elevation, (b) bank full depth, (c) bank full width and (d) bank full area.

Appendix B. Synthetic experiment for the calibration of MIKE Hydro River model by using Levenberg-Marquardt local optimization method.

Scenario B1: Calibration of spatiotemporally varying Manning–Strickler coefficients $M$ using in-situ data only. This scenario is set for a river stretch monitored by discretely distributed monitoring stations. Considering that the station data was continuously collected with a short time interval, lots of information will be lost if we utilize only a few days for steady-state calibration. Here, the MIKE Hydro River model is used for WSE simulating, and the local optimization is used for calibrating $M$. The initial value is essential for the optimization, and the initial $M$ was set to $20 \text{ m}^{1/3}/\text{s}$ for all the river stretches. Please be aware that it is extremely
time-consuming if we set the calculation grid spacing as 20 m when using the MIKE Hydro River model for Vejle case, thus propagations only calculated in each cross section.

Scenario B2: this scenario is the same as the former one, but with additional UAS altimetry collected in February and June 2020 and partially covered Vejle Å, as shown in Figure 6b.

Figure B1. Calibration results of synthetic experiment for Scenario C1 and C2 for calibrating MIKE HYDRO River model by using local optimization method: (a) the calibrated spatiotemporally distributed Manning–Strickler coefficients M, and (b) 1-1 line between the calibrated M and the synthetic truth for Scenario B1; (c) and (d) are the same but for Scenario B2; the accuracy of the simulated WSE are displayed in (c) for Scenario B1 and (d) for Scenario B2.

References
Attari, M., Hosseini, S.M., 2019. A simple innovative method for calibration of Manning’s roughness coefficient in rivers using a similarity concept. J. Hydrol. 575, 810–823. https://doi.org/10.1016/j.jhydrol.2019.05.083

Attari, M., Taherian, M., Hosseini, S.M., Niazmard, S.B., Jeiroodi, M., Mohammadian, A., 2021. A simple and robust method for identifying the distribution functions of Manning’s roughness coefficient along a natural river. J. Hydrol. 595, 125680. https://doi.org/10.1016/j.jhydrol.2020.125680

Bandini, F., Jakobsen, J., Olesen, D., Reyna-Gutierrez, J.A., Bauer-Gottwein, P., 2017. Measuring water level in rivers and lakes from lightweight Unmanned Aerial Vehicles. J. Hydrol. 548, 237–250. https://doi.org/10.1016/J.JHYDROL.2017.02.038

Bandini, F., Sunding, T.P., Linde, J., Smith, O., Jensen, I.K., Köppl, C.J., Butts, M., Bauer-Gottwein, P., 2020. Unmanned Aerial System (UAS) observations of water surface elevation in a small stream: Comparison of radar altimetry, LIDAR and photogrammetry techniques. Remote Sens. Environ. 234, 111487. https://doi.org/10.1016/j.rse.2019.111487

Blöschl, G., Kiss, A., Viglione, A., Barriendos, M., Böhms, O., Brázdil, R., Coeur, D., Demarée, G., Llasat, M.C., Macdonald, N., Retsö, D., Roald, L., Schmocker-Fackel, P., Amorim, I., Bělinová, M., Benito, G., Bertolin, C., Camuffo, D., Cornel, D., Doktor, R., Elleeder, L., Enzi, S., Garcia, J.C., Glaser, R., Hall, J., Haslinger, K., Hofstätter, M., Komma, J., Limanówka, D., Lun, D., Panin, A., Parajka, J., Petrič, H., Rodrigo, F.S., Rohr, C., Schönbein, J., Schulte, L., Silva, L.P., Toonen, W.H.J., Valent, P., Waser, J., Wetter, O., 2020. Current European flood-rich period exceptional compared with past 500 years. Nature 583, 560–566. https://doi.org/10.1038/s41586-020-2478-3

Cowan, W.L., 1956. Estimating hydraulic roughness coefficients. Agric. Eng. 37, 473–475.

Duan, Q., Sorooshian, S., Gupta, V., 1992. Effective and efficient global optimization for conceptual rainfall-runoff models. Water Resour. Res. 28, 1015–1031.

Duan, Q.Y., Gupta, V.K., Sorooshian, S., 1993. Shuffled complex evolution approach for effective and efficient global minimization. J. Optim. Theory Appl. 76, 501–521.

Hansen, P.C., O’Leary, D.P., 1993. The use of the L-curve in the regularization of discrete ill-posed problems. SIAM J. Sci. Comput. 14, 1487–1503.

Henkel, T., Wilson, H., Krug, W., 2012. Global sensitivity analysis of nonlinear mathematical models - An implementation of two complementing variance-based algorithms. Proc. - Winter Simul. Conf. https://doi.org/10.1109/WSC.2012.6465065

Houska, T., Kraft, P., Chamorro-Chavez, A., Breuer, L., 2015. SPOTting model parameters using a ready-made python package. PLoS One 10, e0145180.
Hunter, N.M., Bates, P.D., Horritt, M.S., Wilson, M.D., 2007. Simple spatially-distributed models for predicting flood inundation: A review. Geomorphology 90, 208–225. https://doi.org/10.1016/j.geomorph.2006.10.021

Jiang, L., Bandini, F., Smith, O., Klint Jensen, I., Bauer-Gottwein, P., 2020. The Value of Distributed High-Resolution UAV-Borne Observations of Water Surface Elevation for River Management and Hydrodynamic Modeling. Remote Sens. 12, 1171. https://doi.org/10.3390/rs12071171

Jiang, L., Madsen, H., Bauer-Gottwein, P., 2019. Simultaneous calibration of multiple hydrodynamic model parameters using satellite altimetry observations of water surface elevation in the Songhua River. Remote Sens. Environ. 225, 229–247. https://doi.org/10.1016/J.RSE.2019.03.014

Kittel, C.M.M., Hatchard, S., Neal, J.C., Nielsen, K., Bates, P.D., Bauer-Gottwein, P., 2021. Hydraulic model calibration using CryoSat-2 observations in the Zambezi catchment. Water Resour. Res. 1–19. https://doi.org/10.1029/2020wr029261

Knox, J.C., 1993. Large increases in flood magnitude in response to modest changes in climate. Nature 361, 430–432. https://doi.org/10.1038/361430a0

Lee, J., Perera, D., Glickman, T., Taing, L., 2020. Water-related disasters and their health impacts: A global review. Prog. Disaster Sci. 8, 100123. https://doi.org/10.1016/j.pdisas.2020.100123

Li, S.-G., Venkataraman, L., McLaughlin, D., 1992. Stochastic theory for irregular stream modeling. Part I: flow resistance. J. Hydraul. Eng. 118, 1079–1090.

Marjoribanks, T.I., Hardy, R.J., Lane, S.N., 2014. The hydraulic description of vegetated river channels: the weaknesses of existing formulations and emerging alternatives. Wiley Interdiscip. Rev. Water 1, 549–560. https://doi.org/10.1002/wat2.1044

Mtamba, J., van der Velde, R., Ndomba, P., Zoltán, V., Mtalo, F., 2015. Use of Radarsat-2 and Landsat TM Images for Spatial Parameterization of Manning’s Roughness Coefficient in Hydraulic Modeling. Remote Sens. 7, 836–864. https://doi.org/10.3390/rs70100836

Pappenberger, F., Beven, K., Frodsham, K., Romanowicz, R., Matgen, P., 2007. Grasping the unavoidable subjectivity in calibration of flood inundation models: A vulnerability weighted approach. J. Hydrol. 333, 275–287. https://doi.org/10.1016/j.jhydrol.2006.08.017

Rokaya, P., Morales-Marin, L., Lindenschmidt, K.E., 2020. A physically-based modelling framework for operational forecasting of river ice breakup. Adv. Water Resour. 139, 103554. https://doi.org/10.1016/j.advwatres.2020.103554

Sauer, I.J., Reese, R., Otto, C., Geiger, T., Willner, S.N., Guillod, B.P., Bresch, D.N., Frieler, K., 2021. Climate signals in river flood damages emerge under sound regional disaggregation. Nat. Commun. 12,
Shi, H., Li, T., Liu, R., Chen, J., Li, J., Zhang, A., Wang, G., 2015. A service-oriented architecture for ensemble flood forecast from numerical weather prediction. J. Hydrol. 527, 933–942. https://doi.org/10.1016/j.jhydrol.2015.05.056

Tuozzolo, S., Langhorst, T., de Moraes Frasson, R.P., Pavelsky, T., Durand, M., Schobelock, J.J., 2019. The impact of reach averaging Manning’s equation for an in-situ dataset of water surface elevation, width, and slope. J. Hydrol. 578. https://doi.org/10.1016/j.jhydrol.2019.06.038

Vélez-Nicolás, M., García-López, S., Barbero, L., Ruiz-Ortiz, V., Sánchez-Bellón, Á., 2021. Applications of Unmanned Aerial Systems (UASs) in Hydrology: A Review. Remote Sens. 13, 1359. https://doi.org/10.3390/rs13071359

Werner, M.G.F., Hunter, N.M., Bates, P.D., 2005. Identifiability of distributed floodplain roughness values in flood extent estimation. J. Hydrol. 314, 139–157. https://doi.org/10.1016/j.jhydrol.2005.03.012

Ye, A., Zhou, Z., You, J., Ma, F., Duan, Q., 2018. Dynamic Manning’s roughness coefficients for hydrological modelling in basins. Hydrol. Res. 49, 1379–1395. https://doi.org/10.2166/nh.2018.175