# The Influence of Floodplain Channel Connectivity on Flood Hydrodynamics

Scott Robert David<sup>1</sup>, Jonathan A. Czuba<sup>2</sup>, Douglas Arthur Edmonds<sup>3</sup>, and Adam Scott Ward<sup>3</sup>

<sup>1</sup>University of Massachusetts Amherst <sup>2</sup>Virginia Tech <sup>3</sup>Indiana University Bloomington

November 26, 2022

#### Abstract

High-resolution topographic data reveal that meandering river floodplains can contain complex floodplain-channel networks. However, the influence of this topography on flood initiation and progression is unknown. In this study, we investigate how floodplain-channel networks influence flooding processes in low-gradient river systems. To accomplish this, we conducted a series of numerical modeling experiments using a two-dimensional (2-D) model built in Hydrologic Engineering Center's River Analysis System (HEC-RAS). First, we simulated floods using 2-D HEC-RAS on the East Fork White River near Seymour, IN, USA, including the current, dense network of floodplain channels. Next, we simulated synthetic versions of this river system where we varied the connectivity among floodplain channels, and also between the floodplain channels and river channel. We found distinct differences in flooding patterns and flood hydraulics among model simulations. Numerical modeling experiments showed that increasing floodplain channel connectivity caused increased spatial variability of wet and dry surfaces across the floodplain, increased residence time of water on the floodplain, and increased floodwave attenuation. Results from this study indicate that topographic connectivity on the floodplain challenges the classic notions of flooding initiation, and potentially increases a floodplains ability to store matter.

# 1 The Influence of Floodplain Channel Connectivity on Flood Hydrodynamics

# 2 Scott R. David<sup>1,2</sup>, Jonathan A. Czuba<sup>3</sup>, Douglas A. Edmonds<sup>2</sup>, and Adam S. Ward<sup>4</sup>

- 3 <sup>1</sup>Department of Geosciences, University of Massachusetts, Amherst, Massachusetts, USA
- 4 <sup>2</sup>Department of Earth and Atmospheric Sciences, Indiana University, Bloomington, Indiana, USA
- <sup>3</sup>Department of Biological Systems Engineering and The Global Change Center, Virginia Tech,
- 6 Blacksburg, Virginia, USA
- 7 <sup>4</sup>School of Public and Environmental Affairs, Indiana University, Bloomington, Indiana, USA
- 8 Corresponding author: Scott David (<u>sdavid@umass.edu</u>)

# 9 Key Points:

- Well-connected floodplain channels promote increased spatial variability in flooding and changes how floodplains fill with water.
- Floodplain channel connectivity influences flood hydraulics and floodwave propagation at low flooding discharges.
- Intermediate connectivity among floodplain channels and the river channel maximizes
   lateral exchange and residence time of floodwaters.

# 16 Abstract

17 High-resolution topographic data reveal that meandering river floodplains can 18 contain complex floodplain-channel networks. However, the influence of this topography 19 on flood initiation and progression is unknown. In this study, we investigate how 20 floodplain-channel networks influence flooding processes in low-gradient river systems. 21 To accomplish this, we conducted a series of numerical modeling experiments using a 22 two-dimensional (2-D) model built in Hydrologic Engineering Center's River Analysis 23 System (HEC-RAS). First, we simulated floods using 2-D HEC-RAS on the East Fork White River near Seymour, IN, USA, including the current, dense network of floodplain 24

25 channels. Next, we simulated synthetic versions of this river system where we varied 26 the connectivity among floodplain channels, and also between the floodplain channels 27 and river channel. We found distinct differences in flooding patterns and flood hydraulics 28 among model simulations. Numerical modeling experiments showed that increasing 29 floodplain channel connectivity caused increased spatial variability of wet and dry 30 surfaces across the floodplain, increased residence time of water on the floodplain, and 31 increased floodwave attenuation. Results from this study indicate that topographic 32 connectivity on the floodplain challenges the classic notions of flooding initiation, and 33 potentially increases a floodplains ability to store matter.

#### 34 **1.0 Introduction**

35 River floodplains are a key human habitat (Di Baldassarre et al., 2013) that 36 provide rich, fertile soils for agriculture, and are among the most productive ecosystems 37 on Earth (Tockner & Stanford, 2002). These ecosystems depend on surface-water 38 connectivity between rivers and floodplains, which ultimately controls bioproductivity, 39 biodiversity, and biogeochemical cycling in floodplains (Costanza et al., 1997; Malard et 40 al., 2002). Surface-water connectivity refers to the exchange of water, and particulate 41 matter between the river and floodplain (Junk et al., 1989; Mitsch & Gosselink, 2000; 42 Tockner & Stanford, 2002; Walling, 1999). At timescales shorter than appreciable 43 surface morphological change, surface-water connectivity is the result of a time-variable 44 hydrograph that drives surface-water (Covino, 2017; Junk et al., 1989; Ward & Stanford, 1995) and hyporheic exchange (Boulton, 2007; Roley et al., 2012; Stanford & Ward, 45

46 1993). The geomorphic surface, which is assumed to be static on timescales of 47 individual events, controls the transfer of water, energy, and material between the river 48 and floodplain, and can change in both time and space through natural and 49 anthropogenic processes (Bracken & Croke, 2007; Poeppl et al., 2012). While most 50 studies have focused on how a fluctuating hydrograph influences surface-water 51 connectivity (e.g., Wohl et al., 2019), we flip the perspective and focus on how different 52 floodplain geomorphic surfaces influence surface-water connectivity for a given 53 hydrologic condition. This perspective is important because it will help us understand 54 the important geomorphic attributes that drive surface-water connectivity (Wohl et al., 55 2019).

56 Floodplain geomorphic surfaces have many kinds of topographic features that 57 can be connected and linked together (commonly called "structural connectivity": 58 Wainwright et al., 2011; Wohl et al., 2019). We define here the concept of "topographic connectivity" as one type of structural connectivity that specifically refers to what aspect 59 60 of the structure is controlling connectivity. One important way floodplains become 61 topographically connected is through formation of channels on the floodplain surface 62 that transport water and sediment and connect otherwise distant parts of the floodplain 63 with the main channel (Czuba et al., 2019; Mertes et al., 1996; Rowland et al., 2009). 64 These floodplain channels are more than just the remnants of the main channel from 65 cutoffs or avulsions; instead they can be an integrated network of channels on the 66 floodplain surface, similar to a drainage network (David et al., 2017; Fagan & Nanson, 67 2004; Kupfer et al., 2015; Rak et al., 2016; Thayer & Ashmore, 2016; Trigg et al., 2012).

These networks form through headcutting (David et al., 2019) and create channels with morphologies and cross-sectional areas different from the main channel (David et al., 2017; Fagan & Nanson, 2004; Trigg et al., 2012). Despite the increasing awareness of floodplain-channel networks, only a few studies have explored their influence on floodplain processes and surface-water connectivity (Czuba et al., 2019; Trigg et al., 2012).

74 Floodplain networks create a distinct scale of topographic connectivity that 75 controls when and where flooding begins and which paths floodwaters will take (Czuba 76 et al., 2019). In fact, these floodplain-channel networks allow water to enter the 77 floodplain from the main channel well before all banks are overtopped. This 78 phenomenon has been observed in floodplains of the Amazon River in Brazil (Rudorff et 79 al., 2014; Trigg et al., 2012), Congaree River in South Carolina (Kupfer et al., 2015), 80 Medway River in southern Ontario (Thayer & Ashmore, 2016), West Fork White River, 81 Indiana, USA (David et al., 2017), and the East Fork White River, Indiana, USA (Czuba 82 et al., 2019). In a particularly compelling case, Czuba et al. (2019) conducted a study 83 along the East Fork White River, Indiana, USA and showed that floodplain channels 84 cause flooding at a 19-day recurrence interval (RI), even though banks were not fully 85 inundated until a 9-month RI.

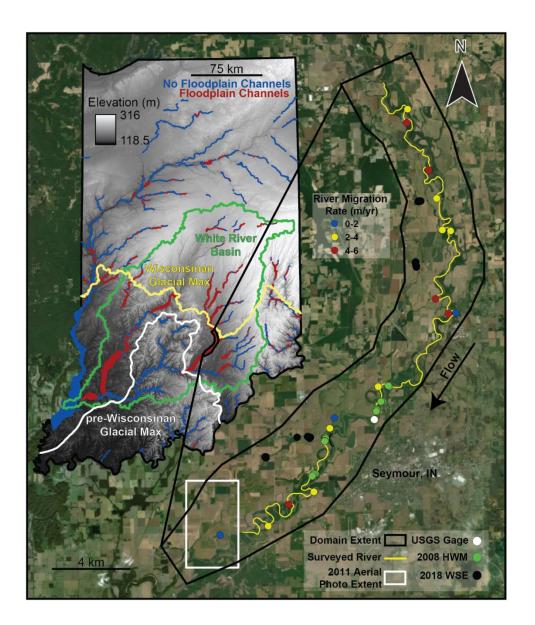
The overarching goal of this study is to test how the topographic connectivity of floodplain-channel networks—both within the network itself and between the network and main channel—affects flooding patterns. Specifically, we address three questions:

89 (1) How does the topographic connectivity between the floodplain and main channel 90 influence spatial patterns of flooding and flooding extent? (2) To what degree does 91 topographic connectivity within the floodplain-channel network influence hydraulics 92 within the floodplain (e.g., depth, velocity)? and (3) How do river-to-floodplain and 93 within-floodplain topographic connectivity influence surface-water residence time and 94 lateral exchange between the river channel and floodplain? To address these questions, 95 we extend the calibrated model from Czuba et al. (2019) of the East Fork White River 96 near Seymour, IN, USA to account for fully unsteady flow. We conduct 2-D surface-97 water flow modeling in Hydrologic Engineering Center's River Analysis System (HEC-98 RAS) exploring flooding processes as a function of various degrees of topographic 99 connectivity between the floodplain and river channel and the topographic connectivity 100 among floodplain channels.

#### 101 2.0 Study Site Description

102 Our study area is located along the East Fork White River between Columbus 103 and Brownstown, IN, USA (Figure 1). We chose this location because it includes a long 104 continuous floodplain containing floodplain channels (Figure 1) and has a high 105 floodplain channel density (~7 floodplain channels per cross-section) making the East 106 Fork White River an ideal setting to study the influence of topographic connectivity on 107 flooding processes. Additionally, this reach contains a USGS gage (gage number 108 03365500) in the middle of the study area, just downstream of a low-head dam near 109 Seymour, IN (Figure 1). The upstream extent of our study area has a drainage area of

110	about 5,120 km <sup>2</sup> . The only major tributary that enters the study area is Sand Creek,
111	which drains 681 km <sup>2</sup> of the White River drainage basin into the East Fork White River.
112	The downstream extent of the study area drains about 6,160 km <sup>2</sup> of land. Land cover in
113	the model area is 75% agriculture, 13% vegetated/forested, 8% urban development,
114	and 4% water (Homer et al., 2015). In the study reach, the main river channel has an
115	average width of 73 m, an average bank height (river channel bottom to top of bank) of
116	3.8 m, a bed slope of $3 \times 10^{-4}$ m m <sup>-1</sup> , a sinuosity of 1.7 (David et al., 2017), and an
117	average river bend migration rate of 3.4 m yr <sup>-1</sup> (Figure 1; Robinson, 2013). In the model
118	domain the floodplain averages 2,700 m wide and has a slope of $5 \times 10^{-4}$ m m <sup>-1</sup> . The
119	floodplain channels along this reach begin to convey water when the river reaches a
120	discharge of 268 m <sup>3</sup> s <sup>-1</sup> (19-day RI; Czuba et al., 2019).



121

122 Figure 1. Study area of the East Fork White River. Imagery of the East Fork White River, where 123 the study area is outlined in black. We show the locations of 2018 water surface elevations 124 (WSE), 2008 high-water marks (HWM) collected by the USGS, and the USGS gage used for 125 calibration and validation. Average river migration rates of specific bends are plotted as blue, 126 yellow, and red dots with increasing migration rates, respectively (Robinson, 2013). The inset 127 image shows the location of the White River drainage basin in Indiana (shown with a green line). 128 The blue lines/polygons show floodplains without floodplain channels and the red lines/polygons 129 show floodplains with floodplain channels (David et al., 2017). The maximum glacial extent of the pre-Wisconsinan and Wisconsinan glaciations are shown with white and yellow lines,respectively.

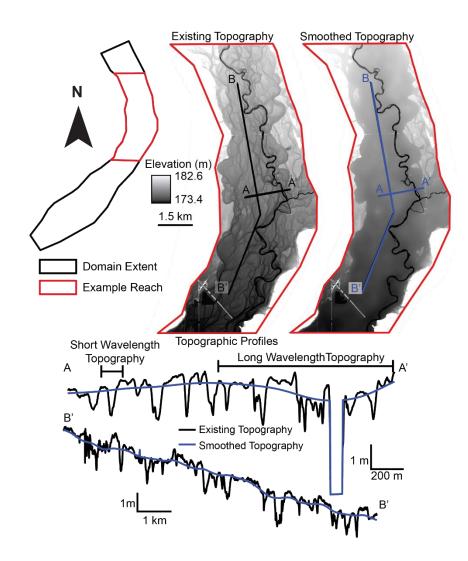
# 132 3.0 Methods

# 133 3.1 Model Development

134 Czuba et al. (2019) developed and calibrated a model of the East Fork White 135 River in 2D HEC-RAS and ran it under steady-state flow using the diffusive wave 136 equations. In this study, we have recalibrated this model to run full unsteady flows using 137 the Saint Venant equations. For a full description of the modeling methods see Czuba et 138 al. (2019) or a stand-alone account of the full methods used here that partially overlaps 139 with those of Czuba et al. (2019) in the supplementary information. In this section we 140 note only the elements of the modeling effort that differ from Czuba et al. (2019). 141 Topographic data used in modeling experiments were constructed from a 1.5 m DEM 142 derived from airborne light detection and ranging (lidar) data and field surveyed 143 bathymetric data. In addition to the existing topography, we also generated five 144 synthetic floodplains based on the East Fork White River floodplain with various 145 degrees of floodplain channel and river-floodplain topographic connectivity. The 146 synthetic floodplain surfaces were generated by extracting the extent of the East Fork 147 White River active floodplain at the 89-year flood of record (Czuba et al., 2019). We 148 then removed all floodplain channels from the floodplain surface by applying a Gaussian 149 filter (Eqn. 1) as:

150 
$$G(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2 + y^2}{2\sigma^2}}$$
 Eqn. 1

151 where, x and y are spatial distances (m) and  $\sigma$  is the standard deviation of the Gaussian 152 distribution (m). The calculation used  $\sigma = 6$  m and iterated over the active floodplain 20 153 times, creating a preliminary smoothed floodplain. The presence of the floodplain 154 channels caused artificially low elevations between floodplain channels during the 155 Gaussian spatial averaging. To overcome this, we removed and interpolated all portions 156 of the active floodplain more than 0.1 m below the preliminary smoothed surface. This 157 eliminated most floodplain channels and the river channel. Additionally, we removed all 158 major road features in the active floodplain domain to avoid any artificial increases in 159 floodplain elevation. We applied the same Gaussian filter as before to the active 160 floodplain with the floodplain channels, river channel, and roads removed, thus 161 producing a smoothed version of the East Fork White River floodplain that maintains 162 long wavelength topography. The river channel, roads, and terraces were then added 163 back into the smoothed floodplain topography creating a floodplain with similar long 164 wavelength topography and floodplain extent, but without floodplain channels (Figure 2).



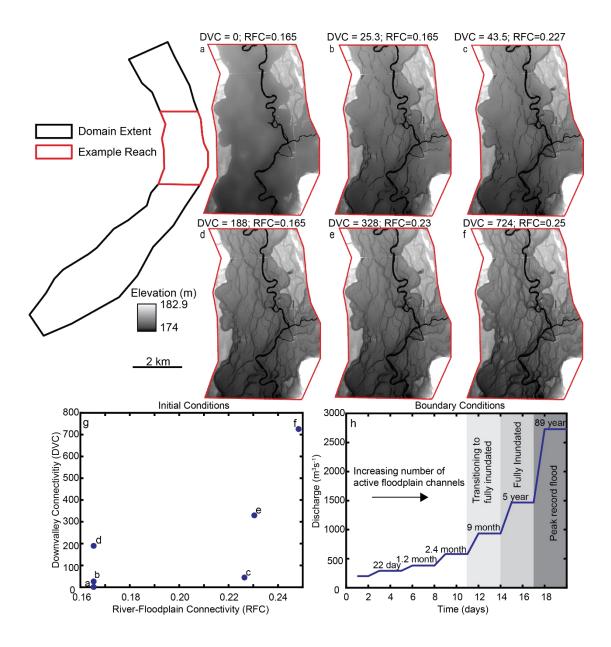
# 165

Figure 2. Smoothed floodplain topography. The left image shows the existing topography along
 the East Fork White River and the right image shows the smoothed topography after applying a
 Gaussian Filter. The topographic profiles illustrate how the Gaussian filter removed all floodplain
 channels, while maintaining long wavelength undulating topography.

170 We used the smoothed floodplain (Figure 3a) and existing floodplain (Figure 3f)

- 171 to generate four additional synthetic floodplains with different topographic connectivity
- 172 between the floodplain channels and the river channel. We envision different floodplain-
- 173 channel network connectivity as being related to the degree of channelization. The

174 present floodplain surface is channelized with a highly integrated floodplain-channel 175 network, and the smooth floodplain surface is the least channelized. We create 176 intermediately channelized floodplains by selectively preserving the deepest parts of the 177 channel network. This creates a floodplain with channel segments that are not 178 connected. To do this we detrend the natural floodplain with the smoothed floodplain, 179 thereby creating a normalized DEM where negative values represent elevations lower 180 than the smoothed floodplain. We then use two floodplain channel masks with threshold 181 values of -0.23 m and -0.84 m and remove all channel cells above the thresholds. This 182 creates two surfaces that isolate and preserve only the lowest-lying floodplain channel 183 cells (threshold of -0.84 m) and both low-lying and mid-elevation floodplain channels 184 (threshold of -0.23 m). The two channel masks were used to extract floodplain channels 185 from the existing topography and add them back to the smoothed floodplain topography. 186 The threshold of -0.84 m created a floodplain with weakly connected floodplain 187 channels (Figure 3c), and the threshold of -0.23 m created a floodplain with better 188 connected floodplain channels (Figure 3e).





190 **Figure 3**. Initial and Boundary Conditions. a-f) Example reaches of the 6 initial conditions with

- 191 varying down-valley floodplain channel connectivity (DVC) and river-floodplain channel
- 192 connectivity (RFC). The illustration on the left shows the location of the example reaches,
- 193 outlined in red, on our model domain, shown in black. g) Plot of parameter space for the
- 194 calculated DVC and RFC values for the entire domain. The example reaches shown above are
- 195 labeled (a-f) on the plot. h) Plot of total discharge used in our modeling. Each step is labeled with
- 196 its respective RI. The shaded portions of the graph indicate the flooding extent for a given
- 197 discharge reported by Czuba et al. (2019) used to guide our selection of discharges.

198

199 Additionally, we constructed two synthetic floodplains with the same floodplain-200 channel connectivity as described above, but we also changed the strength of 201 connections between the floodplain channel and the main river (Figure 3b, d). To 202 accomplish this, all floodplain channels were removed from the two floodplain channel 203 masks within 60 m (approximately two times the average levee width) of the river 204 channel. This effectively removes all natural breaks in the levees and banks created by 205 channels or crevasses. We created one additional floodplain channel mask to delineate 206 the floodplain channels on the existing floodplain using a threshold of -0.15 m. The 207 mask was used for data analysis and guantifying initial conditions.

To quantitatively describe our six different floodplains initial conditions, we developed a metric to describe the connectivity within the floodplain-channel networks (hereafter down-valley connectivity, DVC). DVC was calculated as:

211 
$$DVC = \frac{F_{CA}}{F_{TA}} \times F_I$$
 Eqn. 2

where,  $F_{CA}$  is the floodplain channel surface area (m<sup>2</sup>),  $F_{TA}$  is the total floodplain area (m<sup>2</sup>), and  $F_I$  is the number of floodplain segments surrounded by floodplain channels (an approximation to assess the number of floodplain channel connections).  $F_{CA}$  was calculated with the floodplain channel masks used to extract floodplain channels (described above).  $F_{TA}$  was measured based on the wetted extent of the 89-year flood (peak of record) from Czuba et al., (2019). Hence, larger DVC values indicate a greaternumber of well-connected floodplain channels across the floodplain.

Similarly, we describe the connectivity between the floodplain and main channel as river-floodplain connectivity (RFC). RFC was computed as the coefficient of variation (standard deviation/mean) of the bank height within 30 m (approximately average levee width) of the river channel (Figure 3g). Larger RFC values represent river banks with higher topographic variability, hence an enhanced connection of the river channel to floodplain channels.

# 225 3.2 Boundary Conditions

226 The upstream boundary conditions were specified along the East Fork White 227 River and Sand Creek as a quasi-steady state discharge entering the domain (see Fig. 228 S1 and supplemental methods). The downstream boundary condition was set to 229 maintain normal depth exiting the domain. The guasi-steady state simulations held the 230 discharge entering the domain constant until equilibrium was achieved throughout the 231 entire domain before increasing the discharge (Figure 3h). Our model simulated six 232 discharges ranging from 292 m<sup>3</sup>s<sup>-1</sup> to 2,730 m<sup>3</sup>s<sup>-1</sup> which spanned a range of floodplain 233 inundation extents (Czuba et al., 2019; Figure 3h). The six simulated discharges and six 234 initial conditions created a total of 36 simulations exploring steady state discharges.

In a second set of experiments, we relax the assumption of steady flow and
explore flood wave propagation. For floodwave propagation the model setup was

237 identical to those for the steady state simulations; however, we specified no discharge 238 entering the domain along the sand creek boundary condition and specified a 239 hydrograph at the upstream boundary for the East Fork White River. The input 240 hydrographs were triangular shaped that had peak discharges of 292 m<sup>3</sup>s<sup>-1</sup>, 581 m<sup>3</sup>s<sup>-1</sup>, 241 and 1467 m<sup>3</sup>s<sup>-1</sup>, respectively. The rising limb of the floodwave increased at a rate of 242 18.7 m<sup>3</sup>s<sup>-1</sup> per hour and the falling limb decreased at a rate of 8.2 m<sup>3</sup>s<sup>-1</sup> per hour. The 243 rates for rising and falling floodwave limb is based on a 10-year average of all rising and 244 falling limbs of floodwaves at the gage in Seymour, IN (USGS, 2018).

#### 245 3.3 Calibration and Validation

246 We calibrated the model to the elevation-discharge rating curve developed for 247 the USGS gage located near Seymour, IN (Figure 1). Model calibration was conducted 248 by varying Manning's roughness coefficients for the open water (river channel) and 249 agricultural land cover classes (Homer et al., 2015). Final roughness coefficients for the 250 open water and agricultural land cover classes were 0.022 and 0.025 (Table S1), 251 respectively. The final calibrated roughness coefficients in our study differs from those 252 in Czuba et al. (2019) due to the use of the Saint Venant equations rather than the 253 diffusive wave equations. Comparing our model simulations to the elevation-discharge 254 rating curve (USGS, 2018), we obtained a root mean squared error (RMSE) of 0.16 m 255 and a mean average error (MAE) of 0.15 m (Figure S2). Model performance is 256 comparable to that reported by Czuba et al., (2019). For an extended discussion of 257 model calibration and validation, see supplementary information.

#### 258 3.4 Data Analysis

Initial model outputs from our 36 modeling experiments included water depth, depth averaged velocity magnitude, and 2-D (x and y directed) depth averaged velocity for each cell. We gridded the results at a 15-m resolution for all analysis. From the initial model outputs, we computed the magnitude of specific discharge (q, m<sup>2</sup> s<sup>-1</sup>; Eqn. 3) and a 2-D specific discharge ( $q_{x,y}$ , m<sup>2</sup> s<sup>-1</sup>; Eqn. 4) for each grid cell in all model simulations as:

265 
$$q = \overline{v} * h$$
 Eqn. 3

266 and

267 
$$q_{x,y} = \overline{v_{x,y}} * h$$
 Eqn. 4

where,  $\bar{v}$  is the depth-averaged magnitude of velocity (m s<sup>-1</sup>), *h* is water depth (m), and  $\overline{v_{x,v}}$  is the 2-D depth-averaged velocity (m s<sup>-1</sup>) in the x or y direction, respectively.

To assess the flooding extent in each of our modeling simulations, we produced polygons of the inundated floodplain area and tabulated the percent of the floodplain that was inundated. Additionally, we tabulated the number and area of hydrologic islands (non-inundated areas surrounded by water) in the domain.

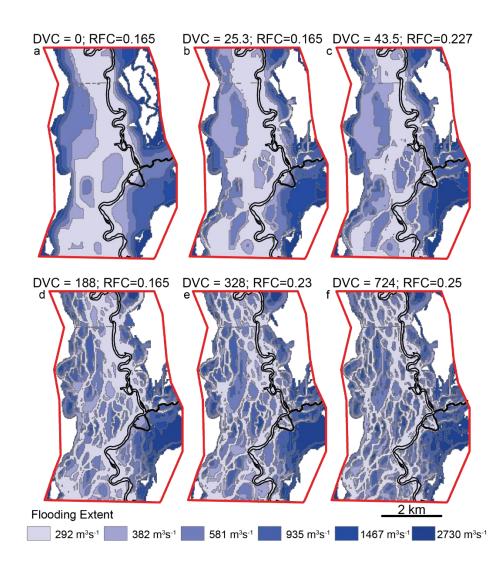
We also tabulated the average flooding depth, velocity magnitude, and specific discharge magnitude in the river channel, entire floodplain, and floodplain channels. 276 This was accomplished using a polygon mask of the river channel, entire floodplain 277 extent, and the floodplain channel masks used to generate the initial conditions (section 278 3.2.1). Averages and standard deviations were computed as the mean and standard 279 deviations for a half-Gaussian distribution for all cells within the extent of a polygon. A 280 half-Gaussian distribution was chosen because it best fit the data distribution. Trend 281 significance of the results were evaluated using an F-test. Additionally, we computed an 282 average lateral exchange of surface water between the river channel and floodplain and 283 a unit residence time of water in the floodplain. These calculations follow the same 284 procedure outlined by Czuba et al. (2019) and are detailed in the supplementary 285 information. Finally, we mapped our model simulations into an average unit residence 286 time-lateral exchange parameter space (Czuba et al., 2019). This parameter space 287 illustrates how much water is exchanged between the river channel and floodplain and 288 how long it resides in a given location along the floodplain.

#### 289 4.0 Results

# 4.1 Spatial variability of flooding is controlled by river-floodplain and down-valley connectivity

292 Spatial flooding patterns varied among the floodplains with different DVC and 293 RFC. Model simulations with a low DVC have flooded areas close to the main river 294 channel at low flooding discharges (Figure 4). As discharge increased, the flooded area 295 incrementally inundated higher elevation topographic features and extended toward the 296 valley margins (Figure 4a-c). In contrast, simulations with a large DVC allowed

297	floodwaters at lower discharges to reach the valley margins through floodplain
298	channels. As discharge increased for high DVC scenarios, the floodplain segments
299	between floodplain channels became incrementally inundated (Figure 4d-f).
300	Additionally, we found that the spatial distribution of floodwaters was strongly influenced
301	by long-wavelength topography in simulations with a low DVC causing hydrologic
302	islands to form around broad topographic highs (Figure 4a-c). Simulations with a high
303	DVC were weakly influenced by the long-wavelength topography as flow at lower stages
304	was routed though floodplain channels (Figure 4d-f). Simulations with a low RFC
305	caused flooding to inundate the majority of the river banks at low flooding discharges
306	(Figure 4a, b, d), whereas simulations with a high RFC had more variability of wet and
307	dry banks at lower discharges (Figure 4c, e, f).

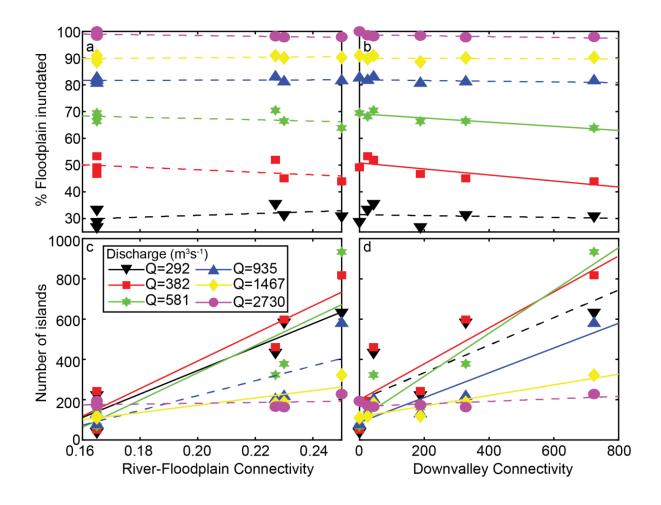


308

Figure 4. Spatial variability of flooding. a-f) Examples of flooding spatial patterns for six different
initial conditions varying DVC and RFC. The shades of blue indicate flooding extent for different
discharges, where darker blues show the new areas flooded at progressively higher discharges.
The black line delineates the river-channel banks. The example locations are the same reach of
river shown in figure 3.

- 314 Topographic connectivity also influences the proportion of floodplain that is
- 315 inundated. Changes in RFC resulted in no statistically significant changes in the
- 316 proportion of floodplain inundated (Figure 5a). When 80% or more of the floodplain was

317	inundated (Q=935 $m^3s^{-1}$ ), the influence of DVC was negligible (Figure 5b). However, Q <
318	935m <sup>3</sup> s <sup>-1</sup> , increasing DVC decreased the percent of floodplain inundated because water
319	is confined within channels (Figure 5b). Analysis of the number of hydrologic islands in
320	the floodplain showed that increasing DVC and RFC increased the number of
321	hydrologic islands (Figure 5c, d). As the number of islands increases, we expect more
322	spatially varied flood pathways as water takes increasingly tortuous paths across the
323	floodplain. As discharge increases for a given DVC and RFC we generally find the
324	number of hydrologic islands increase until a discharge of 581 m <sup>3</sup> s <sup>-1</sup> , beyond which the
325	number of hydrologic islands decreases with increasing discharge (Figure 5c, d).



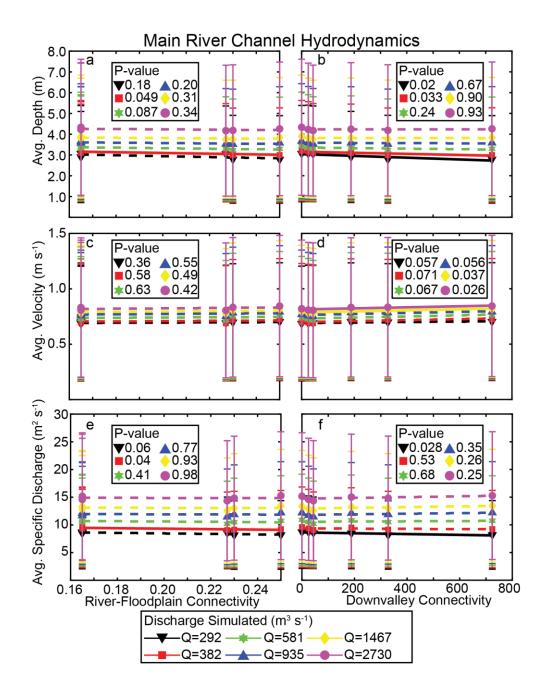
326

Figure 5. Inundated area and island analysis for entire domain. a, b) Percent of floodplain inundated as a function of varying RFC and DVC. The lines show the best fit for each steady state discharge. c, d) Number of hydrologic islands in the floodplain as a function of RFC and DVC. Solid lines indicate trends with statistical significance (p<0.05) and dashed line are not statistically significant.

# 332 **4.2** Increases in DVC and RFC have the most influence on surface-water flow

- 333 characteristics at lower flooding discharges
- In nearly all cases, changes in DVC and RFC only have statistically significance when the incoming discharge is less than  $382 \text{ m}^3 \text{ s}^{-1}$  (e.g. Figure 6-8). At these low flooding discharges increasing RFC and DVC generally causes the depth (Figure 6a, b)

- 337 and specific discharge (Figure 6e, f) in the main channel to decrease. The effect on the
- 338 main channel velocity is unclear (Figure 6c, d). The response across the entire
- 339 floodplain show that the average velocity and specific discharge increase with
- increasing connectivity (p < 0.05 for Q = 292 and 382 m<sup>3</sup> s<sup>-1</sup>; Figure 7c-f). Flow
- 341 characteristics within the floodplain channels did not significantly change as a function
- of DVC or RFC.



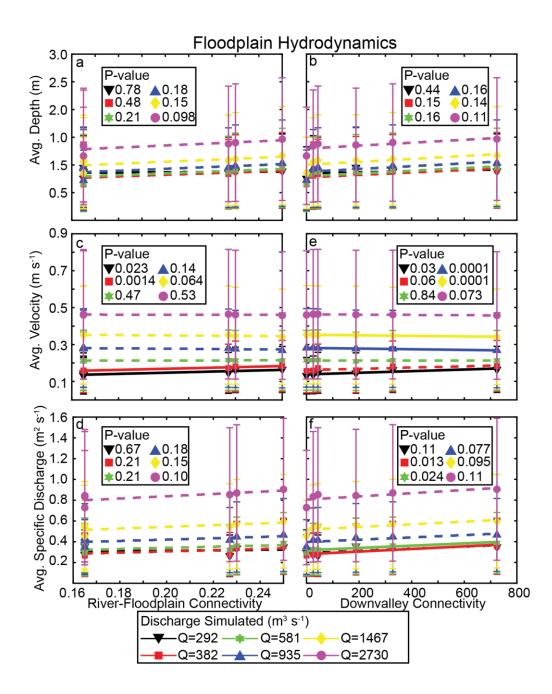
343

344 **Figure 6.** Spatially averaged main river channel flow dynamics throughout the domain. The

345 colored lines are the best fit for each steady state discharge simulated and error bars show one

346 standard deviation in the data. Solid lines indicate trends with statistical significance (P<0.05) and

347 dashed line are not statistically significant.



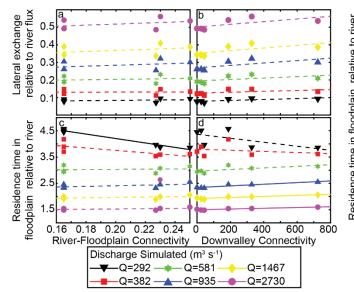
348

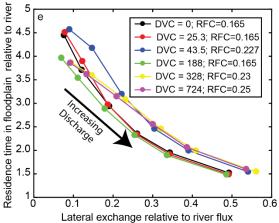
- 349 Figure 7. Spatially averaged flow dynamics in the floodplain. The colored lines are the best fit for
- each steady state discharge simulated and error bars show one standard deviation in the data.
- 351 Solid lines indicate trends with statistical significance (p<0.05) and dashed line are not statistically
- 352 significant.

#### 354 **4.3 Controls on the lateral exchange and residence time of surface water**

355	Lateral exchange of surface waters between the river and floodplain is
356	predominantly controlled by river stage. We find no significant trends between lateral
357	exchange and RFC or DVC (Figure 8a, b). At low flooding discharges, residence time in
358	the floodplain decreased as RFC increased (Figure 8c). For higher discharges,
359	residence time increased slightly as DVC increased (Figure 8d).

At low flooding discharges, we found that a low DVC maximized the lateral exchange and average residence time for water in the floodplain (Figure 8e). At higher discharges, larger RFC maximized the lateral exchange-unit residence relationship (Figure 8e). In general, our results suggest that floodplains with moderate DVC and high RFC will promote the highest lateral exchange-unit residence time under most discharges.





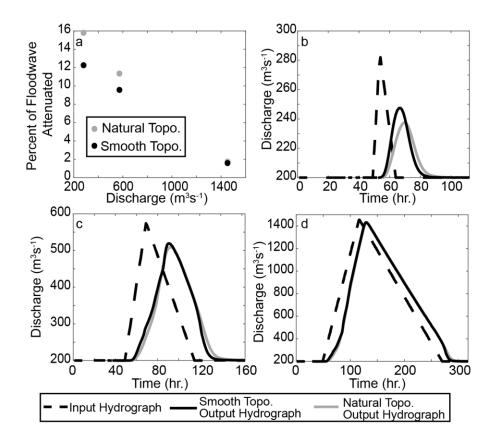
367 Figure 8. Unitless lateral exchange and unitless residence time. Colored lines in a-d show best 368 fits for each simulated discharge, solid lines indicate trend is statically significant (P<0.05) and 369 dashed lines indicate non-statically significant trend. a, b) Average lateral exchange between the 370 river channel and floodplain normalized by the average flux through the river channel as a 371 function of RFC and DVC. c, d) Average residence time-per-unit length of floodplain normalized 372 by the average residence time-per-unit length in the river as a function of 373 RFC and DVC. Simulations varying RFC showed a statistically significant trend for a discharge 374 of 292 m<sup>3</sup> s<sup>-1</sup> (P=0.00048). Variations in DVC showed statistically significant trends at discharges 375 of 935 m<sup>3</sup> s<sup>-1</sup>, 1467 m<sup>3</sup> s<sup>-1</sup>, and 2730 m<sup>3</sup> s<sup>-1</sup> (P=0.006, P=0.013, P=0.01, respectively). e) 376 Exchange-residence time parameters space. Colored lines indicate results for different initial 377 RFC and DVC values.

# 378 4.4 Increases in DVC and RFC influence floodwave propagation

379 Our steady state simulations suggest that increasing DVC and RFC should drive

380 floodwave attenuation by increasing flow path lengths (Figure 4) and increasing volume

- of water flowing in the floodplain (Figure 8f). To see how increasing DVC and RFC
- 382 affects floodwave attenuation, we ran an additional six models for the smoothed
- floodplain (Figure 4a) and the natural floodplain (Figure 4f). Our simulations show that
- 384 floodplain channels do attenuate floodwaves and their influence is accentuated at lower
- discharges (Figure 9a). We find that from our simulations with floodwaves of a peak
- discharge 292 m<sup>3</sup>s<sup>-1</sup>, 581 m<sup>3</sup>s<sup>-1</sup>, and 1467 m<sup>3</sup>s<sup>-1</sup> the floodplain channels resulted in a
- 387 3.5%, 1.8%, and, 0.16% percent increase in floodwave attenuation, respectively (Figure
- 388 9a). Additionally, we find that the majority of floodwave attenuation occurs at the initial
- portion of the rising limb and the final portion of the falling floodwave limb Figure (9b-d),
- 390 further suggesting floodplain channels have the strongest influence on flood
- 391 hydrodynamics at lower flooding discharges.



392

Figure 9. Floodwave dynamics. a) Plot showing percentage of peak discharge attenuated for the existing topography (grey) and the smoothed topography (black). b-d) Plots showing how the resulting hydrographs were reshaped from the initial input hydrograph (black dashed line) to the downstream hydrograph for the smooth (black solid line) and natural (grey solid line) topography.

# 397 5.0 Discussion

# 398 **5.1 Floodplain channels alter how floodplains become inundated**

399 Floodplain channel presence is an important control on flooding processes and

400 floodplain hydrodynamics. For instance, consider the classical model for river flooding

- 401 based on the notion of bankfull discharge (Leopold et al., 1964; Williams, 1978), where
- 402 after a river stage threshold is met water spills over the banks and spreads out across

403 the floodplain. Our model simulations with no floodplain channels and floodplain 404 channels with a low DVC behave similarly to the classical model (Figure 4a-c). In these 405 simulations, water spilled over the banks and incrementally increased the wetted width 406 until reaching the valley walls, creating hydrologic islands around only long-wavelength 407 topography. In contrast, simulations with a high DVC and at the lowest discharges, 408 water extended out to the floodplain margins (Figure 4d-f) and created many hydrologic 409 islands across the floodplain surface (Figure 5d). As discharge increases, the water 410 level in the floodplain channels rises inundating the floodplain segments between 411 floodplain channels (Figure 4d-f). Hence, when DVC is high, floodplains are inundated 412 from water rising in the floodplain channels, rather than from the widening of the wetted 413 flood pool. Similar flooding patterns have been observed on the Congaree River in 414 South Carolina (Kupfer et al., 2015) and the Ogeechee River in Georgia (Benke et al., 415 2000).

416 Our results show that floodplain inundation pattern is more sensitive to DVC than 417 to RFC (compare Figure 4a-c to d-f). This suggests that floodplains with a high DVC do 418 not conform to the classical model of overbank topping and floodplain inundation during 419 low discharge flooding events. Hence, classical models are insufficient to characterize 420 the complex transitions from river channel to overbank flow, which are important to 421 consider given that low discharge flooding events occur frequently in these systems 422 (Czuba et al., 2019). Accounting for floods occurring before all river banks are 423 overtopped is important as it will create increased variability in wet-dry transitions along 424 the river banks and in the floodplain (Figure 4d-f). The increased variability should

promote the development ecological and bio-geochemical hotspots (Frei et al., 2012) in
floodplains with a high DVC, thus affecting floodplain functioning.

# 427 **5.2** Increases in RFC promote increased floodplain functioning by increasing

#### 428 exchange and residence time

We applied the methodological framework outlined by Czuba et al. (2019) for quantifying lateral exchange and residence-time parameter space of surface water. This parameter space allows us to examine the quantity and duration of water on the floodplain in our model runs (Figure 8e). It is worth noting that our computed residence time is measured as a time-per-unit length in the floodplain and in the river, rather than a total time along the entire pathway.

435 In this parameter space (Figure 8e) we can explore how DVC and RFC influence 436 floodplain functioning. The upper right corner of the parameter space indicates when the 437 most water enters the floodplain and resides there the longest. This portion of 438 parameter space should maximize the ability of a floodplain to attenuate floodwaves 439 (Lininger and Latrubesse, 2016), recharge aguifers (Morin et al., 2009; Sophocleous, 440 2002), and store sediment, solutes, and nutrients (Junk et al., 1989; Mitsch & Gosselink, 441 2000; Tockner & Stanford, 2002; Walling, 1999). Our results suggest that higher RFC 442 pushes floodplain functioning towards this space. Surprisingly, DVC has virtually no 443 impact on residence time or lateral exchange (Figure 8e). This suggests to us that the 444 processes that drive RFC are also important for floodplain functioning even if they do 445 not strongly affect inundation patterns.

446 As we have shown, floodplain channels have an influence on the functioning of 447 floodplains especially in their role to increase RFC. Because of this they should be 448 considered in floodplain restoration projects. Restoration projects often rely on the 449 removal of artificial levees to enhance lateral connectivity of rivers and floodplains 450 (Opperman et al., 2009; Tockner & Stanford, 2002). Floodplains are often engineered 451 after the classical meandering river model (Nanson & Croke, 1992), which presents 452 floodplains as relatively flat, featureless accumulations of sediment. However, our 453 models show that topographic connectivity of the floodplain influences flooding 454 processes and may alter floodplain functioning when compared to a relatively 455 featureless floodplain. For example, increasing topographic connectivity increases the 456 volume and residence time of water in the floodplain (Figure 8e), which would enhance 457 solute diffusion (Bryant-Mason et al., 2013; Forshay & Stanley, 2005; Tockner et al., 458 1999), sediment deposition and retention (Croke et al., 2013; Malard et al., 2002; 459 Tockner et al., 1999), and water infiltration into the subsurface (Morin et al., 2009; 460 Sophocleous, 2002). Floodplain restoration, guided by our results, would benefit by 461 considering how floodplain channels connecting to the main river channel enhance 462 restoration efforts.

#### 463 **5.3 Floodplain channels affect floodwave propagation at low flooding discharge**

Floodplain channel connectivity may also have important implications for
floodwave dynamics. We already know that topographic lows on floodplains have been
shown to aid in floodwave attenuation through water retention and adding topographic

467 roughness. For instance, paleo-meander cutoffs attenuated the peak flood by 30% on 468 the Araguaia River in Brazil (Lininger & Latrubesse, 2016). Moreover, paleo-meander 469 cutoffs can be linked together by secondary channels to form an integrated floodplain-470 channel network (David et al., 2017). Our result that floodwave propagation is affected 471 by floodplain channels at low discharges is consistent with these ideas and the recent 472 modeling results from Czuba et al., (2019). They showed that as the floodplain became 473 more inundated the surface-water flow paths were less influenced by floodplain 474 channels, which explains why floodplain channels are less effective at attenuating 475 floodwaves during large flooding events.

476 While our unsteady modeling results suggest that floodplain channels increase 477 floodwave attenuation, we do not simulate some important processes that may further 478 complicate this relationship. For instance, simulations with a high DVC and RFC 479 produce more wet-dry transitions, which could result in increased aguifer recharge that 480 would further attenuate a translating floodwave. Additionally, floodplains with a high 481 DVC and RFC may be able to drain more water, leaving less trapped in topographic 482 lows than a floodplain rich in geomorphic features that are not well connected. Hence, 483 further modeling and field work is necessary to fully assess how floodplain geomorphic 484 connectivity and floodplain channels affect floodwave dynamics.

- 485 5.4 Floodplain topography is a critical control on flooding processes at low 486 discharge, frequent flooding

487 Our modeling results provide insight into understanding the relative roles of a 488 fluctuating hydrograph and the topographic connectivity on setting flood hydrodynamics. 489 The influence of floodplain topography is most significant at the lowest flooding 490 discharges simulated in this study. We only simulated discharges that cause flooding, 491 and when considering the full range of flows, the low flooding discharges simulated here 492 are in the 50-75<sup>th</sup> percentile of all flows (Czuba et al., 2019). This is not entirely 493 surprising since at high discharges most of the low-relief floodplain topography we 494 investigate here is fully inundated and at the lowest discharges, water remains in the 495 main channel, and floodplain channels are inactive (Czuba et al., 2019). Still, increased 496 RFC creates more lateral exchange even at higher discharges (Figure 8).

Our results suggest that these low-discharge flooding events could be an
important part of floodplain functioning. At our study site, low-level floods have a RI of
19 days (Czuba et al., 2019) compared to RIs of once a year (or less frequent) for larger
events. Because of their frequency these low-level floods may be important components
that drive hyporheic exchange and biogeochemical processing in the floodplain. Both of
these processes are sensitive to the kind of smaller-scale topography we investigated
here (Frei et al., 2012).

504 The well-connected topographic configuration of the floodplain surface opens a 505 window for flooding processes to initiate that does not occur in threshold systems that 506 only put water on the floodplain above some bankfull discharge. It remains an open and 507 interesting question exactly how the dynamics of hyporheic exchange and nutrient

processing are affected by highly connected river-floodplain systems that repeatedlyflood at below bankfull stages.

# 510 6.0 Conclusion

511 In this study, we investigated how the connectivity of floodplain topographic lows 512 influence flooding processes. Results suggest that floodplain topography influences 513 flooding most at low flooding discharges because at high discharge those topographic 514 features are fully inundated and no longer significantly steer flow. With minimal 515 connectivity of topographic lows, floodplain inundation incrementally extends to the 516 valley margins as discharge increases. Whereas at high connectivity, inundation 517 extends to the valley margin at low flooding discharges and creates many hydrologic 518 islands. As discharge increases the hydrologic islands are incrementally inundated. At 519 the lowest discharges simulated here, highly connected floodplain topography, both 520 down-valley and lateral with the river channel, decreases average specific discharge in 521 the main channel because flow is lost to the floodplain. Subsequently, the specific 522 discharge on the floodplain increases as connectivity increases. Additionally at low 523 flooding discharges, high down-valley connectivity decreases residence time of surface 524 waters, whereas at high discharges increased lateral connectivity of the river to 525 floodplain increases lateral exchange. Our results suggest that topographic connectivity 526 between the floodplain and the main channel has an important effect on flooding 527 processes at low flooding discharges by driving surface water exchange and increasing 528 residence time on the floodplain.

#### 529 7.0 Acknowledgements & Data Availability

530	SRD would like to acknowledge the Geological Society of America grant number
531	11550-17 for supporting of this work. DAE would like to thank the donors of the
532	American Chemical Society Petroleum Research Fund for supporting this work and the
533	Indiana University Grand Challenges Preparing for Environmental Change for partial
534	support. JAC was partially supported by Virginia Agricultural Experiment Station and
535	USDA Hatch program (1017457). A portion of ASW's time was supported by National
536	Science Foundation (NSF) awards EAR 1652293 and EAR 1331906, Department of
537	Energy award DE-SC0019377, and the Burnell and Barbara Fischer Faculty Fellowship
538	at Indiana University.

Land cover, USGS stream flow, 2008 HWMs, aerial imagery, and lidar data is available from Homer et al. (2015), USGS (2018), Morlock et al. (2008) and Indiana Geospatial Data Portal (imagery and lidar; https://gis.iu.edu/), respectively. 2018 WSEs, bathymetric data, and polygon masks of active floodplain extent, floodplain channels, and river channel will be made publically available in Indiana University Scholar Works, an open access, repository.

# 545 **References**

Benke, A. C., Chaubey, I., Ward, G. M., & Dunn, E. L. (2000). Flood Pulse Dynamics of
an Unregulated River Floodplain in the Southeastern U.s. Coastal Plain. *Ecology*, *81*(10), 2730–2741. https://doi.org/10.1890/00129658(2000)081[2730:FPDOAU]2.0.CO;2

- Boulton, A. J. (2007). Hyporheic rehabilitation in rivers: restoring vertical connectivity. *Freshwater Biology*, *52*(4), 632–650. https://doi.org/10.1111/j.13652427.2006.01710.x
- Bracken, L. J., & Croke, J. (2007). The concept of hydrological connectivity and its
   contribution to understanding runoff-dominated geomorphic systems.
   *Hydrological Processes*, *21*(13), 1749–1763. https://doi.org/10.1002/hyp.6313
- BryantMason, A., Xu, Y. J., & Altabet, M. A. (2013). Limited capacity of river corridor
  wetlands to remove nitrate: A case study on the Atchafalaya River Basin during
  the 2011 Mississippi River Flooding. *Water Resources Research*, *49*(1), 283–
  290. https://doi.org/10.1029/2012WR012185
- Costanza, R., d'Arge, R., de Groot, R., Farber, S., Grasso, M., Hannon, B., et al. (1997).
  The value of the world's ecosystem services and natural capital. *Nature*,
  387(6630), 253–260. https://doi.org/10.1038/387253a0
- 563 Covino, T. (2017). Hydrologic connectivity as a framework for understanding
  564 biogeochemical flux through watersheds and along fluvial networks.
  565 *Geomorphology*, 277, 133–144. https://doi.org/10.1016/j.geomorph.2016.09.030
- 566 Croke, J., Fryirs, K., & Thompson, C. (2013). Channel-floodplain connectivity during an
   567 extreme flood event: implications for sediment erosion, deposition, and delivery:
   568 CHANNEL-FLOODPLAIN CONNECTIVITY. *Earth Surface Processes and* 569 *Landforms*, n/a-n/a. https://doi.org/10.1002/esp.3430
- 570 Czuba, J. A., David, S. R., Edmonds, D. A., & Ward, A. S. (2019). Dynamics of Surface571 Water Connectivity in a Low-Gradient Meandering River Floodplain. *Water*572 *Resources Research*, *55*(3), 1849–1870. https://doi.org/10.1029/2018WR023527
- 573 David, S. R., Edmonds, D. A., & Letsinger, S. L. (2017). Controls on the occurrence and
  574 prevalence of floodplain channels in meandering rivers: Controls on Floodplain
  575 Channels in Meandering Rivers. *Earth Surface Processes and Landforms*, *42*(3),
  576 460–472. https://doi.org/10.1002/esp.4002
- 577 David, S.R., Czuba, J. A., & Edmonds, D. A. (2019). Channelization of meandering river
  578 floodplains by headcutting. *Geology*, *47*(1), 15–18.
  579 https://doi.org/10.1130/G45529.1
- 580 Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Salinas, J. L., & Blöschl, G. (2013).
   581 Socio-hydrology: conceptualising human-flood interactions. *Hydrology and Earth* 582 System Sciences, 17(8), 3295–3303. https://doi.org/10.5194/hess-17-3295-2013

- Fagan, S. D., & Nanson, G. C. (2004). The morphology and formation of floodplainsurface channels, Cooper Creek, Australia. *Geomorphology*, *60*(1–2), 107–126.
  https://doi.org/10.1016/j.geomorph.2003.07.009
- Forshay, K. J., & Stanley, E. H. (2005). Rapid Nitrate Loss and Denitrification in a
  Temperate River Floodplain. *Biogeochemistry*, *75*(1), 43–64.
  https://doi.org/10.1007/s10533-004-6016-4
- Frei, S., Knorr, K. H., Peiffer, S., & Fleckenstein, J. H. (2012). Surface micro-topography
  causes hot spots of biogeochemical activity in wetland systems: A virtual
  modeling experiment. *Journal of Geophysical Research: Biogeosciences*, *117*(G4). https://doi.org/10.1029/2012JG002012@10.1002/(ISSN)21698961.SYNTHESIS1
- Homer, C., Dewitz, J., Yang, L., Jin, S., Danielson, P., Coulston, J., et al. (2015).
  Completion of the 2011 National Land Cover Database for the Conterminous
  United States Representing a Decade of Land Cover Change Information. *PHOTOGRAMMETRIC ENGINEERING*, 11.
- Junk, W. J., Bayley, P. B., & Sparks, R. E. (1989). The flood pulse concept in riverfloodplain systems. *Canadian Special Publication of Fisheries and Aquatic Sciences*, *106*(1), 110–127.
- Kupfer, J. A., Meitzen, K. M., & Gao, P. (2015). Flooding and Surface Connectivity of
   *Taxodium-Nyssa* Stands in a Southern Floodplain Forest Ecosystem:
   CONNECTIVITY OF TAXODIUM-NYSSA STANDS. *River Research and Applications*, *31*(10), 1299–1310. https://doi.org/10.1002/rra.2828
- Leopold, L. B., Wolman, M. G., & Miller, J. P. (1964). *Fluvial Processes in Geomorphology*. San Francisco, California: W.H. Freeman.
- Lininger, K. B., & Latrubesse, E. M. (2016). Flooding hydrology and peak discharge
  attenuation along the middle Araguaia River in central Brazil. *CATENA*, 143, 90–
  101. https://doi.org/10.1016/j.catena.2016.03.043
- Malard, F., Tockner, K., Dole-Olivier, M.-J., & Ward, J. V. (2002). A landscape
  perspective of surface-subsurface hydrological exchanges in river corridors. *Freshwater Biology*, *47*(4), 621–640. https://doi.org/10.1046/j.13652427.2002.00906.x
- Mertes, L. A. K., Dunne, T., & Martinelli, L. A. (1996). Channel-floodplain
   geomorphology along the Solimões-Amazon River, Brazil. *Geological Society of America Bulletin*, 19.

- Mitsch, W. J., & Gosselink, J. G. (2000). The value of wetlands: importance of scale and
  landscape setting. *Ecological Economics*, *35*(1), 25–33.
  https://doi.org/10.1016/S0921-8009(00)00165-8
- Morin, E., Grodek, T., Dahan, O., Benito, G., Kulls, C., Jacoby, Y., et al. (2009). Flood
  routing and alluvial aquifer recharge along the ephemeral arid Kuiseb River,
  Namibia. *Journal of Hydrology*, *368*(1–4), 262–275.
  https://doi.org/10.1016/j.jhydrol.2009.02.015
- 624 Morlock, S. E., Menke, C. D., Arvin, D. V., & Kim, M. H. (2008). *Flood of June 7-9, 2008,* 625 *in central and southern Indiana*. US Geological Survey.
- Nanson, G. C., & Croke, J. C. (1992). A genetic classification of floodplains. *Geomorphology*, 4(6), 459–486. https://doi.org/10.1016/0169-555X(92)90039-Q
- Opperman, J. J., Galloway, G. E., Fargione, J., Mount, J. F., Richter, B. D., & Secchi, S.
  (2009). Sustainable Floodplains Through Large-Scale Reconnection to Rivers. *Science*, *326*(5959), 1487–1488. https://doi.org/10.1126/science.1178256
- Poeppl, R. E., Keiler, M., elverfeldt, K. V., Zweimueller, I., & Glade, T. (2012). The
  influence of riparian vegetation cover on diffuse lateral sediment connectivity and
  biogeomorphic processes in a medium-sized agricultural catchment, austria. *Geografiska Annaler: Series A, Physical Geography*, *94*(4), 511–529.
  https://doi.org/10.1111/j.1468-0459.2012.00476.x
- Rak, G., Kozelj, D., & Steinman, F. (2016). The impact of floodplain land use on flood
  wave propagation. *Natural Hazards*, *83*(1), 425–443.
  https://doi.org/10.1007/s11069-016-2322-0
- Robinson, B. (2013). USGS Scientific Investigations Report 2013–5168 Recent (circa
  1998 to 2011) Channel-Migration Rates of Selected Streams in Indiana.
  Retrieved from https://pubs.usgs.gov/sir/2013/5168/
- Roley, S. S., Tank, J. L., & Williams, M. A. (2012). Hydrologic connectivity increases
  denitrification in the hyporheic zone and restored floodplains of an agricultural
  stream: DENITRIFICATION IN STREAM ECOTONES. *Journal of Geophysical Research: Biogeosciences*, *117*(G3), n/a-n/a.
- 646 https://doi.org/10.1029/2012JG001950
- Rowland, J. C., Stacey, M. T., & Dietrich, W. E. (2009). Turbulent characteristics of a
  shallow wall-bounded plane jet: experimental implications for river mouth
  hydrodynamics. *Journal of Fluid Mechanics*, 627, 423–449.
  https://doi.org/10.1017/S0022112009006107

- Rudorff, C. M., Melack, J. M., & Bates, P. D. (2014). Flooding dynamics on the lower
  Amazon floodplain: 1. Hydraulic controls on water elevation, inundation extent,
  and river-floodplain discharge: HYDRAULIC CONTROLS OF FLOODING ON
  THE LOWER AMAZON. *Water Resources Research*, *50*(1), 619–634.
  https://doi.org/10.1002/2013WR014091
- Sophocleous, M. (2002). Interactions between groundwater and surface water: the state
  of the science. *Hydrogeology Journal*, *10*(1), 52–67.
  https://doi.org/10.1007/s10040-001-0170-8
- Stanford, J. A., & Ward, J. V. (1993). An Ecosystem Perspective of Alluvial Rivers:
  Connectivity and the Hyporheic Corridor. *Journal of the North American Benthological Society*, *12*(1), 48–60. https://doi.org/10.2307/1467685
- Thayer, J. B., & Ashmore, P. (2016). Floodplain morphology, sedimentology, and
  development processes of a partially alluvial channel. *Geomorphology*, 269,
  160–174. https://doi.org/10.1016/j.geomorph.2016.06.040
- Tockner, K., & Stanford, J. A. (2002). Riverine flood plains: present state and future
  trends. *Environmental Conservation*, *29*(3), 308–330.
  https://doi.org/10.1017/S037689290200022X
- Tockner, K., Pennetzdorfer, D., Reiner, N., Schiemer, F., & Ward, J. V. (1999).
  Hydrological connectivity, and the exchange of organic matter and nutrients in a dynamic river–floodplain system (Danube, Austria). *Freshwater Biology*, *41*(3), 521–535. https://doi.org/10.1046/j.1365-2427.1999.00399.x
- Trigg, M. A., Bates, P. D., Wilson, M. D., Schumann, G., & Baugh, C. (2012). Floodplain
   channel morphology and networks of the middle Amazon River: AMAZON
   FLOODPLAIN CHANNEL MORPHOLOGY AND NETWORKS. *Water Resources*
- U.S. Geological Survey (USGS) (2018). USGS 03365500 East Fork White River at
   Seymour, IN. Reston, VA: U.S. Geological Survey. (last accessed 01 Jan. 2018)
- Wainwright, J., Turnbull, L., Ibrahim, T. G., Lexartza-Artza, I., Thornton, S. F., & Brazier,
  R. E. (2011). Linking environmental régimes, space and time: Interpretations of
  structural and functional connectivity. *Geomorphology*, *126*(3–4), 387–404.
  https://doi.org/10.1016/j.geomorph.2010.07.027
- Walling, D. E. (1999). Linking land use, erosion and sediment yields in river basins. In J.
  Garnier & J.-M. Mouchel (Eds.), *Man and River Systems* (pp. 223–240).
  Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-94-017-2163-9\_24

- Ward, J. V., & Stanford, J. A. (1995). Ecological connectivity in alluvial river ecosystems
  and its disruption by flow regulation. *Regulated Rivers: Research & Management*, *11*(1), 105–119. https://doi.org/10.1002/rrr.3450110109
- 687 Williams, G. P. (1978). Bank-full discharge of rivers. *Water Resources Research*, *14*(6),
   688 1141–1154. https://doi.org/10.1029/WR014i006p01141
- Wohl, E., Brierley, G., Cadol, D., Coulthard, T. J., Covino, T., Fryirs, K. A., et al. (2019).
- 690 Connectivity as an emergent property of geomorphic systems: Geomorphic
- 691 connectivity. *Earth Surface Processes and Landforms*, 44(1), 4–26.
- 692 https://doi.org/10.1002/esp.4434

693

# **@AGU**PUBLICATIONS

# Water Resources Research

## Supporting Information for

# The Influence of Floodplain Channel Connectivity on Flood Hydrodynamics

## Scott R. David<sup>1,2</sup>, Jonathan A. Czuba<sup>3</sup>, Douglas A. Edmonds<sup>2</sup>, and Adam S. Ward<sup>4</sup>

<sup>1</sup>Department of Geosciences, University of Massachusetts, Amherst, Massachusetts, USA

<sup>2</sup>Department of Earth and Atmospheric Sciences, Indiana University, Bloomington, Indiana, USA

<sup>3</sup>Department of Biological Systems Engineering and The Global Change Center, Virginia Tech, Blacksburg, Virginia, USA

<sup>4</sup>School of Public and Environmental Affairs, Indiana University, Bloomington, Indiana, USA

## Contents of this file

Text S1 Figures S1 to S3 Tables S1

## Introduction

This supporting information file contains an extended description of the methods that are unique to this study and those that partially overlap with Czuba et al. (2019)

## **Text S1: 1.0 Extended Methods**

## 1.1.0 Model Development

We developed a 2-D unsteady surface-water hydrodynamic model for the East Fork White River and its adjacent floodplain in HEC-RAS version 5.0.3 using the Saint Venant equations. The computational mesh contained a total of 187,955 cells and used a combination of structured and unstructured meshes. The structured computational mesh has square cells, each 900 m<sup>2</sup>. Breaklines were enforced along major roadways (cell spacing of ~3m), river banks, middle of the river (cell spacing of ~12m), and across the low head dam (cell spacing of ~1.5m; Figure S1) producing the unstructured portion of the mesh. A spatially varied Manning's

roughness was applied to the mesh, based on 30 m resolution land cover data (Homer et al., 2015), and the coefficients were chosen based on model calibration discussed in section 1.2. The topography data used in the model was a 1.5m digital elevation model (DEM) derived from light detection and ranging (lidar) data, bathymetric data, and theoretical topography for connectivity scenarios constructed by modifying the empirical elevation datasets. The topographic and bathymetric data collection and manipulation is described in section 1.1.1. Boundary conditions were set at three locations on the model grid: the upstream model extent of the East Fork White River, the upstream model extent of Sand Creek, and the downstream model extent of the East Fork White River (Figure S1). Our choice in boundary conditions is discussed in section 1.1.2.

#### 1.1.1 Topography and Bathymetry Data

Topographic data used in the model consisted of a combination of empirical and theoretical topographic datasets. The empirical data used were constructed from a 1.5m DEM derived from aerial lidar flown on March 23, 2011 (http://www.indianamap.org). The lidar sensor could not measure topography through surface water, hence data points with water on the day of data acquisition were removed and replaced with a flat or sloping plane, a process called hydro-flattening. But the geometry of the main channel is important for the flooding processes we seek to understand here. We surveyed the river channel using a single-beam acoustic profiler measuring water depth and spatial location. The portion of the reach we surveyed is shown with a yellow line in figure 1. Additionally, we measured water-surface profiles with a real-time kinematic geographic position system (RTK-GPS) along the river during the day of surveying. To construct the bed-elevation surface we subtracted the depth data from the measured water-surface elevation data. Bed elevation data were processed into a DEM by taking the average depth along 30 m (approximately half the average river width) segments of the river centerline. The average depth along the segment was then assigned to a cross-section along that river segment. A triangulated irregular network was generated from the crosssections, averaging all cross-channel variability while maintaining down-valley pool and riffle sequences. River reaches without bathymetric data were lowered by 1.5m to match the overall slope of our measured bathymetric data.

In addition to the actual topography, we also generated five synthetic floodplains based on the East Fork White River floodplain with various degrees of floodplain channel and riverfloodplain connectivity. The synthetic floodplain surfaces were generated by extracting the extent of the East Fork White River active floodplain at the 89-year flood of record. We then removed all floodplain channels from the floodplains surface by applying a Gaussian filter (Eqn. 1) as:

$$G(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2 + y^2}{2\sigma^2}}$$
 Eqn. 1

where, *x* and *y* are spatial distances (meters) and  $\sigma$  is the standard deviation of the Gaussian distribution. The calculation used  $\sigma = 6$  m and iterated over the active floodplain 20 times, creating a preliminary smoothed floodplain. The presence of the floodplain channels caused artificially low inter-channel areas during the spatial averaging. To overcome this, we removed and interpolated all portions of the active floodplain ~0.1m lower than the preliminary smoothed surface. This eliminated most floodplain channels and the river channel. Additionally, we removed all major road features in the active floodplain domain to avoid any artificial increases

in floodplain elevation. We applied the same Gaussian filter as before to the active floodplain with the floodplain channels, river channel, and roads removed, thus producing a smoothed version of the East Fork White River floodplain that maintains long wavelength topography. The river channel, roads, and terraces were then added back into the smoothed floodplain topography creating a floodplain with a similar long wavelength topography and floodplain extent, but without floodplain channels (Figure 2).

We used the smoothed floodplain (Figure 3a) and existing floodplain (Figure 3f) to generate four additional floodplains with different topographic connectivity between the floodplain channels and the river channel. We envision different floodplain-channel network connectivity as being related to the degree of channelization. The present floodplain surface is channelized with a highly integrated floodplain-channel network, and the smooth floodplain surface is the least channelized. We create intermediately channelized floodplains by selectively preserving the deepest parts of the channel network. This creates a floodplain with channel segments that are not connected. To do this we detrend the natural floodplain with the smoothed floodplain, thereby creating a normalized DEM where negative values represent elevations lower than the smoothed floodplain. We then use two floodplain channel masks with threshold values of -0.23 m and -0.84 m and remove all channel cells above the thresholds. This creates two surfaces that isolate and preserve only the lowest-lying floodplain channel cells (threshold of -0.84 m) and both low-lying and mid-elevation floodplain channels (threshold of -0.23 m). The two channel masks were used to extract floodplain channels from the existing topography and add them back to the smoothed floodplain topography. The threshold of -0.84 m created a floodplain with weakly connected floodplain channels (Figure 4c), and the threshold of -0.23 m created a floodplain with better connected floodplain channels (Figure 4e).

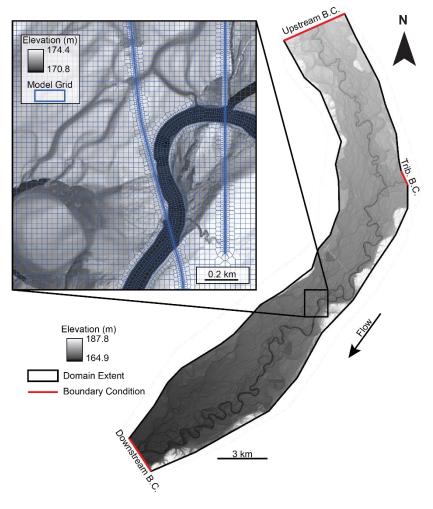
Additionally, we constructed two synthetic floodplains with the same floodplain-channel connectivity as described above, but we also changed the strength of connections between the floodplain channel and the main river (Figure 3b, d). To accomplish this, all floodplain channels were removed from the two floodplain channel masks within 60 m (approximately two times the average levee width) of the river channel. This effectively removes all natural breaks in the levees and banks created by channels or crevasses. We created one additional floodplain channel mask to delineate the floodplain channels on the existing floodplain using a threshold of -0.15 m. The mask was used for data analysis and quantifying initial conditions.

To quantitatively describe our six different initial conditions, we developed a metric to describe the connectivity within the floodplain-channel networks (hereafter down-valley connectivity, DVC). DVC was calculated as:

$$DVC = \frac{F_{CA}}{F_{TA}} \times F_I$$
 Eqn. 2

where,  $F_{CA}$  is the floodplain channel surface area (m<sup>2</sup>),  $F_{TA}$  is the total floodplain area (m<sup>2</sup>), and  $F_{I}$  is the number of floodplain segments surrounded by floodplain channels (an approximation to assess the number of floodplain channel connections).  $F_{CA}$  was calculated with the floodplain channel masks used to extract floodplain channels (described above).  $F_{TA}$  was measured based on the wetted extent of the 89-year flood (peak of record) from Czuba et al., (2019). Hence, larger DVC values indicate a greater number of well-connected floodplain channels across the floodplain.

Similarly, we describe the connectivity between the floodplain and main channel as riverfloodplain connectivity (RFC). RFC was computed as the coefficient of variation (standard deviation/mean) of the bank height within 30 m (approximately average levee width) of the river channel (Figure 3g). Larger RFC values represent river banks with higher topographic variability, hence an enhanced connection of the river channel to floodplain channels.



**Figure S1**. Model setup along the East Fork White River. The inset shows an example of the computational grid used in the study. Note the floodplain contains a structured grid, while the river and roads have unstructured grids. Locations of the boundary conditions are shown with red lines.

# 1.2 Boundary Conditions

The upstream boundary conditions were specified along the East Fork White River and Sand Creek (Figure S1) as a quasi-steady state discharge entering the domain. The quasisteady state simulations held the discharge entering the domain constant until equilibrium was achieved throughout the entire domain before increasing the discharge (Figure 3h). Discharge entering the domain at the upstream boundaries was chosen based on modeling work by Czuba

et al. (2019), which simulated a variety of discharges (7-day to 89-yr. recurrence interval; RI) on the same reach of the East Fork White River. For our modeling experiments, we used six different discharges ranging from 292 m<sup>3</sup>s<sup>-1</sup> to 2,730 m<sup>3</sup>s<sup>-1</sup> which spanned a range of floodplain inundation extents (Figure 3h). Discharges were specified as 90% of the flow entering the domain from the East Fork White River and 10% entering along Sand Creek, based on comparing relative drainage areas. The downstream boundary was specified along the downstream extent of the East Fork White River and its floodplain was set as normal depth (Figure S1). The computation of normal depth required a friction slope (energy grade line slope) which was set to 0.001 along the boundary. The six simulated discharges and six initial conditions created a total of 36 simulations exploring steady state discharges. Additionally, we ran six simulations for unsteady discharges using the smoothed and existing topography. For the unsteady simulations, we specified no discharge entering the domain along the Sand Creek boundary condition and specified a hydrograph at the upstream boundary for the East Fork White River. The input hydrographs were triangular shaped that had peak discharges of 292 m<sup>3</sup>s<sup>-1</sup>, 581 m<sup>3</sup>s<sup>-1</sup>, and 1467 m<sup>3</sup>s<sup>-1</sup>, respectively. The rising limb of the floodwave increased at a rate of 18.7 m<sup>3</sup>s<sup>-1</sup> per hour and the falling limb decreased at a rate of 8.2 m<sup>3</sup>s<sup>-1</sup> per hour. The rates for rising and falling floodwave limb is based on a 10-year average of all rising and falling limbs of floodwaves at the gage in Seymour, IN (USGS, 2018; Figure 9).

#### 1.3 Calibration and Validation

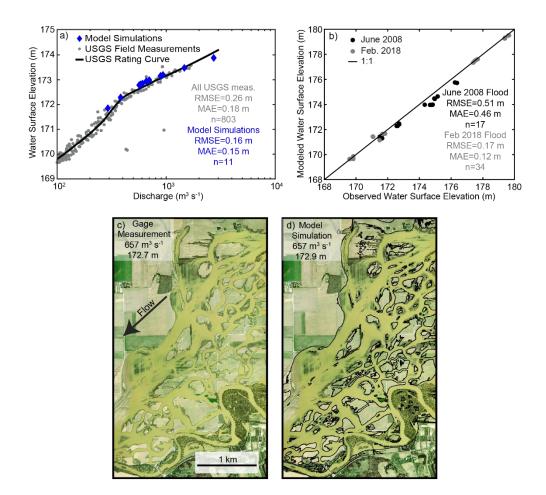
We calibrated the model to the elevation-discharge rating curve developed for the USGS gage located near Seymour, IN (USGS, 2018; Figure 1). Model calibration was conducted by varying Manning's roughness coefficients for the open water (river channel) and agricultural land cover classes (Homer et al., 2015). Final roughness coefficients for the open water and agricultural land cover classes were 0.022 and 0.025 (Table S1), respectively. The final calibrated roughness coefficients in our study differs from those in Czuba et al. (2019) due to the use of the Saint Venant equations rather than the diffusive wave equations. Comparing our model simulations to the elevation-discharge rating curve, we obtained a root mean squared error (RMSE) of 0.16 m and a mean average error (MAE) of 0.15 m. The error we obtained from our model simulations was within the error of the USGS field data used to compute the elevation-discharge rating curve (RMSE= 0.26 m, MAE = 0.18 m; Figure S2a).

Land cover class	Default n	Final <i>n</i>
Agricultural Vegetation	0.04	0.025
Open Water	0.035	0.022
Forest & Woodland	0.12	0.12
Undifferentiated Barren Land	0.04	0.04
Developed, Open Space	0.04	0.04
Developed, Low Intensity	0.08	0.08
Developed, Medium Intensity	0.1	0.1
Developed, High Intensity	0.15	0.15

**Table S1**. Land cover classes and their associated Manning's Roughness coefficients (*n*). The table shows the default Manning's Roughness coefficients (Brunner, 2016) based on land cover classes and our final coefficients after calibration.

Model validation was accomplished using surveyed high-water marks collected by the USGS in 2008 (Morlock et al., 2008), water-surface elevations collected during flooding in February, 2018, and aerial imagery of flooding collected in April, 2011 (locations shown in Figure 1). The 2008 high-water marks were measured using mud, drift, debris, and seed lines on trees, fences, buildings, and utility poles (Morlock et al., 2008) as a proxy for maximum water-surface elevation. The measurements corresponded to the peak of record on June 8, 2018 with a discharge of 2,730 m<sup>3</sup>s<sup>-1</sup>. The 2018 water-surface elevations were measured on February 26, 2018 using RTK-GPS and corresponded to a flow of ~890 m<sup>3</sup>s<sup>-1</sup> at the USGS gage in Seymour, IN. Comparing our model simulation of the existing topography to the measured high-water marks gave a RMSE of 0.51m and a MAE of 0.46m (Figure S3b). A comparison between our model simulation and direct measurements of water-surface elevations collected in 2018 was more accurate with a RMSE of 0.17 m and a MAE of 0.12 m (Figure S3b).

The aerial photo of flooding (Figure S2c) was taken on April 7, 2011 at ~12:30 pm corresponded to a discharge of ~657 m<sup>3</sup>s<sup>-1</sup> and a water-surface elevation of 127.7 m at the USGS gage in Seymour, IN. Comparing our model simulation with a discharge of ~657 m<sup>3</sup>s<sup>-1</sup> and a water-surface elevation of 172.9 m (at the location of the river gage) to the aerial imagery, the simulation slightly over-predicts the extent of inundation, but still captures the majority of land-water transitions (Figure S2d) in high detail.



**Figure S2.** Model calibration and validation data. a) Model calibration to the elevation-discharge rating curve, gage location is shown in Figure 1. b) Simulated vs. measured water surface elevations for high water marks measured from the peak record flood in June 2008 and water surface elevations from flooding on Feb. 26, 2018. c) Aerial photography of flooding on April 7, 2011. d) Model simulation showing transition of water to land as black lines corresponding to the same discharge when the image was taken.

#### 3.3 Data Analysis

Initial model outputs from our 36 modeling experiments included water depth, depth averaged velocity magnitude, and 2-D (x and y directed) depth averaged velocity for each cell. We gridded the results at a 15-m resolution for all analysis. From the initial model outputs, we computed the magnitude of specific discharge (q, Eqn. 3) and a 2-D specific discharge ( $q_{x,y}$ ; Eqn. 4) for each grid cell in all model simulations as:

$$q = \bar{v} * h$$
 Eqn. 3

and

$$q_{x,y} = \overline{v_{x,y}} * h$$
 Eqn. 4

where,  $\bar{v}$  is the depth-averaged magnitude of velocity (m s<sup>-1</sup>), *h* is water depth (m), and  $\bar{v}_{x,y}$  is the 2-D depth-averaged velocity in the x or y direction, respectively (m s<sup>-1</sup>).

To assess the flooding extent in each of our modeling simulations, we produced water masks from our depth data. Water masks were constructed by converting the gridded depth data into polygons and merging the depth polygons into a single polygon representing the wetted extent of the floodplain. The wetted extent polygons were then used to compute the percent of the floodplain that was inundated. Additionally, water masks were used to compute the number and area of hydrologic islands in the domain. Hydrologic islands are defined as dry areas surrounded by water.

We measured the average flooding depth, velocity magnitude, and specific discharge magnitude in the river channel, entire floodplain, and floodplain channels. This was accomplished using a polygon mask of the river channel, entire floodplain extent, and floodplain channel masks used to generate the initial conditions (section 3.2.1). Averages and standard deviations were computed as the mean and standard deviations for a half-Gaussian distribution for all cells within the extent of a polygon. Trend significance of the results were evaluated using a F-test.

We computed an average lateral exchange of surface water between the river channel and floodplain for each steady state model run. Lateral exchange was measured perpendicular to lines situated parallel and positioned 30 m (approximate levee width) from the river banks. The lines were discretized into 90 m long segments and the average  $q_x$  and  $q_y$  were calculated over each 90m line segment. Between vertices, along the 90 m line segment, we used vector decomposition to solve for the magnitude of specific discharge perpendicular to each line segment ( $q_p$ , m s<sup>-1</sup>), where positive  $q_p$  values indicate a flux into the river channel and negative values indicate a flux into the floodplain. The average lateral exchange for each side of this river ( $\overline{q_{ex}^{L,R}}$ , *L* is river left and *R* is river right) is calculated as:

$$\overline{q_{ex}^{L,R}} = (\sum_{j} |q_{j}^{L,R}| d_{j}^{L,R}) \frac{1}{D^{L,R}}$$
 Eqn. 5

where,  $d_j^{L,R}$  (meters) is the length of individual line segment *j* and  $D^{L,R}$  (meters) is the total distance of all line segments along a given side of the river. The absolute value was taken to account for all flux between the river channel and floodplain. Whereas if the absolute value was not taken, we would compute a net flux between the river and floodplain giving a value of ~0, as flow entering the river and exiting the river would negate each other. The lateral exchange through the left and right side of the river were added together and normalized by the average specific discharge in the river channel ( $\overline{q_r}$ ) to produce normalized unitless river-floodplain exchange ( $q_{ex}$ ; Eqn. 6).

$$q_{ex} = \frac{\overline{q_{ex}^L} + \overline{q_{ex}^R}}{\overline{q_r}}$$
 Eqn. 6

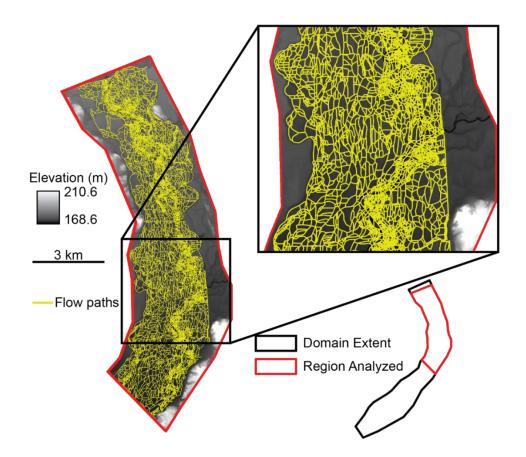
To assess the unit residence time of water in the floodplain, we used a defined network of simulated flow paths that were manually traced by Czuba et al. (2019) in the upper portion of our domain. Flow paths were delineated by systematically increasing discharge, and all new flow paths were traced for each increase in flow. In total, there were 23,211 paths mapped with a cumulative distance of ~1,050 km (Figure S3). Average flow velocity ( $v_i$ ; m s<sup>-1</sup>) was calculated

for each line segment that existed in the wetted extent of each model simulation. A lengthaveraged velocity ( $\overline{v_f}$ ; m s<sup>-1</sup>) in the floodplain over all the line segments was computed as:

$$\overline{v_f} = \frac{(\sum v_i l_i)}{L}$$
 Eqn. 7

where,  $l_i$  is the length of a line segment and L is the length of the total active flow paths. A residence time per unit length of floodplain ( $t_i$ , s m<sup>-1</sup>) was calculated as the inverse of  $v_i$ , which describes the time water spends along a certain length scale. Additionally, we calculated a residence time per unit length for the river ( $t_c$ ; s m<sup>-1</sup>) by taking the inverse of the average magnitude of velocity in the river channel. We normalized unit residence time ( $t_i$ ) by the residence time in the river, creating a unitless residence time in the system as:

$$t_r = \frac{t_f}{t_c}$$
 Eqn. 8



**Figure S3.** Flow paths for unit residence time calculation. The yellow lines show the flow paths delineated by Czuba et al. (2019), used to compute the average unit residence time in the floodplain. The portion of the domain for which the analysis was performed is shown in red and the entire model domain is shown in black.