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Technical Note: Resolution enhancement of flood inundation grids

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S1 Inundation Performance Metrics

Quantitative evaluation of flood inundation grids is commonly accomplished using a diverse set of metrics that communicate and quantify over- and under-predictions and their proportions. To compute these metrics, simulations for maximum inundation are evaluated against some observed binary data grid of wet and dry cells. First, each cell is classified according to Table S1 by comparing the simulated to the observed data grids to generate a confusion map. From this confusion map, the total counts of each of the four classifications is computed. These total counts are then used to calculate the domain-wide inundation metrics commonly used in flood inundation evaluation shown in Table S2.

Table S1. Inundation confusion matrix. For a given simulation, each cell in the domain is compared to the corresponding cell in the observed grid and classified according to this table. Adapted from Wing et al. (2017).

		Simulated	
		Wet	Dry
Observed	Wet	True Positive (TP)	False Negative (FN)
	Dry	False Positive (FP)	True Negative (TN)

Table S2. Flood inundation performance metrics. See Table S1 for acronyms. Adapted from Wing et al. (2017).

Metric	Equation	Poor	Perfect	Description
Critical Success Index	$\frac{TP}{TP+FP+FN}$	0	1	ratio of accurate wet cells to total wet cells and missed wet cells
Hit Rate	$\frac{TP}{TP+FN}$	0	1	portion of observed wet cells reproduced by the model
False Alarms	$\frac{FP}{TP+FP}$	1	0	portion of modelled wet cells which are erroneous
Error Bias	$\frac{FP}{FN}$	0 or inf	1	ratio of over-predictions to under-predictions

S2 Hydrodynamic Model Calibration

To obtain accurate water level grids at coarse ($s2 = 32m$) and fine ($s1 = 4m$) resolutions, twin hydrodynamic models are constructed in the RIM2D platform and calibrated using a mix of brute force and scipy's implementation of the Newton-Conjugate Gradient algorithm (Nocedal and Wright, 2006; Virtanen et al., 2020). Roughness values for built-up and channel/floodplain are treated as two (independent) free parameters for the optimization. A single performance metric, Critical Success Index (CSI) defined in Table S2, is calculated against the observed inundation for each iteration and used to optimize with the free parameters. Optimization trials were undertaken on a Tesla P100 GPU using python scripts.

Results of the two calibration trials are shown in Fig. S1 and S2. The performance metrics shown in Table S2 are also shown; however, only CSI was used for optimization. In general, the fine ($s1 = 4m$) model replicates the target inundation with over- and under-predictions roughly balancing (Error Bias = 1.2) while the coarse model ($s2 = 32m$) generally under-predicts when CSI is optimized (Error Bias = 0.33). Focusing on water surface elevations (which were not part of the optimization), the fine ($s1 = 4m$) model has lower WSE values upstream and higher WSE values downstream when compared to the coarse ($s2 = 32m$); likely owing to the difficulties in modelling the narrower channel in this region at the coarser resolutions. While this difference would be problematic for some hydrodynamic model applications, here we focus on inundation extents – not elevations. If elevations and flow dynamics were the focus, the coarse hydrodynamic model would be an inappropriate choice, because the model resolution is about 3 times larger than the width of the river, which results in the observed deviations in water slope profile compared to the fine resolution model. For an estimation of the flood extent, however, the coarse model can provide useful results despite the deficiencies in simulating the flow dynamics. Because of our focus on flood extent, we use a simple calibration of two roughness parameters to optimize the Critical Success Index which is a measure of fit to the observed inundation extents. It is therefore not surprising that inundation is reproduced well by both models while water elevations are less satisfactory. A more sophisticated (e.g., multi-metric optimization) calibration could have been pursued to try and address this; however, as our paper focuses on downscaling (not model calibration) we felt this would be distracting. Note the performance metrics reported in the manuscript are computed on a smaller domain.

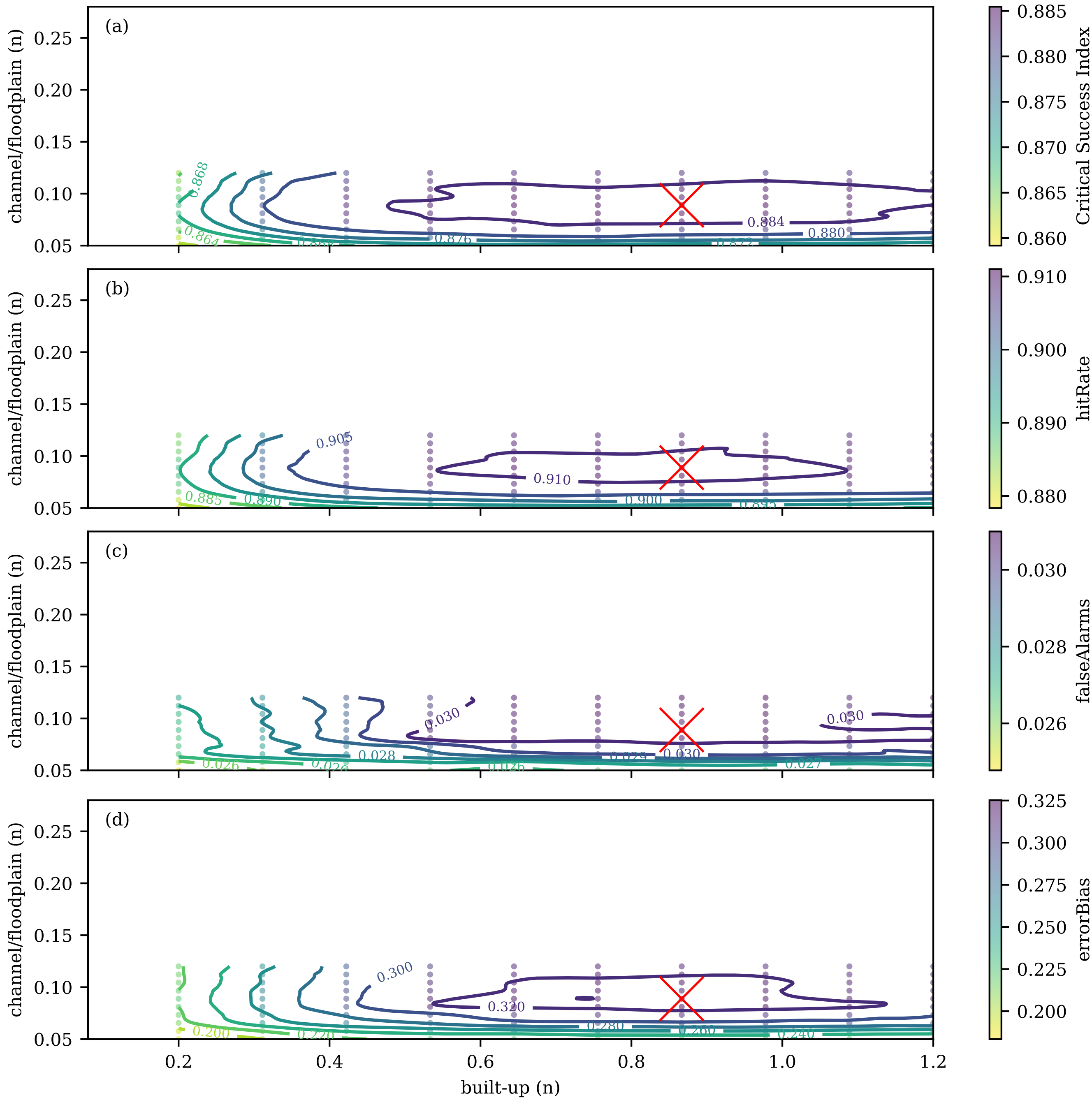

Figure S1. Calibration results for 32 m hydrodynamic model showing the four metrics from Table S2. Points denote individual model runs (at the shown roughness) and contours are computed via interpolation of the metric value at each point. Red ’X’ marks the optimal (using the maximum CSI) and the parameterization used for downscaling.

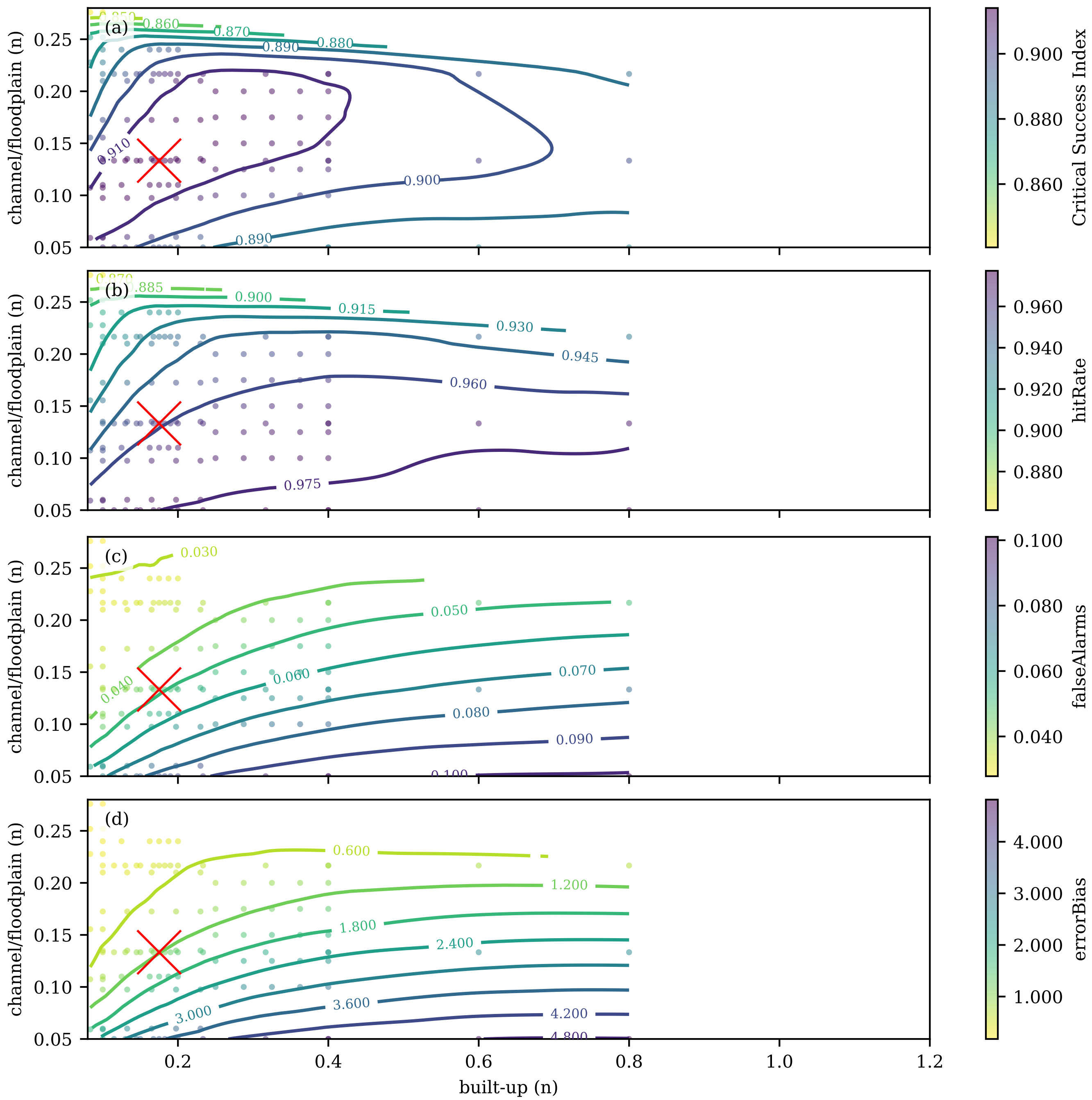

Figure S2. Calibration results for 4 m hydrodynamic model similar to Figure S1.

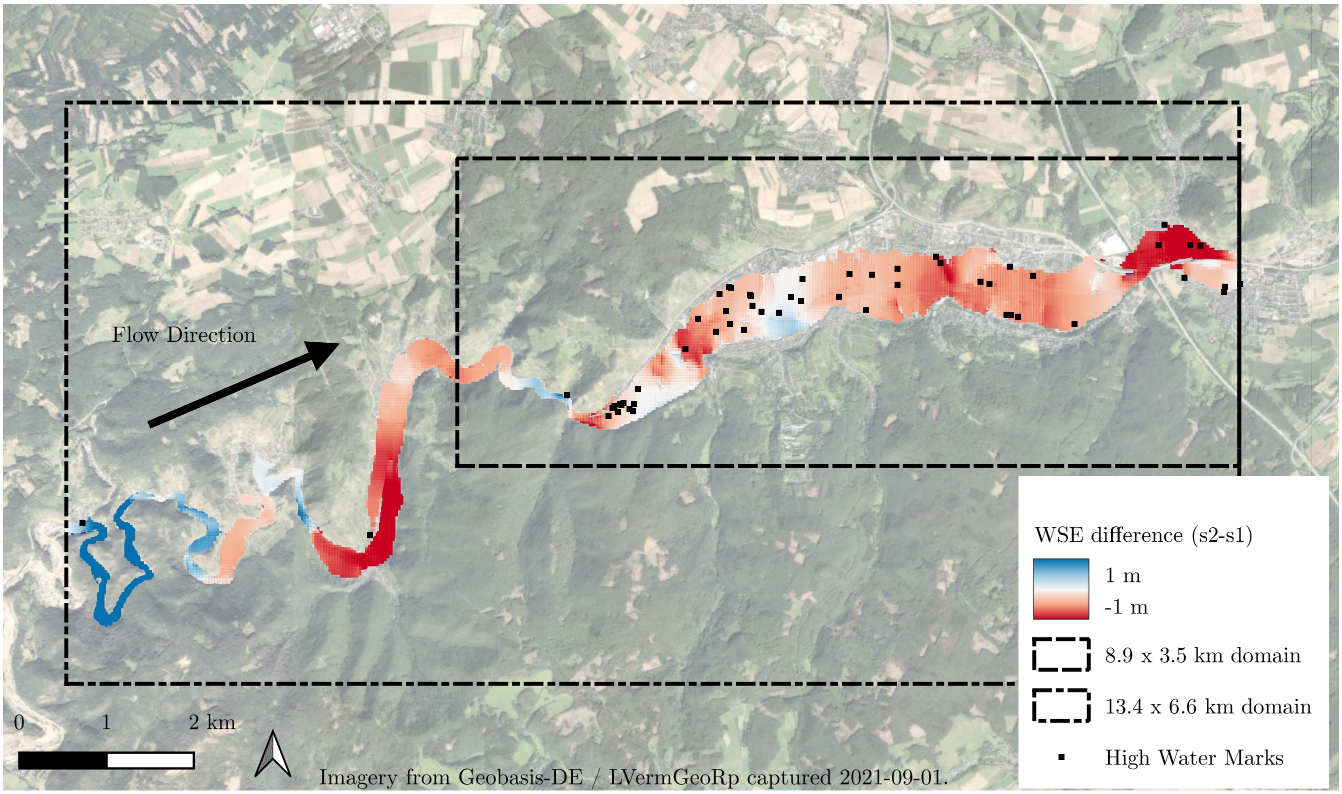

Figure S3. WSE max difference between coarse ($s2 = 32m$) and fine ($s1 = 4m$) models at their respective optimum roughnesses clipped to intersecting inundation region. Red denotes regions where the fine ($s1 = 4m$) solution yielded higher or larger water depths than the coarse ($s2 = 32m$). Domain used for hydrodynamic modelling (13.4 x 6.6 km) and subset used for downscaling analysis (8.9 x 3.5 km) shown in black for reference.

S3 Additional Results Figures

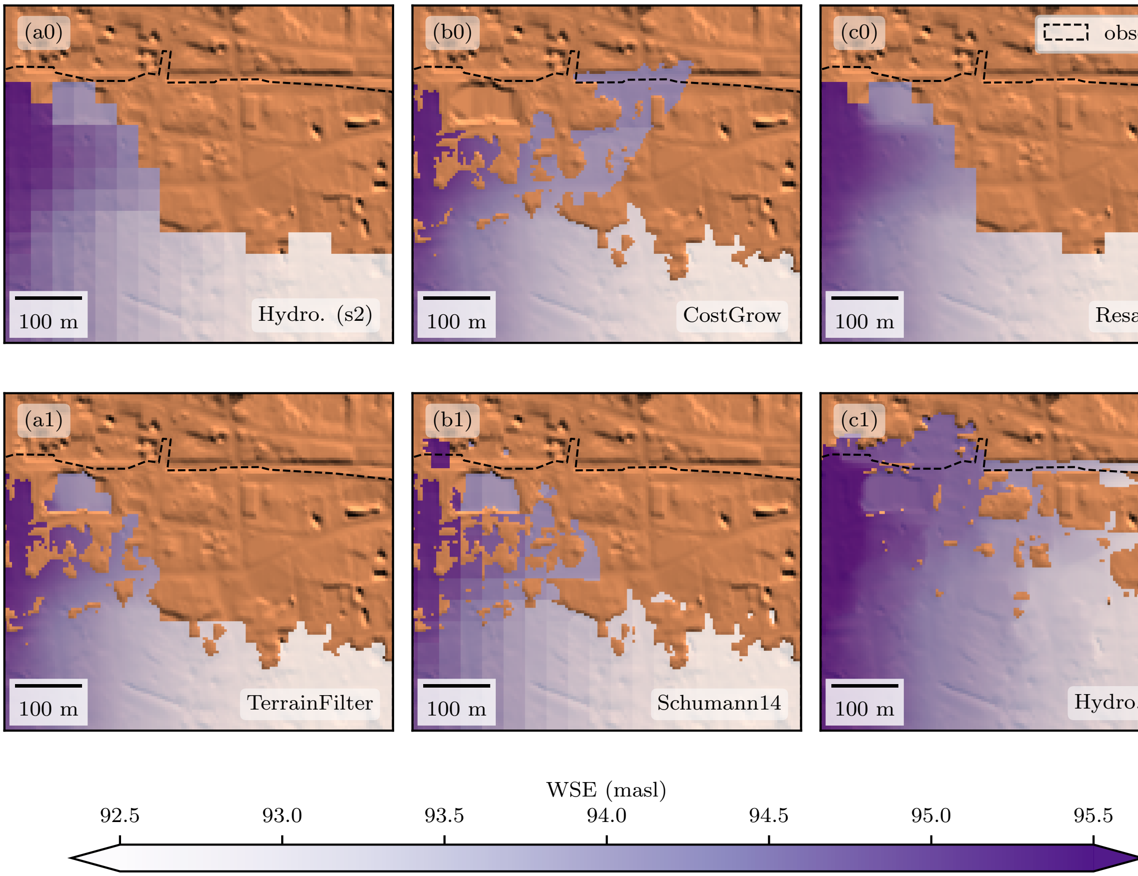

Figure S4. Downscale and hydrodynamic model WSE detail results as in Figure 8 for a separate location.

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