

24 **Abstract**

25 Two-dimensional (2D) satellite imagery has been increasingly employed to improve
26 prediction of floodplain inundation models. However, most focus has been on validation
27 of inundation extent, with little attention on the 2D spatial variations of water elevation
28 and slope. The availability of high resolution Interferometric Synthetic Aperture Radar
29 (InSAR) imagery offers unprecedented opportunity for quantitative validation of surface
30 water heights and slopes derived from 2D hydrodynamic models. In this study, the
31 LISFLOOD-ACC hydrodynamic model is applied to the central Atchafalaya River Basin,
32 Louisiana, during high flows typical of spring floods in the Mississippi Delta region, for
33 the purpose of demonstrating the utility of InSAR in coupled 1D/2D model calibration.
34 Two calibration schemes focusing on Manning's roughness are compared. First, the
35 model is calibrated in terms of water elevations at a single *in situ* gage during a 62 day
36 simulation period from 1 April 2008 to 1 June 2008. Second, the model is calibrated in
37 terms of water elevation changes calculated from ALOS PALSAR interferometry during
38 46 days of the image acquisition interval from 16 April 2008 to 1 June 2009. The best-fit
39 models show that the mean absolute errors are 3.8 cm for a single *in situ* gage calibration
40 and 5.7 cm/46 days for InSAR water level calibration. The optimum values of Manning's
41 roughness coefficients are 0.024/0.10 for the channel/floodplain, respectively, using a
42 single *in situ* gage, and 0.028/0.10 for channel/floodplain the using SAR. Based on the
43 calibrated water elevation changes, daily storage changes within the size of $\sim 230 \text{ km}^2$ of
44 the model area are also calculated to be of the order of $10^7 \text{ m}^3/\text{day}$ during high water of
45 the modeled period. This study demonstrates the feasibility of SAR interferometry to

- 46 support 2D hydrodynamic model calibration and as a tool for improved understanding of
- 47 complex floodplain hydrodynamics.

48 **1. Introduction**

49 The Atchafalaya River Basin, a low-lying catchment in southern Louisiana
50 consisting of wetlands and bayous, is the principal distributary of the Mississippi River.
51 Given both its proximity and make-up, the Atchafalaya basin plays an important role in
52 mitigating floods and preserving wetland resources in coastal Louisiana. For example,
53 Mississippi River floodwaters in May 2011, resulting from unusually high precipitation
54 in the watershed, were diverted through the Morganza Spillway into the Atchafalaya
55 River Basin to prevent major inundations in populated cities including Baton Rouge and
56 New Orleans [USACE, 2011]. Also, flood damage caused by Hurricane Katrina in
57 August 2005 and Hurricane Rita in September 2005, although significant, was mitigated
58 by flooding into the Atchafalaya basin [LPBF, 2008; Knabb *et al.*, 2006, 2007]. Flood
59 management has been enabled through the construction of levees, bank protection and
60 spillways along the Lower Mississippi River, the Atchafalaya, and their tributaries.

61 Although the man-made levees and river diversions abate flood damage, they also
62 disrupt the natural floodplain environment. Of principal concern is the reduction by more
63 than 50% in the historically large sediment loads deposited within the Lower Mississippi
64 River delta [LPBF, 2010], which is a major factor in the land loss in southeastern
65 Louisiana [Meade, 1995]. Annual wetland loss in Louisiana has been estimated at 100–
66 150 km² and the loss rate is increasing exponentially [Walker *et al.*, 1987; Templet and
67 Meyer-Arendt, 1988], although the Atchafalaya wetland is actually increasing in size.
68 Comprehensive flood control and wetland loss studies on coastal Louisiana including the
69 Atchafalaya River Basin have been initiated to further the understanding of its important
70 role [USEPA, 1987].

71 Despite its importance to the Atchafalaya basin, knowledge of its floodplain
72 dynamics remains poor. This is primarily due to a lack of *in situ* gage measurements in
73 the floodplain. Most operational gages are located along main river channels and bayous
74 for practical and economic reasons and rarely in floodplains [Allen *et al.*, 2008; Kim *et*
75 *al.*, 2009]. Thus, despite long historical data records for the channels, there are
76 insufficient *in situ* data for detailed calibration of 2D models resulting in limited accuracy
77 [Allen *et al.*, 2008]. This is because water flow across wetlands is more complex than
78 channel routing [Alsdorf *et al.*, 2007; Jung *et al.*, 2010] as flow paths and water sources
79 are not constant in space and time, but rather vary with floodwater elevations. Therefore,
80 2D flood modeling combined with emerging remotely sensed data would greatly
81 facilitate the investigation of the temporal and spatial variations of the floodplain water
82 movement and further the understanding of the linkage between channels and
83 floodplains.

84 The first popular approach to fluvial hydraulics modeling was one-dimensional
85 finite difference solutions of the full St. Venant equations along the river reach [e.g.
86 Fread, 1984; Samuels, 1990; Ervine and MacLeod, 1999] since the 1D model design and
87 implementation are simple and computationally efficient (e.g. MIKE11 [DHI Water and
88 Environment, 2001], ISIS [Halcrow and HR Wallingford, 2001], FLUCOMP [Samuels
89 and Gray, 1982] and HEC-RAS [USACE, 2001]). However, when applied to floodplain
90 flows, the 1D model cannot simulate lateral diffusion of the flood wave. This is because
91 floodplain topography is discretized as cross-sections rather than as a surface and flow
92 depends on the location and orientation of finite cross-section measurements [Hunter *et*
93 *al.*, 2008].

94 The advances in computing resources and the growing availability of spaceborne
95 data have enhanced the opportunities to estimate flood inundation extent, floodplain
96 water elevation, and to model floodplain hydrodynamics [Hess *et al.*, 1995; Smith, 1997;
97 Alsdorf *et al.*, 2000; Bates *et al.*, 1992]. For instance, high-resolution Light Detection
98 And Ranging (LiDAR) elevation maps enable modelers to represent an improved spatial
99 resolution of channel and floodplain hydraulics that are consistent with known processes
100 [Bates *et al.*, 2005]. Repeat-pass synthetic aperture radar (SAR) interferometry has
101 recently been employed to estimate water level changes with time [Alsdorf *et al.* 2000]
102 and when combined with modeling storage changes [Alsdorf, 2003] and flow hydraulics
103 [Alsdorf *et al.*, 2005]. Satellite SAR interferometry offers the opportunity to characterize
104 complex fluvial environments in combination with sparse *in situ* gages and satellite
105 altimetry [Kim *et al.*, 2009; Lu *et al.*, 2009; Lee *et al.*, 2009; Jung *et al.*, 2010]. The
106 floodplain waters and lake habitats can provide double-bounce backscattering, which
107 allows SAR interferometric coherence to be maintained and provides water elevation
108 changes [Lu *et al.*, 2005; Lu and Kwoun, 2008; Jung and Alsdorf, 2010].

109 Two-dimensional models in conjunction with suitably resolved and accurate
110 digital elevation models (DEMs) of the channel and floodplain surface, and with suitable
111 inflow and outflow boundary conditions, allow the water depth and depth-averaged
112 velocity to be computed [Bates *et al.*, 2005]. Many 2D hydraulic modeling approaches
113 discretized the floodplain as a high resolution regular grid [e.g. TUFLOW [Syme, 1991],
114 DIVAST [Falconer, 1986], TRENT [Villanueva and Wright, 2006], JFLOW [Bradbrook
115 *et al.*, 2004], and LISFLOOD-FP [Bates and De Roo, 2000], and structured grid 2D flood

116 inundation modeling has been widely used to predict floodplain inundation since first
117 proposed by Zanobetti *et al.* (1970).

118 The work presented here complements previous investigations of Atchafalaya
119 River hydrology. For example, previous modeling studies have focused on the spatial and
120 volumetric changes of water, sediment, and salinity in the delta and coastal regions
121 located at outlets of the Atchafalaya River Basin [e.g. Donnell *et al.*, 1991; Donnell and
122 Letter, 1992; Wang *et al.*, 1995; Vaughn *et al.*, 1996]. However, these studies did not
123 implement 2D hydrodynamic modeling to reveal the floodplain water variations within
124 the levee-protected areas. Other studies using SAR interferometry showed the feasibility
125 to measure floodplain water elevation changes in combination with *in situ* measurements
126 and altimetry [Lu *et al.*, 2005; Lu and Kwoun, 2008; Lee *et al.*, 2009; Kim *et al.*, 2009].
127 These studies were focused on the number of SAR data acquisition and areas of
128 coverage. Other studies using visible and infrared Landsat imagery have delineated land-
129 water classification within the Atchafalaya River Basin [Allen *et al.*, 2008].

130

131 **2. Study Objective**

132 The calibration of 2D floodplain modeling investigations is usually limited by few
133 or no water level gages in the floodplain. In many counties, post-flood field surveys are
134 conducted to determine flood damage and extent. While coupled 1D/2D flood modeling
135 offers improved estimation of inundation extent, few studies are able to validate detailed
136 spatial variations in floodplain water elevations. Remote sensing methods for flood
137 inundation extent were utilized to measure the fitness of the floodplain model results [e.g.
138 Wilson *et al.*, 2005; Di Baldassarre *et al.*, 2009]. Few modeling studies have taken

139 advantage of current satellite SAR interferometric phase measurements of water elevation
140 changes since the SAR interferometric processing is not straightforward to generate the
141 hydrologic products for the specified model use.

142 The goal of the present study is to investigate to what extent SAR interferometry
143 can be used to improve model calibration. Specifically, the 2D LISFLOOD-ACC model
144 [Bates *et al.*, 2010] is applied to the central Atchafalaya River Basin together with repeat-
145 pass interferometry from the Advanced Land Observing Satellite (ALOS) Phased Array
146 type L-band Synthetic Aperture Radar (PALSAR). LISFLOOD provides 1D diffusive
147 channel flow and 2D simplified shallow water floodplain flow [Bates *et al.*, 2010].
148 Satellite InSAR data, namely PALSAR, are used to derive flood levels changes and water
149 surface slopes at times of SAR data acquisitions.

150 LISFLOOD is calibrated using two different approaches, both focusing primarily
151 on Manning's equation. First, a traditional approach using gage measurements is
152 employed. Second, the same model is calibrated using the 2D water level and slope data
153 extracted from two PALSAR interferometric images, acquired 46 days apart. The results
154 of both approaches are compared and the merits and disadvantages of each are discussed.
155 The PALSAR-derived floodplain water elevation change is also used to generate time
156 series of water storage change in the model area.

157 This study offers to add new insights in 2D hydrodynamic modeling particularly
158 in floodplain environments. The complexity of floodwaters has not been well captured
159 because floodwaters move laterally across wetlands and this movement is not bounded
160 like that of typical channel flow. This study of 2D hydrodynamic modeling and
161 implementation of SAR interferometry for model calibration aims to improve our

162 understanding of the Atchafalaya floodplain dynamic knowledge and provide an
163 opportunity to investigate the impacts of flood hazard in the coastal Louisiana regions.

164

165 **3. Study Area**

166 The Atchafalaya River Basin is located west of the Lower Mississippi River in
167 south Louisiana within the coastal margin of the Gulf of Mexico. This region includes
168 about 2,500 km² of the Nation's most significant extents of bottomland hardwoods,
169 swamps, bayous, and backwater lakes [Allen *et al.*, 2008]. The Atchafalaya River's
170 immense floodplain is bounded on the east and west sides by levees. Gates along the
171 main stem are used to divert nearly 30% of the Mississippi River water into the
172 Atchafalaya and this flows south through the floodplain to the Gulf of Mexico along
173 approximately 225 km of river reach [LDNR, 2010; Kim *et al.*, 2009].

174 As a consequence of frequent flooding, the basin is a sparsely populated area
175 holding a rich abundance and diversity of terrestrial and aquatic species. In the spring, the
176 basin receives well-oxygenated water carrying high loads of sediment and nutrients
177 [Allen *et al.*, 2008]. In addition to the Atchafalaya River, Wax Lake Outlet inside the Six
178 Mile Lake Water Management Unit (WMU) governs the outflow from the levee
179 protected basin to the Gulf of Mexico for water management.

180 Figure 1 shows the location map including rivers, levees, gages, ALOS PALSAR
181 swath, and model area. The USGS National Wetlands Research Center and the U.S.
182 Army Corps of Engineers (USACE) provide current stage data on nearly three dozen
183 stations in the basin. Gage stations used in this study are indicated in Figure 1.

184 The USACE has identified 13 subbasins or WMUs because of morphological
185 diversity within the basin [USACE, 1982]. Figure 2 shows the WMUs outlined in gray.
186 Because of the unique character of each WMU, fluctuating river levels can result in very
187 different patterns of water distribution among the WMUs. The seasonal flow of water
188 through the basin is critical to maintaining its ecological integrity.

189 For the current study, LISFLOOD is applied specifically to the Buffalo Cove
190 WMU, an area of 230 km² in the central Atchafalaya River Basin (See Figure 1, 2). The
191 WMU is characterized by a swamp forest with paths of slowly moving water or bayous.
192 This WMU is selected because of the proximity of *in situ* and satellite measurements, and
193 because its upstream, downstream, and lateral boundaries are well defined. Buffalo Cove
194 is surrounded by the main channel on the east and a levee on the west (Figure 2) with
195 water level gage stations at Myette Points (C3) in the channel and Buffalo Cove (B1) in
196 the bayou, shown in Figure 3. Moreover, the Buffalo Cove and Upper Bell River WMUs
197 show clearer flow pattern of floodwater in the PALSAR interferometric phase as compared
198 to any other WMUs (Figure 4). This provides more spatial variation in water elevation
199 changes and is therefore a more rigorous test of the floodplain model performance.

200

201 **4. Methods and Data**

202 **4.1. Hydrodynamic Model**

203 An inertial and parallel version of LISFLOOD-FP hydrodynamic model, or
204 LISFLOOD-ACC [Bates and De Roo, 2000; Bates *et al.*, 2010], is applied to the Buffalo
205 Cove WMU. LISFLOOD-ACC is a simplified shallow water model that allows the use of
206 a larger stable time step than previous LISFLOOD-FP variants, and hence quicker run

207 times in addition to a better representation of the flow physics [Bates *et al.*, 2010; Neal *et*
 208 *al.*, 2011]. Channel flow is represented using the diffusive approximation to the full 1D
 209 St. Venant equations solved using a fully implicit Newton-Raphson scheme. Floodplain
 210 flows decoupled in x and y are implemented for a raster grid to give an approximation to
 211 a 2D inertial wave. Mass conservation was simulated through the continuity equation
 212 (Equation 1). The LISFLOOD-ACC momentum equation includes the gravity and local
 213 acceleration terms from the shallow water equations but not the convective acceleration
 214 and is solved using an explicit finite difference scheme (Equation 2).

215

$$216 \quad h_{i,j}^{t+\Delta t} = h_{i,j}^t + \Delta t \frac{Q_{x_{i,j-1}}^t - Q_{x_{i,j}}^t + Q_{y_{i,j-1}}^t - Q_{y_{i,j}}^t}{\Delta x^2} \quad (1)$$

$$217 \quad Q^t = \frac{q^t - g h_{flow}^t \Delta t \frac{\Delta(h^t + z)}{\Delta x}}{\left(1 + g h_{flow}^t \Delta t n^2 |q^{t-\Delta t}| / (h_{flow}^t)^{10/3}\right)} \Delta x \quad (2)$$

218

219 where h is the cell water depth, h_{flow} is the depth between cells through which water can
 220 flow, Q is the flow between cells, Δx is the cell size, n is Manning's roughness
 221 coefficient, q is Q from the previous time step divided by cell width and g is gravity.
 222 Model implementation involves use of the diffusive solver for channel flow and
 223 Equations (1) and (2) for 2-D inundation flow modeling, which has been parallelized
 224 using the shared memory Open Multi Processor (OpenMP) [Neal *et al.*, 2009] to reduce
 225 model run time.

226 The Buffalo Cove model was run over a 62-day simulation period from 1 April
 227 2008 to 1 June 2008 to accommodate at least two ALOS PALSAR acquisition dates on
 228 April 16 2008 and 1 June 2008. Figures 3a and 3b illustrate that the simulation period

229 runs during high flow conditions associated with upper Mississippi River basin snowmelt
230 and spring rains, typical for this time of year.

231 Inputs include floodplain topography, bathymetric depths, channel widths, flow
232 boundary conditions, and Manning’s roughness coefficients for channels (n_C) and
233 floodplains (n_F). The floodplain topography was constructed using a high resolution 1 m
234 LiDAR DEM of the whole basin published by USGS National Geospatial Program and
235 USGS Coastal and Marine Geology Program [USGS, 2011]. The LiDAR survey was
236 acquired in November 2010 during an optimal data collection window in terms of
237 average river stage, average minimum temperature, and tree canopy as compared to the
238 previous LiDAR data collections in years of 2000, 2002, and 2003. The vertical accuracy
239 requirements meet or exceed the required RMSE of 18.5 cm. The 1 m LiDAR data was
240 aggregated to 90 m to decrease grid resolutions and reduce model run time. The pixel-to-
241 pixel noise is uncorrelated and reduces linearly in proportion to $1/\sqrt{n}$ as the data are
242 aggregated, where n is the number of pixels being averaged [Rodriguez *et al.*, 2006]. The
243 input LiDAR noise for model grids at 90 m is less than 0.2 cm. The averaging can result
244 in a terrain data error due to smoothing out hydraulically relevant topography. This
245 resolution has been shown in a number of previous studies to be appropriate to predict
246 flood inundation in rural areas providing care is taken over the representation of linear
247 features, such as embankments or levees, which can control the flow development [Bates
248 and De Roo, 2000; Horritt and Bates, 2001]. Levees in the domain are narrow, typically
249 less than 10 m wide and are sufficiently high so that floodwaters cannot overtop them for
250 the chosen simulation period. In order to handle these subgrid-scale features [Yu and
251 Lane, 2011], the levees in 1 m resolution are vectorized, extracted, and input into the 90

252 m resolution floodplain topography directly, without averaging out adjacent elevations
253 that would have resulted in an uncharacteristically low height at 90 m resolution.

254 Bathymetry was based on USACE data. The USACE developed updated flood
255 control, navigation maps, and hydrographic survey maps for the Atchafalaya River as
256 part of a comprehensive mapping project [USACE, 2006]. The mapping project provided
257 bathymetric depth measurements every ten feet along the river cross sections. Based on
258 the bathymetry dataset, the average bed elevations and channel widths were calculated as
259 equivalent area rectangular cross sections at about every 1 km along the 34 km reach of
260 the main channel in the Buffalo Cove region.

261 To facilitate model set up, the model coordinates were rotated 15.67° clockwise
262 about the North. The coordinate rotation makes the vertical component of Y axis in the
263 model system parallel to the main channel direction and the horizontal component of X
264 axis to the floodplain flow condition. Figure 2 shows schematic local hydrodynamics in
265 the study area. Flow pathways are well protected by high levees, thus water discharge per
266 each cross section along the main river channel is conservative. The continuity constraint
267 is given by:

268

$$269 \quad Q_{C1}^t + Q_{F1}^t = Q_{C2}^t + Q_{F2}^t = Q_{C3}^t + Q_{F3}^t \quad (3)$$

270

271 where the superscript t represents time varying discharge (Q), subscript digits are cross
272 section locations, and the subscript letters C and F represent the channel and floodplain,
273 respectively. The channel flow from upstream to downstream results in more overbank
274 flooding into the floodplain, thus the upstream channel discharge is greater than the

275 downstream channel discharge (i.e. $Q_{C1}^t > Q_{C2}^t > Q_{C3}^t$). The upstream floodplain
 276 discharge is lower than the downstream floodplain discharge and floodplains around
 277 WMU1 and WMU2 are not flooded due to high levees which prevent overbank flow
 278 (i.e. $Q_{F3}^t > Q_{F2}^t > Q_{F1}^t = 0$).

279 Boundary conditions for fluvial flooding applications normally consist of the
 280 time-dependent discharge in the compound channel at the upstream end of the reach and
 281 the time varying water elevation or gradient at the downstream end of the channel [Bates
 282 *et al.*, 2005]. Since there is no discharge station at the upstream boundary of the WMU1
 283 domain, a virtual location C2 was created for which flow, Q_{C2}^t was estimated using an
 284 inverse distance squared weighting (IDW) interpolation with channel discharges Q_{C1}^t at
 285 Krotz Springs and Q_{C3}^t at Myette Point [Heijden and Haberlandt, 2010]. The upstream
 286 channel boundary condition is thus calculated as:

287

$$288 \quad Q_{C2}^t = f(Q_{C1}^t, Q_{C3}^t)_{IDW} = \frac{Q_{C1}^t \cdot d_{C2C3}^2 + Q_{C3}^t \cdot d_{C1C2}^2}{d_{C1C2}^2 + d_{C2C3}^2} \quad (4)$$

289

290 where d_{ij} is the distance between locations of i and j .

291 In addition to upstream channel discharge, upstream floodplain discharge is also
 292 set as a boundary condition. Although non-channel flow at the boundary of the domain is
 293 usually negligible for fluvial flooding applications [Bates *et al.*, 2005], a time dependent
 294 floodplain discharge is necessary since the upper domain boundary crosses the floodplain
 295 and substantial flow crosses into the domain during the 62 day simulation period. The
 296 upstream floodplain discharge derived from Equation (3) and (4) (i.e. $Q_{F2}^t = Q_{C1}^t +$

297 $Q_{F1}^t - Q_{C2}^t; Q_{F1}^t = 0$) was distributed equally among all the upstream boundary grid
298 cells.

299 For the downstream condition, water elevation data at Myette Point (H_{C3}^t) were
300 used. The other boundaries of the domain within the rectangular grid are set to a free flux
301 condition to force the model to calculate the slope used for the normal depth calculation
302 between the last two points. Figure 3 shows daily time series of water elevations and
303 discharges at gage stations. Gage stations are located at Krotz Springs (C1) and Myette
304 Point (C3) along the main channel and at Buffalo Cove (B1) in the bayous, whereas C2 is
305 a virtual station. The gage vertical datum are converted from the National Geodetic
306 Vertical Datum of 1929 (NGVD29) into the National American Vertical Datum of 1988
307 (NAVD88) [Milbert, 1999] to fit the LiDAR floodplain elevations and bathymetry
308 dataset from USACE. In this study, focus is on right (i.e. west) bank flooding in the
309 Buffalo Cove WMU from the main channel of the Atchafalaya River.

310 To calibrate the model response to Manning's roughness coefficients, a matrix of
311 36 simulations was run with values of n_C varying from 0.020 to 0.030 in steps of 0.002 in
312 the channel, and n_F varying from 0.05 to 0.30 in steps of 0.05 in floodplain. The range of
313 values was chosen based on tables of typical n in various types of channels and
314 floodplain [Chow, 1959]. Previous modeling in the Atchafalaya River Delta suggested
315 that Manning's roughness coefficients in the area ranged from 0.01 to 0.06 for navigable
316 waters, 0.01 to 0.02 for bayous, 0.03 to 0.06 for obstructed canals, and 0.2 to 0.5 for
317 marsh and/or subaerial delta lobes [Donnel *et al.*, 1991; Donnel and Letter, 1992].

318 The Mean Absolute Error (MAE) and bias were used to evaluate the sensitivity of
319 the model to the range of Manning's coefficients, or:

320

$$321 \quad MAE = \frac{1}{N} \sum_{i=1}^N |M_i - O_i| \quad (5)$$

322

$$323 \quad bias = \frac{1}{N} \sum_{i=1}^N (M_i - O_i) \quad (6)$$

324

325 where M is model and O is observation (i.e. gage height or interferometry height
326 differences). The MAE and bias were computed for all points where there were
327 observations and were weighted equally. All model results for the total model period of
328 62 days are included in this calibration. Further details of both calibration approaches,
329 using water elevations of gage measurements and water elevation changes from SAR
330 interferometry, are described in 5.1 and 5.2, respectively.

331

332 **4.2. SAR Interferometry**

333 The Japan Aerospace Exploration Agency's (JAXA's) Advanced Land Observing
334 Satellite (ALOS), a follow-on mission for the Japanese Earth Resources Satellite-1 (JERS-
335 1), carries the Phased Array type L-band Synthetic Aperture Radar (PALSAR). The
336 PALSAR scenes are HH polarized and L-band (wavelength: 23.62 cm). The incidence
337 angles of PALSAR scenes are approximately 38.7° from descending passes. The
338 PALSAR swath of path 168 and frame 590 were collected on 16 April 2008 and 1 June
339 2008. As illustrated in Figure 1, the SAR image covers the central Atchafalaya River
340 Basin including the Buffalo Cove WMU.

341 Measurements of water elevation changes (dh/dt) for the model domain were
342 obtained from repeat-pass PALSAR interferometry and are used in model calibration.

343 SAR Interferometric processing follows the two pass method [Massonnet *et al.*, 1993].
344 The interferometric phase includes satellite orbit, topographic relief, and any changes in
345 the radar range (i.e. floodplain water elevation change in this study). The orbit related
346 phase is subtracted through flat earth phase removal that calculates satellite state vectors
347 given by the system file and adjusts baseline errors based on the residual phase in the
348 interferogram. As the most critical parameter in SAR interferometry, baseline is a
349 measure of the distance between the two SAR antenna locations. The topographic related
350 phase is subtracted using the Shuttle Radar Topography Mission (SRTM) C-band
351 elevation data to make the remaining differential phase dependent on floodplain water
352 elevation changes. Interferometrically measured water elevation changes in the direction
353 of the radar line-of-sight (LOS) are converted to a vertical displacement in terms of the
354 wavelength and incidence angle of the PALSAR scenes [Massonnet and Feigl, 1998]. In
355 this processed interferogram, 2π radians of interferometric phase are equivalent to 15.1
356 cm of vertical height change.

357 Figure 4 shows differential wrapped interferometric fringes in the floodplain. The
358 patterns of a cycle of interferometric phase (i.e. fringe) imply that the basin consists of
359 various independent hydrodynamic units as defined by the USACE (1982). Distinct
360 changes in the interferometric dh/dt measurements are located along WMU boundaries.
361 Most of the WMUs exhibit homogenous values in the interferogram. However, WMUs
362 Buffalo Cove and Upper Bell River show sheet flow pattern and WMU Bayou DeGlais
363 shows a sharp distinction in the middle of the floodplain due to a navigable waterway.
364 The differential phase wrapped in a cycle of 2π radians is unwrapped with minimum cost
365 flow techniques and a triangular irregular network to provide water elevation changes. In

366 the phase unwrapping stage, adaptive radar interferogram filtering is applied to reduce
367 noise and enhance fringe visibility. The unwrapped differential phase corresponds to
368 relative water elevation changes. The interferometric SAR measurements require a
369 reference datum to convert from the relative water elevation changes to absolute values
370 [Jung *et al.*, 2010]. For this reference datum, gage B1 was used, where the water level
371 decreased 71 cm. (i.e. $dh/dt = -71$ cm over 46 days from 16 April 2008 to 1 June 2008,
372 see h_{B1} in Figure 3b). The unwrapped and absolute interferometric measurements, shown
373 in Figure 8c, were used to calibrate model water elevation changes.

374

375 **5. Results**

376 **5.1. Calibration of Model Water Elevations (h) with Gage Measurement**

377 LISFLOOD was first calibrated in terms of water elevations at the Buffalo Cove
378 (B1) gage using a matrix of 36 simulations with various Manning's roughness
379 coefficients of the channel (n_C and the floodplain, n_F . For each simulation, the MAE was
380 computed based on the daily water elevation differences between model and gage
381 measurement for the entire 62 day simulation period. The best-fit model of n_C and n_F
382 was then determined as the lowest MAE in the three dimensional space plot of MAE, n_C
383 and n_F . Figure 5 shows calibration surfaces for MAE and bias. The models with 0.022 to
384 0.026 in n_C and 0.10 to 0.20 in n_F show less than 10 cm in MAE. The optimum lies at
385 0.024 in n_C and 0.10 in n_F with 3.8 cm in MAE. The calibration surfaces show the L-
386 shaped optimal region typical for 2D hydraulic models optimized against single gage or
387 flood extent data (see for example Fewtrell *et al.*, 2011). Here an increase in channel
388 friction can be compensated for by a decrease in floodplain friction (and vice versa) to

389 yield identical MAE or global goodness of fit for a range of channel and floodplain
390 friction combinations. It can be seen that as one moves away from the optimal L-shaped
391 region, MAE is greater with increasing gradient.

392 The bias calibration surface shows that as n_C increases, bias increases and
393 becomes less sensitive to n_F . It implies that modeling water elevations at gage B1 in
394 bayous is more dependent on the Manning's roughness coefficient of the main channel
395 relative to that of the surrounding floodplain. The generally positive bias means that
396 modeled water elevations are greater than the gage measurement (see Equation 6). This
397 agrees with the notion that water elevation and storage must increase since higher
398 channel roughness decreases water velocity, thereby requiring a greater cross-section to
399 maintain the same outflow. The daily time series of water elevation in the best-fit model
400 is shown in Figure 6. It reveals that after 2 days of initiating the simulation, the model
401 reaches a stable stage and the model results fit the gage water elevations within ± 4 cm
402 MAE. This is an excellent result given typical terrain and discharge errors, and within an
403 engineering study would likely be used to indicate a model that could be used to take
404 flood risk management decisions. In scientific terms, it is however a relatively limited
405 test since the model performance is only evaluated at a single point with the domain.

406

407 **5.2. Calibration of Model Water Elevation Changes (dh/dt) with SAR**

408 **Interferometry**

409 The model is calibrated in terms of water elevation changes in the Buffalo Cove
410 WMU using the same simulations as performed in 5.1. However, instead of using one *in*

411 *situ* gage with a continuous height record, calibration is conducted using two images of
412 height covering the entire flooded domain, separated by 46 days.

413 The MAE is again used to find the best-fit model of n_C and n_F against water
414 elevation changes calculated from ALOS PALSAR interferometry from 16 April 2008 to
415 1 June 2008. Figure 7 shows calibration surfaces for MAE and bias. The models with
416 0.024 to 0.028 in n_C and 0.10 in n_F show a MAE of less than 8 cm over the 46 day
417 period. The optimum lies at 0.028 in n_C and 0.10 in n_F with a MAE of 5.7 cm, which are
418 similar but not identical to Manning's roughness coefficients calibrated in 5.1. The bias
419 calibration surface shows that as n_F increases, bias decreases, being less sensitive to n_C .
420 It implies that obtaining an optimal match between floodplain dh/dt measurements and
421 the LISFLOOD-ACC model for the Buffalo Cove WMU is more dependent on the
422 Manning's roughness coefficient of the floodplain compared to that of the main channel.
423 The negative bias means that model water elevation change is actually less than that
424 indicated by the interferometric measurements (see Equation 6). This is consistent with
425 the notion that floodplain water elevations are less sensitive with higher roughness in the
426 floodplain due to the lower floodplain velocities. Total frictional force (F) is proportional
427 to Manning's roughness (n) and the square of flow velocity (v^2) so model sensitivity to
428 friction is a non-linear function of the flow velocity (v). When v is low, the modeled
429 water levels become dramatically less sensitive to n .

430 Figure 8 shows water elevation change maps calculated from the best-fit model
431 and SAR interferometry. The modeled dh/dt is calculated by subtracting the water
432 elevation map on 16 April 2008 from that on 1 June 2008. The interferometrically
433 measured dh/dt in Figure 8 is absolute water elevation changes which are referenced

434 and unwrapped from the differential wrapped interferogram in Figure 4. The dh/dt in
 435 Buffalo Cove WMU ranges from -100 to -50 cm over 46 days showing that the
 436 floodplain is draining over the this period. The largest difference in dh/dt between
 437 model and SAR interferometry is exhibited in the southwest part of the WMU. It appears
 438 that inside waterways hold floodwater moving from east to west and add more
 439 complexity into the local floodplain dynamics than is captured by this model. The
 440 Amazon floodplain channels are discovered to govern the complex water flow in the
 441 locally confined hydrodynamics [Alsdorf *et al.*, 2007; Jung *et al.*, 2010]. The
 442 interferometry demonstrates that the southwest part exhibits a distinct difference in the
 443 spatial gradients of water elevation changes as compared to the surrounding area, which
 444 is micro-terrain effects that are not predicted by the model in a 90 m grid,

445

446 **5.3. Estimation of Water Storage Changes (dS/dt) in Buffalo Cove WMU**

447 The daily modeled dS/dt is calculated by multiplying dh/dt by the grid cell
 448 area. The model dh/dt calibrated by SAR interferometry is used to calculate dS/dt .

449

$$450 \quad dS^t/dt = S^t - S^{t-1} = \sum_{i=1}^N (h_i^t - h_i^{t-1}) \cdot dx \cdot dy \quad (7)$$

451

452 where t ranges from 1 to 62 as a simulation day and dx and dy are 90 m for a given grid
 453 box.

454 The time series dS/dt is shown in Figure 9a for daily as well as 5 and 10 day moving
 455 averages. The daily storage changes in the model domain of about 230 km² range
 456 approximately from +10⁷ m³/day to -10⁷ m³/day during the modeled period. The water

457 storage changes are positive at the beginning whereas they turn to be negative after 27
458 April 2008 with some variations.

459 The relationship between the model water storage changes (dS/dt) and water
460 elevation changes (dh/dt) at the Buffalo Cove gage (B1), shown in Figure 9b, shows a
461 strong linear relationship, except for three outliers generated at the beginning of the
462 simulation. It implies that the model requires more than 3 days to wet the whole
463 floodplain and to provide reasonable values of water elevations in the floodplain of the
464 WMU. The first polynomial regression model ($y = 2216650 \cdot x + 52421$; $y: dS/dt$,
465 $x: dh/dt$) exhibits an R^2 of 0.94. The residuals of the regression model explain that
466 dh/dt at the Buffalo Cove gage cannot be representative of dh/dt across all of the
467 Buffalo Cove WMU floodplain. As can be seen in Figure 8, the dh/dt varies markedly in
468 space. Maps of h and dh/dt in Figure 10 exhibit water storage changes that are positive,
469 near zero, and negative. The maps of h show instances of floodplain filling and emptying.
470 For instance, the average dh/dt of the WMU between 15 April 2008 and 16 April 2008
471 is 2.4 cm/day when the corresponding dS/dt is 5.5×10^6 m³/day. On the contrary, the
472 dh/dt average of the WMU between 31 May 2008 and 1 June 2008 is -2.9 cm/day when
473 the corresponding dS/dt is -6.6×10^6 m³/day. The dh/dt maps in the lower panel of
474 Figure 10 show less variation within the WMU as compared to the dh/dt maps shown in
475 Figure 8 because the time interval (dt) is 1 day shorter than 46 days in Figure 8.

476

477 **6. Discussion**

478 Two approaches to calibrate a 2D hydrodynamic model were investigated, one
479 using a single *in situ* gage measurement and the second using SAR interferometry. Each

480 approach calibrates the model in terms of different model products that have different
481 space (i.e. dimensionality) and time scales. The first calibration uses time series of water
482 elevations at one specified gage station for the total simulation period of 62 days. Due to
483 the gage location in the bayou, the calibration shows more dependency on channel
484 roughness relative to floodplain roughness.

485 The second calibration uses water elevation changes calculated from SAR
486 interferometry across the whole WMU area for one time interval of 46 days between two
487 successive overpasses of the PALSAR satellite. The latter is a particularly stern test for a
488 2D hydrodynamic model as to require accurate prediction of spatial patterns of water
489 elevation change over a long simulation period. Since SAR interferometry receives strong
490 scatters in the floodplain due to the double bounce effect as compared to specular
491 scattering of open water [Lu and Kwoun, 2008; Jung and Alsdorf, 2010], this calibration
492 shows more dependency on floodplain roughness.

493 Most 2D floodplain modeling requires a longer spin-up time, as compared to 1D
494 channel modeling, in order to wet the floodplain as well as channel for stabilization of the
495 floodplain dynamic in the model. The spin-up time in the calibration with SAR
496 interferometry requires at least 3 days more than the 2 days required with only gage
497 measurements. The different calibration methods suggest the same floodplain roughness,
498 but different channel roughness in their best-fit models, which can be explained by
499 different model products used in their calibrations. The pattern and trend of the MAE and
500 bias calibration surfaces imply that calibration against different data sets would lead a
501 user to make different conclusions regarding the model's differential sensitivity to
502 channel and floodplain friction. Practically, the real meaning of roughness as an effective

503 parameter is a component of topography that has to be calculated to optimize the
504 agreement between model predictions and measurements [Lane, 2005]. The calibrated
505 roughness can be a valuable reference to the hydrodynamic modeling community as it is
506 properly adjusted along water stage, grid resolution, and model feature.

507 The impact of the results to uncertainty in upstream discharge was investigated by
508 changing the flow by +/- 20 percent in increments of 5 %, for both calibration
509 approaches. Root-Mean-Square-Deviation (RMSD) in the modeled h and dh/dt was
510 computed for each flow, averaged across the domain, using the best-fit model of 0.028 in
511 n_C and 0.10 in n_F . Assuming that even for good gages, Q error is likely to be $\pm 10 \%$,
512 Figure 11 indicates that this likely error in upstream Q leads ~ 10 cm of errors in the
513 modeled h maps on both 16 April 2008 and 1 June 2008 and less than 2.5 cm in the
514 modeled dh/dt map (Figure 11). This implies that the effect of an error in Q on the
515 absolute water elevations is much larger than the effect of the same Q error on the water
516 elevation changes. The deviation on absolute water elevations can be compensated for in
517 any modeling study with a uniform offset derived from a contemporaneous ground truth
518 campaign. The deviation of 2.5 cm in the modeled dh/dt can be regarded as the range of
519 acceptable differences between the observed dh/dt and the modeled one. It suggests that
520 within the $Q \pm 10 \%$ error ranges, 54 % of dh/dt map in Figure 8d shows a good
521 agreement between the model and the interferometric measurement. The slight difference
522 in channel roughness between two calibration methods (i.e. 0.024 / 0.1 and 0.028 / 0.1 in
523 n_C / n_F , respectively) leads ~ 1.5 cm of the modeled dh/dt difference in Figure 7a and
524 this can be also explained by within the $Q \pm 10 \%$ error ranges.

525 SAR interferometry with a short baseline is the more appropriate to provide water
526 elevation changes and calibrate the corresponding model products as compared to long
527 baseline. Short perpendicular components in the baseline yield more topographic relief
528 per phase cycle than long baselines, thus more reliable estimates of water elevation
529 changes [Zebker and Villasenor, 1992]. In this study, the ALOS PALSAR L-band
530 interferogram were processed with a perpendicular baseline of -219 m at the center of the
531 satellite acquisition. The short baseline indicates that 2π radians of phase are equivalent
532 to ~ 204 m of topographic relief (i.e. the ambiguity height) whereas depending on the
533 incidence angle, the same 2π radians are also equivalent to about 15.1 cm of vertical
534 water elevation change [Massonnet and Feigl, 1998]. The short perpendicular baselines
535 and the C-band SRTM relative height errors of 5.5 m [Farr *et al.*, 2007] cause 0.17
536 radians of phase change, which are equivalent to 0.4 cm of vertical displacement. The
537 accuracy of this displacement measurement is a function of the local coherence as well as
538 of our ability to separate the topographic phase component from the total observed phase.
539 The mean coherence of 0.35 in the modeled floodplain yields an expected phase noise
540 value of less than 0.4 radian error for 21 looks used in the processing [Zebker and
541 Villasenor, 1992; Li and Goldstein, 1990], which is equivalent to less than 1.0 cm of
542 vertical displacement. The scale errors in the observed dh/dt are small enough to
543 calibrate the modeled dh/dt and provide the optimum Manning's roughness.

544 In both gage stage h and interferometric SAR dh/dt calibrations, the tolerable
545 difference between model and data is much smaller as some of key errors drop out. Error
546 sources in the LiDAR data, a terrain data error resulting from the averaging to 90 m, the
547 observed h data, and the measured dh/dt are less than 1 cm whereas the likely $\pm 10\%$

548 errors in Q result in less than 2.5 cm in the modeled dh/dt . It is noted that these errors
549 are not necessarily additive and not all will be at a maximum at the same time.

550 This model domain is mostly covered with woody wetland, yet the Atchafalaya
551 River Basin includes more various land covers of urban, pasture, cultivated crops, woody
552 wetlands, and emergent herbaceous wetlands in 2006 National Land Cover Data
553 (NLCD) distributed by USGS [Fry *et al.*, 2011]. For large floodplain modeling, the
554 roughness can be assigned in more detail based on land use and land cover [Kalyanapu *et*
555 *al.*, 2009]. To take advantage of land cover data to the roughness assignment,
556 optimization algorithms need to be utilized for multi parameter calibration [Zhang *et al.*,
557 2008].

558

559 7. Conclusions

560 The 2D LISFLOOD-ACC model was applied to spring flooding in the central
561 Atchafalaya River Basin and calibrated using two independent approaches. A traditional
562 approach used a continuous temporal record of *in situ*, point water level gage
563 measurements. The second new approach, employed temporal (dh/dt) and spatial
564 (dh/dx , dh/dy) variations of water levels derived from ALOS PALSAR interferometry,
565 observed at two separate times. Although the two different approaches yielded slightly
566 different values for channel Manning's n , the close comparison in results establish the
567 feasibility of satellite based approach, at least for this particular basin and flow
568 conditions. Results were facilitated by a relatively simple spring hydrograph with few
569 spikes in river discharge, and well defined floodplain boundaries. Overall, the results

570 offer a new approach for satellite-based calibration of hydrodynamic models, especially
571 in regions of sparse *in situ* data.

572 The slight difference in calibration results are to be expected given that the two
573 independent approaches relied on two different data sets, in one case a continuous time
574 series of channel elevations at a single point, and in the second, a continuous spatial
575 distribution of water levels and slopes at two points in time. However, differences also
576 might be due to artifacts in the observed data, or micro-terrain effects that are not picked
577 up in a 90 m grid, or error associated with assumptions in the hydraulic model. Results
578 indicate that even a few observations can quantify the floodplain water elevation and
579 reveal the complexity of the floodplain hydrodynamics. This study highlights the
580 importance and potential advantage of 2D interferometric SAR techniques to support 2D
581 floodplain model calibration.

582 Second, results on the spatial and temporal variations of water elevations ($\frac{dh}{dt}$,
583 $\frac{dh}{dy}$) are demonstrated to be useful to estimate daily time series of water storage changes
584 (dS/dt) in Buffalo Cove WMU. Since the model is validated in terms of dh/dt from
585 SAR interferometry, the improved model can generate reliable estimates of dS/dt and
586 the moving averages can be useful to see the trend of basinwide water storage changes.

587 Lastly, results indicate the feasibility of using SAR interferometry for enhanced
588 prediction and assessment capabilities for future flood events in the floodplain. The
589 hydrodynamic modeling calibrated by SAR interferometry can be extended into higher
590 grid resolution and/or larger domains to study the floodplain hydrodynamics in more
591 detail. For the purpose of future flood control and risk management, modeling could

592 focus on monitoring the basin in near real time with the help of parallel computation
593 using multi core processors.

594

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606

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787

788

789 **Figure Captions**

790 **Figure 1.** LiDAR map over the study area. The Atchafalaya River Basin is bounded on
791 the east and west sides by levees in south central Louisiana, United States. The upstream
792 main channel in the basin diverts the Lower Mississippi River and flows out to the Gulf
793 of Mexico. The orange rectangular box locates hydrodynamic model study area and green
794 diagonal box indicates the ALOS PALSAR swath used in this study. The Atchafalaya
795 River and Mississippi River are represented by blue lines. Levees and gages are marked
796 with red lines and inverted black triangles. Gage stations are located at Krotz Springs
797 (C1) and Myette Point (C3) along the main channel and at Buffalo Cove (B1) in bayou
798 whereas C2 is a virtual station.

799

800 **Figure 2.** Schematic of local hydrodynamics in the Atchafalaya River Basin including 13
801 water management units (WMUs): 1-Lake Henderson , 2-Alabama Bayou, 3-Werner, 4-
802 Lost Lake, 5-Cow Island, 6-Bayou DeGlais, 7-Cocodrie Swamp, 8-Pigeon Bay, 9-Beau
803 Bayou, 10-Flat Lake, 11-Buffalo Cove, 12-Upper Bell River, 13-Six Mile Lake [USACE,
804 1982]. Black and light blue arrows are indicative of channel and floodplain flow
805 directions. Light blue dotted lines represent floodplain flow boundary condition segments
806 in the model. These lines are normal to the main channel direction between C2 and C3.

807

808 **Figure 3.** Daily time series of water discharges and elevations at gages in the model area
809 during 2008. Panels (a) and (b) show a one year hydrograph including the model period
810 during high water. The solid lines represent the first and last day in simulation on 1 April
811 2008 and 1 June 1 2008. Channel water elevations H_{C3} and H_{B1} are required for

812 downstream channel boundary condition and calibration, respectively. Channel discharge
813 Q_{C2} and floodplain discharge Q_{F2} are collected and calculated for upstream boundary
814 condition. Panels (c) and (d) are fitted in the model period. The vertical dashed lines
815 represent the ALOS PALSAR acquisition dates on 16 April 2008 and 1 June 2008.

816

817 **Figure 4.** Differential wrapped interferogram of L-band PALSAR superimposed on the
818 image reflectivity map in the Atchafalaya River Basin. The orange rectangular box
819 locates the LISFLOOD model area. The color scale represents one cycle of
820 interferometric phase that can be interpreted as 15.1 cm in vertical displacement. These
821 fringes represent water elevation changes between 16 April 2008 and 1 June 2008.

822

823 **Figure 5.** Calibration surfaces for mean absolute error (left) and bias (right) in terms of
824 water elevations at gage Buffalo Cove (B1) as function of channel (horizontal axis) and
825 floodplain (vertical axis) Manning's roughness coefficients. The optimum roughnesses,
826 determined as the lowest MAE equal to 3.8 cm, lies at 0.024 for channel n_c and 0.10 for
827 floodplain n_f .

828

829 **Figure 6.** Model water elevations compared to actual water elevations at gage Buffalo
830 Cove (B1). The model after 2 days in simulation starts to fit the gage water elevations
831 within ± 4 cm in MAE with Manning's roughness coefficients of 0.024 in the channel
832 and 0.10 in the floodplain.

833

834 **Figure 7.** Calibration surfaces for mean absolute error (left) and bias (right) in terms of
835 water elevation changes in the Buffalo Cove WMU as function of channel (horizontal
836 axis) and floodplain (vertical axis) Manning's roughness coefficients (n). The optimum
837 lies at 0.028 for channel n_c and 0.10 for floodplain n_f with 5.7 cm MAE for the 46 day
838 simulation.

839

840 **Figure 8.** (a) Water elevation maps on April 16 2008 (upper) and June 1 2008 (lower).
841 (b) Water elevation change map calculated from the calibrated model. (c) Water elevation
842 change map from SAR interferometry. (d) Difference of water elevation change from
843 between the model (b) and the SAR interferometry (c).

844

845 **Figure 9.** (a) Daily time series of water storage changes in the area of $\sim 230 \text{ km}^2$ in the
846 Buffalo Cove WMU. The 5 and 10 day moving averages are performed to demonstrate
847 the trend of the water storage changes. (b) Relationship between model dS/dt in Buffalo
848 Cove WMU and dh/dt at the Buffalo Cove gage (B1). The goodness of fit (R^2) is 0.94
849 based on the first polynomial regression model without three outliers that are generated
850 before the model is stabilized.

851

852 **Figure 10.** (Upper) Water depth maps relative to the LiDAR floodplain elevation, and
853 (lower) water depth change maps when dS/dt is positive (a), near zero (b), and negative
854 (c).

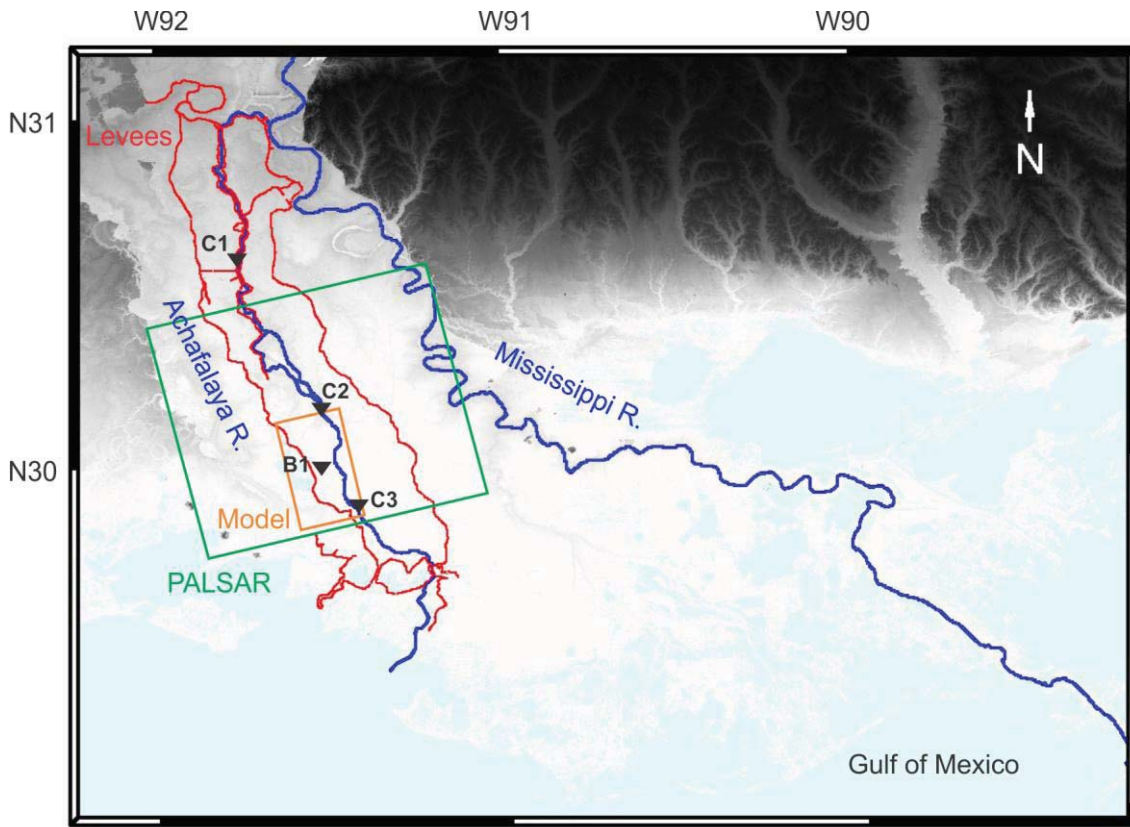
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856 **Figure 11.** Results of the modeled h and dh/dt to uncertainty in upstream Qs , varying
857 from -20 % and 20 % in steps of 5 %. The calibrated model of 0.028 in n_C and 0.10 in
858 n_F is used as a behavioral model. The h maps on 16 April 2008 and 1 June 2008 and
859 dh/dt map for the 46 days are shown in Figure 8a and 8b.

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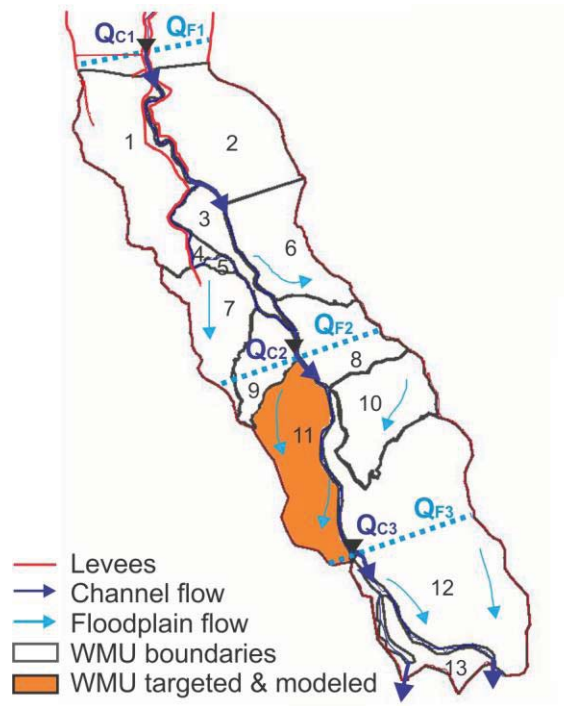
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1 **Figures**



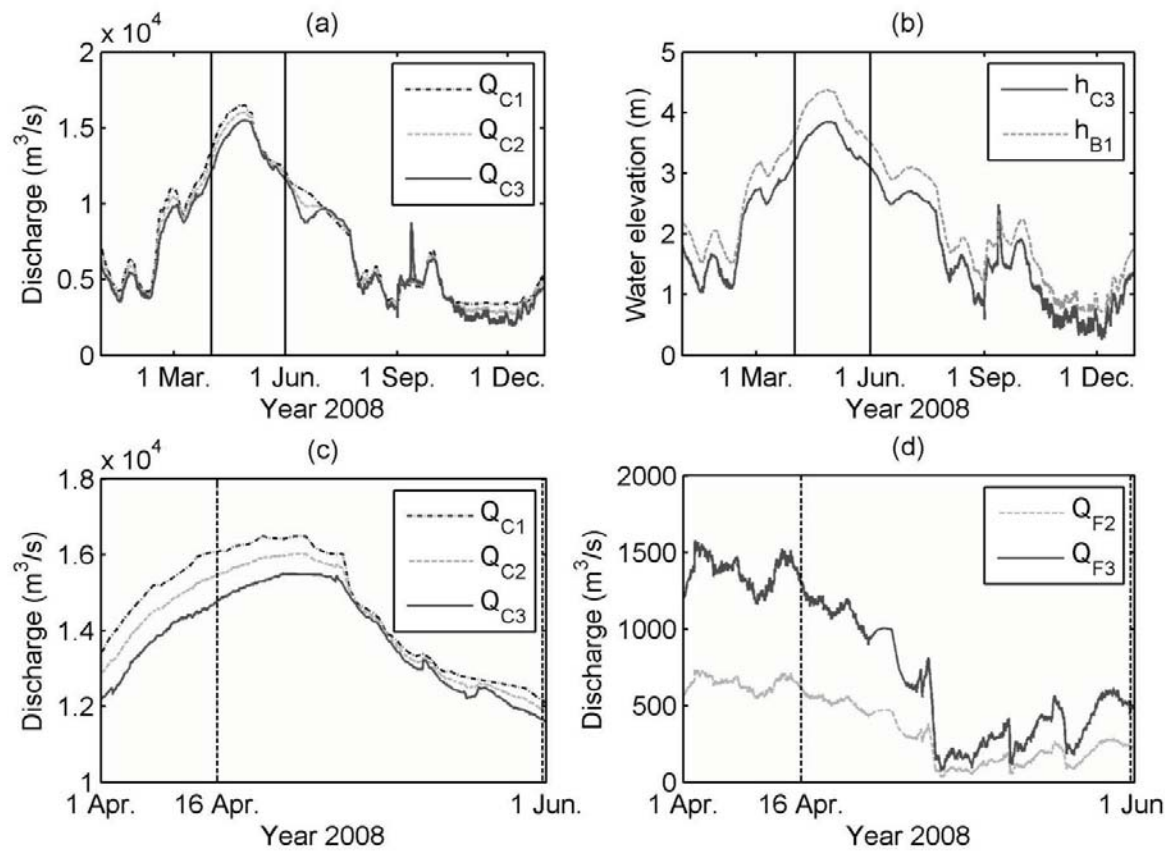
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Figure 1.



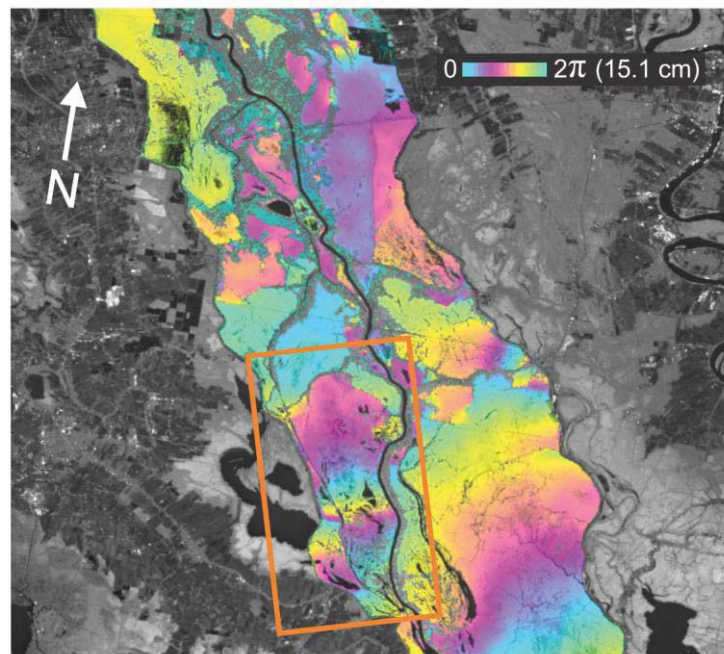
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Figure 2.



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Figure 3.



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Figure 4.

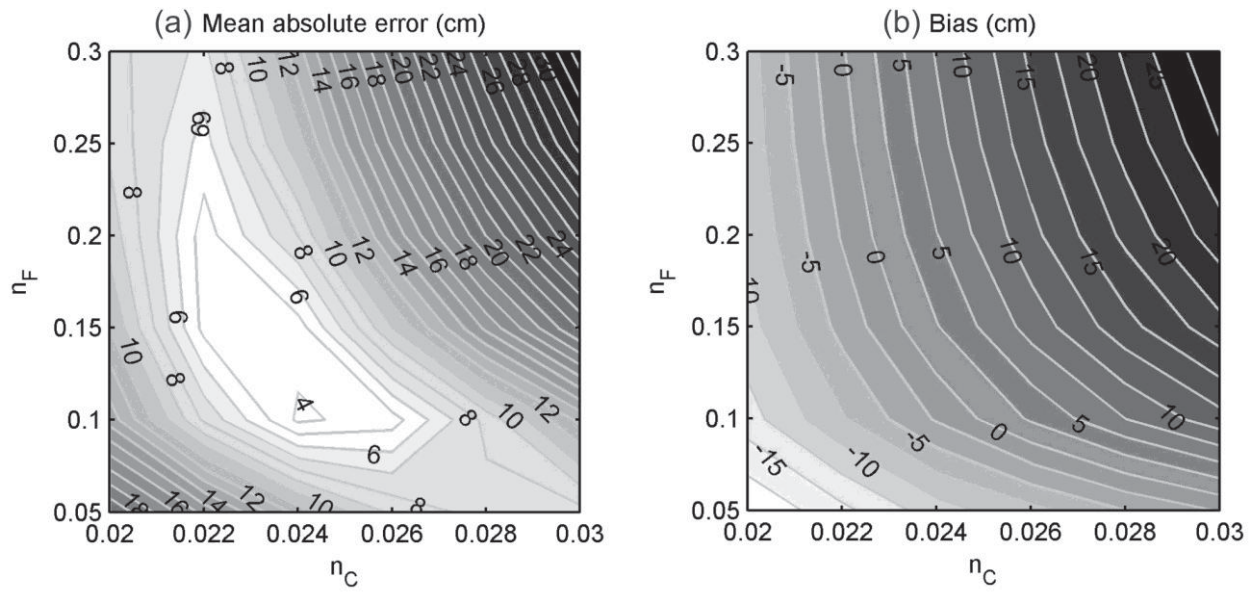


Figure 5.

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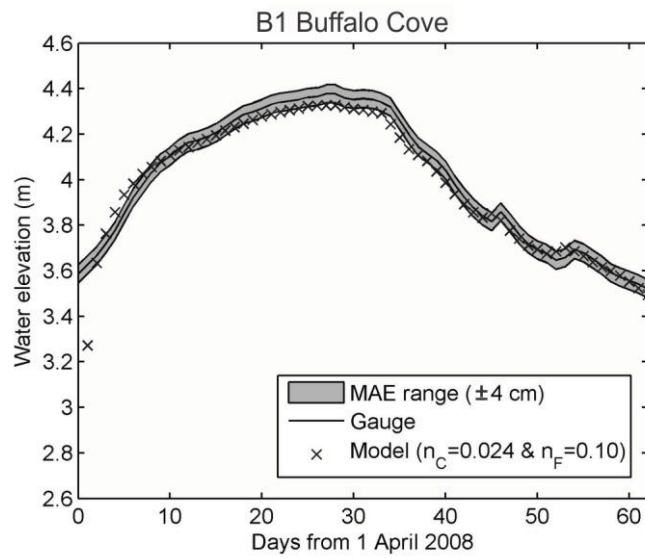


Figure 6.

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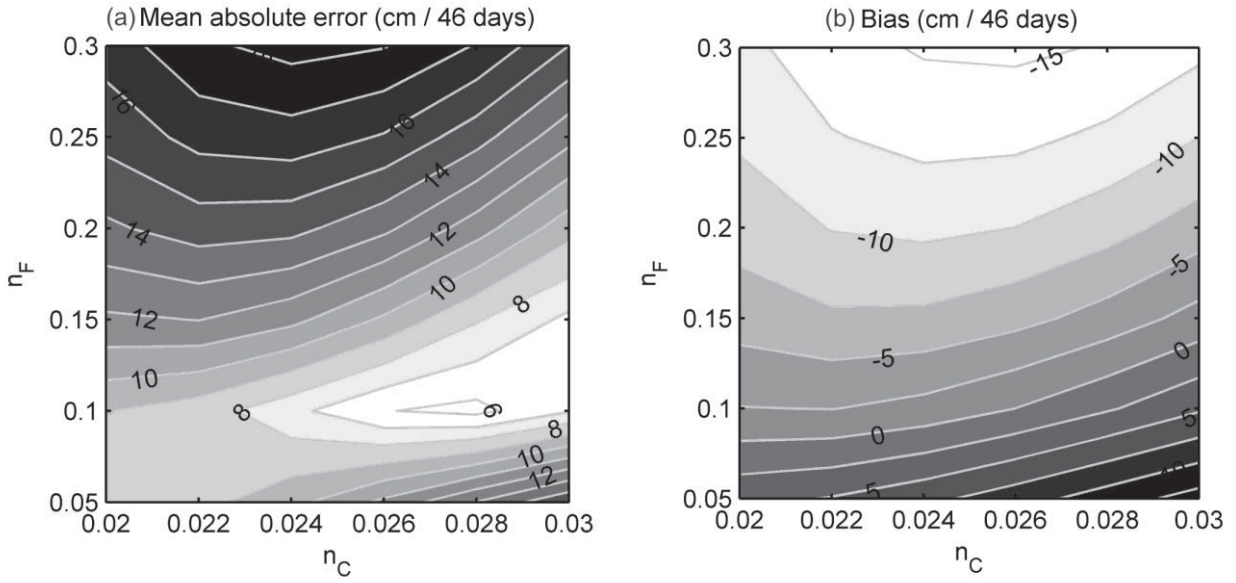


Figure 7.

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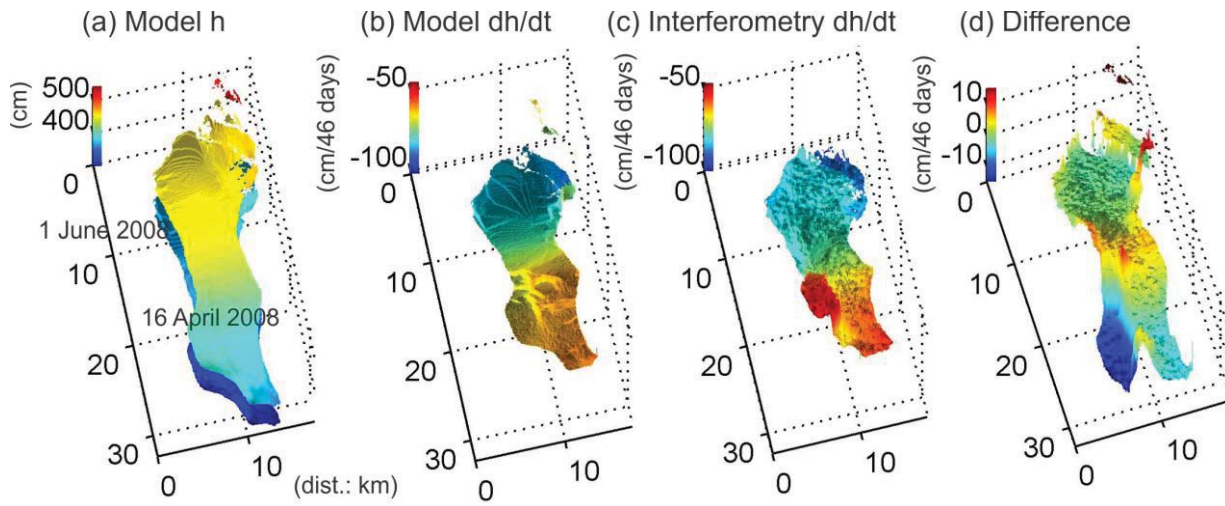


Figure 8.

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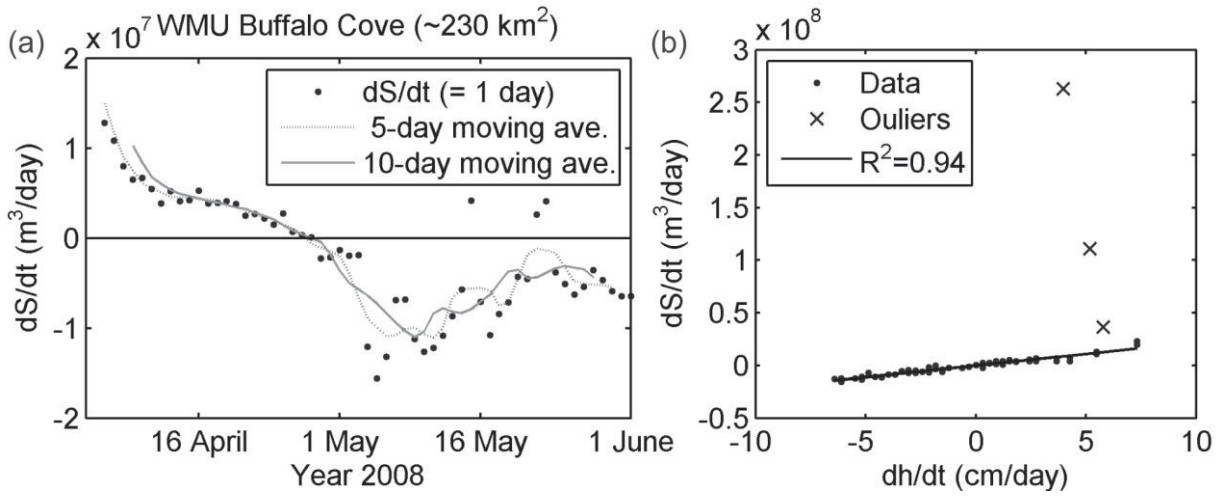


Figure 9.

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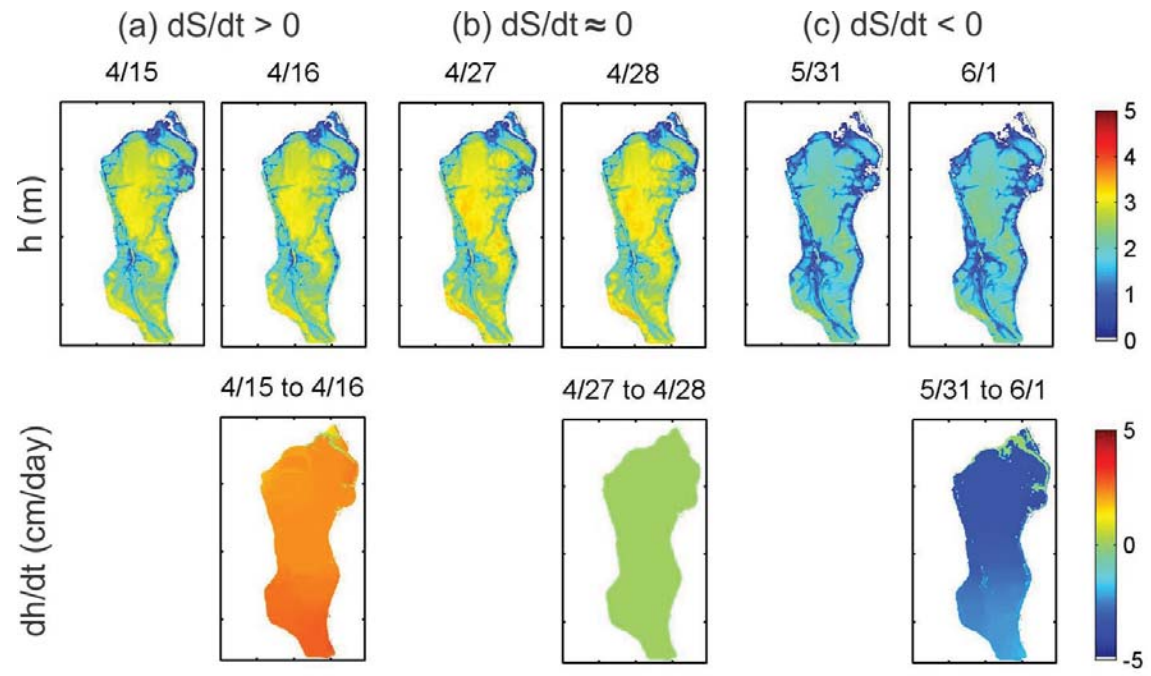
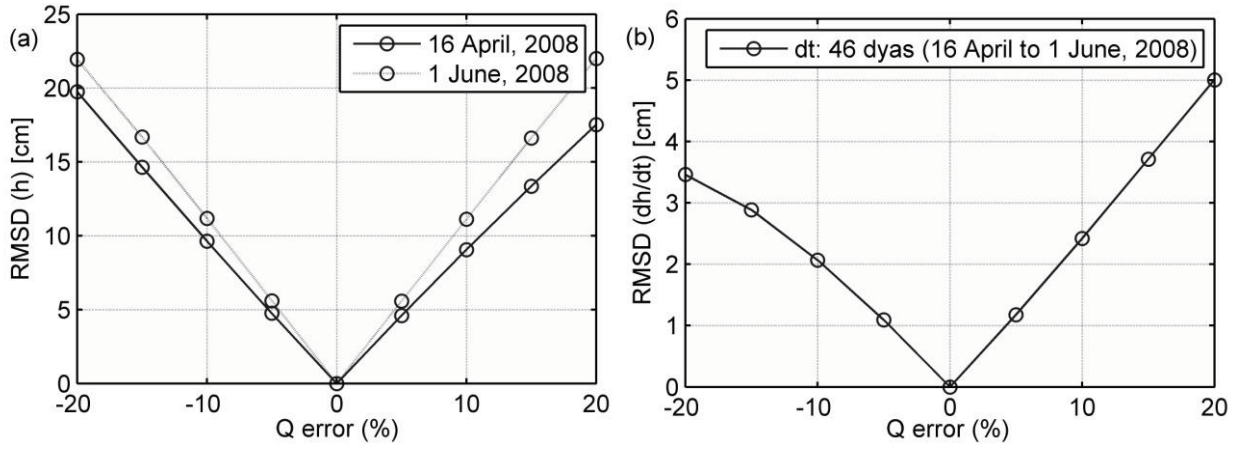


Figure 10.

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Figure 11.