**Testing the skill of numerical hydraulic modeling to simulate spatiotemporal flooding
patterns in the Logone floodplain, Cameroon**

Alfonso Fernández^{1,2,*,**}

1) Department of Geography, The Ohio State University.

2) Byrd Polar and Climate Research Center, The Ohio State University.

136 Scott Hall, 1090 Carmack Rd, Columbus OH, 43210, USA.

Email: fernandez-rivera.1@osu.edu

Phone: +1-614-688-7971

*Corresponding author

**Present address: Department of Geography, Universidad de Concepción.

Calle Victoria s/n, Concepción, Chile.

Mohammad Reza Najafi³

3) Pacific Climate Impacts Consortium, University of Victoria.

PO BOX 1700 Stn CSC, Victoria, BC V8W 2Y2, Canada.

Email: rnajafi@uvic.ca

Phone: +1-250-721-7373

Michael Durand^{2,4}

2) Byrd Polar and Climate Research Center, The Ohio State University.

4) School of Earth Sciences, The Ohio State University.

275 Mendenhall Laboratory, 125 South Oval Mall, Columbus, OH 43214, USA.

Email: durand.8@osu.edu

Phone: +1-614-272-4835

Bryan G. Mark^{1,2}

1) Department of Geography, The Ohio State University.

2) Byrd Polar and Climate Research Center, The Ohio State University.

1136 Derby Hall, 154 North Oval Mall, Columbus OH, 43210, USA.

Email: mark.9@osu.edu

Phone: +1-614-247-6180

Mark Moritz⁵

5) Department of Anthropology, The Ohio State University.

4058 Smith Laboratory, 174 W. 18th Avenue, Columbus, OH 43210, USA.

Email: moritz.42@osu.edu

Phone: +1-614-247-7426

Hahn Chul Jung^{6,7}

6) Science Systems and Applications, Inc. (SSAI)

10210 Greenbelt Road, Lanham, MD 20706, USA

7) Hydrological Sciences Laboratory, NASA Goddard Space

Flight Center

8800 Greenbelt Road, Greenbelt, MD 20771, USA

Email: hahnchul.jung@nasa.gov

47 Phone: +1-301-614-5563

48
49 Jeffrey Neal⁸

50 8) School of Geographical Sciences, University of Bristol
51 Office 1.8Bn, University Road, Clifton, Bristol BS8 1SS, UK.

52 Email: j.neal@bristol.ac.uk

53 Phone: +44-0-117-928-9113

54
55 Apoorva Shastry⁴

56 4) School of Earth Sciences, The Ohio State University.
57 275 Mendenhall Laboratory, 125 South Oval Mall, Columbus, OH 43214, USA.

58 Email: shastry.7@buckeyemail.osu.edu

59 Phone: +1-614-272-4835

60
61 Sarah Laborde⁵

62 5) Department of Anthropology, The Ohio State University.
63 4100 Smith Laboratory, 174 W. 18th Avenue, Columbus, OH 43210, USA.

64 Email: laborde.7@osu.edu

65 Phone: +1-614-247-8634

66
67 Sui Chang Phang⁹

68 9) Department of Evolution Ecology and Organismal Biology, The Ohio State University.
69 390 Aronoff Laboratory, 318 W. 12th Avenue, Columbus, OH 43210, USA.

Email: phang.6@osu.edu

Phone: +1-614-292-9147

Ian M. Hamilton^{8,9}

8) Department of Evolution Ecology and Organismal Biology, The Ohio State University.

9) Department of Mathematics, The Ohio State University.

390 Aronoff Laboratory, 318 W.12th Avenue, Columbus, OH 43210, USA.

Email: hamilton.598@osu.edu

Phone: +1-614-292-9147

Ningchuan Xiao¹

1) Department of Geography, The Ohio State University.

1036 Derby Hall, 154 North Oval Mall, Columbus OH, 43210, USA.

Email: xiao.37@osu.edu

Phone: +1-614-292-4072.

Abstract

Recent innovations in hydraulic modeling have enabled global simulation of rivers, including simulation of their coupled wetlands and floodplains. Accurate simulations of floodplains using these approaches may imply tremendous advances in global hydrologic studies and in biogeochemical cycling. One such innovation is to explicitly treat sub-grid channels within two-dimensional models, given only remotely sensed data in areas with limited data availability. However, predicting inundated area in floodplains using a sub-grid model has not been rigorously validated. In this study, we apply the LISFLOOD-FP hydraulic model using a sub-grid channel parameterization to simulate inundation dynamics on the Logone River floodplain, in northern Cameroon, from 2001 to 2007. Our goal was to determine whether floodplain dynamics could be simulated with sufficient accuracy to understand human and natural contributions to current and future inundation patterns. Model inputs in this data-sparse region include in situ river discharge, satellite-derived rainfall, and the shuttle radar topography mission (SRTM) floodplain elevation. We found that the model accurately simulated total floodplain inundation, with a Pearson correlation coefficient greater than 0.9, and RMSE less than 700 km², compared to peak inundation greater than 6,000 km². Predicted discharge downstream of the floodplain matched measurements (Nash-Sutcliffe efficiency of 0.81), and indicated that net flow from the channel to the floodplain was modeled accurately. However, the spatial pattern of inundation was not well simulated, apparently due to uncertainties in SRTM elevations. We evaluated model results at 250, 500 and 1000-m spatial resolutions, and found that results are insensitive to spatial resolution. We also compared the model output against results from run of LISFLOOD-FP in which the sub-grid channel parameterization was disabled, finding that the

sub-grid parameterization simulated more realistic dynamics. These results suggest that analysis of global inundation is feasible using a sub-grid model, but that spatial patterns at sub-kilometer resolutions still needs to be adequately predicted.

Keywords

Flooding modeling, Flood Inundation Mapping, Logone floodplain, hydroclimatic changes

1. Introduction

Large areas of sub-Saharan Africa comprise wetlands and flat terrain prone to flooding (Rebelo et al., 2010). These African floodplains are important for the lives and livelihoods of millions of inhabitants, as seasonal flooding controls a range of economic and social activities such as agriculture, fishing, and pastoralism (e.g. Denny, 1993; Acreaman and Hollis, 1996; Thompson and Polet, 2000; Westra and De Wulf, 2009). These landscapes have also undergone manmade alterations, transforming the hydrological system into a palimpsest of structures, from irrigation channels to dams (Loth, 2004), where natural and human-induced hydrological phenomena concur and interact in complex ways. Some of these human modifications of the landscape, in combination with future climate change, may threaten the development of economic activities (Niang et al., 2014) and the preparedness for hazardous floods (Tschakert et al., 2010).

However, research on flooding in the sub-Saharan region is still relatively underdeveloped (Tarhule, 2005; Tschakert *et al.*, 2010). For instance, the causes (climatic or human-induced) of hydrologic shifts are often unknown, as climate and human forcings tend to occur simultaneously on these dynamic floodplains. One reason for this lack of understanding is that inferring climatic and human contributions to flooding dynamics requires abundant hydroclimatic and hydraulic data. Beyond basic hydrometeorological data of precipitation and evaporation, some of the most important variables that are needed include river discharge, channel geometry, and flooding extent, among others. Unfortunately, suitable continuous climatic and hydrologic datasets are generally sparse in this region (van de Giesen et al., 2014), limiting the ability of current hydroclimatic predictions (IPCC, 2013). Furthermore, while remotely sensed data can be helpful

for obtaining time-series of flooding extent (e.g. Westra and De Wulf, 2007), they need reliable validation from ground observations and hydrological flow monitoring, which are commonly unavailable. Given the lack of hydroclimatic information about flooding, it is necessary to test methods that require minimal input data.

Flood models capable of simulating the hydraulics associated with natural and anthropogenic features have been extensively developed (e.g. Beffa and Connell, 2001; Liang et al., 2008; Bates *et al.*, 2010). In particular, there is an increasing interest in expanding the use of hydraulic models at the global scale in order to supply information for decision makers, according to scenarios of future environmental changes (Schumann et al., 2014). However, accuracy of these models is highly dependent upon the quality of the topographic data utilized (Neal et al., 2012). Available elevation datasets from space-borne radar or visible-band measurements combined with photogrammetric techniques are often not of adequate quality for hydraulic modeling (Sanders, 2007). In addition, most validation datasets are only available in developed countries, limiting the accuracy assessment to specific contexts, such as pre-established return periods and extreme events (Sampson et al., 2015).

The Logone River floodplain in Cameroon and Chad exemplify both the importance of understanding and the challenge of modeling complex social-ecological systems with a relative paucity of data. The Logone floodplain, known in Cameroon as the “*Yaayre*”, exhibits strong interactions among multiple social, ecological, and hydrological systems (Delclaux et al., 2010). The intra-annual and inter-annual variations in the area, depth, and duration of seasonal flooding have direct and indirect impacts on ecosystems and human lives and livelihoods (Iongh et al.,

1998). When inundated, the *Yaayre* is highly productive, providing breeding grounds for fish, dry season pastures that support cattle and other livestock, and fertile land for growing rice, flooded rice production and flood recession cropping. Indeed, the annual flooding of the floodplains is critical for the ecological and economic productivity of the area. Major human modifications of the landscape impact the *Yaayre*, including a large dike along the Logone and a dam that created the large reservoir of Lake Maga, and the construction of over 1,000 small canals utilized for fishing. Government agencies and regional populations would be greatly served by a better understanding of how human decision-making impacts these systems, as well as the threats they face in a changing climate. Simple hydraulic models of the area were constructed in past years (Evans, 1999; Wesseling et al., 1994). However, recent advances in the field of hydraulic modeling have enabled multi-scale rivers and canals to exist within 2-D models as sub-grid features (Neal et al., 2012), leading to the possible ability to advance on previous hydraulic modeling efforts.

In the present paper, we utilize the LISFLOOD-FP hydraulic model (Bates *et al.*, 2010; Neal et al., 2012) to determine if, using available data (see section 3 on methods) the floodplain dynamics can be simulated with sufficient accuracy to (a) better understand the human and natural contributions to floodplain functioning, and (b) to predict how the floodplain might be affected in the future by human decisions and by future changing climate. One of the recent innovations of LISFLOOD-FP is to explicitly treat sub-grid channels within two-dimensional models, given only remotely sensed data in areas with limited data availability. Accurate simulations of floodplains using these approaches may imply tremendous advances in global and large-region hydrologic studies and in biogeochemical cycling. However, sub-grid model

performance in predicting inundated area has not been rigorously validated in floodplains. For these reasons, our research goals comprise an original approach to flood modeling and assessment. We focus on multi-year flooding dynamics over a large area (see next section) instead of the traditional analysis of specific events (Neal et al., 2011), seasonal features (Jung et al., 2012), or given return periods (Smith et al., 2015). Our study diverts from those approaches because in our case inundation is a normal feature of the landscape, an essential part of the socio-economic dynamics, which has evolved into a complex system across centuries. The temporal scale in which human and natural components of this system interact requires studying continuous flooding dynamics. As our focus is inherently different from the most previous research, our working temporal scale challenges the skill of numerical models to represent spatial patterns of flooding. For example, using relatively coarse resolution digital elevation models such as SRTM with well-known uncertainties (Rodriguez et al., 2005), it is expected that flooding simulations will not capture spatial patterns accurately. Furthermore, by studying an African wetland, we cover an environment that still presents many uncertainties for global flooding modeling (Sampson et al., 2015). Our case study is also relevant for simulation of floodplains in data-sparse areas, which is a ubiquitous problem in the developing world (Schumann et al., 2014). Finally, and given the large study region (see next section), this study is a performance test for the use of sub-grid channel parameterization at this scale.

2. Study Area

The Logone floodplain, is part of the Lake Chad Basin and covers approximately 8,000 km² in the Far North Region of Cameroon (Figure 1). The floodplain contains the Waza National Park

(1,700 km²) and the Kalamaloue National Park (45 km²). This area is flooded annually by water from the Logone River and its tributaries during September and October (Jung et al., 2011). The area is relatively flat with floods spreading over an average area of 6,747 km² (Westra and De Wulf, 2009) before draining back to the Logone River and the El Bëid River in the north, which forms at the confluence between the Komarka and Ambabare Rivers. During the dry season, water flowing through the floodplain is mostly channelized through the Logone and its two tributaries, namely the Logomatya and Lorome Mazra, located to the west of the Logone.

FIGURE 1 AROUND HERE

Three mechanisms contribute to the flooding: local rainfall directly on the floodplain; seasonal rivers (mayos) from the Mandara Mountains to the west; and overbank flow from the Logone River. Previous studies point out that the mayos contribute relatively less flow (e.g. Naah, 1990), and that the overbank flow from the Logone River (and its other major channels) is the most important. The role of local rainfall is still somewhat uncertain. According to Evans and Loth (2004), the overbank flow from the Logone predominates. However, according to data presented in Naah (1990) the rainfall contribution to the floodplain is almost equivalent to the overbank flow.

The extent of the flooding depends primarily on the magnitude of the peak flow and the duration of the floodwater exceeding the capacity of the Logone River (Delclaux et al., 2010; Jung et al., 2011; Westra and De Wulf, 2007). Potential evapotranspiration (PET) on the floodplain are remarkable. On the basis of measurements taken with piché evaporimeters, Naah (1990)

estimates an annual evaporation rate between 2,700 mm to 3,000 mm, while direct precipitation over the floodplain is less than 1,000 mm; this underscores the dependence of the floodplain on seasonal upstream forcing. After the Logone floods its banks in September and October, the southern shift of the Intertropical Convergence Zone (ITCZ) brings hot, dry air. During the full extent of the flooding, this increases the potential of evaporation as a flood recession agent.

It is important to highlight, however, that the highest PET rates are observed between February and April (Naah, 1990), corresponding to the dry season, when there is no flooding on the study area. The closest relatively continuous record of PET comes from N'Djamena (Figure 2). This record shows that the rate is significantly higher than precipitation over this, while average monthly temperature is always above 20°C with a modest annual amplitude of about 10°C. Only during the rainy season is the PET rate lower than precipitation, which coincides with the highest relative humidity. Although N'Djamena data adequately depict the main hydroclimatic features of the whole region, such as the peak rainfall in July-August and the maximum evaporation in February-April, it is important to highlight that the Logone floodplain has a relatively short rainy season that often begins in May, with few sporadic rain events (Naah, 1990).

FIGURE 2 AROUND HERE

In the last few decades, several factors have caused significant modifications of the flooding regime in the Logone floodplain, including but not limited to, drought episodes, construction of dams, irrigation infrastructure, and manmade canals utilized for fishing. In 1979, the Cameroonian government constructed a dike along the Logone River and a dam between

Guirvidig and Pouss to create a 400 km² reservoir (Lake Maga, see Figure 1) for the irrigated rice cultivation project SEMRY II (Loth, 2004). The dams changed the hydrology and ecology of the floodplain and led to a significant reduction in flooding. In order to reverse the ecological degradation and promote sustainable socio-economic development of the floodplain, the Waza-Logone Project started a pilot re-flooding effort in 1994. This effort was deemed to be successful: the ecological system rebounded and the pastoral, agricultural, and fishery systems experienced strong economic development (Loth, 2004; Scholte, 2005).

3. Methods

3.1. The modeling approach using LISFLOOD-FP

LISFLOOD-FP is a hydraulic model first developed by Bates and De Roo (2000) that includes a 1D river channel and a 2D floodplain representation. Recent version of the model includes a sub-grid channel parameterization (Neal et al., 2012) that allows for complex small floodplain channels to be explicitly represented in the model, without the need for fine resolution simulations, which can be computationally intractable over large areas. This feature of the model was particularly useful in our context, as most of the river network is thinner than the grid-cell sizes we tested (see below), notably the Logomatya and Lorome Mazra. Large-scale floodplain simulation using the LISFLOOD-FP model has been conducted in several regions (e.g. Wilson *et al.*, 2007; Trigg *et al.*, 2009; Neal *et al.*, 2012; Coulthard *et al.*, 2013; Schumann *et al.*, 2013).

The sub-grid version of LISFLOOD-FP uses the floodplain inundation model of Bates *et al.* (2010) and a one-dimensional channel model fully described by Neal *et al.* (2012). Both channel and floodplain models use an explicit finite difference method to solve a simplification of the one-dimensional Saint Venant equations, where the convective acceleration term is neglected. This yields a model where the continuity of momentum equation calculates the flow between two cells given the water surface slope at the cell interface, the cross-sectional area of flow at the interface (on either the channel or floodplain), Manning's friction coefficient and the local inertia from the previous time-step. Given this flow, a continuity of mass equation then calculates the change in volume and level in each cell given the flow between cells and model time step. The advantage of using the sub-grid model over a purely two-dimensional gridded model is that it allows for simulation of river channels that have smaller widths than the cell resolution, by calculating an additional flow between cells if a river channel is present within the cell. The continuity equations can then be adjusted to account for the additional within-channel storage.

3.1.1. Hydraulic and hydroclimatic boundary conditions

In this work, we used the channel width (w) to approximate the average bankfull depth (h) at each cell using a power law relationship:

$$h = rw^p \quad (1)$$

The parameters r and p were derived using river cross-sections from MacDonald (1999), and bankfull width values calculated from satellite images as described in the next paragraph. For widths of the smaller channels we analyzed field photographs along with datasets from surveys in the study area. Table 1 shows model parameters obtained for different zones of the channel network. Optimal values for the floodplain and channel roughness coefficients were determined to be 0.1 and 0.025 respectively by calibrating the model based on flow discharge at Logone Gana (Table 2). For the floodplain, we calculated the Root Mean Square Error (RMSE) between the observed discharge and different versions of the simulated flow at 1000-m spatial resolution using the range 0.08 to 0.14 for the coefficient, which is within the values commonly assumed as representative of floodplains with medium to dense brush in summer (Chow, 1959). The average RMSE was 125.39 m³/s and varied less than 12.4% across the choice of roughness coefficients, implying that the model was not very sensitive to the choice of this parameter. Thus, we selected the values giving the lowest RMSE.

TABLE 1 AROUND HERE

In order to map the Logone river network, we utilized the RivWidth software (Pavelsky and Smith, 2008) to obtain the Logone River centerline and widths, along with a Landsat image of the region. This software takes a binary mask as input, and determines the width in two steps. First, the image is utilized to derive the centerline of the river. Second, a number of transects, orthogonal to the centerline, is used to calculate the width on each section (Pavelsky and Smith, 2008). The centerlines of smaller rivers such as the Logomatya and Lorome Mazra were mapped

manually using Landsat and other visible-band imagery. Channel widths were approximated based on the same images and on images from the field.

We used in situ measurements of daily flow rates at Katoa, Bongor and Logone Gana stations in the Logone River as upstream boundary condition (Katoa and Bongor) to calibrate and evaluate the model (Logone Gana), respectively (Table 2). The measurements of water heights were performed by the Chad's Direction de Ressources en Eau et l'Environnement (DREM) and the German Federal Ministry for Economic Cooperation and Development (e.g. Krekeler and Seeber, 2013). Logone Gana is located at the middle of the study area and Katoa lies at the east of Lake Maga, providing time-series of flow rates and water heights in the Logone River. The Bongor station is located ~60 km south of Katoa, outside the spatial domain utilized in the simulations. Previous studies suggest that part of the water between Bongor and Katoa is lost to the overbank flooding, entering the floodplain through a diffusive flow from the south on the east bank of the Logone into Chad (Naah, 1990; Seeber, 2013). In our model set-up, we accounted for this process by including an additional inflow cell near the southeast corner of the domain with flow rate equal to the difference between the flow at Bongor and Katoa.

Monthly open-water evaporation rates were taken from Naah (1990) and were assumed to be uniform over the whole region without considering the diurnal cycle; the same values were used for each year. This assumption seemed reasonable considering that previous work showed that this region presents little spatial and seasonal differences compared to other areas of the Chad Lake Basin (Boronina and Ramillier, 2007). Tropical Rainfall Measurement Mission (TRMM) daily accumulated precipitation (from 00 to 21 hours, in mm) data were used; this product is

derived from the 3-hourly, TRMM-3B42 product, which in turn is derived from an algorithm that merges data from various satellites, delivering a $0.25^{\circ} \times 0.25^{\circ}$ spatial resolution precipitation estimate that extends across the globe between latitudes 50°N and 50°S (Huffman et al., 2007). For this study, we selected the closest TRMM grid-cell to the Logone floodplain using the GIOVANNI (Geospatial Interactive Online Visualization AND aNalysis Infrastructure) tool at NASA's Goddard Earth Sciences Data and Information Services Center (Acker and Leptoukh, 2007). We evaluated the time-series using the Lake Maga station, which contains a record of monthly cumulative precipitation (Table 2).

We performed pre-screening and data quality analyses on the time-series. Given that most of the historical records (Table 2) were digitized from original datasheets in paper format, tests of consistency had to be used to check for data gaps, systematic and random errors (WMO, 2011). Original flow data were found to contained 366 daily values for all years, including records for February 29th in non-leap years. The data providers indicated that those extra days were calculated by averaging February 28th and March 1st of the same year (Sara Vassolo, written communication). Examination of the datasets confirmed this for Logone Gana but not for Bongor and Katoa. The averaging showed differences as high as $6 \text{ m}^3/\text{s}$ and lacked any recognizable temporal pattern, compared to the constant, nearly zero value (± 0.05) calculated for Logone Gana. We assumed these as systematic shifting errors that occurred in the translation of paper-based records to digital databases. We corrected these "shifted" time-series by reducing the cumulative effect of the extra day and found a cumulative delay of 19 and 21 days by 2008 for Bongor and Katoa, respectively, when aggregated over the time-series. We used these corrected

inflows as model input. No problems were found in the precipitation data from Lake Maga except a record missing for December 2004.

TABLE 2 AROUND HERE

3.1.2. Topographical data

We used the Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (Rabus *et al.*, 2003) to represent the Logone floodplain surface topography in LISFLOOD-FP. Despite being one of the best sources of topographic information for data-sparse areas such as our target location, the height accuracy of STRM in sub-Saharan areas is around ± 2 -m (Rodriguez *et al.*, 2005). This uncertainty is in the range of observed water heights during flooding season (e.g. Jung *et al.*, 2011). This means that the SRTM had to be preprocessed before its actual use in LISPFLOOD-FP in order to eliminate artifacts such as artificial crests and troughs that may interfere with the water flow. However, we did not try to remove vegetation given that the mission to produce this global digital elevation model flew during the first weeks of February 2000 (Rodriguez *et al.*, 2005), when the annual flooding had typically retreated and the associated biomass was close to zero (Scholte, 2007), suggesting that the vegetation was very low. The SRTM was preprocessed as follows. First, we re-gridded it to a coarser cell-size by averaging the elevation values as suggested by Le Coz *et al.* (2009) in a study targeting the area around the Lake Chad. Second, we applied a hole-filling method to the re-gridded version of the SRTM in order to filter out remnant troughs, and ensure that no depressions exist. We used the *imfill* function in Matlab©, which is an implementation of the “Annular Filter” described in

Heijmans and Ronse, (1999) and in Soille (1999). The algorithm seeks pixels that are surrounded by higher elevation neighbors and then increases its elevation to accord with those neighbors. In order to assess the impact of this procedure, we performed three LISPFLOOD-FP simulations in which the SRTM is re-gridded from the original, 90-m resolution, to 250-m, 500-m, and 1-km spatial resolution.

3.2. Evaluation of model output

To evaluate the model, we generated 52 flood inundation maps from multi-temporal Landsat ETM+ imagery from 2001 to 2007 (see details of this procedure in the next section). This was the only period in which continuous river discharge records (2001-2007), TRMM precipitation (1997-2015), and such a large number of these high-resolution satellite images coincided (2000-2015). Landsat images for the period 1984 to 1999 were mostly unavailable for the floodplain due to changes in Landsat acquisition and commercialization problems (USGS customer service, email communication February 20, 2015). Performance of model output in estimating the flood extent was assessed based on a flood area index (FAI):

$$FAI = \frac{M_i O_i}{(M_i O_i + M_i O_n + M_n O_i)} \quad (2)$$

where M corresponds to the model and O represents the observations. $M_i O_i$ is the number of inundated cells both in reality and in the model. $M_i O_n$ is the number of non-inundated cells that the model simulates as inundated. $M_n O_i$ represents the number of inundated cells that the model simulates as non-inundated cells. In FAI, 100% shows perfect agreement and zero shows no

skill. This index is a spatial version of the Threat Score (TS), a forecast verification index widely utilized in the atmospheric sciences (Wilks, 2006). As such, FAI (TS) is a good indicator of performance during the flooding season, but it is somewhat meaningless during the rest of the year because it does not account for the proportion non-flooded grid-cells correctly simulated by the model. In addition, uncertainties in the use of FAI arise depending on how observed grids are resampled to match the model's spatial resolution and how wet and dry cells are identified. In order to supplement the information given by FAI we use the Pierce Skill Score (PSS, Wilks, 2006) which accounts for performance on non-event (in our case non-inundated) cells:

$$PSS = \frac{M_i O_i \times M_n O_n - M_i O_n \times M_n O_i}{(M_i O_i + M_n O_n) \times (M_i O_n + M_n O_i)} \quad (3)$$

where $M_n O_n$ corresponds to the cells correctly simulated (or correct negatives) as non-inundated and n is the total number of cells. This skill score allows a better assessment of the probability that the modeled event is better or worse than a random forecast. A perfect match between observations and simulations gives a PSS equal to one, a zero score means that the model is no better than a random forecast, while negative numbers indicate that the simulation is inferior to a random forecast. Unlike FAI, the application of PSS in our case allowed us to evaluate the ability of the model to simulate non-inundated areas by comparing the probability of correct detection ($M_i O_i$ and $M_n O_n$) versus the probability of false alarms ($M_n O_i$ and $M_i O_i$).

Given that one of our goals was to study the suitability of this model to accurately represent flooding dynamics, we performed an additional comparison between our model output and a simulation in which we disabled the sub-grid channel parameterization for a small area of the

Logone floodplain. We ran a one-year, 500-m spatial resolution simulation for each LISFLOOD-
FP model configuration and compared flooded area, stored volume, and mean water depth. For
flooded area, we also utilized flooding maps derived from Landsat, as described in the next
section.

3.3. Processing of satellite imagery

The use of satellite imagery to study flood dynamics and to evaluate models is common
(Schumann et al., 2009) and procedures to detect open water at various spatial scales have been
devised, such as the Normalized Difference Water Index (NDWI) using optical images (Gao,
1996), or the use of data assimilation procedures combining different sensors and hydraulic
modeling (Ticehurst et al., 2015). Remote sensing methods include using imagery from the
visible to the near infrared spectrum (McFeeters, 1996) as well as from passive microwave
sensors or a combination of both (Bates et al., 2006; Karim et al., 2011). In the case of optical
imagery, flooding events lasting a couple of days or weeks are commonly studied using scenes
from the Moderate-Resolution Imaging Spectroradiometer (MODIS). The reason is that MODIS,
despite its coarse spatial resolution (250-m to 1-km), may provide one to two images per day
(Karim et al., 2011). Due to this coarse resolution, however, MODIS tends to miss details in the
flooding extent, which has motivated researchers to develop subpixel classification techniques in
order to determine the proportion of open water on each cell (e.g. Ticehurst et al., 2015).
Landsat, on the other hand, supplies images in the optical spectrum at 30-m spatial resolution
every 16 days (NASA, 2009). The advantage of these images is the possibility of revealing
flooding patterns at great detail over large areas, which can be aggregated to coarser spatial

resolutions if needed. However, this detailed description of flooding comes at the expense of the temporal resolution, since Landsat provides no more than two observations per month. In our case, we considered Landsat the best option for evaluation, because our interest is on the details of multi-year flooding dynamics and not on specific rapid flooding events.

The steps to obtain suitable flood maps from Landsat images involved co-registration of all available scenes (Figure 3) to the same cartographic projection (UTM33N WGS84), gap-filling, extraction of open water pixels, determination of cloud cover, and the final mapping using a digital threshold. The last four steps are described below.

3.3.1. Gap filling

The Scan Line Corrector (SLC) instrument failed onboard Landsat 7 on 31 May 2003 (NASA, 2009). Though each SLC-off scene misses data by about 22% (Maxwell et al., 2007), it can still provide useful image data to land cover and land use applications. To take advantage of the temporal availability of the Landsat archive images (Figure 3), we filled no-data pixels in Landsat ETM+ SLC-off scenes by using linear least squares regression analysis of their SLC-on counterparts.

FIGURE 3 AROUND HERE

3.3.2. Open water extraction

Water bodies were extracted and masked out to focus on floodplain inundation dynamics. Open water on the Logone River and for Lake Maga were classified using the Iterative Self-organizing Data Analysis (ISODATA) clustering method (Jung et al., 2011) from a Landsat 7 SLC-on image dated 21 October 2001.

3.3.3. Cloud determination

We included only scenes with little cloud cover order to maximize the temporal resolution of these flood inundation maps. Cloud cover areas were derived from a majority analysis of 3 by 3 window size for pixels in which blue reflectance (i.e. Landsat ETM+ band 1) is greater than 0.2 (Sakamoto et al., 2007). Cloud-shadowed areas were masked using these cloudy areas plus a buffer of 10 pixels.

3.3.4. Flood inundation mapping

Westra and De Wulf (2009) have recently demonstrated the threshold-based classification of the MODIS short-wave infrared (SWIR) images to delineate the flooding area in the Logone floodplain. They found that a threshold of 0.08 in reflectance units gives satisfactory results. To apply the approach to the Landsat ETM+ data used in the study, the digital numbers (DN) of the original Landsat ETM+ band 7 (wavelength: 2.09–2.35 μm) were converted through spectral radiance at the sensor's aperture into top of atmosphere (TOA) reflectance.

In order to compare model output to these flood maps derived from Landsat images, we considered a modeled cell to be flooded if it had more than 0.1 m of water depth. Simulated flow depth was recorded once every two days and was used to obtain the total inundated area by considering the size of each cell according to the spatial resolution of each simulation. For consistency, each observation is re-gridded to the spatial resolution of model output before calculating the total area.

4. Results

4.1. Flow, storage and mass balance

Changes in water balance components of the model including the incoming and outgoing flow rates and basin storage at different spatial resolutions are shown for 2001-2007 (Figures 4 and 5). For discharge, we compared whole time-series and timing between peak inflow and outflow. We define “peak” as the ten maximum simulated daily discharges per each calendar year. No detectable differences between time-series of these outputs were observed, except for the 250-m simulation of the outflow, which had peak discharge marginally higher than the other two grid-cell resolutions, most notably in 2001 and 2003. In 2005, the 1000-m simulation presents the highest outflow. The coefficient of variation among simulations was similar (Table 3), and only the timing from peak inflow to peak outflow between the 250-m and 1000-m simulations showed a slight but statistically significant difference (Kolmogorov-Smirnov test with $p=0.032$). The 250-m simulation featured the longest time between peak inflow and peak outflow, with an all-period mean of 21.7 ± 6.4 days (1 standard deviation) compared to the 19.4 ± 5.4 days this takes for

the 1000-m simulation. The 500-m output was similar to the 1000-m, with 19.7 ± 5.2 days.

FIGURE 4 AROUND HERE

TABLE 3 AROUND HERE

Storage was marginally higher in the 250-m simulation throughout the simulation, although this was most noticeable in peak and low periods (Figure 5). The 500-m often stored the lowest amount, specifically during the recession period, when it tended to empty faster compared to the other simulations. At this resolution, the average storage was 86.8% and 90.5% that of 250-m and 1000-m, respectively. This indicates that 500-m output presented less variability compared to the other two. This was partly corroborated by the application of the Levene's test, which showed that the variance of the 500-m simulation was statistically different from 250-m at $p=0.0003$ but not different from 1000-m, with $p=0.461$; 1000-m and 250-m were statistically different at $p=0.0025$.

FIGURE 5 AROUND HERE

We compared interannual average values of water balance components over the model domain for the simulated period and there are no substantial differences in the balance across resolutions, with precipitation being the largest input and evaporation the largest loss, and the magnitude of precipitation and evaporation approximately equal (Figure 6). Consequently, input discharge at Logone (Katoa and the diffuse floodplain flow to the south) was balanced by the combined outflow of the Logone (near N'Djamena) and the Komarka and Ambabare (which join

downstream of our domain to become the El Beïd). No significant differences between the floodplain mass balance were apparent at the three different spatial resolutions.

FIGURE 6 AROUND HERE

We found that the flow rate at Logone Gana gaging station was accurately simulated by the model (Figure 7), with a Nash Sutcliff Efficiency (NSE) of 0.81. More than 80% of the time the difference between modeled and observed flow was less than $150 \text{ m}^3/\text{s}$. Since the model was able to reproduce the yearly peak inflow at Katoa (Figure 4) and the rate at Logone Gana, this indicates that the model accurately allocated water in the floodplain between these two locations. This was also coincident with the spatial agreement at Logone Gana that is depicted in more detail in the next section.

FIGURE 7 AROUND HERE

4.2. Inundated area

We compared satellite-observed and model-predicted total inundated area across the floodplain (Figure 8). Peak observed inundated extent ranged from $4,000 \text{ km}^2$ to $7,000 \text{ km}^2$. On the whole, the model predicted the flood peak and duration of flooding well. On average, the model predicted peak flood extent within $82 \pm 26\%$ of observed values for the 2003, 2004 and 2006. In addition, considering observations during both high and low flows, the RMSE was slightly higher in the 250-m simulation with respect to the other two; conversely, that simulation showed

the lowest Pearson correlation coefficient, although at all spatial resolutions it was high (Table 4). Regarding the bias, the 250-m simulation was the only showing a positive figure while the 1000-m was the highest absolute value. The bias for the 1000-m simulation was approximately 2% of the typical maximum observed inundation extent (4,000 km²). The largest difference was for 2001, where simulated maximum flooded extent was only 57% of what Landsat images detect. All simulations tended to correctly simulate the length of the flood season, although model outputs retained more water during the descending limb compared to what observations show.

FIGURE 8 AROUND HERE

TABLE 4 AROUND HERE

To assess the ability of the model to map flooded areas spatially, we compared the PSS and FAI for the dates represented in the Landsat time-series (Figure 9). In general, both indices showed that performance was highly seasonal; during peak flooding, simulations tended to reach relatively high correspondence to observations, while low flows were poorly simulated. During the flooding period the performance reached values above 50% (0.5) for FAI (PSS), as for example in 2001. The averages of non-zero scores are presented in Table 5 and show that there was a strong agreement among spatial resolutions. In the low flow (see Figure 8 and 9b), PSS values suggested that the model simulates flooding correctly in terms of the total flooded area, but was less skilled in reproducing the spatial distribution of the floods.

FIGURE 9 AROUND HERE

TABLE 5 AROUND HERE

Figure 10 compares observations and model output for the year 2006. We show only the 1000-m simulation since we have already demonstrated that spatial patterns do not differ significantly. In general, the spatial distribution was well represented. During the dry period (January – July) the model does not produce large overbank flow. The relatively poor correspondence between observed and simulated flooding patterns during the dry season supported our interpretation of the PSS index. April, the only month for which the observations does not have any flooded cells, was modeled with isolated inundated patches due to rainfall in the model, representing a marginal mismatch between simulations and observations. In September, observations indicated that flooding had begun on the east bank of the Logone (i.e. in Chad), with some isolated areas also flooding to the north of the Logone-Logomatya confluence; the model did not reproduce these features at all on September 1st. By September 17th, the model had begun to show some flooding, though it was significantly less than the observed inundation. From October onwards, the model correctly simulated inundation along most of the east bank of the Lorome Mazra as well as to the north of Logone Gana. In October, the primary areas of slight discrepancy were to the west of the Logomatya, and to the southeast; these areas are labeled as “A” and “B”, respectively, in Figure 10, and will be further discussed below.

FIGURE 10 AROUND HERE

4.3. A closer look at the spatiotemporal disagreement

We attempted to correct the spatial disagreement of inundation patterns by varying channel parameters such as bankfull depth and roughness coefficient in order to correct the spatial disagreement of inundation patterns, but without success. We then explored two possibilities for the spatial disagreement: errors in floodplain topography, or in precipitation inputs to the model. Topography, represented by the SRTM, determines flow pathways and areas of accumulation. On the other hand, precipitation can alter the timing of the flooding season. In both cases, unrealistic input fields may introduce errors in the results.

Figure 11 shows the SRTM elevations of the two primary areas of model and observation discrepancy as described in previous paragraphs (identified in the inset boxes A and B in Figure 10) where flow directions can be derived from. In the northern section (A in Figure 10, upper panels in Figure 11), the Logomatya runs along the edge of the eastern boundary of the area, and the elevations decrease generally from southeast to northwest, promoting flooding of this area. The Landsat imagery (Figure 10 and upper rightmost panel in Figure 11) showed that the entire area between the Logomatya and UTM easting of ~485 km was inundated in October, but that the model was dry to the west of the Logomatya. The elevation differences revealed the cause: between UTM northing ~1,220 to 1,250 km, flow direction was towards the Logomatya River, in an area where elevation differences are around 1 to 5 meters. These features were found to be largely consistent across spatial resolutions and clearly inhibited the inundation of this area.

FIGURE 11 AROUND HERE

662 In the southern section (B in Figure 10, lower panels in Figure 11) the Logone River appears on
663 the western boundary, while the Ba-Illi runs along the northeast of the area. Elevations generally
664 increase from north to south, and the lowest point in the area actually occurs in the northeast.
665 The Landsat (Figure 10) showed that the entire area between the Logone and UTM easting of
666 ~531 km was inundated in October of 2006, but that the model predicted no inundation to the
667 east of ~520 km UTM easting. All resolutions showed similar patterns of elevation distribution
668 and flow direction. Across all resolutions there was a pattern of flow direction pointing mostly
669 toward the west, starting from the southeast corner pointing diagonally toward UTM northing
670 ~1,235 km. The difference in local elevation inside this area was approximately 4 to 6 meters.
671 Thus, the DEM causes flow to be routed to the northwest to the Logone, rather than north to the
672 Ba-Illi; this leads to an overall underestimation of the inundation in the area.

673
674 Figure 12a shows monthly in situ measured and satellite-derived TRMM precipitation. TRMM
675 had a high correlation with the in situ precipitation, with a Pearson correlation coefficient of 0.92
676 and a RMSE of 36.97 mm/month. Dry and wet seasons were well represented by TRMM.
677 Overall, the satellite time-series was able to rank these years in a similar order as was the in situ,
678 with 2001, 2002 and 2005 as the rainiest wet seasons in the period. In 2001, when the highest
679 discrepancy between model and observed maximum flooded area was detected, TRMM showed
680 the highest monthly precipitation of all rainy seasons in our study period. In Figure 12b and c,
681 we show TRMM precipitation intensity and number of rainy days during the period attributed to
682 the 2001 inundation (August 19 to October 11) for each LISFLOOD-FP simulated year, TRMM
683 showed that precipitation intensity was greatest in 2001. We hypothesize that the cause for the

significant flooding event in 2001 shown in Figure 8 was not likely to be an inaccurate specification of precipitation, as the precipitation compares favorably to in situ data.

FIGURE 12 AROUND HERE

4.4.- Performance of sub-grid versus standard raster model.

To understand whether the sub-grid parameterization adds more skill to the simulation of flooding dynamics in the Logone floodplain, we compared the performance of this model to the standard raster version of LISFLOOD-FP with sub-grid parameterization disabled (Figure 13). Our results indicate that neither model yielded a significantly improved simulation seemed to surpass of surface area during the flooding period; while the simulation using the standard raster model tended to over-predict, the sub-grid model mostly under-predicted flooded area (Figure 13a). However, the sub-grid model followed the observed seasonal pattern of surface area more closely, while the version with no sub-grid parameterization depicted a more abrupt and unrealistic dynamics. A greater difference occurred with the volume of water in this area, since the standard raster model stored several times more water compared to the other model (Figure 13b). This resulted in the model without sub-grid parameterization generating mean flooding water depths several times higher than the sub-grid model (Figure 13c), with many 2 to 3 meters above the range between 1 to 3-m described in the literature (e.g. Benech et al., 1982; Loth, 2004).

FIGURE 13 AROUND HERE

5. Discussion and conclusion

This study used satellite remote sensing measurements of precipitation, topography, and river topology, along with in situ measurements of flow to develop a 2-D hydraulic model of flooding processes in a data sparse area. Short-term, discontinuous hydroclimatic data that characterize this area of Cameroon presented an opportunity to test the skill of this modeling approach to adequately simulate the spatiotemporal features of the seasonal flooding. Inundation timing, flood peak, duration and channel discharge were predicted well by the model. However, the model had mixed results predicting the spatial distribution of flooding. Despite the somewhat inaccurate modeled spatial distribution, our simulations were capable of representing most flooding features that are critical for the activities of thousands of inhabitants that base their lives on agriculture, pastoralism, and fishing; for example, the model provides an unbiased estimate of the overall inundation extent in the floodplain, and reproduces interannual variations in inundated extent. Moreover, most other modeling studies have evaluated flood extent only during maximum inundation or short-term events (Adnan and Atkinson, 2012; Jung and Jasinski, 2015; Jung et al., 2012; Neal et al., 2012, 2011; Viero et al., 2013) rather than multi-year inundation dynamics, including assessments for dry seasons when no flooding is expected, as in our study.

Although total flooded area is simulated well, the spatial distribution of the flooded and non-flooded areas was not adequately resolved. These problems seem to be related to the floodplain topography, derived here from SRTM. It is unlikely that these issues could be resolved by simply running the model at higher spatial resolution. Indeed, varying the grid cell resolution of the

model from 250-m to 1000-m did not significantly alter the output but yielded very small differences between simulated flood volume, discharge, and flooded area. These results expand previous studies that have found similar independence with respect to pixel size for smaller spatial domains and shorter simulations (Neal et al., 2011).

Our findings are also consistent with previous studies in terms of the overall magnitude of the hydrologic fluxes for the Logone (Naah, 1990; Evans and Loth, 2004; Delclaux et al., 2010). Importantly, the simulations at the different spatial resolutions were consistent in quantifying this balance. Generally speaking, precipitation and the Logone river provide the main input to the floodplain, while evaporation, the Logone, and the El Beïd are the primary ways water leaves the floodplain. During wet years, local precipitation input to the floodplain and inflow along the Logone both tend to increase, presumably in response to mesoscale atmospheric processes. Thus, disentangling the relative inputs of precipitation and overbank flow to the seasonal flooding is relatively difficult; both appear to be important.

One aspect that could affect the performance of the model in terms of the spatial distribution of the flooded/non-flooded areas is related to the lack of an accurate representation of the land cover. This controls the selection of the Manning's roughness coefficient for the floodplain (Dorn et al., 2014), in our case assumed uniform across the spatial domain. LISFLOOD-FP has a subroutine that allows the incorporation of spatially variable friction coefficients, but a realistic multi-year simulation would need the model to ingest different spatial distributions according to the time of the year, which is still not implemented. In addition, both rainfall and evaporation are assumed uniform, as the model does not allow the use of spatially distributed fields of these

variables. Improving in these areas is more challenging than doing so for the roughness coefficient, since while there is availability of imagery at small cell sizes to classify the land, such as Landsat and MODIS; there are no databases of the needed climatic variables at the spatial resolution required. These issues also show up in more conventional flooding modeling without sub-grid channel parameterizations. Our findings underscore that further improvement of flooding needs to consider multi-year dynamics, where many of the important input fields must not be considered static. Furthermore, our comparison between the sub-grid and the standard raster model showed that the sub-grid adds skill to the prediction of flooding dynamics when both models are compared at the same spatial resolution, and more so when the river or channel network is smaller than the cell size. This agrees with Neal et al (2012), who using a small domain to compare these two approaches, found that the sub-grid model was able to reproduce the patterns of a high-resolution conventional gridded approach. Thus, the performance of LISFLOOD-FP suggests that, given today's limitations in flooding model development and data availability, global-scale simulations at 1-km spatial resolution are sufficiently accurate to represent flooding patterns across the world (Sampson et al., 2015) and can still be improved with sub-grid routines in order to attain more accurate spatial representation. Therefore, future modeling studies incorporating some of our suggestions could possibly eliminate the need to over-parameterize entire watersheds as has occurred in several, coarser grid (0.25 to 0.5°) global studies to date (Arnell and Gosling, 2014; Hirabayashi et al., 2013; Ward et al., 2013).

Note that the modeling presented in this paper did not include the effect of smaller canals that connect the main streams to the ubiquitous shallow depressions that may also control the hydraulics of the Logone floodplain. Ponds that develop as these shallow depressions get

inundated can hold water and become connected to the main streams usually through man-made canals in which locals fish using fishing nets, among other techniques (Delclaux et al., 2010). This seasonal infrastructure may impact the recession of the flooding by channelizing and clogging the water stored in the ponds in this area where elevation differences are smaller than 4-m among neighboring cells. Recent surveys have identified growth in number and length of canals across the floodplain (Delclaux et al., 2010), changes that may be influencing the hydraulics of the area. These changes can potentially be captured in further simulations using LISFLOOD-FP, since the model using the presented set-up was able to reproduce: (1) the amount of water in the floodplain between Katoa and Logone Gana; (2) most of the spatial distribution during the flooding season; (3) and the overall floodplain mass balance described in the literature. This indicates that LISFLOOD-FP can be coupled to other models that need accurate total inundated area and timing of flooding. In our current CHANS research, the fish dynamics model is a one-dimensional code that utilizes total inundated area to trigger fish movement. Given the lack of high quality information to perform a more complete simulation, our findings indicate that LISFLOOD-FP is a good option to study the coupled system between climate changes, hydrology and human agency in the Logone floodplain.

6. Acknowledgements

This study was funded by the National Science Foundation, project N° BCS 1211986. We are very grateful to Sara Vassolo for discharge data, Mott McDonald Company for making available river cross-sections, Benjamin Ngounou for monthly rainfall data at Lake Maga, Guy Schumann

and an anonymous reviewer for constructive comments that improved this manuscript, and
Brandon Mohr for his help in some figures.

7. References

Acker, J.G., Leptoukh, G., 2007. Online Analysis Enhances Use of NASA Earth Science Data.
Eos, Trans. Am. Geophys. Union 88, 14. doi:10.1029/2007EO020003

Acreaman, M.C., Hollis, E.G., 1996. Water management and wetlands in sub-Saharan Africa.
IUCN, Gland.

Adnan, N.A., Atkinson, P.M., 2012. Remote sensing of river bathymetry for use in hydraulic
model prediction of flood inundation. Proc. - 2012 IEEE 8th Int. Colloq. Signal Process. Its
Appl. CSPA 2012 159–163. doi:10.1109/CSPA.2012.6194710

Arnell, N.W., Gosling, S.N., 2014. The impacts of climate change on river flood risk at the
global scale. Clim. Change. doi:10.1007/s10584-014-1084-5

Bates, P.D., De Roo, a P.J., 2000. A simple raster based model for flood inundation simulation.
J. Hydrol. 236, 54–77.

Bates, P.D., Horritt, M.S., Fewtrell, T.J., 2010. A simple inertial formulation of the shallow
water equations for efficient two-dimensional flood inundation modelling. J. Hydrol. 387,
33–45. doi:10.1016/j.jhydrol.2010.03.027

Bates, P.D., Wilson, M.D., Horritt, M.S., Mason, D.C., Holden, N., Currie, A., 2006. Reach scale
floodplain inundation dynamics observed using airborne synthetic aperture radar imagery:
Data analysis and modelling. J. Hydrol. 328, 306–318.

Beffa, C., Connell, R.J., 2001. Two-Dimensional Flood Plain Flow. I: Model Description. J.

Hydrol. Eng. 6, 397–405. doi:10.1061/(ASCE)1084-0699(2001)6:5(397)

Benech, V., Quensiere, J., Vidy, G., 1982. Hydrologie et physico-chimie des eaux de la plaine d'inondation du Nord-Cameroun. Cahiers ORSTOM series Hydrologique. XIX, 15-35.

Boronina, A., Ramillien, G., 2007. Application of AVHRR imagery and GRACE measurements for calculation of actual evapotranspiration over the Quaternary aquifer (Lake Chad basin) and validation of groundwater models. J. Hydrol. 348, 98– 109. doi:10.1016/j.jhydrol.2007.09.061

Chow, V. T., 1959. Open-Channel Hydraulics, MacGraw-Hill, New York.

Coulthard, T.J., Ramirez, J. a, Barton, N., Rogerson, M., Brücher, T., 2013. Were rivers flowing across the Sahara during the last interglacial? Implications for human migration through Africa. PLoS One 8, e74834. doi:10.1371/journal.pone.0074834

Delclaux, F., Seignobos, C., Liénou, G., Genthon, P., 2010. Water and People in the Yaere Floodplain (North Cameroon), in: Álvarez, M.A. (Ed.), Floodplains: Physical Geography, Ecology and Societal Interactions. Nova publishers, pp. 1–27.

Denny, P., 1993. Wetlands of Africa: introduction, in: Whighan, D.F., Dykyjova, D., Hejny, S. (Eds.), Wetlands of the World: Inventory, Ecology and Management. Kluwer, Dordrecht, pp. 1–31.

Dorn, H., Vetter, M., Höfle, B., 2014. GIS-based roughness derivation for flood simulations: A comparison of orthophotos, LiDAR and crowdsourced geodata. Remote Sens. 6. 1739-1759. doi:10.3390/rs6021739.

Evans, S.Y., 1999. Logone floodplain model study report. Cambridge.

Evans, S.Y., Loth, P., 2004. Hydrology of the Waza Logone Area, in: Loth, P. (Ed.), The Return of the Water Restoring the Waza Logone Floodplain in Cameroon Restoring the Waza

844 Logone. IUCN, Gland and Cambridge, pp. 33–37.

845 Gao, B.G., 1996. NDWI – a normalized difference water index for remote sensing of vegetation
846 liquid water from space. *Remote Sens. Environ.* 58, 257–266.

847 Heijmans, H.J.A.M., Ronse, C., 1999. Annular filters for binary images. *IEEE Trans. Image*
848 *Process.* 8, 1330–1340. doi:10.1109/83.791959

849 Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., Kim,
850 H., Kanae, S., 2013. Global flood risk under climate change. *Nat. Clim. Chang.* 3, 816–821.
851 doi:10.1038/nclimate1911

852 Huffman, G.J., Bolvin, D.T., Nelkin, E.J., Wolff, D.B., Adler, R.F., Gu, G., Hong, Y., Bowman,
853 K.P., Stocker, E.F., 2007. The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-
854 Global, Multiyear, Combined-Sensor Precipitation Estimates at Fine Scales. *J.*
855 *Hydrometeorol.* 8, 38–55. doi:10.1175/JHM560.1

856 Iongh, H.H., Zuiderwijk, A.B., Hamling, P., 1998. Economic assessment study of the Logone
857 Floodplain, Centre of Environmental Science report 146.

858 IPCC, 2013. Climate Change 2013: The Physical Science Basis. Contribution of Working Group
859 I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.
860 Cambridge University Press, Cambridge and New York.

861 Jung, H., Jasinski, M., 2015. Sensitivity of a Floodplain Hydrodynamic Model to Satellite-Based
862 DEM Scale and Accuracy: Case Study—The Atchafalaya Basin. *Remote Sens.* 7, 7938–
863 7958. doi:10.3390/rs70607938

864 Jung, H.C., Alsdorf, D., Moritz, M., Lee, H., Vassolo, S., 2011. Analysis of the relationship
865 between flooding area and water height in the Logone floodplain. *Phys. Chem. Earth* 36,
866 232–240. doi:10.1016/j.pce.2011.01.010

867 Jung, H.C., Jasinski, M., Kim, J.W., Shum, C.K., Bates, P., Neal, J., Lee, H., Alsdorf, D., 2012.
 868 Calibration of two-dimensional floodplain modeling in the central Atchafalaya Basin
 869 Floodway System using SAR interferometry. *Water Resour. Res.* 48, 1–13.
 870 doi:10.1029/2012WR011951

871 Karim, F., Petherman, C., Marvanek, S., Ticehurst, C., Wallace, J., Gouweleeuw, B., 2011. The
 872 use of hydrodynamic modelling and remote sensing to estimate flooding inundation and
 873 flood discharge in a large tropical catchment. 19th International Congress on Modelling and
 874 Simulation (Modsim2011), Perth, Australia, 3796-3802.

875 Krekeler, T., Seeber, K., 2013. Sustainable Water Management of the Lake Chad Basin.
 876 Discharge Measurements at Chari, Logone and Koumbou River, Chad. Report N° 5.

877 Le Coz, M., Delclaux, F., Genthon, P., Favreau, G., 2009. Assessment of Digital Elevation
 878 Model (DEM) aggregation methods for hydrological modeling: Lake Chad basin, Africa.
 879 *Comput. Geosci.* 35, 1661–1670. doi:10.1016/j.cageo.2008.07.009

880 Liang, Q., Du, G., Hall, J.W., Borthwick, A.G., 2008. Flood Inundation Modeling with an
 881 Adaptive Quadtree Grid Shallow Water Equation Solver. *J. Hydraul. Eng.* 134, 1603–1610.
 882 doi:10.1061/(ASCE)0733-9429(2008)134:11(1603)

883 Loth, P., 2004. The return of the water Restoring the Waza Logone floodplain in Cameroon
 884 Restoring the Waza Logone. IUCN, Gland and Cambridge.

885 McFeeters, S.K., 1996. The use of the Normalized Difference Water Index (NDWI) in the
 886 delineation of open water features. *Int. J. Remote Sens.* 17, 1425-1432.

887 Maxwell, S.K., Schmidt, G.L., Storey, J.C., 2007. A multi-scale segmentation approach to filling
 888 gaps in Landsat ETM+ SLC-off images. *Int. J. Remote Sens.* 28, 5339–5356.
 889 doi:10.1080/01431160601034902

890 Naah, E., 1990. Hydrologie du Grand Yaéré du Nord Cameroun. l'Université de Yaoundé.

891 NASA, 2009. Landsat 7 Science Data Users Handbook.

892 Neal, J., Schumann, G., Bates, P., 2012. A subgrid channel model for simulating river hydraulics
893 and floodplain inundation over large and data sparse areas. *Water Resour. Res.* 48, 1–16.
894 doi:10.1029/2012WR012514

895 Neal, J., Schumann, G., Fewtrell, T., Budimir, M., Bates, P., Mason, D., 2011. Evaluating a new
896 LISFLOOD-FP formulation with data from the summer 2007 floods in Tewkesbury, UK. *J.*
897 *Flood Risk Manag.* 4, 88–95. doi:10.1111/j.1753-318X.2011.01093.x

898 Niang, I., Ruppel, O.C., Abdrabo, M.A., Essel, A., Lennard, C., Padgham, J., Urquhart, P., 2014.
899 Africa. In: *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional*
900 *Aspects, Contribution of Working Group II to the Fifth Assessment Report of the*
901 *Intergovernmental Panel on Climate Change (IPCC).* doi:10.2753/JES1097-203X330403

902 Pavelsky, T.M., Smith, L.C., 2008. RivWidth: A Software Tool for the Calculation of River
903 Widths From Remotely Sensed Imagery. *IEEE Geosci. Remote Sens. Lett.* 5, 70–73.
904 doi:10.1109/LGRS.2007.908305

905 Rabus, B., Eineder, M., Roth, A., Bamler, R., 2003. The shuttle radar topography mission—a
906 new class of digital elevation models acquired by spaceborne radar. *ISPRS J. Photogramm.*
907 *Remote Sens.* 57, 241–262. doi:10.1016/S0924-2716(02)00124-7

908 Rebelo, L.-M., McCartney, M.P., Finlayson, C.M., 2010. Wetlands of Sub-Saharan Africa:
909 distribution and contribution of agriculture to livelihoods. *Wetl. Ecol. Manag.* 18, 557–572.
910 doi:10.1007/s11273-009-9142-x

911 Rodriguez, E., Morris, C.S., Belz, J.E., Chapin, E.C., Martin, J.M., Daffer, W., Hensley, S.,
912 2005. An assessment of the SRTM topographic products, Technical Report JPL D-31639.

913 Pasadena. doi:0099-1112/06/7203-0249/\$3.00/0
 914 Sakamoto, T., Van Nguyen, N., Kotera, A., Ohno, H., Ishitsuka, N., Yokozawa, M., 2007.
 915 Detecting temporal changes in the extent of annual flooding within the Cambodia and the
 916 Vietnamese Mekong Delta from MODIS time-series imagery. *Remote Sens. Environ.* 109,
 917 295–313. doi:10.1016/j.rse.2007.01.011
 918 Sampson, C.C., Smith, A.M., Bates, P.D., Neal, J.C., Alfieri, L., Freer, J.E., 2015. A high-
 919 resolution global flood hazard model. *Water Resour. Res.* 51, 7358–7381.
 920 doi:10.1002/2015WR016954
 921 Sanders, B.F., 2007. Evaluation of on-line DEMs for flood inundation modeling. *Adv. Water*
 922 *Resour.* 30, 1831–1843. doi:10.1016/j.advwatres.2007.02.005
 923 Scholte, P., 2005. *Floodplain Rehabilitation and the Future of Conservation & Development*,
 924 Leiden University.
 925 Scholte, P., 2007. Maximum flood depth characterizes above-ground biomass in African
 926 seasonally shallowly flooded grasslands. *J. Trop. Ecol.* 23:63–72. doi:
 927 10.1017/S026646740600366X
 928 Schumann, G.J.P., Bates, P.D., Horritt, M., Matgen, P., 2009. Progress integration of remote-
 929 sensing-derived flood extent and stage data and hydraulic models. *Rev. Geophys.* 47,
 930 RG4001.
 931 Schumann, G.J.P., Bates, P.D., Neal, J.C., Andreadis, K.M., 2014. Technology: Fight Floods on
 932 a Global Scale. *Nature* 507, 169. doi:10.1038/507169a
 933 Schumann, G.J.P., Neal, J.C., Voisin, N., Andreadis, K.M., Pappenberger, F.,
 934 Phanthuwongpakdee, N., Hall, a. C., Bates, P.D., 2013. A first large-scale flood inundation
 935 forecasting model. *Water Resour. Res.* 49, 6248–6257. doi:10.1002/wrcr.20521

936 Seeber, K., 2013. Lake Chad Basin: Sustainable water management. 2nd Mission on discharge
 937 measurements at Chari, Logone and Koumbou River, Chad.

938 Smith, A., Newing, A., Quinn, N., Martin, D., Cockings, S., Neal, J., 2015. Assessing the Impact
 939 of Seasonal Population Fluctuation on Regional Flood Risk Management. ISPRS Int. J.
 940 Geo-Information 4, 1118–1141. doi:10.3390/ijgi4031118

941 Soille, P., 1999. Morphological Image Analysis: Principles and Applications. Springer-Verlag.

942 Tarhule, A., 2005. Damaging rainfall and flooding: The other Sahel hazards. Clim. Change 72,
 943 355–377. doi:10.1007/s10584-005-6792-4

944 Thompson, J.R., Polet, G., 2000. Hydrology and land use in a sahelian floodplain wetland.
 945 Wetlands 20, 639–659. doi:10.1672/0277-5212(2000)020[0639:HALUIA]2.0.CO;2

946 Ticehurst, C., Dutta, D., Karim, F., Petherman, C., Guerschman, J.P., 2015. Improving the
 947 accuracy of daily MODIS OWL flood inundation mapping using hydrodynamic modelling.
 948 Nat. Hazards 78, 803-820.

949 Trigg, M.A., Wilson, M.D., Bates, P.D., Horritt, M.S., Alsdorf, D.E., Forsberg, B.R., Vega,
 950 M.C., 2009. Amazon flood wave hydraulics. J. Hydrol. 374, 92–105.
 951 doi:10.1016/j.jhydrol.2009.06.004

952 Tschakert, P., Sagoe, R., Samuel, G.O., Codjoe, N., 2010. Floods in the Sahel: an analysis of
 953 anomalies, memory, and anticipatory learning. Clim. Change 103, 471–502.
 954 doi:10.1007/s10584-009-9776-y

955 van de Giesen, N., Hut, R., Selker, J., 2014. The Trans-African Hydro-Meteorological
 956 Observatory (TAHMO). Wiley Interdiscip. Rev. Water 1, 341–348. doi:10.1002/wat2.1034

957 Viero, D. Pietro, D’Alpaos, A., Carniello, L., Defina, A., 2013. Mathematical modeling of
 958 flooding due to river bank failure. Adv. Water Resour. 59, 82–94.

959 doi:10.1016/j.advwatres.2013.05.011

960 Ward, P.J., Jongman, B., Weiland, F.S., Bouwman, A., van Beek, R., Bierkens, M.F.P., Ligtvoet,

961 W., Winsemius, H.C., 2013. Assessing flood risk at the global scale: model setup, results,

962 and sensitivity. *Environ. Res. Lett.* 8, 044019. doi:10.1088/1748-9326/8/4/044019

963 Wesseling, J.W., Drijver, C.A., Naah, E., Namba, A., Zuideiwijk, A., 1994. Waza Logone flood

964 restoration study.

965 Westra, T., De Wulf, R.R., 2007. Monitoring Sahelian floodplains using Fourier analysis of

966 MODIS time-series data and artificial neural networks. *Int. J. Remote Sens.* 28, 1595–1610.

967 doi:10.1080/01431160600887698

968 Westra, T., De Wulf, R.R., 2009. Modelling yearly flooding extent of the Waza-Logone

969 floodplain in northern Cameroon based on MODIS and rainfall data. *Int. J. Remote Sens.*

970 30, 5527–5548. doi:10.1080/01431160802672872

971 Wilks, D.S., 2006. *Statistical Methods in the Atmospheric Sciences*, Second. ed. Academic

972 Press, Burlington.

973 Wilson, M.D., Bates, P., Alsdorf, D., Forsberg, B., Horritt, M., Melack, J., Frappart, F.,

974 Famiglietti, J., 2007. Modeling large-scale inundation of Amazonian seasonally flooded

975 wetlands. *Geophys. Res. Lett.* 34, 4–9. doi:10.1029/2007GL030156

976 WMO, 2011. *Guide to Climatological Practices*. WMO-No. 100. World Meteorological

977 Organization.

978

Tables

Table 1: Model parameters for three zones of the channel network.

	Upstream Logone	Downstream Logone	Sub-channels
Coefficient r	-0.47	0.48	1.0
Exponent p	47.0	0.54	0.1

Table 2: Principal features of the *in situ* hydroclimatic data utilized in this study. Values for the simulated period (2001-2007) are shown in parenthesis

Location	Variable	Temporal resolution	Length of the record	Number of records	Data gaps (%)	Shift detected (days)	Use
Logone Gana	River flow	Daily	1953-2008	20395 (2636)	16.2 (0.06)	0 (0)	Calibration, Evaluation
Katoa	River flow	Daily	1948-2008	22280 (2636)	49.9 (12.7)	-21 (-5)	Boundary condition
Bongor	River flow	Daily	1948-2008	22280 (2636)	24.1 (19.5)	-19 (-6)	Boundary condition
Lake Maga	Precipitation	Monthly	1994-2012	228 (96)	0.004 (0.01)	0 (0)	Evaluation

Table 3: Statistical comparison of the timing between inflow and outflow among simulations with different grid resolutions.

Grid resolution of simulation	Mean (days)	Standard deviation (days)	Coefficient of variation (%)
250-m	21.74	6.35	29.21
500-m	19.69	5.19	26.36
1000-m	19.39	5.44	28.10

Table 4: Comparison between satellite-observed and model-predicted total inundated area.

Grid resolution of simulation	RMSE (km ²)	Pearson correlation coefficient	Bias (km ²)
250-m	697.4	0.91	44.8
500-m	621.9	0.93	-69.9
1000-m	689.1	0.93	-83.7

Table 5: Comparison between skill score indices applied to simulations.

	FAI				PSS			
Grid resolution of simulation	Min	Max	Mean*	Standard deviation*	Min	Max	Mean*	Standard deviation*
250-m	0	0.52	0.23	0.16	-0.01	0.50	0.28	0.13
500-m	0	0.53	0.24	0.17	-0.02	0.51	0.28	0.15
1000-m	0	0.55	0.27	0.15	0	0.54	0.32	0.13

* Only for values greater than zero.

Figure captions

Figure 1: Study area including the Logone River, available hydroclimatic records, and toponyms named in the main text. The left panel shows the spatial domain utilized for the LISFLOOD-FP model (black rectangle).

Figure 2: Average monthly precipitation, evaporation, relative humidity and temperature for each month from measurements at N'Djamena, at the confluence between the Logone and Chari rivers, slightly north of our spatial domain. Evaporation and humidity records correspond to the period 1951-1977 according to Naah (1990), For consistency, temperature and precipitation for the same period were calculated from the data available in the Climate Explorer of the Royal Meteorological Office of the Netherlands (<http://climexp.knmi.nl>).

Figure 3: Landsat images utilized in this study. Gray circles represent SLC-off. Numbers below each circle indicate the day of the month in which each image was taken.

Figure 4: Inflow-outflow discharges from modeled mass balances at three spatial resolutions investigated in this study; (a) 250-m grid-cell, (b) 500-m, and (c) 1000-m. Tick marks in the x-axis indicate the beginning of each year.

Figure 5: Modeled water storage at the three spatial resolutions. Tick marks in the x-axis indicate the beginning of each year.

Figure 6: Mean modeled water balance for the studied period, representing study-period means of the simulations at (a) 250-m, (b) 500-m, and (c) 1000-m spatial resolutions.

Figure 7: Comparison between flow rate at the Logone Gana record. (a) deploys time series for the whole studied period and (b) shows the distribution of the differences between model and observations.

Figure 8: Total inundated areas as extracted from Landsat Images compared to LISFLOOD-FP simulations during 2001-2007 at 250-m (a), 500-m (b), and 1000-m (c) spatial resolutions. Circles with black asterisks represent images utilized in Figure 10.

Figure 9: Results of the skill indexes FAI (a) and PSS (b) for the whole period analyzed considering the three spatial resolutions utilized in this study.

Figure 10: Comparison between observed (Landsat-derived) and simulated flooding patterns at 1000-m spatial resolution for the year 2006. Red-bordered rectangles denote the areas detailed in Figure 11. Axes x and y on each panel represent east and north UTM coordinates, respectively.

Figure 11: Elevation of the two areas highlighted in Figure 10 as red-bordered rectangles. The elevations correspond to the different smoothed versions of the SRTM utilized to carry out the hydraulic simulations with LISFLOOD-FP, where preferred flow directions can be inferred. The two rightmost panels correspond to the comparison between modeled and observed flooding for November 20, 2006, as represented in the corresponding panel in Figure 10. Upper panels correspond to rectangle “A” and lower panels to “B”. Axes x and y on each panel represent east and north UTM coordinates, respectively. Blue dots denote the location of the streams.

Figure 12: Analysis of TRMM data utilized as input for the LISFLOOD-FP model. In (a) these data are compared against monthly cumulative rainfall recorded at Lake Maga. (b) and (c) show intensity and number of rainy days for each simulated year between the dates that define the 2001’s inundation (August 19 to October 11).

Figure 13: Comparison between the standard LISFLOOD-FP raster model and LISFLOOD-FP including the sub-grid channel parameterization during one year at 500-m spatial resolution. (a) describes flooded area, (b) stored volume, (c) the ratio between mean water heights (standard model/sub-grid model), and (d) the location of the area used for the comparison (red rectangle). For (a) to (c), DOY means day of the year starting at May 1st. In (d) axes x and y on each represent east and north UTM coordinates, respectively, and blue lines denote the location of the streams.

Figure 02

Figure 03

Figure 05

Figure 07

Figure 08

Figure 09

Figure 10

Figure 11

250m

500m

1000m

2006/11/20

Figure 12

Figure 13