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A hydraulic model of the Amur River informed by ICESat-2 elevation

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ABSTRACT

Accurate predictions of water surface elevation (WSE) in rivers at high spatial and temporal resolution are important for flood/drought risk assessment and flood/drought forecasting and management. WSE in a river is controlled by three main factors: discharge, riverbed geometry, and hydraulic roughness. In remote and poorly instrumented rivers, discharge and riverbed geometry are highly uncertain and WSE is therefore hard to predict. ICESat-2 laser altimetry provides accurate elevation transects across the river at very high spatial resolution (70 cm along track). This paper demonstrates how ICESat-2 elevation transects can be used to parameterize a basin-scale hydraulic model of a continental-scale river. The workflow is demonstrated for the transboundary Amur River in North-East Asia. Simulated WSE is subsequently validated against a large dataset of in situ and satellite altimetry observations, and we demonstrate that the model can reproduce available WSE observations throughout the basin with an accuracy of 1–2 m.

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1 Introduction

Rivers are highly vulnerable to climate extremes and, at the same time, essential for biodiversity and economic development. As a consequence of the 2022 drought and heat wave, which simultaneously affected all three major world economies (EU, US and China), the economic importance of rivers as transport waterways and cooling water reservoirs has come into increased focus. Improved quantitative tools for river management are thus important and timely.

State-of-the-art global-scale inland water modelling and forecasting systems (e.g. Global Flood Awareness System (GLOFAS), Alfieri *et al.* 2013; European Flood Alert System (EFAS), Alfieri *et al.* 2014; DHI Global Hydrological (DHI GHM), Murray *et al.* 2023) rely on the combination of numerical weather prediction systems and simulation models with observational datasets from in situ sensors and satellite earth observation (EO). The hydrological compartment of such systems typically includes two sub-models, one representing the rainfall-runoff phase of the inland water cycle, and the second being a hydraulic model representing flow and inundation processes in rivers and floodplains. The hydraulic model is essential to transform runoff predictions provided by the rainfall-runoff model into predictions of water level along the river. Water level, in turn, is the controlling variable for flood risk assessment and flood early warning (Winsemius *et al.* 2013).

Parameterizing hydraulic models at continental to global scale remains challenging (Neal *et al.* 2012, Bjerklie *et al.* 2018, Pujol *et al.* 2020). A number of approaches have been developed, many of which exploit the increased availability of water surface elevation (WSE) observations from multiple satellite altimetry missions from databases such as Hydroweb (Crétaux *et al.* 2011) and Dahiti (Schwatke *et al.* 2015), and use these datasets to fit simple conceptual river cross-section shapes (e.g. Neal *et al.* 2012, Garambois *et al.* 2017, Schneider *et al.* 2017, Jiang *et al.* 2019). Problems that commonly arise in such workflows include parameter trade-offs between cross-sectional shape parameters and hydraulic roughness as well as rapid changes in flow width occurring around the bankfull depth of the river, which cannot be captured with simple conceptual shapes. To resolve the inherent non-uniqueness of the hydraulic inverse problem, additional hydraulic observations from satellite EO, such as surface water extent and water surface slope, have been used (Bjerklie *et al.* 2018, Pujol *et al.* 2020).

The Ice, Cloud, and Land Elevation Satellite-2 (ICESat-2) mission (Markus *et al.* 2017) provides new opportunities for the parameterization of large-scale hydraulic river models, because it delivers very high-resolution elevation datasets with an along-track resolution of just 70 cm (Neumann *et al.* 2019). ICESat-2 elevation transects across the river, taken during the low-flow season, thus map the river cross-section at a very high level of detail, with the exception of the submerged portion. While ICESat-2 can directly map submerged bathymetry in clear coastal waters (Parrish *et al.* 2019), in most cases, the submerged portion of the riverbed cannot be mapped from ICESat-2 data, because river water transparency is low and the laser beams do not penetrate through the water

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down to the river bed. However, during low-flow periods, the submerged portion of the riverbed is small. Rather than fitting the entire river cross-section using conceptual shapes, one only has to extrapolate a small portion of the cross-section that is submerged at ICESat-2 acquisition time. This reduces parameter trade-offs between cross-section shape and friction parameters.

This paper demonstrates how ICESat-2 elevation datasets can be used for the development of continental-scale hydraulic models and illustrates the workflows for the example of the Amur River. We show that a hydraulic model parameterized using ICESat-2 elevation transects across the river can reproduce water level observations from in situ stations and the available inland water satellite altimetry record, consisting of more than 100 virtual station time series placed along the river course. The workflows developed here are applicable at global scale and provide a consistent methodology for the simulation of WSE in global rivers that can be combined with the global inland water record available from satellite altimetry.

2 Materials and methods

2.1 The Amur River

The Amur (or Heilong Jiang in Chinese) is the world's 10th longest river, with a total drainage basin of ca. 1.89 million km^2 and a total length of ca. 4440 km. The vast majority of the basin is located in Russia (53%) and China (45%). Mongolia hosts the remaining 2% of the basin area (Fig. 1). Over a total distance of ca. 2500 km, the Amur

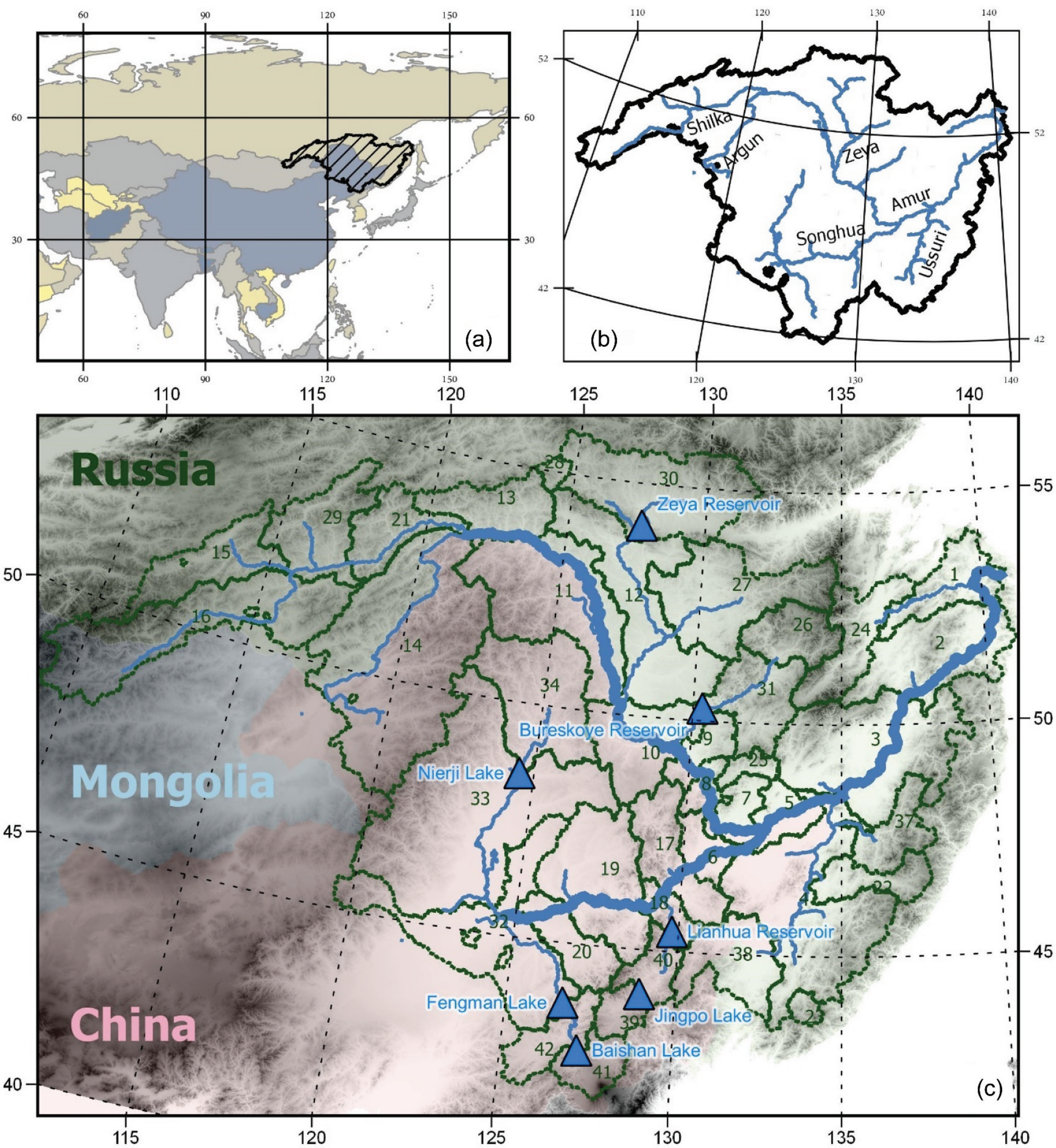

Figure 1. Base map of the Amur River system, indicating (a) geographic location and (b) main rivers. Panel (c) shows reservoirs (blue triangles), routing branches of the model (thin blue lines), hydrodynamic branches (thick blue lines) and sub-catchments of the model (green dotted shapes). Background shading indicates Shuttle Radar Topography Mission (SRTM) elevation.

River forms the border between China and Russia, and on this entire stretch of the river, no in situ discharge observations are available. The Amur River ultimately drains into the Tatar Strait between the Sea of Okhotsk and the Sea of Japan. River width varies from a few hundred metres in the upstream reaches to several kilometres in the downstream portions of the river. The Amur River is a global biodiversity hotspot hosting endemic fish species and large migratory fish populations as well as huge wetland systems (Egidarev *et al.* 2016, Simonov *et al.* 2019). While floodplains on the Chinese side of the river have been severely affected by river regulation (Jia *et al.* 2020), wetlands in the Russian portions of the basin remain largely intact.

Because it is located in a latitude range from 41 to 56 degrees north, the basin is dominated by cold continental weather with dominant snowfall in winter. Large portions of the river are ice-covered during the winter months. Ice-cover monitoring using satellite imagery and satellite altimetry datasets (Zakharova *et al.* 2021) confirms that the river is frozen from end November to end April. The Amur River has several large tributaries (Fig. 1), the largest of which is the Songhua River, joining the Amur from the right-hand side near the town of Tongjiang in China. There are 19 large dams in the Amur River Basin (Simonov *et al.* 2019). Seven reservoirs have a storage capacity larger than 1 km^3, of which two are located in Russia and five in China (Fig. 1). Flooding is common in the Amur basin, and seasonal and inter-annual variations of river flow can be related to large-scale atmospheric patterns (Tachibana *et al.* 2008). The most recent disastrous flood occurred in 2013 (Danilov-Danilyan *et al.* 2014), and another large flood occurred in 2019. The evolution of flood risk in a changing climate is of concern (Nohara *et al.* 2006, Yu *et al.* 2013).

2.2 Rainfall-runoff modelling

In order to estimate spatio-termporally distributed runoff forcings for the hydraulic model of the Amur River, we set up and calibrate a basin-scale rainfall-runoff model, because available in situ discharge records are sparse and unevenly distributed. Kalugin and Motovilov (2018) report the only basin-scale rainfall-runoff modelling effort for the Amur in the open literature. We used the Nedbør-AfstrømningsModel (NAM) rainfall runoff model (Nielson and Hansen 1973), which is integrated into DHI's Mike Hydro River package, for rainfall-runoff simulation. The NAM rainfall-runoff model has been used and discussed in many hydrological modelling studies reported in the international peer-reviewed literature (e.g. Andersen *et al.* 2006, Zhu *et al.* 2008, Vansteenkiste *et al.* 2014). The Amur River basin was divided into 43 individual sub-catchments (Fig. 1), using the Multi-Error-Removed Improved-Terrain (MERIT) hydro Digital Elevation Model (DEM) (Yamazaki *et al.* 2019) and the hydrographic DEM processing software TauDEM (Tesfa *et al.* 2011). The rainfall-runoff model does not include the areas contributing to Lake Hulun in Mongolia, which is essentially endorheic and only occasionally overflows into the Argun River.

As precipitation forcing for the NAM rainfall-runoff model, we used National Aeronautics and Space Administration NASA's Global Precipitation Measurement (GPM) Integrated Multi-satellitE Retrievals for GPM (IMERG) product, more specifically the final precipitation L3 half hourly 0.1 degree × 0.1 degree product, version 06 (Huffman *et al.* 2019), aggregated to daily values. IMERG precipitation was evaluated against a few available in situ precipitation stations, provided by the Russian Hydrometeorological Service, using a straightforward grid-to-point comparison in the time period 2008–2019. The resulting double-mass plots are shown in Fig. 2. The double-

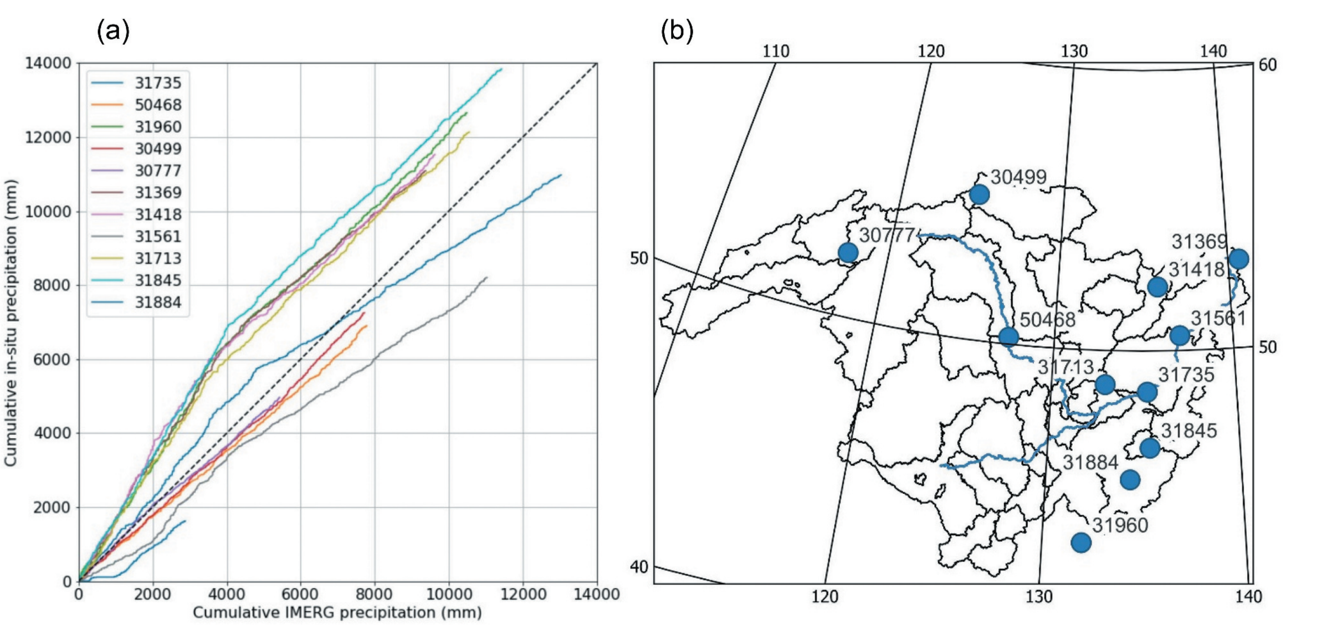

Figure 2. Double-mass plots for selected in situ precipitation stations. The right panel (b) shows the locations of the stations. The left panel (a) plots cumulative station precipitation versus cumulative IMERG precipitation for the pixel on which the station falls. The in situ observation period is 2008–2019 for all stations except 31884, for which it is 2016–2019.

mass plots indicate inconsistencies and shifting biases between the stations and the IMERG product, which may be due to the IMERG product or due to issues with the in situ instrumentation. Because we do not have access to a spatially dense and quality-assured precipitation product based on in situ monitoring networks in the region and because the IMERG product has been shown to perform on par with in situ precipitation when used as hydrological forcing in neighbouring regions of China (Jiang and Bauer-Gottwein 2019), we force the rainfall-runoff model of the Amur river basin with the IMERG product.

Gridded land surface (2 m) temperature estimates were obtained from European Re-Analysis 5 (ERA5)-Land hourly data, provided through the Copernicus Climate Data Store (Muñoz Sabater 2019). Hourly temperature data were aggregated to daily maximum, minimum and average temperatures. Daily temperature statistics were used to estimate reference ET using the approach of Hargreaves and Samani (1985). In the NAM model, daily average temperature further controls snow accumulation and snowmelt via a threshold temperature for snow fall and a temperature index parameterization of snowmelt (Hock 2003).

For the 10 in situ river discharge stations reported in Table 1, the NAM model was automatically calibrated assuming uniform parameters across the entire sub-catchment corresponding to the station. Daily discharge data for the period 2008–2019 was obtained from the Russian Hydrometeorological Service for these stations. Daily discharge is obtained from daily water level observations using rating curves, which are seasonally variable and are confirmed and updated with regular river gauging surveys. The accuracy of the discharge time series is not specified by the data provider, but is likely around 10%. In total, nine NAM parameters (Umax, Lmax, CQOF, CKIF, CK1,2, TOF, TIF, TG and CKBF; refer to Nielson and Hansen 1973, Madsen 2000 for a description of NAM parameters) were automatically adjusted between reasonable a priori bounds to minimize overall root mean square error between simulated and observed runoff and overall water balance error, using a global search algorithm as described by Madsen (2000). Performance was benchmarked against the mean of all observations using the Nash-Sutcliffe Efficiency (NSE). NSE produces optimistic skill scores for seasonal rivers, and we therefore also report a skill score in which runoff climatology (i.e. the average of all historical runoff observations for a given day of the year) was used as the benchmark. The climatology index (CI) is calculated as follows (see also Bennett *et al.* 2013):

$$CI = 1 - \frac{RMSE_{NAM}}{RMSE_{Clim}} \tag{1}$$

where $RMSE_{NAM}$ is the root mean square error between the observations and the NAM simulation and $RMSE_{Clim}$ is the root mean square error between the observations and the runoff climatology.

Transfer of NAM parameters to ungauged sub-catchments was based on catchment similarity, using an approach described by Kittel *et al.* (2020). We used average rainfall, average temperature and average terrain slope as the attributes defining similarity. Ungauged catchments inherited parameters from the gauged catchment that was closest in terms of total normalized distance between the attributes of the two catchments. The standard deviations of the attributes across all 43 sub-catchments were used to normalize the distances. Parameter transfer relationships between catchments are illustrated in Fig. 3.

2.3 Processing of ICESat-2 land elevation datasets

ICESat-2 is a spaceborne green lidar mission (532 nm), mapping the Earth's surface at an unprecedented spatial resolution of approx. 70 cm along track since 2018 (Markus *et al.* 2017). ICESat-2 is configured with three beam pairs that allow for across-track slope determination (90 m between pair members and 3.3 km between pairs). Each beam pair includes a strong beam (right with respect to orbit direction) and a weak beam (left with respect to orbit direction) with a power ratio of 4:1. ICESat-2 is on a 91-day repeat orbit; for this reason, the ground sampling pattern is very dense, while the temporal resolution is low. We used two different ICESat-2 data products: ATL08, which is a low-resolution terrain elevation product (Neuenschwander and Pitts 2019), and ATL03, which is the native-resolution geolocated photon product (Neumann

Table 1. Rainfall-runoff model calibration and validation results. RMSE is the root mean square error, WBE the water balance error or bias, and NSE the Nash-Sutcliffe model efficiency.

Station	Catchment ID	IMERG runoff coefficient	Calibration period	Validation period	RMSE (m^3/s) calibration (% of mean flow)	RMSE (m^3/s) validation (% of mean flow)	WBE (%) Cal.	WBE (%) Val.	NSE Cal.	NSE Val.	Calibration climatology index	Validation climatology index
Novomikhai-lovka	23	0.39	2008–2014	2015–2018	37.3 (74)	66.8 (133)	0.07	−3.70	0.57	0.49	0.17	0.42
Tynda	28	0.49	2008–2014	2015–2018	54.3 (127)	45.9 (107)	−1.00	2.71	0.54	0.55	0.30	0.34
Zvenievoy	22	0.45	2008–2014	2015–2018	159.6 (65)	183.1 (74)	−0.11	−3.70	0.65	0.68	0.31	0.49
Khor	37	0.71	2008–2014	2015–2018	341.8 (74)	351.3 (76)	22.30	20.70	0.54	0.48	−0.05	−0.07
Gouda	24	0.63	2008–2014	2015–2018	350.6 (61)	295.8 (52)	3.10	1.20	0.72	0.75	0.22	0.32
Ust-Niman	26	0.45	2008, 2010, 2011	2012, 2013	353.6 (109)	497.3 (153)	−2.20	17.50	0.42	0.42	−0.15	0.33
Birobidjan	25	0.63	2008–2014	2015–2018	98.1 (80)	97.5 (79)	11.20	7.70	0.60	0.45	0.21	0.06
Ust-Ulma	27	0.49	2008–2014	2015–2018	776.6 (100)	771.1 (99)	2.43	−7.00	0.52	0.48	0.01	0.17
Krasnoya-rovo	15	0.26	2008–2014	2015–2018	104.6 (85)	101.8 (83)	27.60	3.30	0.51	0.76	0.08	0.69
Dalai	33 + 34	0.12	2016–2018	2019	183.60 (40)	427.7 (93)	0.29	3.63	0.80	0.85	0.62	0.83
Mean									**0.59**	**0.59**	**0.17**	**0.36**

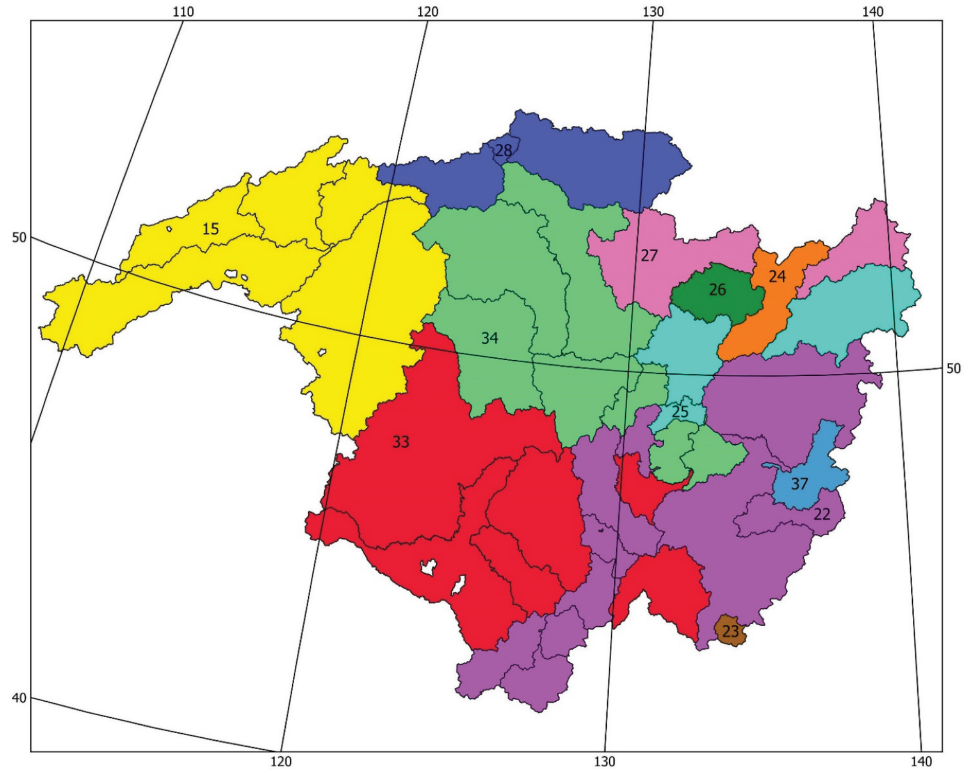

Figure 3. Parameter transfer from gauged to ungauged sub-catchments. NAM parameters calibrated for the numbered catchments were transferred to all catchments with the same colour code.

et al. 2019). We used version 5 of both products and accessed the data through the online portal of the US National Snow and Ice Data Center (https://nsidc.org/data/atl08/versions/5).

The Amur riverbed geometry was extracted from ICESat-2 elevation transects across the Amur River following the workflow outlined in Fig. 4. ATL08 ground tracks were manually inspected

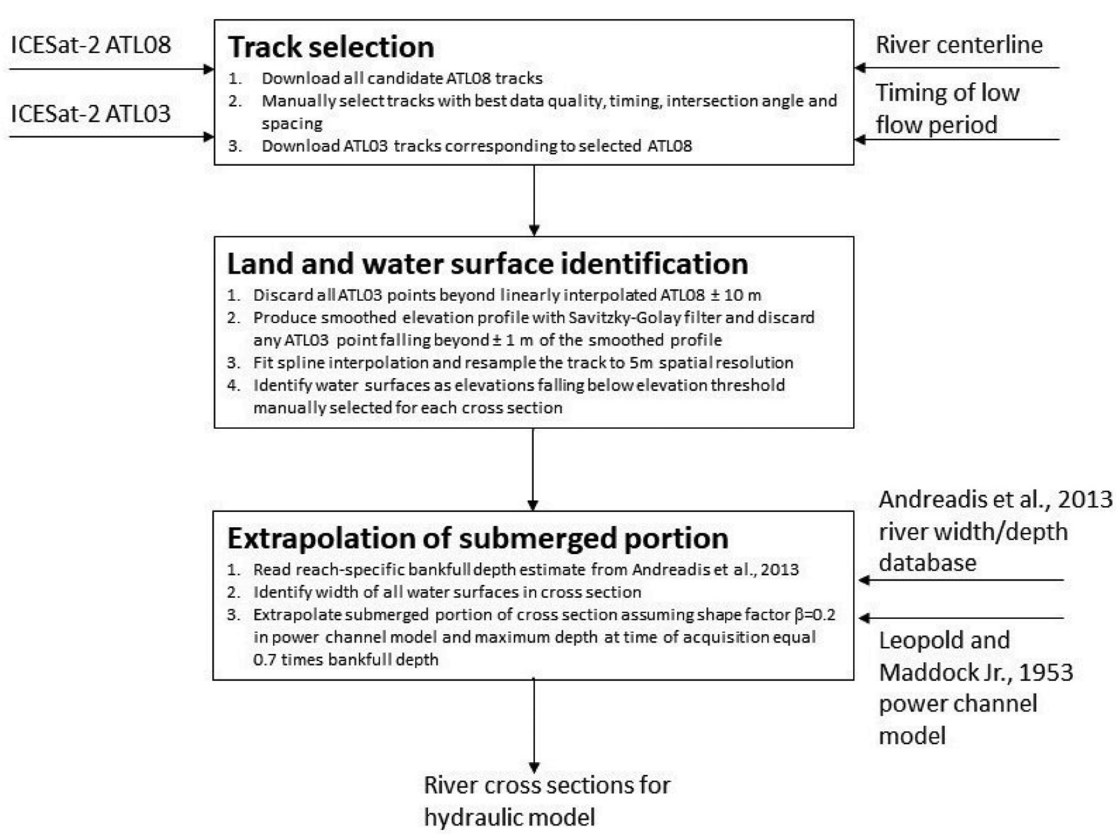

Figure 4. Flowchart for the delineation of river cross-section geometry from ICESat-2 data products.

to find crossings, spaced approximately every 10–20 river-km, with sufficient data density over the area of interest, which were directed approximately perpendicularly to the river centreline. The ICESat-2 laser is sensitive to cloud cover and mist, which strongly reduces the number of crossings that can be used to extract cross-section geometry. Moreover, we only used crossings during the dry and frozen season (i.e. November to April), when water levels in the river are low and a large portion of the cross-section geometry is therefore exposed and observable by ICESat-2. The selected ATL08 transects were used to pre-filter the corresponding ATL03 transects, and ATL03 data points with elevations outside ±10 m of the interpolated ATL08 elevation were rejected. The remaining ATL03 data was smoothed with a Savitzky-Golay filter (Savitzky and Golay 1964) using a third-degree polynomial to fit the ATL03 points and a variable window length to achieve appropriate smoothing of the ATL03 point cloud. Variable window length was necessary, because cross-sections had different absolute length, ranging from hundreds of metres in the upstream portions of the river to tens of kilometres in the large floodplains, and because ATL03 point density varied greatly with atmospheric conditions. All ATL03 points falling more than 1 m from the filtered line were removed.

The surface elevation geometry was created with a smoothing spline function from the remaining ATL03 points. The degree of smoothing was controlled manually for each cross-section to achieve an appropriate representation of the elevation profile. Using the spline interpolation, cross-section geometry was resampled to 5 m spatial resolution. Open water surfaces were identified in the cross-section as entirely flat and smooth surfaces. In the ATL03 datasets for the Amur cross-sections used here, we have been unable to detect useable returns from the submerged riverbed. In some sections, we see scattered photons returned from below the water surface, which may be reflected from the riverbed, but the signal-to-noise ratio is too low to enable robust retrieval of submerged riverbed geometry. For this reason, submerged riverbed elevation was extrapolated using the power channel model (Leopold and Maddock 1953). The power channel model can be written as

$$A = \alpha \cdot d^{\beta}$$

$$w = \frac{\partial A}{\partial d} = \alpha \cdot \beta \cdot d^{\beta - 1} \quad (2)$$

where A is the flow cross-sectional area, w is the flow surface width, and d is the flow depth. The parameters α and β are empirical fitting parameters. We assumed a uniform value of the shape parameter β (= 0.2). Depths were estimated as 0.7 times the bankfull depths reported by Andreadis *et al.* (2013) and available online at http://gaia.geosci.unc.edu/rivers/. In the downstream reaches of the Amur River, which are affected by backwater from the ocean, depths for ICESat-2 cross-section acquisition dates were assumed to be equal to the bankfull depths reported by Andreadis *et al.* (2013). Parameters α were subsequently determined for each cross-section from the assumed depth and β and the observed flow width from ICESat-2.

Once the parameters of the power channel model were determined, we estimated the submerged riverbed elevation at 5 m along-track spacing from the power channel model, and prepared the final cross-section for input into the hydraulic model. This included tagging each cross-section with the corresponding river chainage and the angle of intersection with the river centreline, and sorting the elevations in the direction from left bank to right bank. For selected cross-sections, a priori estimates of depth were subsequently manually updated to match simulated spatio-temporally distributed WSE to observed WSE data from in situ stations and satellite radar altimetry (see the section 2.5 on model validation below).

2.4 Hydraulic modelling

Hydraulics in the main branches of the Amur and Songhua rivers (thick blue lines in Fig. 1) were simulated using the fully dynamic version of the one-dimensional St Venant equations. Tributary flow (i.e. the thin blue reaches in Fig. 1) was simulated using Muskingum routing (Chow 1988), assuming a kinematic wave speed of 100 km per day and Muskingum's X = 0.25. The estimates for the Muskingum routing parameters are reasonable but cannot be validated with the available field observations. Muskingum parameters were varied manually, but showed low sensitivity to the simulated WSE in the main Amur and Songhua rivers.

The seven major reservoirs in the basin (Fig. 1) were implemented as storage nodes in the Muskingum routing scheme. Evaporation from the open reservoir water surface was neglected and, in the absence of information on reservoir operation, the regulated outflow was determined using a standard operation policy (SOP, Maass *et al.* 1962) with the target release equal to the annual average runoff and the flood control volume equal to the reservoir storage capacity. This very approximate representation of reservoir regulation will cause significant errors in simulated river flow locally, but, because only a small fraction of total runoff is regulated, the impact on simulated flows in the main Amur and Songhua River reaches is expected to be moderate. As an alternative, target volume regulation was implemented based on reservoir water storage changes observed with satellite EO. The results obtained from these runs showed that reservoir regulation only affects water levels in the low-flow period and that differences in simulated water levels are generally less than a metre.

A numerical hydrodynamic model for the main Amur and Songhua river reaches was implemented in the Mike Hydro River software (Havnø *et al.* 1995), which uses a six-point finite difference scheme on a staggered grid to solve the coupled continuity and momentum equations (Abbott and Ionescu 1967). We used a maximum grid spacing of 5 km and a fixed time step of 5 minutes in the numerical solution. The hydrodynamic model was forced with boundary runoff from the rainfall-runoff model and the tributary routing reaches. At the ocean boundary, a constant water level at 0 mamsl was assumed. This will introduce significant model errors locally, because the coastal water level in the Tatar Strait, into which the Amur River flows, is subject to significant tidal variations. However, boundary errors only affect simulated water levels a few tens of km upstream of the boundary. Cross-section geometry was imported from the ICESat-2 processing results described in section 2.3. We parameterized the friction between the flow and the river bed using Manning's equation, which expresses the friction slope as dependent on the roughness parameter (Manning's n), the cross-section geometry, and the water level (Chow 1988). We assumed a global uniform value of Manning's n equal to 0.033 s/m$^{1/3}$ during the unfrozen period, except for the most downstream 200-km section of the Amur River, where n = 0.013 s/m$^{1/3}$ was assumed. Moreover, Manning's n during the frozen period of the river (end November to end April) was assumed to be 3 times as high as during the unfrozen period, and a transition period of 15 days was assumed between frozen and unfrozen states, over which Manning's n was assumed to vary linearly in time. The factor of 3 between the Manning numbers for frozen and unfrozen states was derived from the inspection of in situ rating curves prepared by the Russian Hydrometeorological Service, which uses different rating curves in the frozen and unfrozen periods (Kouraev *et al.* 2004).

2.5 Validation with satellite-derived and in situ WSE datasets

In order to validate the hydraulic model and demonstrate its value for water level prediction, simulated water levels were compared with in situ station datasets from 12 stations (seven in Russia and five in China, see Fig. 5) and dozens of satellite altimetry virtual stations (VS, Fig. 5). We included all satellite altimetry time series available on the Hydroweb database (Crétaux *et al.* 2011, https://hydroweb.

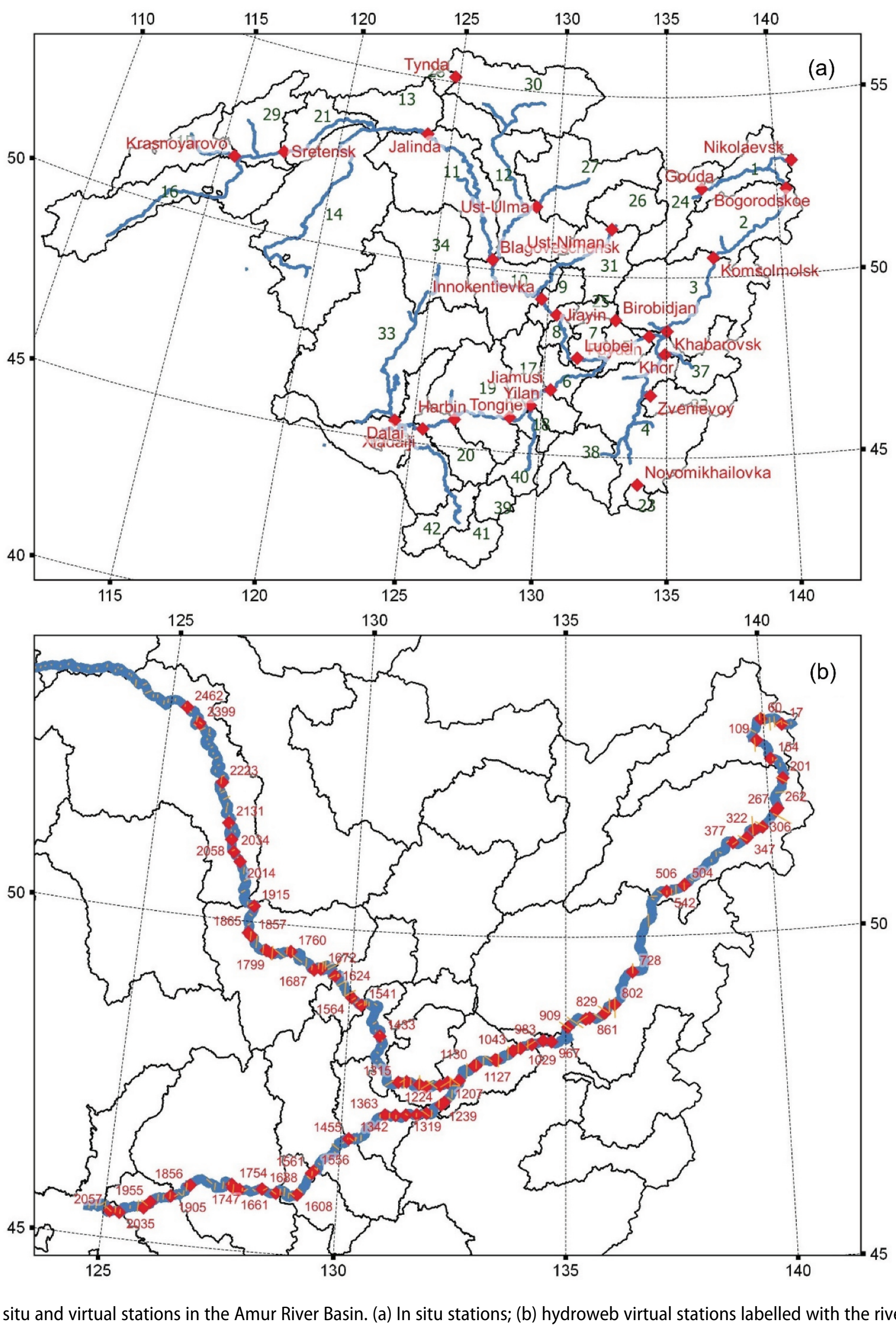

Figure 5. Overview of in situ and virtual stations in the Amur River Basin. (a) In situ stations; (b) hydroweb virtual stations labelled with the river-kilometres used in the hydroweb database (https://hydroweb.theia-land.fr/).

theia-land.fr/) for the simulated domain, i.e. 116 virtual station time series in total. For all in situ and virtual stations, water level time series were extracted from the hydrodynamic model results and were directly compared with the observations. Because we referenced the ICESat-2 cross-sections to the Earth Gravitational Model 2008 (EGM2008) geoid model (Pavlis *et al.* 2012), simulated WSE was also referenced to EGM2008, as were all the satellite altimetry observations at VS. The vertical reference of the in situ stations was unknown and we therefore expect time-constant bias between the model and the in situ observations.

3 Results and discussion

3.1 Hydrological model calibration and validation results

Table 1 reports the calibration and validation results for the calibration catchments. Locations of in situ stations are reported in Fig. 5. Runoff coefficients are reasonable and consistent across the calibration catchments, with the exception of catchment 37, which shows an unreasonably high runoff coefficient when compared to the gauging data from station Khor. This could indicate problems with the IMERG precipitation estimates in this region or problems with the in situ data (e.g. outdated rating curves). Performance during the calibration period is generally satisfactory for all catchments (average NSE is 0.59) and performance does not degrade significantly between calibration and validation periods, with the average NSE of all catchments remaining at 0.59, also for the validation period. This indicates that the model calibration is robust and model parameters are not over-fitted in the calibration. Climatology indices for the individual catchments are mostly positive for both the calibration and the validation period and, for some catchments, approach a value of 1. This indicates that the calibrated NAM rainfall-runoff models forced with IMERG precipitation perform significantly better than runoff prediction based on the long-term average observed runoff. The rainfall-runoff models were further validated at a number of downstream stations as reported in Table 2. These stations integrate runoff from a number of sub-catchments, including ungauged sub-catchments that inherited rainfall-runoff model parameters from similar calibration catchments, and results indicate satisfactory performance in the downstream regions of both the Songhua tributary and the main Amur

Table 2. Rainfall-runoff model validation at a number of in situ discharge stations along the main Amur and Songhua rivers.

Station	Validation period	Average discharge (m^3/s)	RMSE (m^3/s)	RMSE (% of avg discharge)	WBE (m^3/s)	WBE (% of avg discharge)
Khaborovsk	2008–2018	8384	3305	39	1058	13
Komsomolsk	2012–2019	10 259	3587	35	1227	12
Bogorodskoe	2008–2019	11 459	3657	32	305	3
Harbin	2007–2014, 2019	1156	633	55	−60	−5
Xiadaiji	2016–2020	922	476	52	200	22
Tonghe	2007–2014	1265	726	57	61	5
Yilan	2007–2014	1595	931	58	−212	−13
Jiamusi	2007–2014	1756	884	50	−30	−2
Mean				47		4

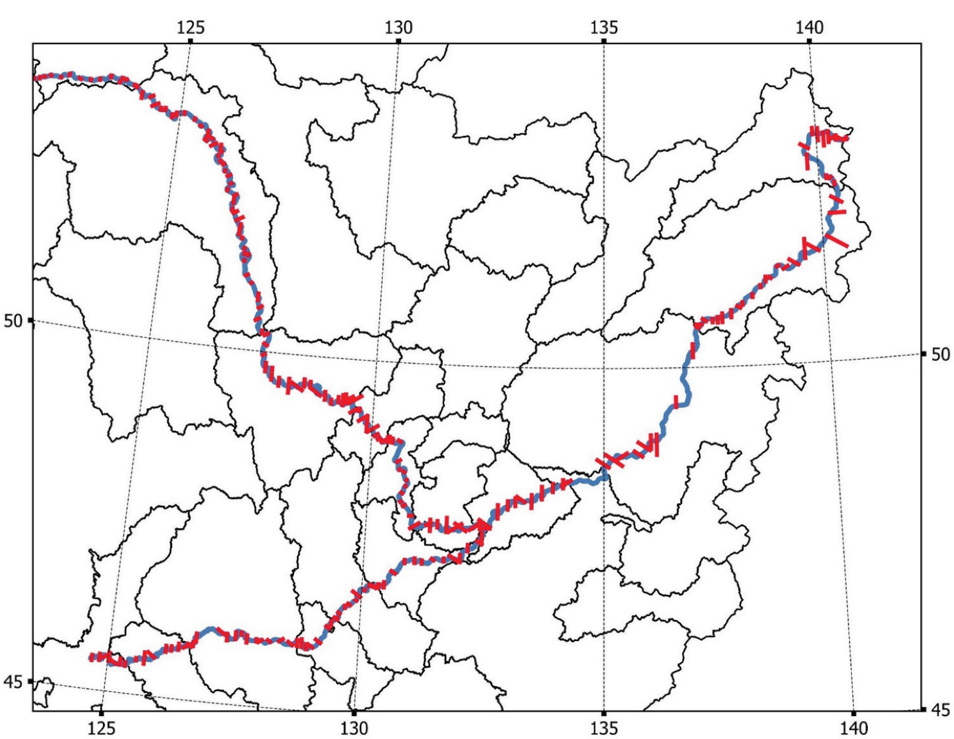

Figure 6. The 217 river cross-sections delineated from ICESat-2 datasets along the main Amur River and the Songhua tributary.

River. Overall, the evaluation of the rainfall-runoff models shows that the models predict runoff reliably; however, model errors due to the coarse spatial disaggregation, the uncertain climate forcings, and insufficient representation of human interventions (reservoir regulation, water abstractions) are significant, as is common for large-scale hydrological models of this type.

3.2 Results of river cross-section delineation from ICESat-2

In total, 217 river cross-sections were prepared from ICESat-2 datasets for the main Amur River and the Songhua tributary (Fig. 6). The distance between cross-sections varies, because the orientation of the river with respect to the ICESat-2 ground tracks is variable. In some south–north-orientated river reaches, useable ground tracks are sparse and the cross-sections are therefore less densely spaced. Fig. 7 illustrates the cross-section processing workflow and its results for one selected cross-section on the Songhua River (Songhua chainage 960 km). Panel A of Fig. 7 shows the ATL03 and ATL08 datasets along this ground track, passing over the river, which is braided in this location, and over the adjacent floodplains. Because the spatial resolution of ATL08 is relatively coarse, the product does not resolve important features such as dikes and levees, which control the hydraulic characteristics of the cross-section. This is evident from Panel B in Fig. 7, and clearly illustrates the added value of using the ATL03 product in the cross-section retrieval workflow. Panel C shows the retrieved riverbed geometry after filtering and smoothing, including the submerged portion of the river, which is extrapolated using the power channel relationships. In this case, the cross-section for the hydraulic model was limited to the region between the first major dikes on each side of the river, and Mike Hydro River assumes vertical banks beyond the first and last points of the mapped cross-section. This implies that the model would not correctly simulate extreme events in which the river overflows the dikes in this river reach. In this location, two major river channels are visible in the ICESat-2

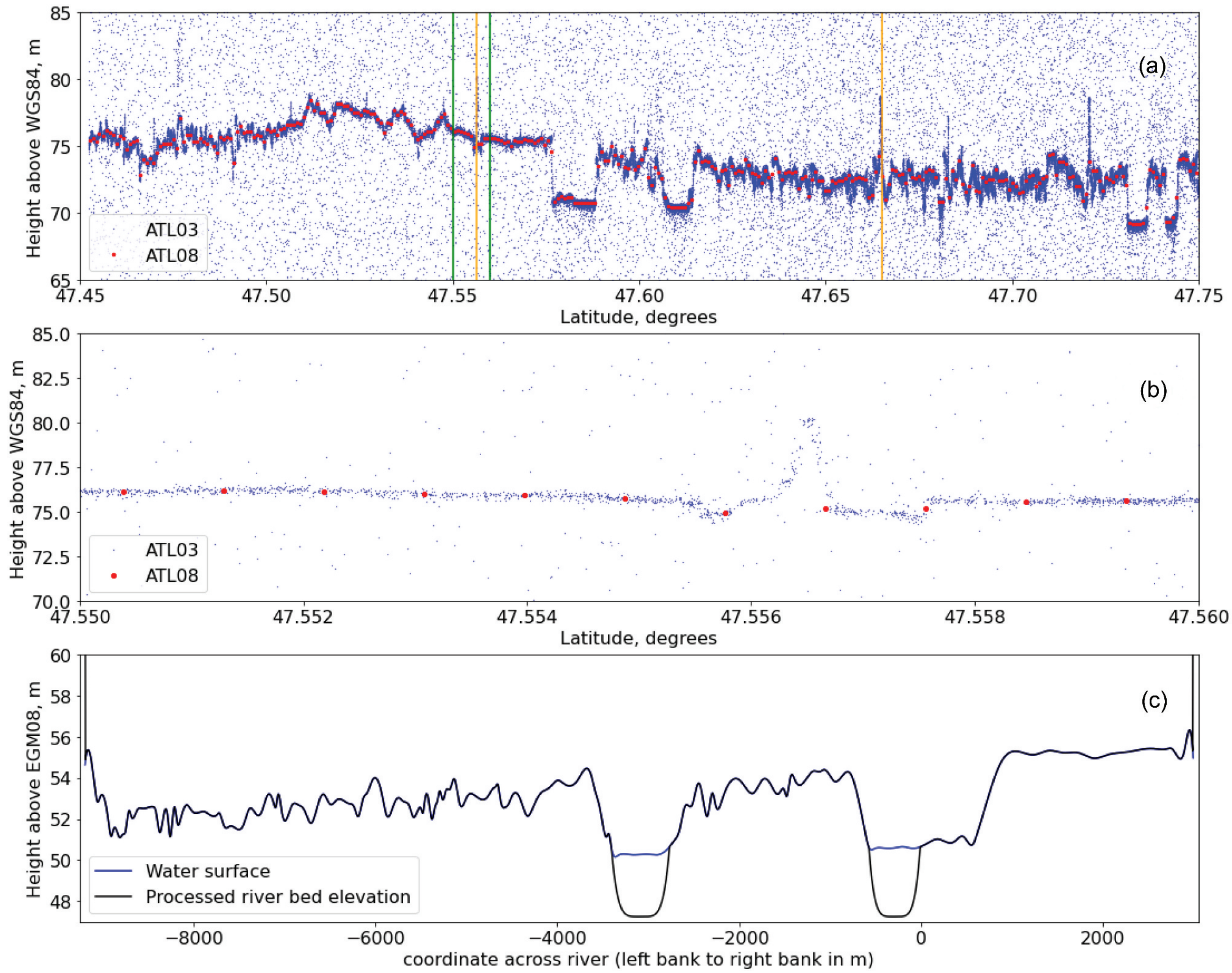

Figure 7. Illustration of the ICESat-2-based river cross-section processing workflow and its results. (a) ATL03 and ATL08 cross-section across the lower Songhua River (chainage 960 km). (b) Zoomed-in view of panel A showing a levee running along the Songhua River, which is clearly mapped by ATL03 but not sampled in ATL08. (c) Processed cross-section for inclusion into the hydrodynamic model. Note the reverse cross-section orientation in (c) to comply with ascending coordinates from left to right bank. ATL03 data is interpolated to 5 m spatial resolution as described in section 2.3 of the paper. The submerged portions of the cross-section are extrapolated using the power channel relationships.

dataset, and extrapolation of the submerged portion was thus applied to both submerged sections of the transect, assuming equal WSE and depth in both channels.

3.3 Hydraulic model results

Using the ICESat-2-derived river cross-sections and the parameterization of Manning's roughness coefficient described in the methods section, the hydraulic model was run for the period 2001–2021, using the runoff and tributary flow forcings provided by the rainfall-runoff models and the reservoir/river routing routine. Simulated WSE and discharge is thus available for a 20-year simulation period at any location of interest on the river network. Fig. 8 compares selected examples of simulated WSE time series at in situ and virtual stations with the corresponding in situ and satellite radar altimetry observations. Generally, the fit to in situ and satellite WSE is satisfactory, with RMSE ranging from less than 1 to about 2.5 m, depending on station location (Fig. 9, Table 3). The vast majority of VS show RMSE values between 1 and 2 m and bias values between −1 and +1 m (Fig. 10). The accuracy of the satellite altimetry observations is expected to be variable across the domain. For the wide rivers in the downstream portions of the basin, the accuracy of the altimetric WSE observations is probably around 0.5 m or better, while accuracy in the upstream, more narrow reaches is likely lower (Jiang *et al.* 2017, 2020).

It is important to note that this performance was achieved without the use of any in situ cross-section geometry observations and without extensive calibration of the hydraulic model. Moreover, the error of the modelled WSE integrates errors in the rainfall-runoff/routing model, including reservoir regulation, and the hydraulic model. The only in situ dataset used in model development is the in situ gauging dataset used for calibration of the rainfall-runoff models. Spatial maps of RMSE and bias for the different VS clearly indicate spatial correlation of model errors (Fig. 9), which could be mitigated by local adjustment of the Manning coefficient and flow depth. However, calibration of the hydraulic model is challenging,

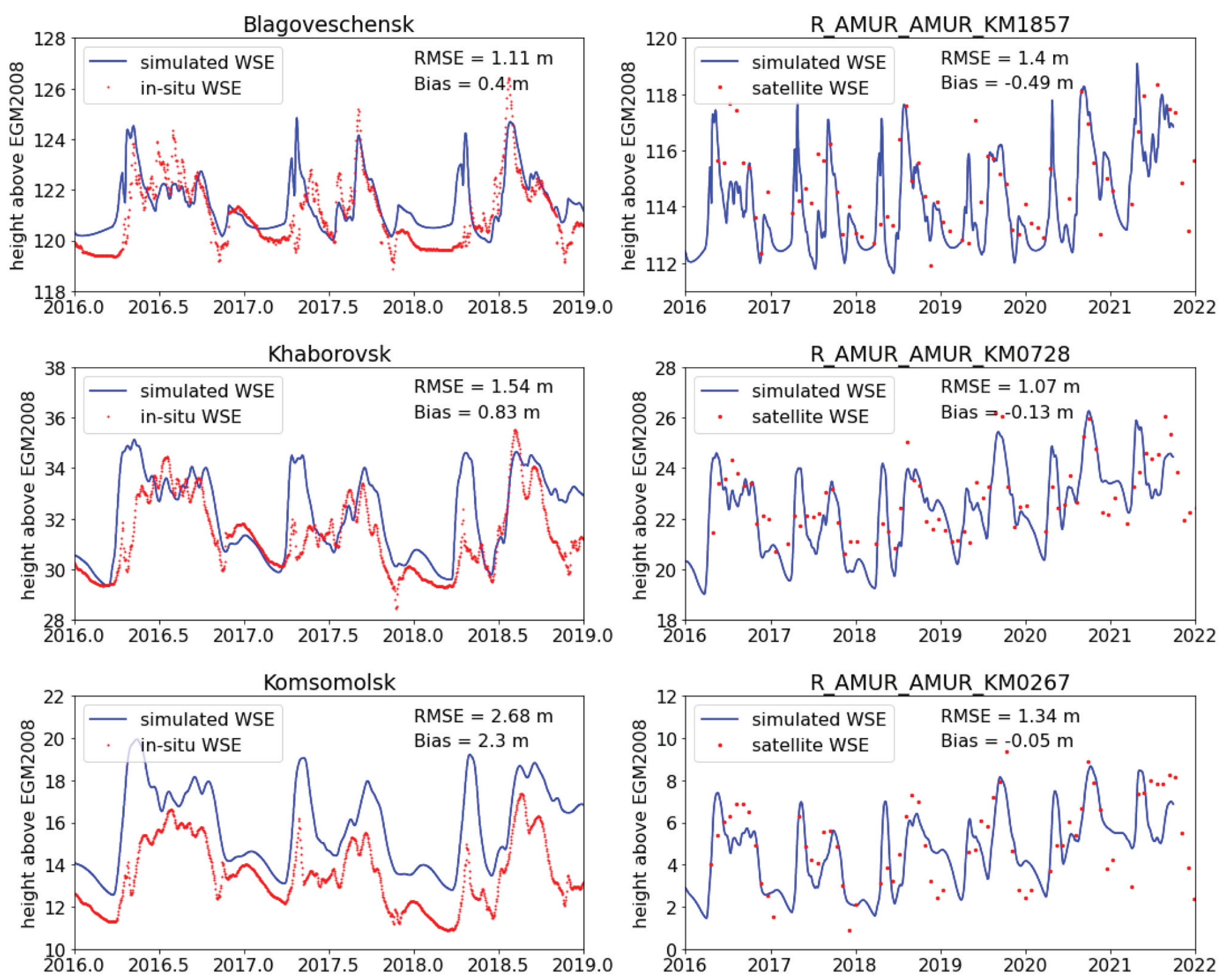

Figure 8. Comparison of simulated and observed WSE time series from selected in situ stations (left) and virtual stations (right).

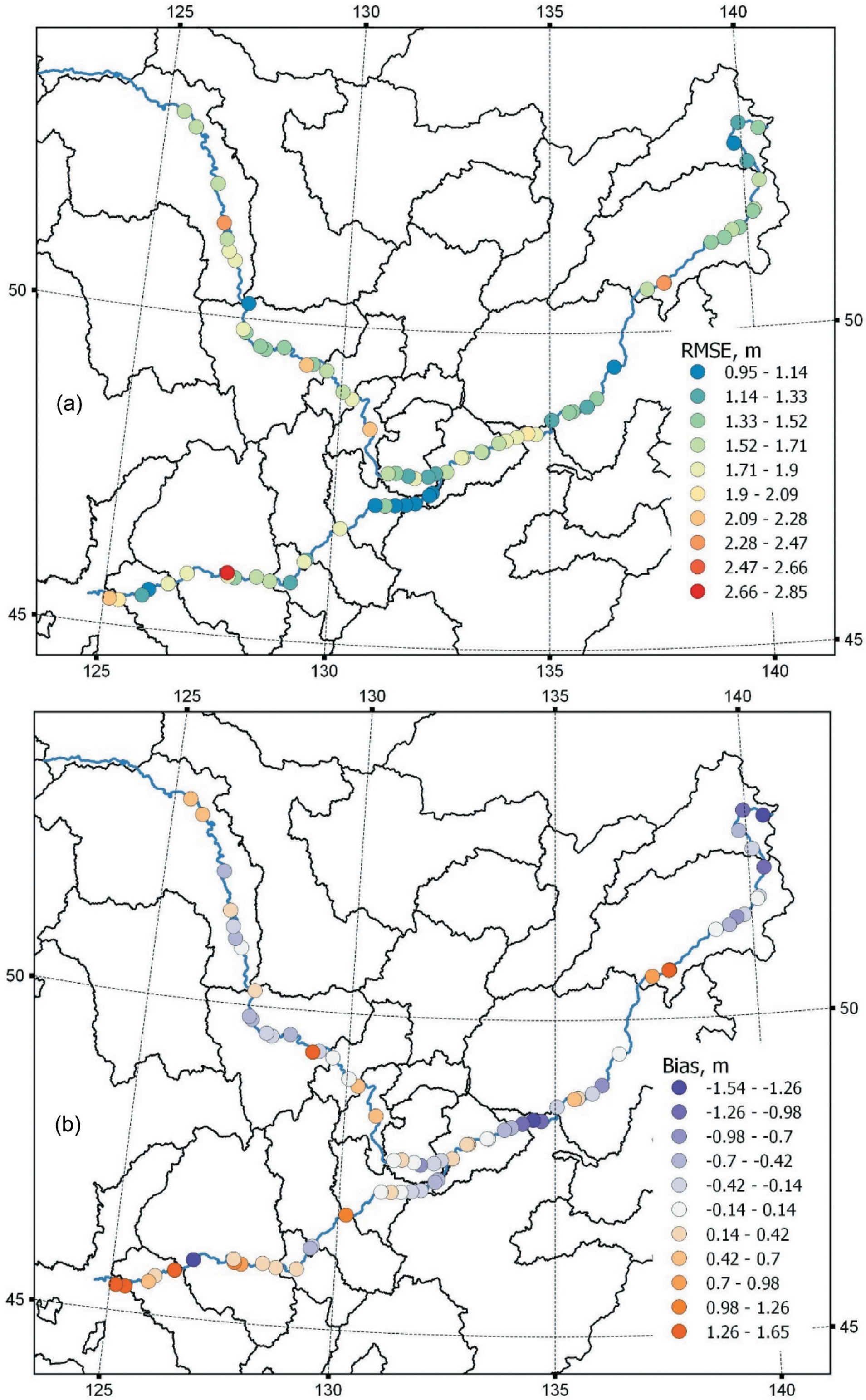

Figure 9. Overview of the spatial distribution of performance characteristics at the different hydroweb virtual stations. The root mean square error of water surface elevation prediction is shown in (a) and distribution of mean error or bias of water surface elevation prediction in (b).

given the size of the model and the resulting computational load (ca. 30 minutes of calculation time for a 20-year simulation period on a 3 GHz Intel i5-9500 CPU with 16 GB RAM), and local refinement and calibration of the model should thus preferably be implemented using smaller-scale sub-models. Moreover, in view of potential global application of this modelling workflow, we would like to focus on a calibration-free cross-section delineation workflow in this study and demonstrate that such a workflow can deliver WSE predictions with satisfactory accuracy.

Table 3. Hydraulic model performance (after adjustment of depth) for in situ stations along the Amur-Songhua.

	RMSE of simulated WSE (m)	Bias of simulated WSE (m)
Nikolaevsk	0.44	0.08
Khaborovsk	1.54	0.83
Bogorodskoe	0.85	0.26
Komsomolsk	2.68	2.30
Innokentievka	1.45	0.87
Blagoveschensk	1.11	0.40
Jalinda	1.32	−0.54
Jiamusi	0.92	0.29
Yilan	0.85	0.08
Tonghe	1.49	−0.97
Harbin	0.92	0.13
Xiadaiji	2.47	2.16

3.4 Model applications

Prospective model applications include the densification of satellite-derived WSE time series in space and time, the estimation of river discharge from satellite altimetry data, and the joint use of satellite EO data and the hydraulic model for operational hydraulic modelling and forecasting, using data assimilation (Schneider *et al.* 2018). Earlier studies focused on the densification of WSE datasets from satellite altimetry using statistical interpolation techniques (Nielsen *et al.* 2022) or river width observations from satellite imagery (Tourian *et al.* 2016). Because such approaches do not require the development of a hydraulic model, they are efficient and suitable for global-scale application. However, the availability of ICESat-2 cross-sections at global scale enables the parameterization of global-scale hydraulic models from satellite remote sensing data only. Unlike statistical WSE densification workflows, densification using a hydraulic model respects the physical processes and phenomena occurring in the river and thus provides a physically consistent interpolation result.

The hydraulic model also provides rating relationships along the entire river course, as illustrated in Fig. 11, including in situ station locations and virtual station locations. Simulated rating relationships show two distinct branches, which correspond to the frozen and unfrozen periods with different Manning numbers. As shown in Fig. 11 for the stations Khaborovsk and Komsomolsk, these two distinct branches of the rating relationship are also observable in the in situ data. Because river gauging requires access to both banks of the river, no in situ discharge data is available for the Amur River along a stretch of more than 1000 km, over which the river forms the border between Russia and China. Modelled rating relationships can be used to translate in situ WSE records into estimated discharge in the transboundary river reach. The same can be done for any virtual station situated in the domain of the hydraulic model. Moreover, the hydraulic model can be used to investigate the shape and uniqueness of the rating relationship for different in situ and virtual stations. For instance, the rating curve at Blagoveschensk is strongly affected by backwater effects originating from the confluence of the Amur and Zeya rivers (Liu *et al.* 2022), which is located a few kilometres downstream of the station. Such effects can also occur at virtual stations, and the hydraulic model can be used to screen the available virtual stations for their suitability for discharge estimation using different types of rating relationships.

Finally, the basin-scale hydraulic model described here can provide boundary conditions for smaller-scale nested models of selected reaches and floodplains along the river. Local models can be refined using hydraulic inverse modelling techniques and can include interactions with the floodplains, using a coupled one-dimensional/two-dimensional (1d–2d) simulation approach. Prospectively, the workflow demonstrated here can be used to prepare a global-scale hydraulic model by combining riverbed geometry datasets from ICESat-2 with global-scale rainfall-runoff simulation models.

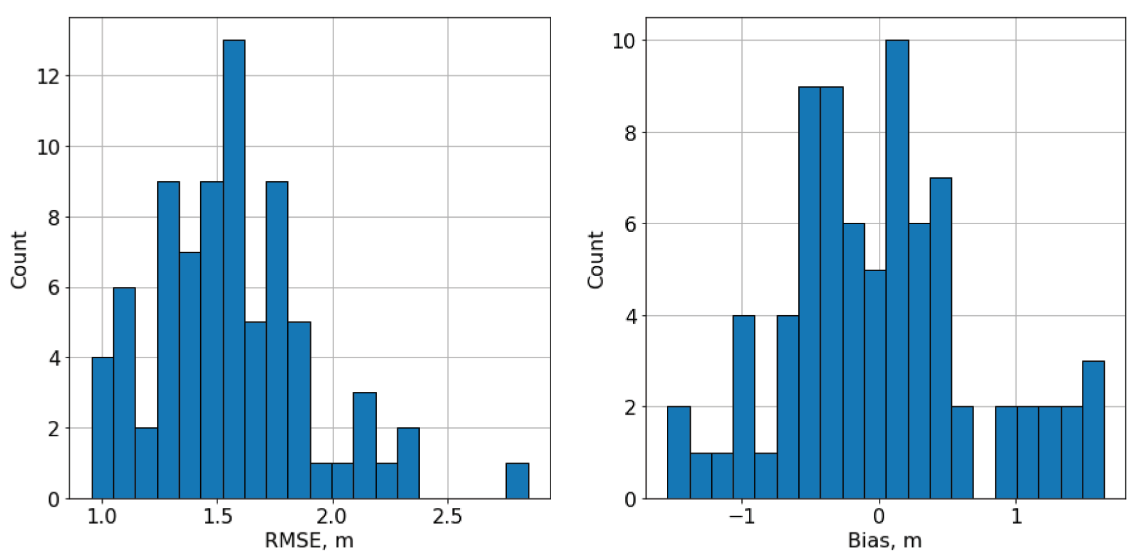

Figure 10. Histograms of water surface elevation RMSE and bias for all hydroweb virtual stations.

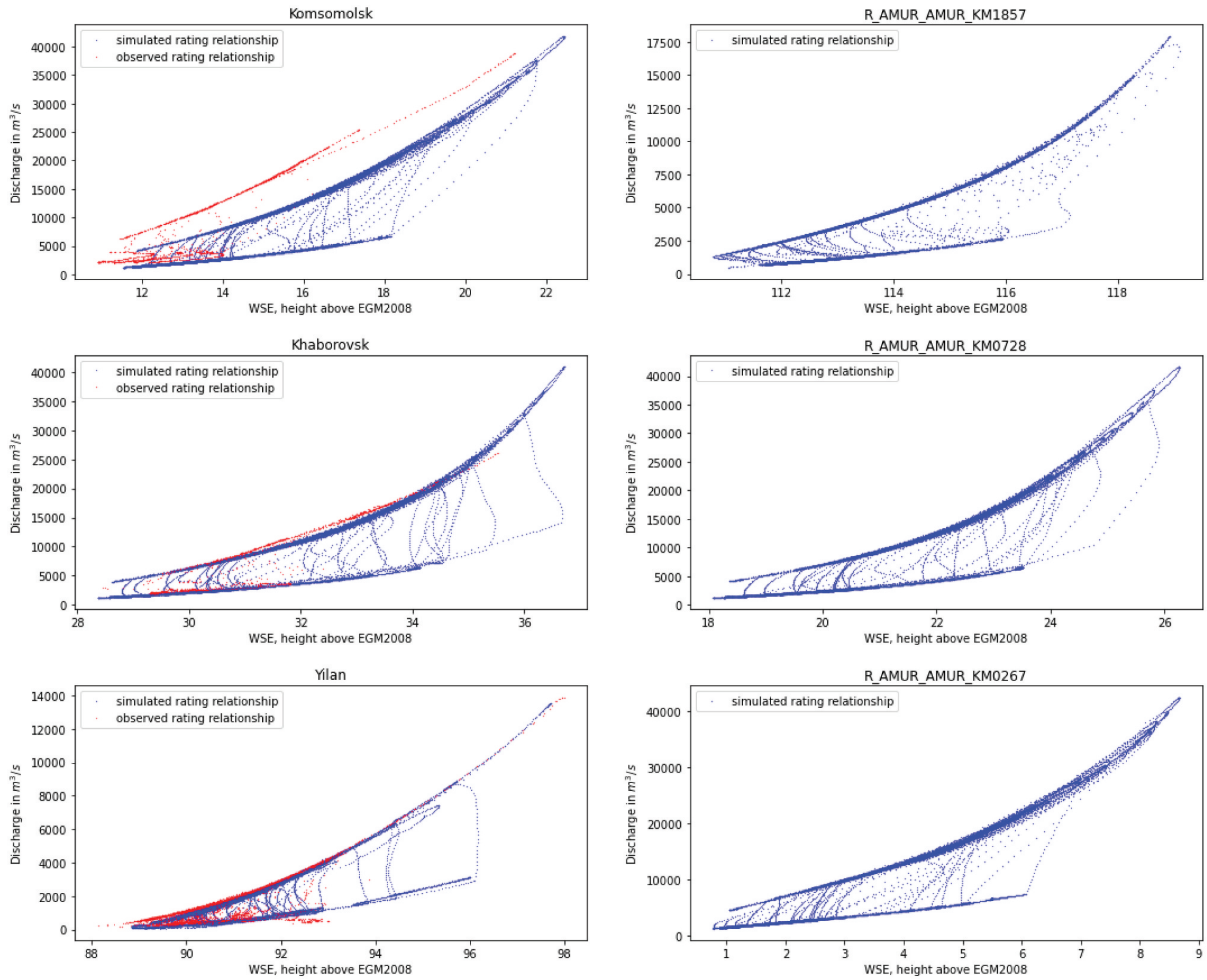

Figure 11. Simulated and observed rating relationships at selected in situ stations (left) and virtual stations (right) on the Amur River.

4 Conclusions

This paper demonstrates a hydraulic modelling workflow for continental-scale rivers. Achieving suitable availability and quality of river cross-section geometry datasets is a common problem for hydraulic model development at this scale, especially in remote and poorly instrumented rivers, and this study demonstrates that ICESat-2 elevation datasets provide important new information in this context. ICESat-2 elevation datasets allow for the retrieval of reliable effective river cross-section geometry and thus enable WSE predictions along entire river courses at continental scale, which can be validated against the global spatio-temporally resolved WSE record available from inland water satellite altimetry. The hydraulic modelling workflow developed here for the Amur is suitable for global-scale application and provides building blocks for operational, global-scale river water level prediction systems based on a combination of rainfall-runoff models, ICESat-2 elevation datasets, and satellite-based WSE observations.

Disclosure statement

No potential conflict of interest was reported by the authors.

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