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Inference of effective river properties from remotely sensed observations of water surface

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ABSTRACT

The future SWOT mission (Surface Water and Ocean Topography) will provide cartographic measurements of inland water surfaces (elevation, widths and slope) at an unprecedented spatial and temporal resolution. Given synthetic SWOT like data, forward flow models of hierarchical-complexity are revisited and few inverse formulations are derived and assessed for retrieving the river low flow bathymetry, roughness and discharge (A_0, K, Q). The concept of an effective low flow bathymetry A_0 (the real one being never observed) and roughness K, hence an effective river dynamics description, is introduced. The few inverse models elaborated for inferring (A_0, K, Q) are analyzed in two contexts: (1) only remotely sensed observations of the water surface (surface elevation, width and slope) are available; (2) one additional water depth measurement (or estimate) is available. The inverse models elaborated are independent of data acquisition dynamics; they are assessed on 91 synthetic test cases sampling a wide range of steady-state river flows (the Froude number varying between 0.05 and 0.5 for 1 km reaches) and in the case of a flood on the Garonne River (France) characterized by large spatio-temporal variabilities. It is demonstrated that the most complete shallow-water like model allowing to separate the roughness and bathymetry terms is the so-called low Froude model. In Case (1), the resulting RMSE on infered discharges are on the order of 15% for first guess errors larger than 50%. An important feature of the present inverse methods is the fairly good accuracy of the discharge Q obtained, while the identified roughness coefficient K includes the measurement errors and the misfit of physics between the real flow and the hypothesis on which the inverse models rely; the later neglecting the unobserved temporal variations of the flow and the inertia effects. A compensation phenomena between the indentifiedvalues of K and the unobserved bathymetry A_0 is highlighted, while the present inverse models lead to an effective river dynamics model that is accurate in the range of the discharge variability observed. In Case (2), the effective bathymetry profile for 80 km of the Garonne River is retrieved with 1% relative error only. Next, accurate effective topography-friction pairs and also discharge can be inferred. Finally, defining river reaches from the observation grid tends to average the river properties in each reach, hence tends to smooth the hydraulic variability.

1. Context of the issue

The spatial and temporal distribution of continental water fluxes including stream and rivers is still roughly known which currently limits our representation of the water cycle and also an integrated and sustainable water management. However, current remote sensing techniques led to interesting results, such as the gravity field of water storage change via GRACE [1,2], surface water elevations via altimetry [3], or radar measurements from the Shuttle Radar Topography Mission [4]. The future Surface Water and Ocean Topography (SWOT) mission with a swath mapping radar interferometer would provide new measurements of inland water surface elevation (WSE) for rivers, wetlands and reservoirs. Maps of water elevations are expected at a resolution of 100 m with a centimetric vertical accuracy when averaged over 1 km^2 [5]. But the highlight of SWOT will be its almost global coverage and temporal revisits on the order of 1 to 4 times per 22-days repeat cycle. These data will offer possibilities to better characterize the spatial and temporal variabilities of inland water surfaces (e.g. [6]).

Estimating river discharge is not straightforward. As a good quality rating curve is needed to estimate discharge accurately from in-situ water depth records, adequate methods are required

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to exploit the informative content of remotely sensed hydraulic information. Based on hydraulic geometry relationships, general statistical relationships between air-space borne observations of river characteristics and discharge were developed from Gauckler–Manning–Strickler equation by Bjerklie et al. [7,8] on a large sample of rivers. Note that all of those methods also rely on data about the depth and/or cross-sectional velocity profiles. Recently, [9] use the equations from [7], water depth estimated from altimetric data ERS-2 and ENVISAT and water surface width from Landsat imagery to estimate discharge on the Mekong River. Statistical approaches based on remotely sensed observations of rivers are pertinent; nevertheless satellite measurements such as SWOT ones will not provide information about the key parameters that river bathymetry and roughness are and equifinality problems exist (e.g. [10]). Generally, the determination of the parameters embedded in open channel flow equations is not straightforward and it is still an opened and active research topic. Several studies tested the feasibility of identifying bathymetry and/or discharge with various density of observations, unknown parameters, model complexity and inverse methods.

Roux and Dartus [11] and Roux [12] on synthetic test cases show the potential of water surface width observation to characterize flood hydrograph, with an a priori bathymetry. Roux and Dartus [13] estimated a synthetic flood hydrograph ($Nash \sim 0.9$) by minimizing the distance between 1D shallow-water (SW) model outputs and flood extents observations rather dense in time, assuming the channel geometry and flow resistance variables are known. Based on 2D SW models, variational methods allowing state variables and/or model parameters identification are proposed in [14–16]. For example, this method is tested on the Pearl River (China) where upstream and downstream boundary conditions on water levels can be identified with water levels measured at gauge stations [15]; the river bathymetry and roughness are supposed to be known. Lai and Monnier [17] estimate the inflow discharge and the roughness for synthetic 2D flood plain flows and the use of different densities of spatially distributed water level observations (snapshot of the flood plain). The inverse mathematical model is based on the 2D SW equations and variational data assimilation combining the partial snapshot images and partial time series of water levels at one gauge station. This variational data assimilation framework is applied to the Moselle River in the case of a flood event [18]. Also, it is demonstrated in [18] that the amount of hydraulic information contained in partial in-situ water depth observations and the flood plain SAR image may be insufficient to identify the inflow discharge.

An essential question is the estimation of the bathymetry for the main channel of rivers which is hardly measurable from space or airborne. Durand et al. [19] estimate the bathymetry and discharge of the Ohio river (mean $RMSE \sim 10.9\%$ over one year) through an optimization in the least square sense based on Gauckler–Manning–Strickler's equation with synthetic SWOT measurements. The estimate is based on the conservation of discharge between two reaches and is applicable only if slope variability is significant between two reaches; the river roughness is supposed to be known. Biancamaria et al. [20] improve the estimation of the bathymetry and discharge of an Arctic river through the assimilation of synthetic SWOT observations, assuming that river bathymetry and roughness are known. In [21,22] basic bathymetries (e.g. a single smooth bump) are identified from extremely dense measurements of water levels by inverting an explicit time-step scheme, while the roughness is supposed to be known. For the same kind of bathymetries, an analytical expression of the bathymetry is proposed in [23] in the case of one in-situ observation. This original analytical approach is revisited and re-analyzed in the present study.

Yoon et al. [24] use a 1D simplified SW model forced with input discharges from a rainfall runoff model. They assimilate synthetic observations corresponding to 8–22-days cycles of SWOT with an ensemble Kalman filter. The discharge estimation over the Ohio river basin is improved (mean $RMSE \sim 10.5\%$). They assume the cross section is rectangular and the roughness coefficient are known a priori. Honnorat et al. [25] demonstrate the feasibility of identifying bathymetry, roughness, surface velocity–mean velocity ratio and inflow discharge in a channel by assimilating particle trajectories at the water surface (Lagrangian data); one of the interesting point is the effective bathymetry highlighted, here in the case of a 3D flow over a weir "viewed" by a 2D shallow water model [26].

From real inundation extent observations, Roux and Dartus [27] with a probabilistic method and uncertainty analysis (GSA-GLUE), identify parameters sets composed of river roughness, bathymetry and downstream discharge. Plausible parameters sets are those producing the best likelihoods values when comparing simulated (with 1D permanent SW equations) and observed flow top width. This method is tested for flood events on a 1.5 km reach of a small river; parameter ranges must be defined a priori. Negrel et al. [28] propose a method for large rivers based on Gauckler–Manning–Strickler equation and on the depth averaged velocity profile. This profile is derived from water surface velocities estimations hence somehow imposing the roughness coefficient. The surface velocities are obtained from SAR measurements (e.g. [29]), or more recently from MODIS data with in situ calibration [30]. Given SWOT observables, i.e. river surface elevation, width and slope, [31] propose an inference based on reach averaged Gauckler–Manning–Strickler equation and mass conservation integrated in time between river snapshots. The latter integration introduces a scaling between the data acquisition interval and the roughness coefficient as it is shown in the present study. Then, a Bayesian MCMC method is used to compute a posteriori distribution functions (requiring an hypothesis on the prior distribution function). The algorithm is tested with three twin experiments for one in bank and one out-of-bank flood events on the Severn river in the UK, for three reaches of about 7 km. The sensitivity of the results to the first guess choice is not be investigated.

In the present paper, the identifiability of flow controls as a triplet $(K, b, Q(t))$ formed by river roughness, bathymetry and discharge from SWOT like measurements is investigated into details; resolutions are performed with simple and well controlled inverse methods. The identification of river properties from remotely sensed observations involves a trade-off between inverse model complexity and data informative content, density and accuracy. Somehow, the question examined in the present paper can be formulated as follows: in the SWOT context, which models (direct and inverse) complexity is adapted for retrieving the (bathymetry, roughness) pair, or effective ones, and finally the discharge? This question is of paramount importance to elaborate reliable river dynamic models. First the forward models are re-derived following a decreasing complexity flow equations in the SWOT context, starting from the classical 1D Saint-Venant equations; next the corresponding inverse model formulations are addressed. The river sections/reaches are defined from the observation grid that is given (e.g. 1 km reach length). It is shown that the most complete physical model which allows to separate the bathymetry from the roughness coefficient is the low Froude model (the so called zero inertia SW in [23]). The inverse models built in this study tackle the question of flow representation given the scale of observation grid. Discharge identifications are performed for various flow configurations and in SWOT context. Moreover, the reliability of the effective bathymetry infered, then the resulting (bathymetry-friction) pairs