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1 Selecting Between One- and Two-Dimensional Hydrodynamic Models for
2 Ecohydraulic Analysis

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Abstract

Aquatic habitat assessment and river restoration design require geospatially explicit maps of hydraulic conditions. Diverse mechanistic ecohydraulic models compute spatially explicit depth and velocity results to evaluate habitat suitability spatially as a function of these abiotic conditions. This study compared depth and velocity results from two-dimensional (2D) and one-dimensional (1D) hydraulic models with algorithms that laterally discretize 1D velocity and interpolate depth and velocity spatially based on the Laplacian heat mapping approach. These 'conveyance distributed' methods constitute 'best 1D modeling practice', and were compared to 2D results for the first time. The 1D and 2D models were applied to three morphologically distinct reaches (leveed, meandering, and anastomosing) for three flows (base, bankfull, and flood flows) of the partially regulated, gravel/cobble lower Yuba River in north-central California. The test metrics were the coefficient of determination (R^2) and the median absolute residual ($|\tilde{d}|$). These metrics quantified the incremental uncertainty 1D approximation incurs, results which make explicit cost-benefit processes of model selection possible. Finally, velocity residual maps were analyzed to identify regions and processes where residuals were high, indicating divergence from the 1D assumptions. Paired data (1D-2D) fell between $0.94 \geq R^2 \geq 1.00$ ($R^2_{\text{mean}}=0.98$ and $R^2_{\text{median}}=0.99$) for depth and median absolute residuals were all $3.8 \leq |\tilde{d}| \leq 7.2\%$ (i.e. 50% of residuals are approximately within ± 1.7 to 3.6%). Higher flows and lower gradient reaches had lower residuals and higher R^2 . Velocity diverged more, particularly for base flow in anastomosing reaches ($0.42 < R^2 < 0.58$). One-dimensional, conveyance distributed, assumptions performed better for other channel types, where $0.69 < R^2 < 0.81$ ($R^2_{\text{mean}}=0.75$ and $R^2_{\text{median}}=0.77$), with median absolute residuals between $9.6\% > |\tilde{d}| > 22.4\%$ (i.e. $\sim \pm 4.6$ to $\pm 11.2\%$), where $|\tilde{d}|_{\text{mean}}=14.2\%$ and $|\tilde{d}|_{\text{median}}=13\%$ ($\sim \pm 7.1$ and 6.5%). The conveyance distributed 1D velocity model performed best where the orthogonal flow assumptions obtained and where side channels did not transition from backwater to conveying area between flows.

Keywords: hydraulic modeling, river modeling, ecohydraulics, ecohydraulic modeling, gravel-bed rivers

43 1 Introduction

44

45 Many riverine habitat studies and projects require ecohydraulic modeling (Mouton et al., 2007;
46 Wu and Mao, 2007; Hauer et al., 2011; Maddock et al., 2013). Prescribed flows and restoration
47 designs are often based on and evaluated with these models (Elkins et al., 2007; Papanicolaou
48 et al., 2011). Models can yield detailed spatial patterns at “near-census” resolution of ~ 1 m
49 over tens of km of river corridor length, which can provide advantages over purely empirical
50 assessments (Pasternack, 2011). Detailed modeling enables sophisticated spatial analyses,
51 which reveals biotic patterns and ecological functions that are space-dependent (Crowder and
52 Diplas, 2000; Grantham, 2013; Pasternack et al., 2014), including emerging individual based
53 bioenergetic modeling (Weber et al., 2006; Railsback et al., 2012; Hafs et al., 2014). Models can
54 also analyze the ecohydraulics of potential river restoration designs, which data and empirical
55 analyses cannot, since designed hydraulic conditions cannot be measured prior to construction
56 (Bockelmann et al., 2004; Pasternack et al., 2004; Jacobson and Galat, 2006; Pasternack and
57 Brown, 2013). River scientists, engineers, and restoration practitioners must understand the
58 opportunities and limitations of different ecohydraulic modeling approaches (Brown and
59 Pasternack, 2009; Pasternack and Senter, 2011; Jowett and Duncan, 2012).

60

61 Ecohydraulic models are often applied to decrease operational uncertainty in river assessment
62 study or restoration design evaluation (Snowling and Kramer, 2001). Therefore, model
63 selection negotiates technical, practical, and social tradeoffs to determine appropriate simulation
64 complexity, optimizing the uncertainty reduction price point according to a cost-benefit analysis,
65 either explicitly or unconsciously. Assessing benefits include estimating incremental uncertainty
66 reductions offered by each modeling approach to select the approach commensurate with
67 project’s risks and resources (Gibson, 2013).

68

69 Spatially distributed depth and velocity maps are the most common hydraulic modeling product
70 used as input for microhabitat modeling (Pasternack, 2011). Four approaches are available to
71 develop these products: (i) 1D statistical modeling using transects, (ii) 1D hydraulic modeling,
72 (iii) 2D hydraulic modeling, and (iv) 3D hydraulic modeling. However, the ecohydraulic literature
73 mostly frames model selection as a choice between 1D statistical models and 2D numerical
74 models (e.g., Sawyer et al., 2010), because most practitioners employ traditional transect data
75 collection with statistical extrapolation (Payne and Bremm, 2003; Payne et al., 2004) whereas
76 mechanistic ecohydraulic modelers have largely skipped over 1D hydraulic modeling to resolve
77 spatial dependencies (Leclerc et al., 1995; Elkins et al., 2007). This work tests the hypothesis
78 that 1D numerical models with lateral discretization algorithms represent a viable intermediate
79 level of complexity for ecohydraulic analysis.

80

81 At least 18 comparisons of the results of 1D and 2D numerical models have been published in
82 recent years to evaluate opportunities and limitations in environmental science and
83 management applications (Ahmad and Simonovic, 1999; Waddle et al., 2000; Horitt and Bates,
84 2002; Werner, 2004; MacWilliams et al., 2006; Lee, 2006; Tayefi et al., 2007; Cook, 2008;
85 Bohorquez and Darby, 2008; Alho and Aaltonen, 2008; Chatterjee et al., 2008; Brown and
86 Pasternack, 2009; Clifford et al., 2010; Pasternack and Senter, 2011; Prestininzi et al., 2011;
87 Leandro et al., 2011; Bladé et al, 2012; Jowett and Duncan, 2012). Though insightful, results
88 were mixed (Gibson, 2013). In several studies, particularly large flood models with naturally
89 orthogonal channel features at flood scales, 1D models performed well (Ahmad et al, 1999;
90 Horitt and Bates, 2002; Gibson, 2005; Lee, 2006; Tayefi et al, 2007; Alho and Aaltonen, 2008;
91 Jowett and Duncan, 2012). However, in highly complex non-orthogonal morphologies 1D results
92 diverged from the 2D or 3D models (Waddle et al. 2000; MacWilliams et al. 2006; Lee, 2006;
93 Brown and Pasternack, 2009). 1D models also under-performed in reaches with difficult-to-
94 identify, non-orthogonal hydraulic controls that transects modeled poorly or missed all together
95 (Pasternack and Senter, 2011). Thus, a key factor in selecting model dimensionality appears to
96 be in the orthogonality and complexity of landforms present at scales and investigation needs to
97 address.

98

99 Even with this extensive literature, two substantial data gaps complicate incremental uncertainty
100 reduction comparisons between numerical 1D and 2D approaches:

- 101 1. Evaluating Laterally Discrete 1D Velocity Algorithms: Only five studies compared 1D
102 and 2D velocities. Four compared 2D results with cross section averaged 1D model
103 velocities (MacWilliams et al, 2006; Brown and Pasternack, 2009; Pasternack and
104 Senter, 2011; Jowett and Duncan, 2012) and one study compared 2D results to lateral
105 velocity data collected at a few locations, interpolated in one dimension (Waddle et al.,
106 2000). None of the studies compared 2D models to “conveyance distributed 1D”
107 velocity results, where cross section average velocities from 1D models are post
108 processed to compute laterally explicit velocities, which represent ‘best practice’ for 1D
109 velocity modeling.
- 110
111 2. Spatially Explicit Comparison of Depth and Velocity: Ecohydraulic applications require
112 spatially distributed hydraulic depth and velocity results. To evaluate a 1D model for
113 ecohydraulic analysis, 1D results must be translated into 2D depth and velocity grids and
114 compared in this spatial framework. No spatially explicit comparisons of depth or
115 velocity grids generated from 1D and 2D hydraulic model results were found.
116 Additionally, most of the studies focused on comparing models for flood flows rather than
117 for in-channel flows critical to ecohydraulic analysis. Revealing how spatial patterns
118 change systematically as a function of discharge is important, because nonuniform
119 channels exhibit flow-dependence of geomorphic processes (MacWilliams et al., 2006;
120 Brown and Pasternack, 2014), habitat quality and abundance (Leclerc et al., 1995;
121 Bovee et al., 1998), and interactions between the two (Pasternack et al., 2008; Hauer et
122 al., 2011)

123

124 This study addressed these two data gaps, comparing spatially explicit, conveyance distributed
125 1D hydraulic model results against comparable 2D output. Depth and velocity maps were
126 computed for three morphologically distinct reaches on the Yuba River, at three ecologically
127 important flows with a 2D model and a conveyance distributed 1D. The model comparison
128 addressed three specific research questions, each with hypotheses and test metrics (Table
129 1)**Error! Reference source not found..**

130 **2 Study Area**

131

132 The Yuba River is a tributary of the Feather River, the north-eastern tributary of the Sacramento
133 River, in northern California (Fig. 1). The river is topographically diverse and highly disturbed.
134 The Yuba river watershed is 3,480 km² and includes contributing area from 10 m elevation
135 valley floodplains to 2,774 m Sierra Peaks (Moir and Pasternack, 2008). This geographic
136 diversity creates a down gradient morphological succession that was useful for this study. The
137 river transitions from a steeper bedrock canyon (Pasternack et al., 2010) to valley-confined with
138 braiding at wide sections (White et al., 2010), to anastomosing (where flood flows spread into
139 multiple, relatively persistent channels), to meandering with moderate gradient, and, finally, to a
140 confined, low gradient, leveed channel just upstream of its confluence with the Feather River in
141 Marysville, CA.

142

143 The river also has a long history of disturbance including an early era (1850-1940) of placer,
144 hydraulic and dredger gold mining, which left the system with a unique and recognizable aerial
145 view and a complex story of sediment load and non-stationarity, followed by a later overlapping
146 era (1910-present) of valley confinement by training berms, debris dams, and eventual,
147 construction of the Englebright dam and consequent flow regulation. However, despite a
148 complex history of landform and flow modifications, frequent overbank flooding and easily
149 mobile alluvium have enabled the lower Yuba River to rapidly adjusted its flow-form dynamics to
150 yield diverse landforms at morphological unit to segment scales (Carley et al., 2012; Wyrick and
151 Pasternack, 2012, 2014). The river supports a diverse fish community (Kozlowski, 2004) and is
152 widely viewed as a lynchpin to maintaining and restoring the salmonid meta-populations in the
153 northern Central Valley region (YARMT, 2013).

154 **3 Methods**

155

156 Three geomorphologically distinct reaches (channelized, meandering, and anastomosing) of the
157 lower Yuba River were modeled at three flows (20% of bankfull discharge, bankfull, and four
158 times bankfull) with the one-dimensional hydraulic model HEC-RAS (USACE, 2010) and the
159 two-dimensional hydraulic model SRH-2D (Lai, 2008; Pasternack, 2011). Modeling specialists

160 applied each model to assure 'skill control' and remove asymmetrical modeler ability as a
161 confounding variable. Both modeling efforts began with the same raw bathymetry data and
162 specified flows, applying best modeling practice for 1D and 2D approaches without reference to
163 the approach or results of the other. HEC-RAS and the GIS post-processor HEC-GeoRAS
164 (USACE, 2009) generated two dimensional depth and velocity grids for each of the nine
165 conditions (three reaches at three flows) from the 1D results. These grids were then compared
166 to the results of an existing, validated two-dimensional SRH-2D model of the lower Yuba River
167 (Barker, 2011; Abu-Aly et al., 2013; Pasternack et al., 2014) to quantify the error introduced by
168 the 1D assumptions. Errors were reported in a flow-reach morphology matrix. Although the 2D
169 model was heavily tested for uncertainty using traditional and novel validation tests, validation
170 data were not collected with the intention of calibrating and validating a 1D model
171 independently; this study is an opportunistic scientific exploration involving model comparison to
172 better understand modeling practices and trade-offs.

173

174 3.1 Reach Selection

175

176 Reaches were selected from a detailed river corridor digital elevation model (DEM) of the lower
177 Yuba, constructed using a combination of ground-based, boat-based, and remote sensing
178 methods (Carley et al., 2012; Pasternack et al., 2014). For the lowermost 28.3 km of the river
179 from which the three study reaches herein were selected, the overall mean subaqueous grid
180 point spacing within the 24.9 m³/s wetted area was one point every 1.3 m. (59.8 pts/100 m²)-
181 though with patches having larger gaps where data collection was hazardous or otherwise
182 difficult- while for the subaerial river terrain at that flow the overall mean grid point spacing was
183 one point every 0.43 m. (554 pts/100 m²). This point density was sufficient to capture the roles
184 of sub-width topographic nonuniformity on hydraulic modeling.

185 [Based on the multi-scalar landform assessment study of Wyrick and Pasternack \(2012\), three morphologically distinct](#)
186 [reaches were selected \(](#)

187 [Table 2\)](#). Reach 1 is a low gradient, confined, urban, leveed channel. Upstream about 4 km,
188 Reach 2 is a moderate gradient meandering section with alternate point bars. Reach 3 is an
189 anastomosing reach with multiple parallel channels and additional side channels at higher flows.
190 Upstream reaches included more backwater zones, floodplain connectivity, flow splits, hydraulic
191 roughness, hydraulic separation zones, steeper slopes, and morphological diversity. While no
192 single metric explains the morphological gradient in a simple monotonic trend, the progression
193 of the combined metrics along Reach 1→Reach 2→Reach 3 fits a gestalt impression of
194 increasing "complexity." However, because of the unhelpful connotations and semantic range
195 of the term complexity, trends will be described in reference to 'gradient' (where Reach 1 is
196 down gradient and Reach 3 up gradient), with basic downstream (Reach 1) to upstream (Reach
197 3) terminology or single thread (Reach 1 and 2) versus multi-thread (Reach 3) when
198 appropriate.

199 3.2 The 2D Model

200

201 This study utilized output from an existing 2D model of the Yuba River developed by co-author
202 Pasternack in collaboration with the Yuba Accord River Management team. Barker (2011) and
203 Pasternack et al. (2014) described the full details of model development and testing. The 2D
204 model was heavily scrutinized through by scientists, and managers, and is now used for diverse
205 applications in both arenas. SRH-2D (Lai, 2008) was used to model ~35 km of the lower Yuba
206 River, from the Englebright Dam to the confluence with the Feather River, except for a ~ 2-km
207 section with unmapped rapids in The Narrows bedrock canyon. The mixed structured-
208 unstructured computational mesh had a typical intermodal spacing of 0.91 to 1.5 m for base and
209 bank full flow and a near uniform 3 m mesh for flood flows.

210

211 The 2D model was validated (Barker, 2011) using independent datasets for water surface
212 elevations, depths, and velocity magnitude and direction collected over a range of discharges
213 (~14 to 170 m³/s). A few performance metrics are provided herein with the full analysis
214 available in Barker (2011). Model mass conservation was within 1%. Mean, signed, water
215 surface elevation residual was -1.8 mm for 197 observations at 24.92 m³/s. For unsigned
216 residuals, 27% were within 3.1 cm, 49% were within 7.62 cm, 70% within 15.25 cm, and 94%
217 within 30.5 cm. Depth observations from cross section surveys yielded a good coefficient of
218 determination (R^2) of 0.66 (n=199). Barker (2011) measured velocity magnitude using two
219 different ways to make a robust validation analysis - one with a traditional cross-section
220 approach suitable for a small number of observations with high accuracy and one using a new
221 approach involving Lagrangian particle tracking. For the former approach, 40-s average velocity
222 magnitude was measured at the standard 0.6-depth vertical position for the same 199 points
223 where depth was observed along traditional cross-sections with either a Marsh-McBirney® Flo-
224 Mate electromagnetic current meter sampling at 30 Hz or a Price AA mechanical impellor
225 current meter. However, for assessing 2D model performance for 33-km of channel over an
226 order of magnitude of flows, the traditional method should be balanced by a rapid observation
227 strategy that provides far more data. Therefore, the Lagrangian surface velocity vector tracing
228 method of Stockdale et al., (2007) was improved upon by switching from differential GPS to
229 real-time kinematic GPS and from unattended floats to a manned kayak wherein one may
230 carefully insure that the kayak adheres to the direction and magnitude of velocity. As the kayak
231 moves with the flow, positions are measured with ~ 0.02-0.05 m accuracy every 5 s and then
232 these positions are differenced over that time interval to yield surface velocity magnitude, which
233 is assigned to the midpoint between each adjacent pair of position observations. Surface
234 velocities are next converted to depth-averaged values using the proper regression equation for
235 the two established for the river. Although this adds some uncertainty for each point, one can
236 measure thousands to tens of thousands of velocities per day covering many kilometers of
237 channel, so the statistical robustness of the predicted versus observed regression relation is far
238 greater compared to that when only a few hundred points are used, yielding an overall superior
239 validation assessment. Methodological details are explained in the ecohydraulics textbook by
240 Pasternack (2011). Using this method, the 2D model yielded an R^2 of 0.79 between predicted
241 and observed. Median unsigned velocity magnitude error was 16%, significantly smaller than
242 commonly reported (Wyrick and Pasternack, 2014; Brown and Pasternack, 2014).

243

244 The SRH-2D model was used to analyze three ecologically interesting flows in this study: base
245 ($28 \text{ m}^3/\text{s}$), bankfull, ($142 \text{ m}^3/\text{s}$), and floodplain filling ($597 \text{ m}^3/\text{s}$) flows – events with >99, 83, and
246 40% annual exceedance probabilities, respectively. Even though Abu-Aly et al. (2013)
247 developed and published on a meter-scale spatially distributed Manning's n scheme using
248 relative surface roughness (i.e., ratio of vegetation canopy height to water depth) obtained from
249 LiDAR data, for this study model runs that exclusively had a universal Manning's n-value (0.04)
250 were used to remove spatial roughness distribution as a confounding variable from the
251 comparison instead of the more complex vegetated models used for the final Yuba analysis. In
252 cases where complex vegetation patterns are present and important to the ecohydraulic
253 problems in question, this could be a deciding factor to use a 2D model and the scheme of Abu-
254 Aly et al. (2013).

255

256 3.3 The 1D Model

257

258 HEC-RAS models were developed for the three selected reaches. A thalweg shape file,
259 computed during the 2D modeling, became the stream center line and HEC-GeoRAS was used
260 to cut cross sections from the TIN used for the 2D model every one-to-two channel widths.
261 Each reach was initially modeled with a single computational reach in the 1D model (i.e. no flow
262 splits). The base n-value (0.04) from the 2D model was applied to the channel and over banks
263 in the 1D model. However, it is common practice (Brickler et al., 2014) to calibrate 1D n-values
264 to multiple flows, specifying flow dependent adjustments to the roughness parameters.
265 Therefore, water surface elevations were extracted from the 2D simulations at the intersection
266 of every other cross section and the stream center line. The “flow roughness factors” in HEC-
267 RAS were adjusted to calibrate the 1D water surface elevations to the 2D water surface
268 elevations. Factors used and the resulting residuals are included in **Error! Reference source**
269 **not found.** and

270 Table 4.

271 An experienced 1D modeler might identify Reach 3 as a good candidate for a ‘split flow’ 1D
272 modeling approach. Split flow modeling is actually an intermediate level of complexity between
273 1D and 2D modeling with intermediate costs and parameterization demands. Although a full
274 presentation is beyond the scope of this article, Reach 3 was also modeled with a split flow 1D
275 approach (Fig.3). Split flow results were compared to the single reach results (Gibson, 2013).

276 3.4 Computing Spatially Explicit Velocity Maps From 1D Results

277

278 Traditionally ecohydraulics involved sampling-based statistical analysis of hydraulic conditions
279 to quantify the statistical relationships between discharge and weighted usable area (Payne et
280 al., 2004). However, ecohydraulics has shifted toward a spatially explicit characterization of
281 habitat in the last decade, with meter-scale prediction of both presence and absence of biotic

282 habitat utilization (e.g., Elkins et al., 2007). As a result, ecohydraulic literature addressing
283 scientific exploration of spatial physical-biotic linkages and meter-scale habitat predictions often
284 dismiss 1D models, because cross section averaged velocities cannot achieve these outcomes.
285 However, HEC-RAS includes analytical methods that compute lateral velocity distributions from
286 cross section averaged results and translates these into velocity maps, which are rarely
287 discussed in ecohydraulic literature and have never been evaluated relative to the results of 2D
288 or 3D models. These methods are widely available in public domain software and include, (i)
289 post processing 1D cross section averaged velocities analytically to compute lateral velocity
290 distributions at each cross section and (ii) spatial interpolation of these laterally discrete
291 velocities based on the Laplace equation to compute a smooth 2D velocity map that follows
292 logical flow paths.

293 3.4.1 Analytical Lateral Velocity Distributions

294

295 After computing cross section averaged velocities to determine water surface elevations, HEC-
296 RAS uses conveyance principles to compute a lateral velocity distribution at each cross section
297 (Fig. 3). The algorithm uses Manning's equation to partition the 1D cross-section velocity into
298 up to 45 laterally discrete 'flow prisms' across the cross section. The non-linearity of Manning's
299 equation generates non-additive conveyance weighted velocities, so the algorithm initially
300 computes a weighted sum of the prism velocities that does not match the 1D cross section
301 velocity. Therefore, after the distributed velocities are computed, they are scaled to ensure the
302 weighted average velocity is the same as the overall velocity computed by the 1D analysis,
303 conserving cross section conveyance (USACE, 2010).

304 3.4.2 Interpolating and Mapping Velocity

305

306 Once lateral velocity distributions are computed at each cross section, a second algorithm
307 translates those results into a 2D velocity grid that can be compared to 2D model results.
308 Interpolating a simple TIN from a velocity point shape file produces noisy velocity maps with
309 spurious results, particularly in meandering channels. Therefore, HEC-GeoRAS includes
310 algorithms that guide inter-cross section velocity interpolation.

311 HEC-RAS computes the centroid of each flow prism and assigns coordinates to the prism
312 velocity, generating an x, y, velocity geodatabase. Then HEC-GeoRAS uses the Laplace
313 equation to develop smooth, curvilinear, transitional streamlines between the stream centerline,
314 the river banks, and the flood boundary (excluding any ineffective flow areas) to guide velocity
315 interpolation between cross sections according to physically reasonable flow paths. The
316 laterally explicit, analytical velocity distribution and the Laplacian interpolation produce a 2D
317 velocity grid from the 1D velocities that can be compared to 2D results.

318 These methods for converting 1D results into a 2D velocity grid are approximate, *ad hoc*, and
319 empirical. But they represent 1D velocity mapping 'best practices' and there is no detailed
320 published attempt to rigorously evaluate their performance. Evaluating their performance on
321 ecohydraulic scales is the primary objective of this work. The combined effects of the

322 conveyance weighted subdivision of the 1D-cross section averaged velocity and the Laplacian
323 mapping approach with be referred to as “conveyance distributed 1D” velocity results, for
324 simplicity.

325 3.5 Evaluation Metrics

326

327 For each reach and flow, the 1D depth and velocity grids were superimposed on the 2D grids.
328 One-dimensional results at each cell were plotted against 2D result and the coefficient of
329 determination (R^2) was computed for each scenario. Additionally, residuals (ε) were computed
330 for each cell, where:

$$331 \quad \varepsilon = \frac{1D_{result} - 2D_{result}}{2D_{result}} \quad (1)$$

332 (Clifford et al., 2005) and the “median absolute residual” ($|\tilde{\varepsilon}|$) was computed to summarize the
333 residuals of each scenario into a single parameter. Velocity residuals were also mapped for
334 each reach and flow to provide context for the summary statistics and generate spatial intuition.
335 Both metrics were used to evaluate results in order to escape analysis artifacts that emerge
336 from the limitations of either statistic, and support conclusions independent of the individual
337 liabilities of each metric.

338 4 Results

339 4.1 How well does a 1D model replicate 2D depth results?

340

341 The 1D model predicted depths well by both test metrics. The 1D depth predictions were more
342 reliable downstream and at higher flows (Table 5; Fig. 4). All reaches and flows returned
343 $R^2 \geq 0.94$ ($R^2_{\text{mean}}=0.98$ and $R^2_{\text{median}}=0.99$) and median absolute residuals were all $|\tilde{\varepsilon}| \leq 7.2\%$ (i.e.
344 50% of residuals are approximately within $\pm 3.6\%$ for the worst case). Additionally the flood
345 flows returned $R^2 \geq 0.99$ and median absolute residuals $|\tilde{\varepsilon}| \leq 4.0\%$ (i.e. 50% of residuals are
346 approximately within $\pm 2.0\%$) for all reaches.

347 4.2 How well does a conveyance distributed 1D model replicate 2D velocity results?

348

349 Velocity residuals were larger and R^2 smaller than depth results (

350 Table 6; Fig.5). Coefficients of determination for velocity results fell between $0.42 \leq R^2 \leq 0.81$,
351 ($R^2_{\text{mean}}=0.70$ and $R^2_{\text{median}}=0.73$). Median absolute velocity residuals ($|\tilde{\varepsilon}|$) were substantially
352 larger and less sensitive to flow and reach type than depth results, including the range $9.6\% \leq$
353 $|\tilde{\varepsilon}| \leq 22.4\%$ (approximately ± 4.6 to 11.2%) with means and medians of $|\tilde{\varepsilon}|_{\text{mean}} = 14.2\%$ and
354 $|\tilde{\varepsilon}|_{\text{median}} = 13\%$.

355 Velocity residual trends were not as easily interpreted as those for depth. R^2 increased
356 monotonically with depth for the meandering and anastomosing reaches (Reaches 2 and 3) but
357 decreased with flow for the channelized reach (Reach 1). Alternately, the bankfull flow returned
358 the minimum median absolute residual for each reach, while the maximum residual was
359 associated with the base flow for Reaches 1 and 3 and flood flow for Reach 2. Additionally,
360 Reach 2 had the highest median absolute residual (for flood flow) and the lowest R^2 (for base
361 flow), both precluding monotonic trends by gradient. Flood flow residuals make more sense in
362 their spatial context, discussed below, but the unusually low R^2 associated with the Reach 2
363 base flow helps categorize these results in the absence of generalized trends.

364 Two of the nine scenarios had R^2 substantially lower than the others: base flow for the
365 meandering and anastomosing reaches (Reaches 2 and 3). Upon closer inspection, these
366 conditions represent similar processes and can be grouped. The “meandering reach” does, in
367 fact, meander for high flows. However, Reach 2 at base flow, the condition with the lowest R^2 ,
368 includes three substantial flow splits affecting 30% of total reach length (versus 48% of the
369 anastomosing reach at base flow), making Reach 2 an anastomosing reach at base flow.
370 Therefore the data can be stratified by this condition. The model performed poorly for
371 anastomosing base flows ($0.42 < R^2 < 0.58$) but performed better and more consistently, ($0.69 <$
372 $R^2 < 0.81$, $R^2_{\text{mean}}=0.75$ and $R^2_{\text{median}}=0.77$) for all other conditions.

373 4.3 What Hydraulic processes generate large velocity residuals? 374

375 Velocity residuals were larger and more spatially interesting than depth results. Therefore, the
376 residual maps for each flow in Reach 1, Reach 2, and Reach 3 are included in Figures 6, 7, and
377 8 respectively. The convention of Blue for negative ($2D > 1D$) and red for positive ($1D > 2D$)
378 residuals is used throughout. The largest velocity residuals were associated with backwater
379 zones ($2D > 1D$) and in the separation zones downstream of outcrops, islands and boulevards
380 ($1D > 2D$). The analysis also returned substantial residuals in side channels and flow separation
381 zones. The multi-channel complex in the downstream section of Reach 3, which transitions
382 between backwater at low flows to active flood conveyance at flood flows was also a region of
383 particularly high residuals. Finally, where the models predicted overbank flooding, the 1D model
384 consistently over-predicted velocity in the channel and under predicted velocity in the floodplain
385 in all three reaches.

386 4.4 Split Flow Results 387

388 Split flow modeling results were mixed. The summary statistics (R^2 and $|\tilde{r}|$) are reported in
389 Table 7. The split flow model improved depth R^2 and residuals for all flows. R^2 improvements
390 were substantial for base flow (0.89 to 0.96) but $|\tilde{r}|$ improvements were much more modest
391 (0.2-1.1%). Stratifying residuals spatially revealed a more complex story.

392 In the classic, persistent split flow region of Reach 3 (the “Long Bar” in Fig.3), the split flow
393 model dropped residuals substantially, approximately halving $|\tilde{r}|$ for each flow. However, in the
394 multi-reach complex at the downstream end of the model Fig.3), where channels transitioned

395 from dry, to backwater zones, to conveying reaches in different models, split flow modeling did
396 not substantially improve depth results and, in some cases increased residuals.

397 The split flow model also increased velocity R^2 for all flows, sometimes substantially, particularly
398 for the problematic base flow anastomosing conditions (Reaches 2 and 3 at the lowest flow),
399 raising R^2 above the 0.7 threshold for all reaches. However, split flow effects on velocity
400 residuals were more modest and not universal. Split flow improved 1D residuals a little (2.1 to
401 2.2%) for the base flow bank full condition, but not for flood flow (where $|\tilde{v}|$ decreased by
402 1.1%). These trends also obtained for the long bar region, where velocity residuals dropped
403 substantially for bank full flow, but modestly for base flow and increased for flood flow.

404 5 Discussion

405

406 5.1 Process Discussion

407

408 The highest depth residuals occurred in zones where the 1D assumptions broke down (Fig.9),
409 like side channels, backwaters, separation zones, and around islands. The 1D model requires a
410 single water surface elevation across the channel, while side channels and backwaters can
411 maintain distinct water surface elevations, generating 1D depth residuals. The 1D model also
412 overpredicted depth downstream and underpredicted depth upstream of obstructions like
413 islands, where localized momentum effects cause stage depression and super elevation
414 respectively, which the 1D model does not simulate.

415 Some of these depth divergence features translated directly into velocity divergence.
416 Overpredicting flow in side channels led and under predicting flow in backwaters generating
417 velocity residuals that were larger than the corresponding depth residuals, consistent with
418 Pasternack et al.'s (2006) finding that errors amplify as they propagate through depth, velocity,
419 and shear computations respectively.

420 Velocity residuals upstream of islands diverged from depth residuals. Super elevation upstream
421 of islands did not translate into appreciable velocity residuals above background. However,
422 velocity residuals downstream of islands were much larger than depth residuals. Velocity
423 residuals around an island in Reach 2 were rescaled in Fig.10 to illustrate the region of
424 maximum divergence (>100%). However, the most egregious residuals mapped within the 2:1
425 expansion zone, which represents the 'rule of thumb' criteria for designating an 'ineffective flow
426 area' to model a non-conveying zone downstream of an obstacle in a 1D model (HEC, 1995;
427 USACE, 2010).

428 Finally, the 1D model tended to overpredict channel velocity and under predict floodplain
429 velocity, implying that the conveyance assumption used in lateral velocity distribution is not
430 complete, and includes simplifications that introduce bias. These trends obtain in the flood flow
431 results of each reach and are responsible for the particularly high residuals for the flood flow of
432 Reach 2, the condition with the most flood plain area. However, they are best illustrated in the

433 relatively simple single bar in from Reach 1 (Fig.11), where there are fewer confounding
434 influences. While the 1D model discretizes flow laterally, based on conveyance, it does not
435 account for viscous losses or momentum transfer between these lateral flow prisms. Therefore,
436 the conveyance distributed, 1D approach tends to overpredict velocities for the deepest prisms
437 with the most inter-prism surface area for lateral momentum exchange. When individual prism
438 velocities are normalized to make the flow average velocity match the 1D cross section velocity,
439 overbank velocities are reduced to compensate for over predicted velocities in the channel,
440 making them under predict. This result is anecdotal and cannot necessarily be generalized.
441 But it highlights an artifact of the analytical lateral velocity distribution that will cause 1D results
442 to diverge from 2D velocities. This would have serious implications if this lateral distribution
443 scheme were used for ecohydraulic analysis of flood refugia, avulsion or toe scour. Even when
444 1D models like HEC-RAS compute edge effects like toe scour, they post process 1D shears
445 with *ad hoc* radial shear partitions, to compute a vertical shear distribution similar to the lateral
446 'conveyance distributed' velocity partition (Gibson *et al.* 2015).

447 The complex relationship of velocity residuals highlights an advantage of 2D models in multi-
448 channel analysis: 'generality.' A 1D split flow model must be designed for a particular flow, in
449 this case, the bank full flow, which is why the split flow improvements were greatest for bank full
450 flow, for both model as a whole and the long bar in particular. The 1D flow split is determined *a*
451 *priori* for a particular flow, which introduces error in higher and lower flows (Fig.12). This cross
452 section lay out separates conveyance at river stations that are connected at higher flows and
453 artificially connects channels that are separated at lower flows, while a 2D modeling domain has
454 the property of *generality*, customizing the flow split around the island for each discharge. A 1D
455 model can mitigate these effects with a lateral structure to model flow exchange over the bar,
456 but adding a lateral structure adds complexity to the 1D model and did not appreciably improve
457 the basic velocity residual trend in this case.

458 5.2 Interpretive Implications of Uncertainty in 2D results

459

460 The above analysis treats the 2D model results as ground truth and evaluates the 1D model
461 based on its ability to reproduce them. However, model evaluation theory often recognizes the
462 implications of ground truth data uncertainty in the process of model evaluation. 2D models of
463 gravel/cobble bed rivers have assumptions and limitations as well. Both roughness
464 parameterization and turbulence closure are well known problems afflicting the type of model
465 used herein. Similarly, 2D model assumptions break down in meanders and steep rapids, both
466 of which occur in the modeled reaches, though the resulting loss in accuracy with decreasing
467 suitability of the assumptions is not well illustrated in the literature. Further, the 2D model
468 assumes a no slip boundary along the bed, but because the bed is highly porous this is not true.
469 In terms of limitations, airborne LiDAR mapping of subaerial terrain and single-beam
470 echosounder mapping of subaqueous terrain have high uncertainty relative to the precision of
471 model predictions and thus accurate topography remains the key limitation as well understood
472 from past studies (Anderson and Bates, 1994; Marks and Bates, 2000; Pasternack *et al.*, 2006).

473 Both the number of velocity validation observations and the goodness of fit in the 2d LYR model
 474 were among the highest ever reported for a 2D velocity calibration (Wyrick and Pasternack,
 475 2014), plus this study was among the rare few that actually evaluated velocity direction. For the
 476 base flow anastomosing reaches (Reaches 2 and 3 for the lowest flow) the performance of the
 477 1D model, as indicated by the velocity R^2 , was underwhelming ($0.42 < R^2 < 0.58$), substantially
 478 less than the implicit uncertainty of the 2D model. However, the 2D model's uncertainty
 479 ($R^2=0.784$) is comparable to that observed between 1D and 2D results in the other seven reach-
 480 flow pairs ($R^2_{\text{mean}}=0.75$ and $R^2_{\text{median}}=0.77$).

481 Several classical model evaluation metrics reduce the residual by the uncertainty of the
 482 observed data, including Relative Mean Absolute Error (RMAE) such that:

$$483 \quad RMAE_{Depth} = \frac{|H_c - H_m| - \Delta H_m}{H_m} \quad \text{and} \quad RMAE_{Vel} = \frac{|V_c - V_m| - \Delta V_m}{V_m} \quad (2)$$

484 where H_c is computed depth, H_m is measured depth, V_c is computed velocity, V_m is measured
 485 velocity and ΔH_m and ΔV_m are the error in the measured depth and velocity respectively. In this
 486 case, where the 1D is the computed and 2D is 'measured' the analogy would be:

$$487 \quad RMAE_{Depth} = \frac{|H_{1D} - H_{2D}| - \Delta H_{2D}}{H_{2D}} \quad \text{and} \quad RMAE_{Vel} = \frac{|V_{1D} - V_{2D}| - \Delta V_{2D}}{V_{2D}} \quad (3)$$

488 RMAE assumes that the residuals between the 1D and 2D model and the 2D model and the
 489 velocity observations are uncorrelated, and, therefore, on average, counteracting. In this case,
 490 considering the uncertainty in the 2D could improve the relative results of the 1D model in
 491 comparison. However, if these residuals (1D vs 2D and 2D vs measured) are correlated, then
 492 they will be additive, decreasing the value of the 1D results. Because physical observations
 493 spanned the entire lower Yuba, there were not enough in the considered reaches to incorporate
 494 2D residuals explicitly in 1D-2D comparison. However, it is worth noting that outside of base
 495 flow for anastomosing reaches, the 1D to 2D comparisons generated R^2 s on the order of the 2D
 496 to measurement comparisons. Overall, more systematic studies that evaluate the performance
 497 of 1D and 2D models with incrementally greater degrees of violation of assumptions would
 498 benefit the understanding and application of hydraulic models.

499

500 5.3 Non-Statistical Implications for Model Selection

501

502 The discussion above provides data on the 'benefit' side of a cost-benefit approach to model
 503 selection. It presumes that moving from a 1D to a 2D model represents a substantial and easily
 504 quantifiable cost increase (usually in the form of bids or scope of work proposals), that can now
 505 be compared to the benefit of incremental uncertainty reduction for a matrix of morphologies
 506 and flows documented in Fig. Figure 4, Table 5, Fig.5, and

507 Table 6

508 However, there are at least two, non-statistical considerations that should frame these results
509 and their application to a cost-benefit approach to model selection:

- 510 1. The 1D model used tight cross section spacings in this study, on the order of 1 to 2
511 channel widths. These are not unusual if a complete digital elevation model, including
512 both channel and overbank bathymetry, exists (Kootenai Tribe, 2014; Shelley and
513 Gibson, 2015; USACE, 2009; Bales et al., 2007). The cost of cutting new cross sections
514 on a digital landscape is minor, though because automated methods are still not
515 recommended, it does increase effort. However, acquiring a detailed, “near-census”
516 (i.e., meter-scale) bathymetry is often the primary cost of 2D modeling. Near-census
517 bathymetry can be used for many purposes beyond just the 2D model study, so more
518 river managers are collecting it. On the other hand, in the absence of near-census
519 bathymetry, 1D models can have problems if important hydraulic controls in the river are
520 not known *a priori* or are known but are not assigned cross-sections. This can happen if
521 the controls are underwater and difficult to see, especially for long reaches with poor
522 accessibility. The incremental cost of moving from a 1D to a 2D model can be small
523 compared to the cost of acquiring detailed bathymetry. This 1D-2D comparison
524 presumes that detailed bathymetry already exists and does not inform a common
525 decision between modeling the system with a 1D model based on existing, surveyed,
526 widely spaced cross sections and investing in the bathymetry to make a 2D model
527 possible. As the incremental cost of moving from a 1D to a 2D model decreases, a
528 thinner uncertainty reduction (benefit) justifies moving to the 2D model.
529
- 530 2. This study controlled for modeler skill by entrusting the 1D and 2D modeling to
531 specialists. However, 2D models handle more of the physics explicitly and, therefore,
532 require fewer modeling ‘tricks’ and subjective modeling decisions (e.g. bank stations,
533 flow split locations, and ineffective flow areas in a multi-reach complex). 1D modeling is
534 more sensitive to modeler decisions, making the simpler model, counter intuitively, more
535 sensitive to modeler skill. Therefore, 1D model results are more variable than 2D
536 results. Vulnerability to user variability (Dawdy and Vanoni, 1986) adds to 1D
537 uncertainty in ways this study did not capture.

538 6 Conclusions

539
540 This study compared results from conveyance distributed 1D depth and velocity modeling,
541 including analytical lateral velocity computations and Leplacian mapping algorithms for inter-
542 cross section mapping, to 2D results for three flows in three morphologically distinct reaches.

543 The 1D goodness of fit was between $0.94 \leq R^2 \leq 1.00$ ($R^2_{\text{mean}}=0.98$ and $R^2_{\text{median}}=0.99$) for depth
544 and median absolute residuals were all $3.8\% \leq |\bar{r}| \leq 7.2\%$ (i.e. 50% of residuals are approximately
545 within ± 1.7 to $\pm 3.6\%$). Higher flows and lower gradient reaches with fewer side channels and
546 backwaters had lower depth residuals.

547 The velocity goodness of fit fell between $0.42 < R^2 < 0.81$, but the anastomosing base flows were
548 much worse ($0.42 < R^2 < 0.58$) than the other seven conditions ($0.69 < R^2 < 0.81$, $R^2_{\text{mean}}=0.75$ and
549 $R^2_{\text{median}}=0.77$). Velocity residuals were substantially higher than depth residuals, spanning
550 $9.6\% > |\tilde{v}| > 22.4\%$ (e.g. 50% of the residuals fell approximately between $\pm 4.6\%$ for the best 1D
551 model and $\pm 11.2\%$ for the worst) with means and medians of $|\tilde{v}|_{\text{mean}}=14.2\%$ and $|\tilde{v}|_{\text{median}}=13\%$
552 (50% of residuals falling within approximately ± 7.1 and $\pm 6.5\%$ respectively). The highest
553 residuals were concentrated in backwaters, flow separation zones, island velocity shadows, side
554 channels, complex, and multi-reach reaches, particularly where some reaches transition
555 between backwater to conveyance as flow increases. Additionally, the 1D analytical lateral
556 velocities algorithm consistently over predicted velocity in the channel and under predicted
557 velocity in the flood plain. While split flow improved depth results substantially ($\sim 50\%$) in a
558 classic bifurcation situation, it was less effective in a multi-channel complex and did not improve
559 velocity results substantially or universally. Opportunities for additional research include
560 evaluating the sensitivity of conveyance weighted modeling results to the number of prisms
561 (initial investigation suggest rapid diminishing returns for more than three to five prisms) and
562 translating the error incurred by selecting a simplified model into some measure of project risk.

563 Many comparisons of 1D and 2D models return conclusions that the latter are better than the
564 former (Bohorquez and Darby, 2008; Tayefi et al., 2007; Brown and Pasternack, 2009;
565 Prestininzi et al., 2011), that model results are comparable (Alho and Aaltonen, 2008; Horitt and
566 Bates, 2002) or, sometimes, that a particular 1D model outperformed a particular (usually
567 gridded) 2D model for a particular situation (Jowlett and Duncan, 2012; Gibson, 2005). But this
568 is not the most useful model selection question. The pertinent management question is not, “is
569 a 2D model better than 1D model?” A well constructed, high resolution, multi-dimensional
570 model with comparable features (e.g. algorithms to simulate hydraulic structures) should
571 outperform a 1D model constructed at a comparable scale with comparable expertise.

572 Instead, the pertinent questions are “how much better is the 2D answer than the 1D answer?”
573 and “does the risk reduction achieved by selecting 2D justify upgrading from the 1D option?” A
574 cost benefit analysis between levels of modeling complexity requires quantifying benefits to
575 compare to the costs. This work helped quantify those benefits, the incremental uncertainty
576 reductions of moving from a 1D to 2D modeling framework, to allow explicit cost-benefit
577 approaches to model selection.

578

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580

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775 **Table 1: Research questions, hypotheses and test metrics.**

Question	Hypothesis	Metric and Test Applied to Evaluate
Question 1: How well does a 1D model replicate 2D depth results?	1D depth residuals will be relatively small but will increase upstream (e.g. channelize residuals < meandering residuals < anastomosing residuals).	<ol style="list-style-type: none"> 1. Computed depth residuals between each cell of the 1D and 2D depth grids and the evaluate residual distributions, summarizing them with a 'median absolute residual depth' statistic. 2. Plot 1D depths against 2D depths (scatter plot) and evaluate the performance of the 1D model based on the R^2 of the relationship.
Question 2: How well does a conveyance distributed 1D model replicate 2D velocity results?	1D velocity residuals will be much larger than the depth residuals and will also increase upstream.	<p>Compare 1D and 2D velocity results with the same metrics and analyses as the depth residuals (from Question 1):</p> <ol style="list-style-type: none"> 1. Median absolute velocity residual. 2. Scatter plot, slope, R^2.
Question 3: What Hydraulic processes generate large 1D residuals?	1D results will diverge from the 2D results in regions where lateral velocities are significant (e.g. flow separation, flow shadows, backwaters).	Map residuals to identify regions of high residual, and associate the hydraulic process connected to these regions.

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777 **Table 2: Morphological metrics and classifications of the three reaches.**

	Reach 1	Reach 2	Reach 3
Entrenchment Ratio ($2XQ_{max}$)*	2.2	1.7	0.8
Entrenchment Ratio ($2XD_{max}$)*	4.6	1.7	1.0
Width/Depth Ratio	23	73	41
Sinuosity	1.18	1.07	1.19
Slope	0.00058	0.0017	0.0022
Gradation (d_{mean})	9-107 mm	47-116 mm	61-179 mm
Rosgen Classification	C3c	C3/4	D3

778 *computed for a water surface profile twice the max flow

779 **computed for a water surface profile twice the max depth

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Table 3: Flow-roughness factors used to calibrate 1D Reaches.

Flow	Reach 1	Reach 2	Reach 3
Base Flow (28 cms)	1.1	1	1.2
Bank Full (142 cms)	0.99	0.95	1.1
Flood Flow (497 cms)	1.03	1	1.06

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Table 4: Average calibration residuals and standard deviation of residuals (cm) after application of flow roughness factors.

Flow	Reach 1	Reach 2	Reach 3
	Average/SD	Average/SD	Average/SD
Base Flow (28 cms)	-0.2/6.0	-2.7/8.1	-0.7/10.8
Bank Full (142 cms)	-0.5/4.4	-0.3/4.0	-1.5/7.8
Flood Flow (497 cms)	-1.0/3.6	-1.3/5.2	-1.5/8.4

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Table 5: Median relative depth residuals for the three reaches and three flows modeled.

	Reach 1	Reach 2	Reach 3
	Confined	Meander	Anastomosing
Base Flow	3.9%	6.4%	7.2%
Bank Full	2.0%	3.6%	5.4%
Flood Flow	0.5%	2.6%	4.0%

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Table 6: Median relative velocity residuals for the three reaches and three flows modeled.

	Reach 1	Reach 2	Reach 3
	Confined	Meander	Anastomosing
Base Flow	12.9%	13.0%	18.1%
Bank Full	9.6%	12.7%	14.6%
Flood Flow	10.2%	22.4%	16.2%

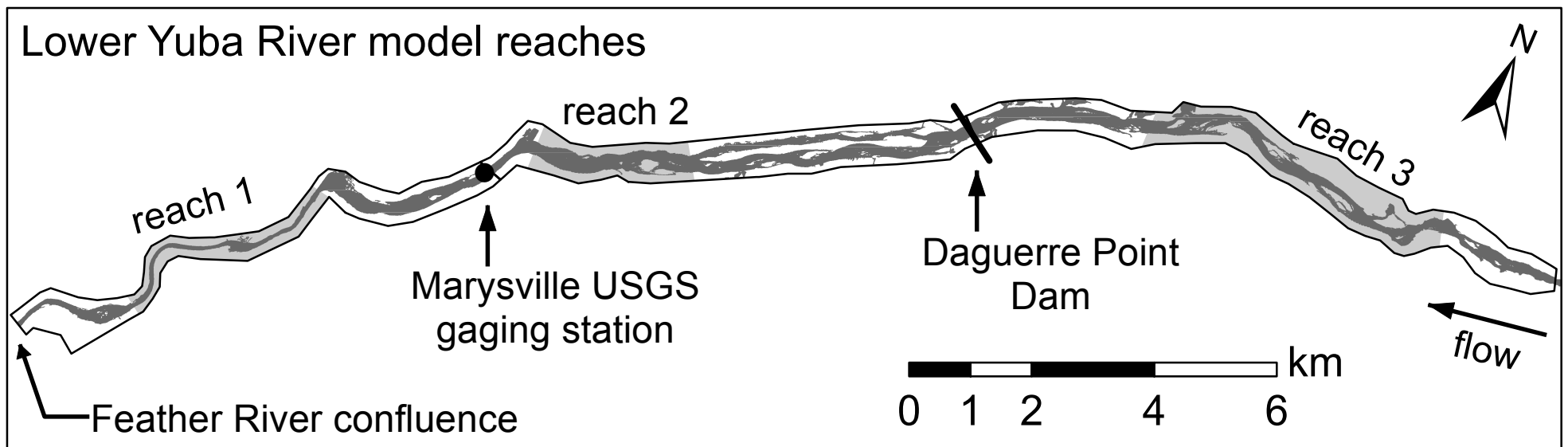
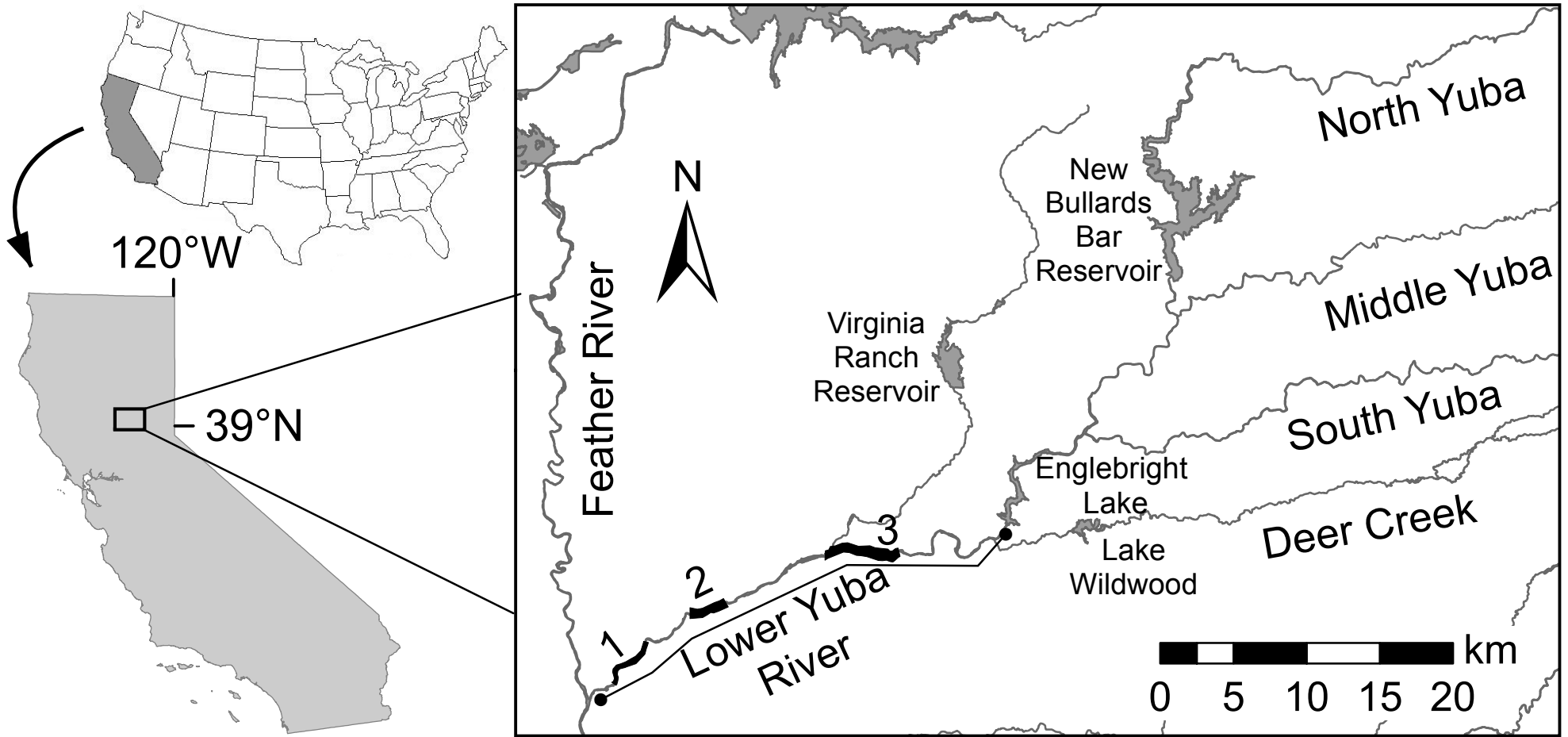
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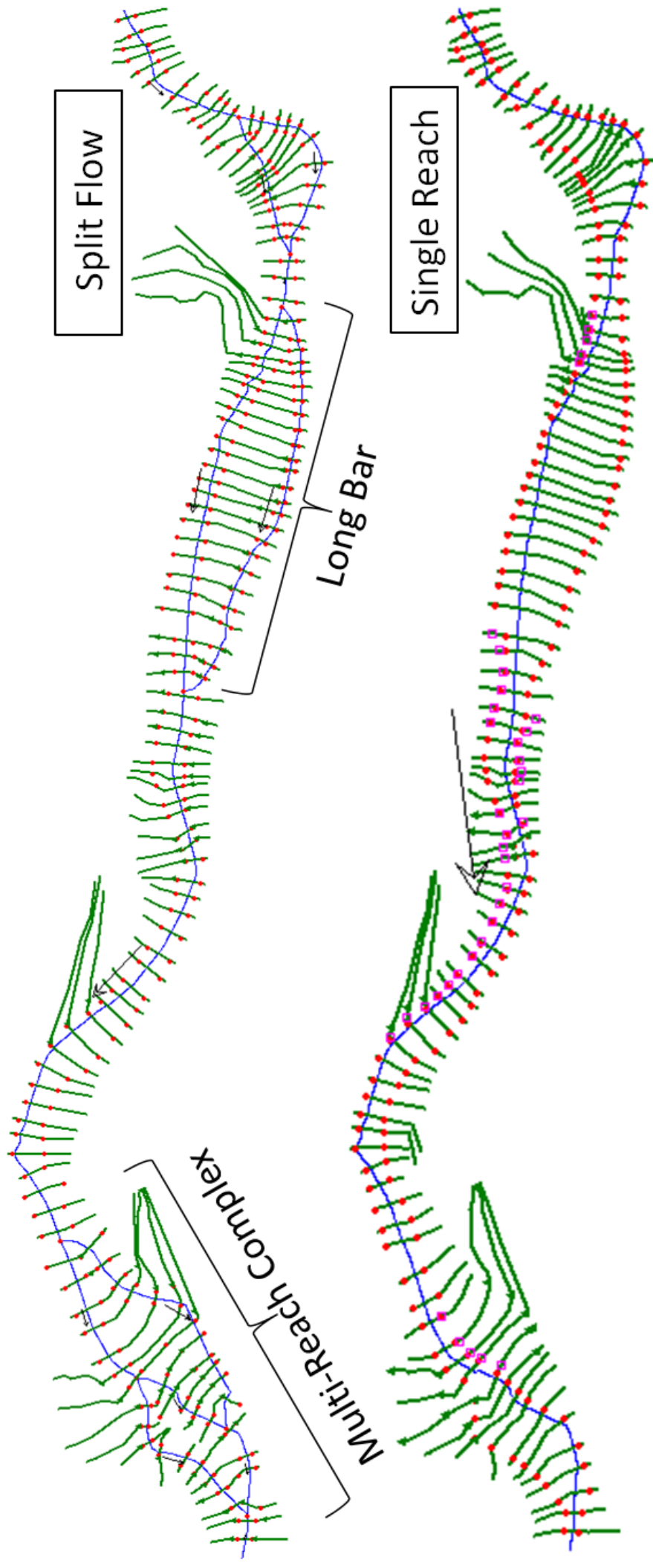
Table 7: Coefficient of Determination and Median Absolute Residuals for Reach 3, for all three flows, with the single reach and split flow modeling approaches.

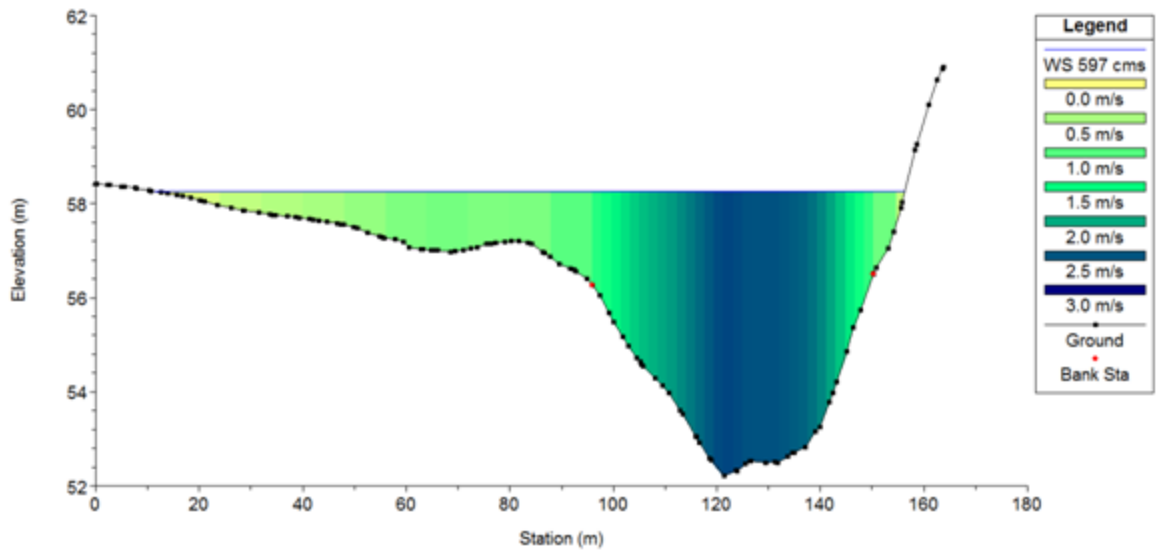
	Depth		Velocity	
	Reach 3	Reach 3	Reach 3	Reach 3
	Single Reach	Split Flow	Single Reach	Split Flow
	$R^2 / \tilde{d} $	$R^2 / \tilde{d} $	$R^2 / \tilde{d} $	$R^2 / \tilde{d} $
Base Flow	0.89/7.2%	0.96/6.9%	0.52/18.1%	0.70/16.6%
Bank Full	0.96/5.4%	0.97/4.3%	0.69/14.6%	0.77/12.5%
Flood Flow	0.98/4.0%	0.98 /3.8%	0.81/16.2%	0.84/17.3%

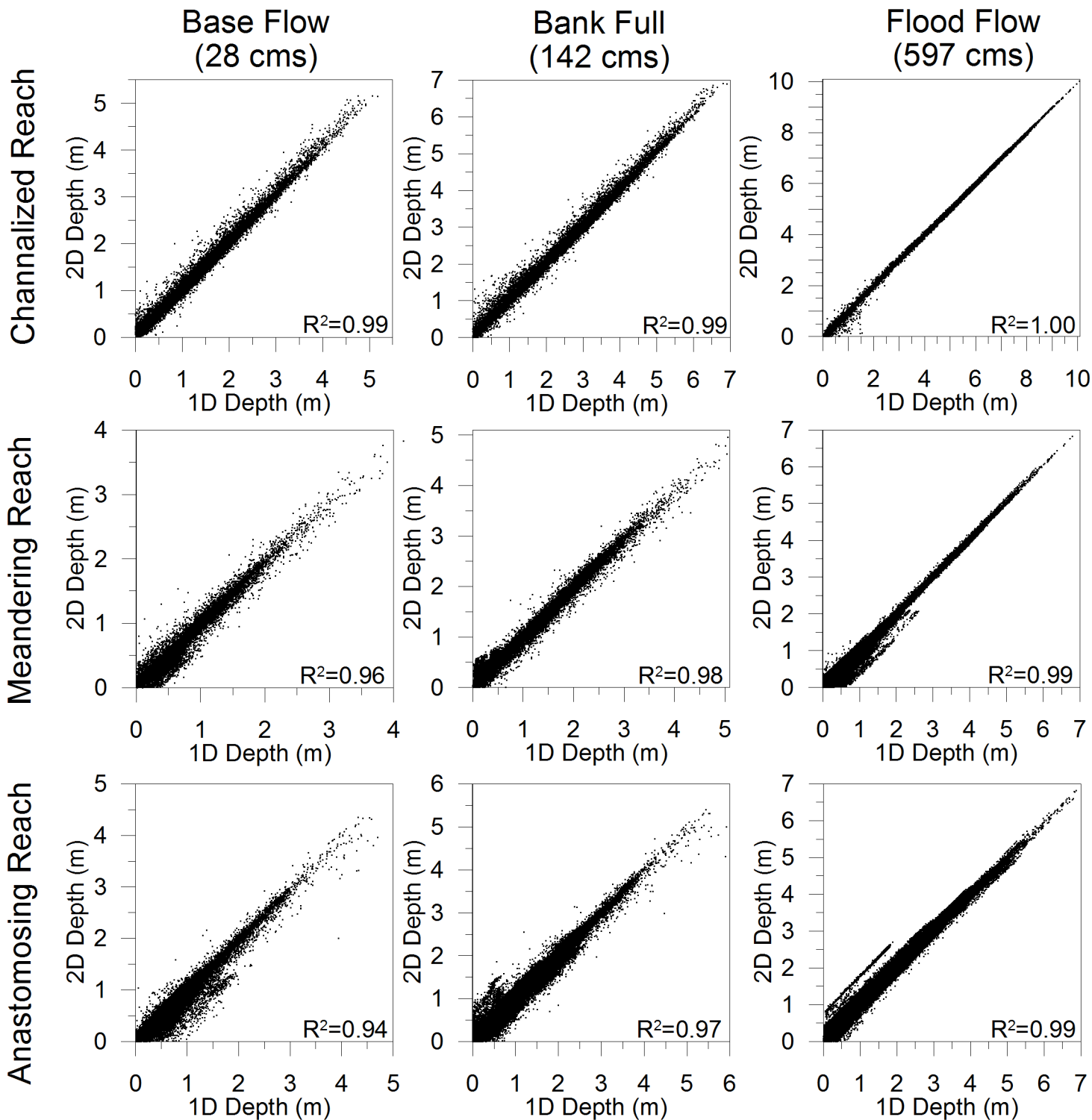
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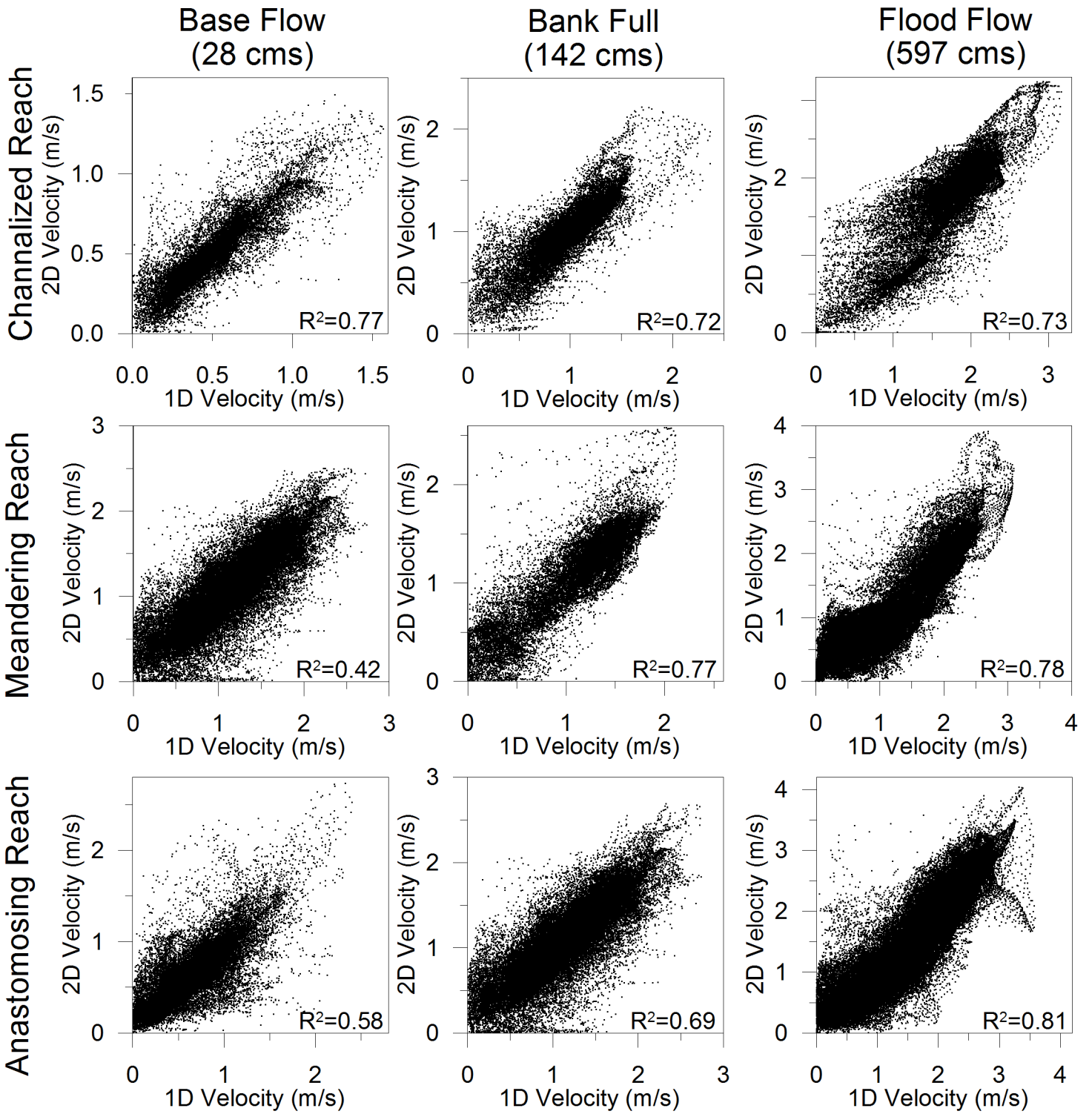
- 804 **Figure 1: Map of the lower Yuba River with the three modeling reaches.**
- 805 **Figure 2: HEC-RAS geometries for split flow and single reach models for Reach 3.**
- 806 **Figure 3: Cross section velocity plot from HEC-RAS, where laterally distributed velocities are computed from the section**
807 **average velocity with conveyance principles. HEC-RAS computed a composite cross section weighted velocity of 2.0 m/s for**
808 **this cross section and a composite channel velocity of 2.4 m/s.**
- 809 **Figure 4: Scatter plot depth results and coefficient of determination for paired 1D and 2D depth results from each grid cell.**
- 810 **Figure 5: Scatter plot velocity results and coefficient of determination for paired 1D and 2D velocity results from each grid**
811 **cell****Figure 6: Velocity residuals for the three flows in Reach 1.**
- 812 **Figure 7: Velocity residuals for the three flows in Reach 2.**
- 813 **Figure 8: Velocity residuals for the three flows in Reach 3.**
- 814 **Figure 9: Depth and velocity residuals for the flood flow in Reach 2 with high residual zones annotated.**
- 815 **Figure 10: Zone of maximum velocity residual with 2:1 expansion rule of thumb for ineffective flow areas.**
- 816 **Figure 11: 1D velocity map, 2D velocity map and velocity residual map of the classical bar geometry in Reach 1.**
- 817 **Figure 12: Schematic of errors introduced at flows higher and lower than the design flow for 1D, split flow, modeling.**
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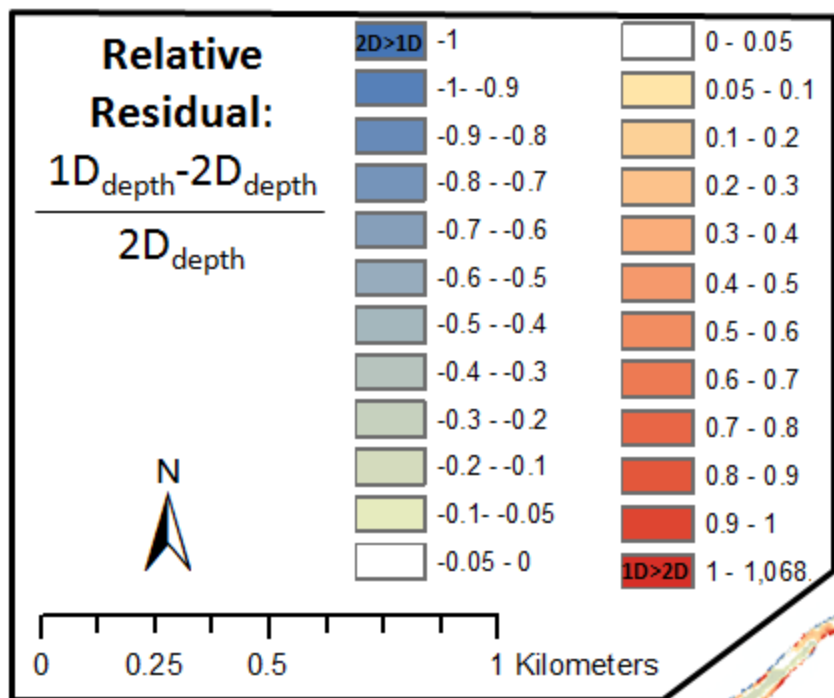










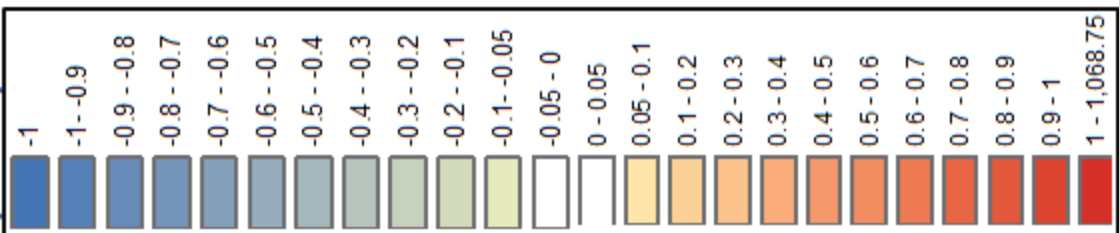


Base Flow
28 cms

Bank Full
142 cms

Flood Flow
597 cms

(2D>1D)

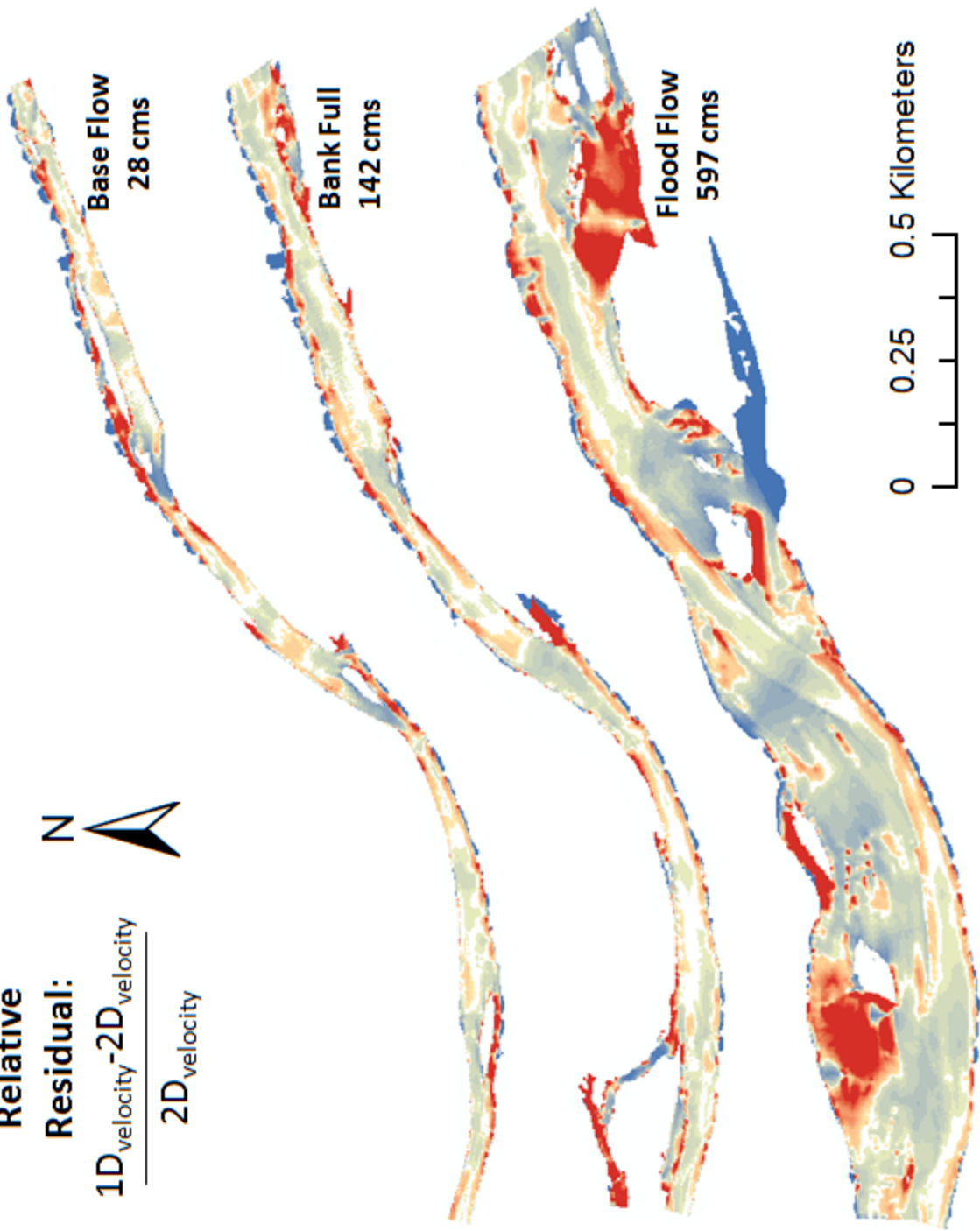


Relative

Residual:

$$\frac{1D_{\text{velocity}} - 2D_{\text{velocity}}}{2D_{\text{velocity}}}$$

$2D_{\text{velocity}}$



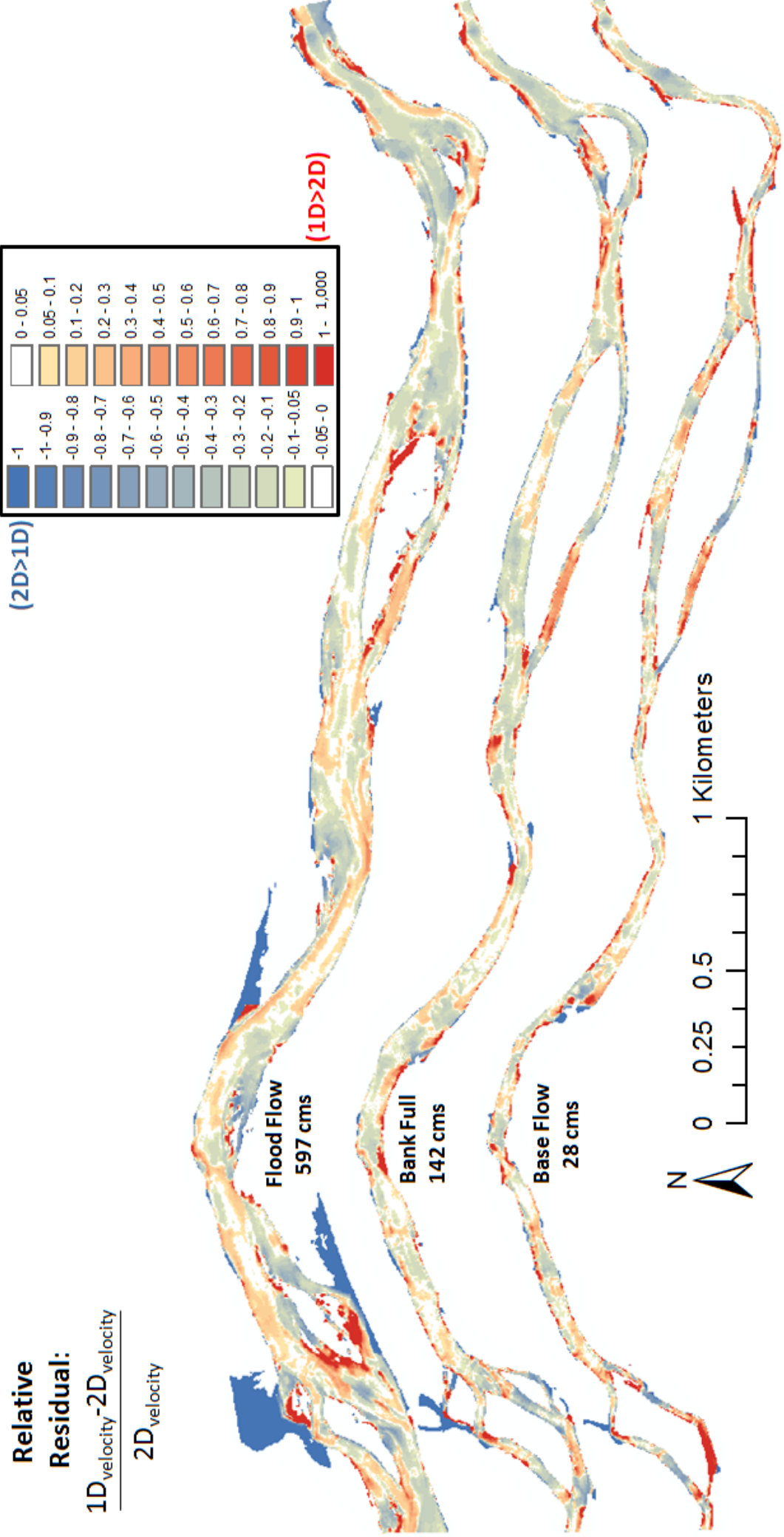
Base Flow
28 cms

Bank Full
142 cms

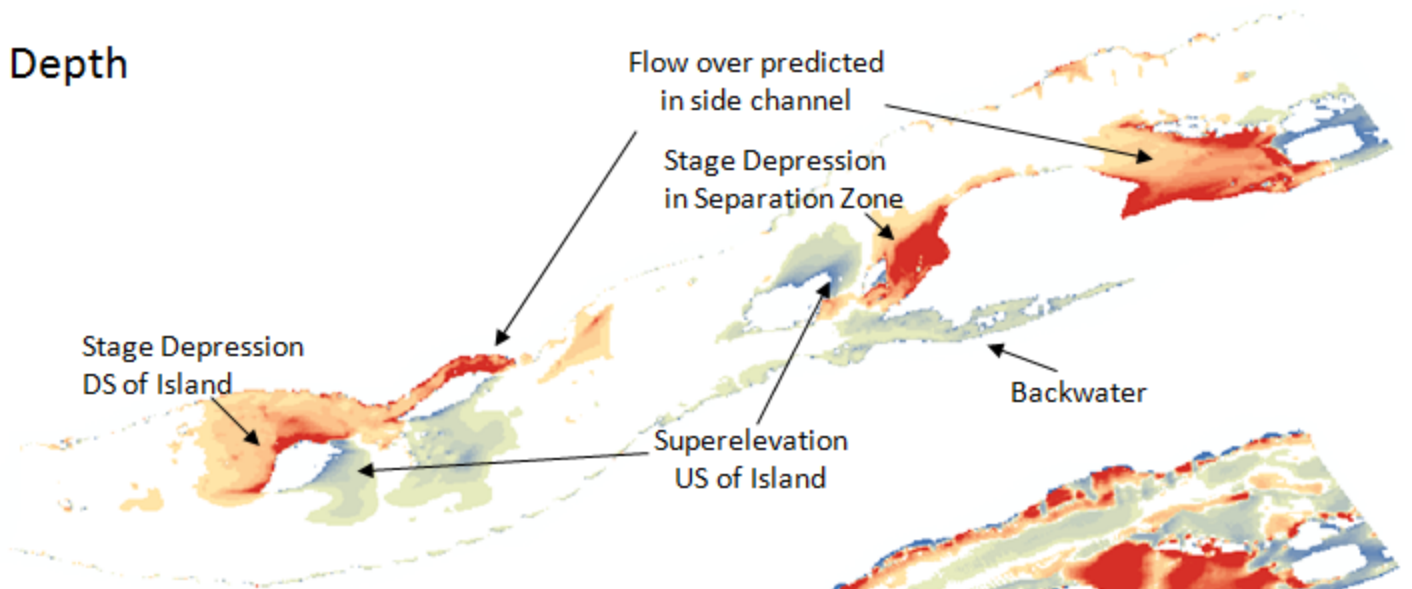
Flood Flow
597 cms

0 0.25 0.5 Kilometers

(1D>2D)



Depth



Velocity

