

1 **Propagation of hydro-meteorological uncertainty in a**
2 **model cascade framework to inundation prediction**

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7 **Abstract**

8 This investigation aims to study the propagation of meteorological uncertainty within a
9 cascade modelling approach to flood prediction. The methodology was comprised of a
10 Numerical Weather Prediction Model (NWP), a distributed rainfall-runoff model and a 2D
11 hydrodynamic model. The uncertainty evaluation was carried out at the meteorological and
12 hydrological levels of the model chain, which enabled the investigation of how errors
13 originated in the rainfall prediction, interact at a catchment level and propagate to an
14 estimated inundation area and depth. For this, a hindcast scenario is utilised removing non-
15 behavioural ensemble members at each stage, based on the fit with observed data. At the
16 hydrodynamic level, an uncertainty assessment was not incorporated; instead, the model was
17 setup following guidelines for the best possible representation of the case study. The selected
18 extreme event corresponds to a flood that took place in the Southeast of Mexico during
19 November 2009, for which field data (e.g. rain gauges; discharge) and satellite imagery were
20 available. Uncertainty in the meteorological model was estimated by means of a multi-physics
21 ensemble technique, which is designed to represent errors from our limited knowledge of the
22 processes generating precipitation. In the hydrological model, a multi-response validation was
23 implemented through the definition of six sets of plausible parameters from past flood events.
24 Precipitation fields from the meteorological model were employed as input in a distributed
25 hydrological model, and resulting flood hydrographs were used as forcing conditions in the
26 2D hydrodynamic model. The evolution of skill within the model cascade shows a complex
27 aggregation of errors between models, suggesting that in valley-filling events hydro-
28 meteorological uncertainty has a larger effect on inundation depths than that observed in
29 estimated flood inundation extents.

1 **1 Introduction**

2 Hydro-meteorological hazards can have cascading effects and far-reaching implications on
3 water security, with political, social, economic and environmental consequences. Millions of
4 people worldwide are forcibly displaced as a result of natural disasters, creating political
5 tensions and social needs to support them. These events observed in developed and
6 developing nations alike, highlight the necessity to generate a better understanding on what
7 causes them and how we can better manage and reduce the risk.

8 The assessment of flood risk is an activity that has to be carried out under a framework full of
9 uncertainty. The source of these uncertainties may be ascribed to the involvement of different,
10 and often rather complex models and tools, in the context of environmental conditions that are
11 at best, partially understood (Hall, 2014). In addition to this, flooding events are dynamic over
12 a range of timescales, due to climate variability and socio-economic changes, among others,
13 which further increases the uncertainty in the projections. Therefore, numerous types of
14 uncertainties can arise when using formal models in the analysis of risks.

15 Uncertainty is often categorised between aleatory and epistemic (Hacking, 2006): aleatory is
16 an essential, unavoidable unpredictability, and epistemic uncertainty reflects lack of
17 knowledge or the inadequacy of the models to represent reality. In the context of any
18 modelling framework, epistemic uncertainties may be ascribed to the definition of model
19 parameters and to the model structure itself (limited knowledge).

20 In a technological era characterised by the advent of computers, there is an increased ability
21 of more detailed hydrological and hydraulic models. Their use and development has been
22 motivated as they are based on equations that have (more or less) physical justification; and
23 allow a more detailed spatial representation of the processes, parameters and predicted
24 variables (Beven, 2014). However, there are also disadvantages, these numerical tools take
25 more computer time and require the definition of initial, boundary conditions and parameter
26 values in space and time. Generally, at a level of detail for which such information is not
27 available even in research studies. Moreover, these models may be subjected to numerical
28 problems such as numerical diffusion and instability. All of these disadvantages can be
29 interpreted as sources of uncertainty in the modelling process.

30 Due to wide range of uncertainty sources in the flood risk assessment process, it is of great
31 interest to investigate the propagation and behaviour of these different uncertainties from the
32 start of the modelling framework to the result. The size of registered damages and losses in

1 recent events around the world, reveal the urgency of doing so, even under a context of
2 limited predictability.

3 In September 2013, severe floods were registered in Mexico as a result of the exceptional
4 simultaneous incidence of two tropical storms, culminating in serious damage and widespread
5 persistent flooding (Pedrozo-Acuña et al., 2014a). This unprecedented event is part of a recent
6 set of extreme flood events over the last decade caused by record-breaking precipitation
7 amounts across Central Europe (Becker and Grünwald, 2003), United Kingdom (Slingo et
8 al., 2014), Pakistan (Webster et al., 2011), Australia (Ven den Honert and McAneney, 2011),
9 Northeastern US (WMO, 2011), Japan (WMO, 2011) and Korea (WMO, 2011). In all cases,
10 the immediate action of governments through the implementation of emergency and action
11 plans was required. The main aim of these interventions was to reduce the duration and
12 impact of floods. In addition, risk reduction measures were designed to ensure both a better
13 flood management and an increase in infrastructure resilience.

14 One key piece of information in preventing and reducing losses is given by reliable flood
15 inundation maps that enable the dissemination of flood risk to the society and decision makers
16 (Pedrozo-Acuña et al., 2013). Traditionally, this task requires the estimation of different
17 return periods for discharge (Ward et al., 2011) and their propagation to the floodplain by
18 means of a hydrodynamic model. There is currently a large range of models that can be used
19 to develop flood hazard maps (Horritt and Bates, 2002; Horritt et al., 2006).

20 The aforementioned accelerated progress of computers has given way to the development of
21 model cascades to produce hydrological forecasts, which make use of rainfall predictions
22 from regional climate models (RCMs) with sufficient resolution to capture meteorological
23 events (Bartholomes and Todini, 2005; Demeritt et al., 2010). Within this approach, the
24 coupling of different operational numerical models is carried out, using numerical weather
25 prediction (NWP) with radar data for hydrologic forecast purposes (Liguori and Rico-
26 Ramirez, 2012; Liguori et al., 2012), or NWP with hydrological and hydrodynamic models to
27 determine inundation extension (Pappenberger et al., 2012; Cloke et al., 2013; Ushiyama et
28 al., 2014).

29 The use of RCMs in climate impact studies on flooding has been reported by Deutschbein and
30 Seibert (2010) and Beven (2011), noting that despite their usefulness, the spatial resolution of
31 models (~25km) remains coarse to capture the spatial resolution of precipitation. This is
32 particularly important, as higher resolution is needed to effectively model the hydrological

1 processes essential for determining flood risk. To overcome this limitation, the utilisation of
2 dynamic downscaling in these models has been significantly growing (Fowler et al., 2007;
3 Leung and Qian, 2009; Lo et al., 2008).

4 Significant challenges remain in the foreseeable future, among these, the inherent
5 uncertainties in the predictive models are likely to have an important role to play. For
6 example, it is well known that the performance skill of NWP deteriorates very rapidly with
7 time (Lo et al., 2008). To overcome this, the long-term continuous integration of the
8 prediction has been subdivided into short-simulations, involving the re-initialisation of the
9 model to mitigate the problem of systematic error growth in long integrations (Giorgi, 1990;
10 Giorgi, 2006; Qian et al., 2003). Moreover, the use of ensemble prediction systems to obtain
11 rainfall predictions for hydrological forecasts at the catchment scale is becoming more
12 common among the hydrological community as they enable the evaluation and quantification
13 of some uncertainties in the results (Buizza 2008; Cloke and Pappenberger, 2009; Bartholmes
14 et al. 2009). In these studies, an ensemble is a collection of forecasts made from almost, but
15 not quite, identical initial conditions.

16 A key question that arises when using a cascade modelling approach to flood prediction or
17 mapping is: how uncertainties associated to meteorological predictions of precipitation
18 propagate to a given flood inundation map? Previous work has been devoted to the
19 examination of uncertainties in the results derived from different ensemble methods, which
20 address differences in the initial conditions in the NWP or even differences in using a single
21 model ensemble vs. multi-model ensemble (Pappenberger et al. 2008; Cloke et al., 2013; Ye
22 et al., 2014). However, less attention has been paid to the behaviour of errors within a model
23 chain that aims to represent a flood event occurring at several spatial scales. In order to
24 understand how errors propagate in a chain of models, this investigation evaluates the
25 transmission of uncertainties from the meteorological model to a given flood map. For this,
26 we utilize a cascade modelling approach comprised by a Numerical Weather Prediction
27 Model (NWP), a rainfall-runoff model and a standard 2D hydrodynamic model. This
28 numerical framework is applied to an observed extreme event registered in Mexico in 2009
29 for which satellite imagery is available. The investigated uncertainty is limited to the model
30 parameter definition in the NWP model, by means of a multi-physics ensemble technique
31 considering several multi-physics parameterization schemes for the precipitation (Bukovsky
32 and Karoly, 2009). The resulting precipitation fields are used to generate spaghetti plots by

1 means of a distributed hydrological model, enabling the propagation of meteorological
2 uncertainties to the flood hydrograph. Hence, the resulting hydrographs represent the runoff
3 associated to each precipitation field estimated with the NWP. In order to complete the
4 propagation of the uncertainty through the cascade of models to the flood map, the
5 hydrographs are used as forcing in a standard 2D hydrodynamic model.

6 On the other hand, it is acknowledged that each of the other models (hydrological and
7 hydrodynamic) within the model cascade, will introduce other epistemic and random
8 uncertainties to the result. In order to reduce their influence, the numerical setup of both these
9 models is constructed with the best available data (e.g. LiDAR for the topography) and
10 following recent guidelines for the assessment of uncertainty in flood risk mapping (Beven et
11 al. 2011). In this way, the uncertainty associated to the meteorological model outputs is
12 propagated through the model cascade from the atmosphere to the flood plain. Thus, the aim
13 of this investigation is to study the uncertainty propagation from the meteorological model
14 (due to model parameters), to the determination of an affected area impacted by a well-
15 documented hydro-meteorological event.

16 This work is organised as follows: Section 2 provides a description of both, the study area and
17 the extreme hydro-meteorological event, which are employed to test our cascade modelling
18 approach; Section 3 introduces the methodology, incorporating a brief description of the
19 selected models setup. Additionally, we incorporate a description of the multi-physics
20 ensemble technique used to quantify and limit the epistemic uncertainty in the NWP model.
21 The resulting precipitation fields, hydrographs and flood maps are compared with available
22 field data and satellite imagery for the event. In Section 4, a discussion of errors along the
23 model cascade, is also presented with some conclusions and future work.

24

25 **2 Case Study**

26 The selected study area is within the Mexican state of Tabasco, which in recent years has been
27 subjected to severe flooding as reported by Pedrozo-Acuña et al. (2011; 2012). This region
28 comprises the area of Mexico with the highest precipitation rate (2000-3000 mm/year), which
29 mostly occurs during the wet season of the year between May and December. The rainfall
30 climatology is also influenced by the incidence of hurricanes and tropical storms arriving
31 from the North.

1 In this paper, the extreme hydro-meteorological event selected for the analysis corresponds to
2 that registered in the early days of November 2009 in the Tonalá river. As it is shown in
3 [Fig.1](#), the river is located in the border of Tabasco and Veracruz and during the event, the
4 substantial rainfall intensity provoked its overflowing leaving extensive inundated areas along
5 its floodplain. Top panel of [Fig. 1](#) shows the geographical location of the catchment, with an
6 area of 5,021 km², as well as the location of 18 weather stations installed within the region by
7 the National Weather Service. The event was the result of heavy rain induced by the cold
8 front #9, which persisted for four days along Mexico's Gulf Coast, forcing more than 44,000
9 people to evacuate their homes and affecting more than 90 communities. High intensities in
10 rainfall were recorded in rain gauges from the 31st October to 3rd November, with
11 cumulative daily precipitation values reporting more than 270 mm. The river is
12 approximately 300 km long and before discharging into the Gulf of Mexico, the stream
13 receives additional streamflow from other smaller streams such as Agua Dulcita in Veracruz,
14 and Chicozapote in Tabasco. The bottom panel of the same Figure illustrates the lower Tonalá
15 River, where severe flooding was registered as it is shown in the photographs on the right.
16 The yellow, blue and red dots on the panel represent the location at which the photographs
17 were taken.

18 The hydrometric data in combination with the satellite imagery for the characterisation of the
19 affected areas, enabled an accurate investigation of the causes and consequences that
20 generated this flood event. The high quality of the available information, allowed the
21 application of a cascade modelling approach comprised by state-of-the-art meteorological,
22 hydrological and hydrodynamic models. This numerical approach is utilised with the intention
23 to carry out an assessment of the modelling framework, with particular emphasis on the
24 propagation of the epistemic uncertainty from the meteorological model to the spatial extent
25 of an affected area. Such investigation paves the road towards a more honest knowledge
26 transfer to decision-makers, whom consider the reliability of the model results.

27

28 **3 Methodology and Results**

29 The methodology is comprised of a Numerical Weather Prediction Model (NWP), a
30 distributed rainfall-runoff model and a standard 2D hydrodynamic model. It is anticipated that
31 the selected modelling approach will support the advance of the understanding of the
32 connections among scales, intensities, causative factors, and impacts of extremes. This model

1 cascade with state-of-the-art numerical tools representing a hydrological system enables the
2 development of a framework by which an identification of the reliability of simulations can be
3 undertaken. It should be noted that the model cascade contains several sources of uncertainty
4 at every level of the numerical framework (meteorological, hydrological and hydrodynamic).
5 However, the uncertainty evaluation is only carried out at the meteorological and hydrological
6 levels of the model chain. This enables the investigation of how errors originated in the
7 rainfall prediction interact at a catchment level, and propagate to determine a given inundation
8 area and depth. Therefore, the aim is not to reproduce an observed extreme event, but to use a
9 state of the art numerical framework to examine how errors aggregate in a hindcast scenario.

10 An uncertainty assessment is not carried out at the hydrodynamic level of the model cascade.
11 Instead, the 2D hydrodynamic model is setup following recommendations of published
12 guidelines for the best possible representation of the case study, more specifically with
13 regards to the selected spatial resolution, boundary conditions and roughness values (see
14 Asselman et al. 2008).

15 The proposed investigation is important as uncertainties are cascaded through the modelling
16 framework, in order to provide better understanding on how errors propagate within models
17 working at different temporal and spatial scales. It is acknowledged that this information
18 would enhance better flood management strategies, which would be based on the honest and
19 transparent communication of the results produced by a modelling system constrained by
20 intrinsic errors and uncertainties.

21

22 **3.1 Meteorological model**

23 Simulated precipitation products from numerical weather prediction systems (NWPs)
24 typically show differences in their spatial and temporal distribution. These differences can
25 considerably influence the ability to predict hydrological responses. In this sense, in this study
26 we utilise the advanced research core of the Weather Research and Forecasting (WRF) model
27 Version 3.2. The WRF model is a fully compressible non-hydrostatic, primitive-equation
28 model with multiple nesting capabilities ([Skamarock et al., 2008](#)).

29 As it is shown in [Fig. 2](#), the model setup is defined using an interactive nested domain inside
30 the parent domain. This domain is selected in order to simulate more realistic rainfall, with
31 the inner frame enclosing the Tonalá river catchment within a 4 km resolution. The 4 km

1 horizontal resolution is considered good enough to compute a mesoscale cloud system
2 associated to a cold front. It is shown that this finer grid covers the central region of Mexico,
3 while in the vertical dimension, 28 unevenly spaced sigma levels were selected. The initial
4 and boundary conditions were created from the NCEP Global Final Analysis (FNL) with a
5 time interval of 6 hours for the initial and boundary conditions. Each of the model
6 simulations was reinitialised every two days at 1200 UTC, considering a total simulation time
7 from the 27th October 2009 until the 13th November 2009.

8 Epistemic uncertainty is considered in the WRF model by means of the sensitivity of the
9 results for precipitation, due to variations in the model setup. For this, we utilise a multi-
10 physics ensemble technique proposed by [Bukovsky and Karoly \(2009\)](#), where the sensitivity
11 of simulated precipitation in the model results is examined through variations in the specific
12 setup options by means of twenty three different combinations. The comparison of computed
13 precipitation fields against real measurements from weather stations within the catchment,
14 enabled the quantification of uncertainty in the meteorological model for this event. [Table 1](#)
15 shows a summary of the different multi-physics parameters used in the WRF model to
16 generate the physics ensemble. As it is shown on this table, there is a large discrepancy in the
17 model skill results in all 23 simulations Error metrics reported in this table are computed
18 using information from all available stations within the numerical domain; which comprised
19 stations that are outside the area of the catchment. It is demonstrated that only 13 of these
20 model runs report a positive Nash-Sutcliff Coefficient (NSC), which indicates a better
21 accuracy for those realisations. In contrast, model runs with negative NSC were dismissed for
22 the numerical reproduction of the event, as this condition is a clear indicator that the observed
23 mean is a better predictor than the model.

24 Therefore, meteorological model runs that comply with a criteria defined by a NSC>0.3 and a
25 Correlation coefficient (Cor)>0.8 (for the whole numerical domain) are utilised to investigate
26 the propagation of meteorological uncertainties through the modelling framework. This
27 criteria narrows down the meteorological model runs to 12, which will be cascaded to the
28 hydrological model stage to attain streamflow predictions. In this approach, the selected 12
29 multi-physics ensemble runs of the model represent a plausible and equally likely state of the
30 system in the future.

31 [Fig. 3](#) illustrates the cumulative precipitation curves computed for each of the 23 model runs
32 of the multi-physics ensemble at four different stations located within the catchment. In this

1 figure differences in the spatial distribution and intensity of precipitation are evident.
2 Moreover, the selected 12 members by the criteria (NSC>0.3 and Cor>0.8) are illustrated by
3 the blue solid lines, while the grey solid lines show those members that were rejected by it.
4 Notably, dismissed members tend to underestimate the amount of precipitation in all four
5 locations that are presented in this figure. For completeness, the rainfall measurements at each
6 meteorological station are also shown by the black solid line, while the red dotted line depicts
7 the mean value of the selected model runs to be propagated through the model cascade. If the
8 12 selected members are considered in the estimation of ensemble metrics at each station, it is
9 shown that at Station No. 27075, the spread of the estimated cumulative precipitation curves
10 is limited and quantified by a NSC=0.917 and a NRMSE = 10.7%, indicating a good skill of
11 the selected WRF precipitation estimates at this point. In contrast, at Station No. 27007 the
12 spread of the cumulative precipitation is large and characterised by a NSC=0.766 and a
13 NRMSE=19.4%, showing less skill in the model performance than that observed in the
14 previous case. The observed differences of estimated precipitation for this event, highlight the
15 importance of incorporating ensemble techniques in the reproduction of precipitation with this
16 type of models.

17 **Fig. 4** illustrates the cumulative precipitation fields computed for each of the 12 selected
18 members of the multi-physics ensemble, where differences in the spatial distribution and
19 intensity of precipitation were evident. These results suggest that for this event, the
20 precipitation field estimated with the WRF was highly sensitive to the selection of multi-
21 physics parameters. To revise in more detail the performance of the WRF in reproducing this
22 hydro-meteorological event, the estimated cumulative precipitation by each of the selected 12
23 members of the multi-physics ensemble was compared against measurements at the eighteen
24 weather stations located within and close to the Tonalá catchment.

25 **Table 2** presents a summary of the most well-known error metrics calculated at each weather
26 station and for each member of the ensemble. Among these are the: Normalised Root-Mean
27 Square Error (NRMSE), BIAS, Nash-Sutcliffe Coefficient (NSC), and the Correlation
28 coefficient (Cor). The columns show the local value of each coefficient for a given member of
29 the ensemble (M1, ..., M12). As shown in all columns (i.e. member runs), the error metrics
30 have a great spatial variability, hence, indicating the regions of the study area where the
31 model performs better. To illustrate the performance of this ensemble technique at each
32 weather station, the ensemble average of these error metrics is introduced in the last column

1 and indicated by $< >$. Again, the spatial variability of the metrics is evident. The two bottom
2 rows in each sub-table correspond to the average of the ensemble averages for the whole
3 catchment and for all the stations. It is shown, that when the average of all stations is
4 taken into account, the skill decreases. However, in this investigation the error that is of
5 interest is the one corresponding to the average of those weather stations located within the
6 catchment, as these will be used as input in the hydrological model. This will enable the
7 propagation of errors in the meteorological model within the model cascade. For clarity, in the
8 same table the stations within the catchment are highlighted in blue.

9 A question that has been seldom explored in the literature, is how the uncertainty in the
10 prediction of the precipitation (i.e. errors described in this section), cascade into an estimated
11 flood hydrograph determined by a distributed hydrological model. In this sense, the next step
12 in this work, considers the non-linear transfer of rainfall to runoff using a distributed rainfall-
13 runoff model. For this, we employ each one of the selected 12 precipitation fields derived
14 from the WRF as input to determine the associated river discharge with the hydrological
15 model.

16

17 **3.2 Hydrological model**

18 The hydrological model used in this study was applied to the Tonalá River catchment in an
19 early work presented by [Rodríguez-Rincón et al. \(2012\)](#). This numerical tool was developed
20 by the Institute of Engineering – UNAM ([Domínguez-Mora et al., 2008](#)), and comprises a
21 simplified grid-based distributed rainfall–runoff model. The model has been previously
22 applied with success in other catchments in Mexico (e.g. [Pedrozo-Acuña et al., 2014b](#)).

23 The model is based on the method of the Soil Conservation Service (SCS) with a modification
24 that allows the consideration of soil moisture accounting before and after rainfall events. The
25 parameters that are needed for the definition of a runoff curve number within the catchment
26 are the hydrological soil group, land use, pedology and the river drainage network. [Fig. 5](#)
27 shows for the Tonalá River catchment, the spatial definition of the river network (center
28 panels) and the runoff curve (right panels). For the numerical setup of the hydrological model,
29 we employ topographic information from a LiDAR data set, from which a 10m resolution
30 Digital Elevation Model (DEM) is constructed.

1 There are two main hypothesis that underpin the SCS curve number method. Firstly, it is
2 assumed that for a single storm and after the start of the runoff, the ratio between actual soil
3 retention and its maximum retention potential is equal to the ratio between direct runoff and
4 available rainfall. Secondly, the initial infiltration is hypothesised to be a fraction of the
5 retention potential.

6 Thus, the water balance equation and corresponding assumptions are expressed as follows:

7
$$P = P_e + I_a + F_a \quad (1)$$

8
$$\frac{P_e}{P_a - I_a} = \frac{F_a}{S} \quad (2)$$

9
$$I_a = \lambda S \quad (3)$$

10 Where P is rainfall, P_e effective rainfall, I_a is the initial abstraction, F_a is the cumulative
11 abstraction, S is the potential maximum soil moisture retention after the start of the runoff and
12 λ is the scale factor of initial loss. The value of λ is related to the maximum potential
13 infiltration in the basin.

14 Through the combination of equations (1) - (3) and expressing the initial abstraction (I_a) by
15 $0.2*S$ we have:

16
$$P_e = \frac{(P - 0.2S)^2}{P + 0.8S} \quad (4)$$

17 where, the value of S [cm] is determined by:

18
$$S = \frac{2450 - (25.4CN)}{CN} \quad (5)$$

19 CN is the runoff curve number, as defined by the Agriculture Department of the USA ([USDA, 1985](#)). Values for this parameter vary from 30 to 100, where small numbers indicate low
20 runoff potential while larger numbers indicate an increase in runoff potential. Thus, the
21 permeability of the soil is inversely proportional to the selected curve number. Another
22 parameter that allows the modification of the curve number is the soil water potential given
23 by F_s , following $S = S * F_s$.

24 The model includes a parameter to reproduce the effects of evaporation on the ground
25 saturation (F_o). This parameter is useful when the event to be reproduced lasts for several

1 days; however, due to the duration of this event it is assumed equal to 0.9 in all cases. The
2 computation of the runoff in the basin is carried out through the addition of the runoff
3 estimated in each cell to then construct a general hydrograph (See Rodríguez-Rincón et al.
4 2012). With regards to the definition of values for the other two free parameters in the
5 hydrological model (λ and F_s), a traditional calibration process is implemented. For this, we
6 utilise flood hydrographs from past extreme events (2001, 2005, 2007, 2008, 2009 and 2011)
7 observed in this river. For these events, we employ as rainfall input the registered
8 precipitation at the same 4 weather stations that are within the river catchment, which location
9 is shown in the top panel of **Figure 1**. Therefore, we determine six sets of free parameters that
10 are good enough to represent the rainfall-runoff relationship in this catchment. The selected
11 sets of values are illustrated in **Table 3**, where the correlation coefficient and NSC are also
12 reported for each of the years. It is shown that in all the events, the selected set of parameters
13 ensures a good correlation against the observed discharge which is given by $\text{Cor}>0.7$, as well
14 as a positive NSC (accuracy).

15 It is well known that both the amount and distribution of rainfall can significantly affect the
16 final estimated river discharge (Ferraris et al. 2002; De Roo et al., 2003; Cluckie et al., 2004).
17 In consequence, the propagation of meteorological uncertainty to the rainfall-runoff model is
18 carried out using the 12 WRF rainfall precipitation ensembles as an input in the hydrological
19 model, considering the six sets of free parameters reported in **Table 3**. This procedure enabled
20 the generation of 72 hydrographs that could represent the 2009 event with different skill.
21 Error metrics of all the computed hydrographs are reported in **Table 4**.

22 For completeness, **Fig. 6a** illustrates the 72 computed hydrographs for the Tonalá River
23 catchment in relation to the measured river discharge for the 2009 event (blue dashed line). It
24 is shown that if all 72 hydrographs are taken into account, uncertainty bounds are significant.
25 Indeed, this illustrates the interaction of the meteorological uncertainty with that coming from
26 the setup of the hydrological model (definition of free parameters). However, the purpose of
27 this study is to investigate in a model cascade framework, how errors in the meteorological
28 prediction stage propagate down to a predicted inundation. In this sense, we narrow down the
29 number of hydrographs shown in **Fig. 6a**, by selecting only those with a $\text{Cor}>0.7$ and
30 $\text{NSC}>0.6$., as reported in **Table 4** only 31 out of 72 (shown in bold) follow this condition.
31 **Fig. 6b** displays the 31 selected hydrographs along with the measured discharge for the 2009
32 event. Although there is a reduction in the uncertainty bounds, it is shown that errors in the

1 predicted rainfall are indeed propagated to the hydrological model, which employs a finer
2 spatial resolution (1 km). It has been established that, in some cases, an error in the
3 meteorological model can be compensated by an error in the hydrological model and vice-
4 versa. To illustrate this in more detail, average values of the calculated error metrics for the 31
5 selected hydrographs are estimated and reported in **Table 4**, with $NSC=0.79$, $Cor=0.96$ and
6 $BIAS=1.11$. Values of the NSC for selected hydrographs in **Table 4** illustrate the resulting
7 differences in skill resulting from the combination of different setups in the hydrological
8 model with the multi-physics ensemble. For instance, in the rows corresponding to the
9 parameters determined for the 2011 event, member M12 indicates a $NSC=0.738$ showing a
10 poorer skill at reproducing the river discharge with the precipitation derived from this
11 member, in comparison to that registered for member M2 with $NSC=0.938$. The change in the
12 values of the NSC indicates that results from the regional weather model can be enhanced or
13 weakened by the performance of the hydrological model.

14 The utilisation of the 31 selected hydrographs in a 2D hydrodynamic model enables the study
15 of the propagation of errors within the cascade of models. In particular, for estimating the
16 flood extent during this extreme event.

17

18 **3.3 Flood inundation model**

19 Several 2D hydrodynamic models have been developed for simulating extreme flood events.
20 However, any model is only as good as the data used to parameterise, calibrate and validate
21 the model. 2D models have been regarded as suitable for simulating problems where
22 inundation extent changes dynamically through time as they can easily represent moving
23 boundary effects (e.g. [Bates and Horritt, 2005](#)). The use of these numerical tools has become
24 common place when flows produce a large areal extent, compared to their depth and where
25 there are large lateral variations in the velocity field ([Hunter et al., 2008](#)).

26 In this study, given the size of the study area the modelling system utilised is comprised by
27 the flow model of MIKE 21 flexible mesh (FM). This numerical model solves the two
28 dimensional Reynolds-averaged Navier–Stokes equations invoking the approximations of
29 Boussinesq and hydrostatic pressure (for details see [DHI, 2014](#)). The equations are solved at
30 the centre of each element in the model domain.

1 The numerical setup is based on a previous work on the study area (Pedrozo-Acuña et al.
2 2012), with selected resolutions for the elements of the mesh with a size that guarantees the
3 proper assimilation of a 10 m DEM to characterise the elevation in the floodplain. The
4 topographic data has been regarded as the most important factor in determining water surface
5 elevations, base flood elevation, and the extent of flooding and, thus, the accuracy of flood
6 maps in riverine areas (NRC, 2009). Therefore, the elevation data used in this study
7 corresponds to LiDAR data set provided by INEGI (2008). The choice of a 10-m DEM is
8 based on recommendations put forward by the Committee on Floodplain Mapping
9 Technologies, NRC (2007) and Prinos et al. (2008), as such a DEM ensures both accuracy and
10 detail of the ground surface. The model domain is illustrated in Fig. 7, along with the
11 numerical mesh and elevation data, it comprises the lower basin of the Tonalá River and
12 additional main water bodies. The colours represent the magnitude of the elevation and
13 bathymetric data assimilated in the numerical mesh, where warm colours identify high ground
14 areas and light blues represent bathymetric data. The integration of high quality topographic
15 information in a 2D model with enough spatial resolution, enables the investigation of the
16 propagation of the meteorological uncertainty to the determination of the flood extent.
17 Moreover, as it is illustrated in Fig. 7 the numerical mesh considers three boundary
18 conditions. These are input flow boundary where the hydrograph from the rainfall-runoff
19 model is set (red dot); the Tonalá's river mouth, where the astronomical tide occurs for the
20 period of the event (27th October – 12th November 2009) (yellow dot) and the Agua Dulcita
21 river set where a constant discharge of 100 m³/s is introduced (blue dot). The astronomical
22 tide (microtidal in nature with tidal range <1 m) is determined using the monthly tidal forecast
23 at a nearby point, which is published by CICESE (Centro de Investigación Científica y de
24 Educación Superior de Ensenada) and it is available at (<http://predmar.cicese.mx/calmen.php>).
25 On the other hand, hydraulic roughness is a lumped term known as Manning's coefficient that
26 represents the sum of a number of effects, among which are skin friction, form drag and the
27 impact of acceleration and deceleration of the flow. The precise effects represented by the
28 friction coefficient for a particular model depend on the model's dimensionality, as the
29 parameterisation compensates for energy losses due to unrepresented processes, and the grid
30 resolution (Bates et al., 2014). The lack of a comprehensive theory of “effective roughness”
31 have determined the need for calibration of friction parameters in hydraulic models.
32 Furthermore, the determination of realistic spatial distributions of friction across a floodplain
33 in other studies, have showed that only 1 or 2 floodplain roughness classes are required to

1 match current data sources (Werner et al., 2005). Indeed, this suggests that application of
2 complex formulae to establish roughness values for changed floodplain land use are
3 inappropriate until model validation data are improved significantly. Therefore, in this study
4 hydraulic roughness in the floodplain is assumed to be uniform and different from the main
5 river channel, in this sense two values for the Manning number are used, one for the main
6 river channel ($M=32 \text{ m}^{1/2}\text{s}^{-1}$) and another for the floodplain ($M=28 \text{ m}^{1/2}\text{s}^{-1}$).

7 It should be noted that several investigations confirm that there is significant uncertainty
8 associated with flood extent predictions using hydraulic models (e.g. Aronica et al., 1998,
9 2002; Bates et al. 2004; Pappenberger et al., 2005, 2006, 2007; Romanowicz and Beven,
10 2003). These uncertainties may be ascribed to differences in spatio-temporal resolutions or
11 the hydraulic roughness that is used in the hydraulic model. In this investigation, however, a
12 more detailed analysis of the different sources of uncertainty in the hydraulic model is not
13 implemented. The numerical setup of the hydraulic model is built following published
14 guidelines for an accurate representation of the case study (see Asselman et al. 2008), which
15 enables us to build the discussion on how an uncertainty generated at the meteorological stage
16 of the model chain propagates and influences a resulting flooded area and depth.

17 In order to assess whether the 2D model is able to reproduce the flood extent observed in
18 2009, numerical results of flood extent are compared against the affected area determined
19 from a SPOT image (resolution of 124m). This practice is widely used in the literature to
20 evaluate the results from inundation models and to compare its performance (Di Baldassare et
21 al, 2010b; Wright et al., 2008).

22 **Fig. 8a** introduces the result of the hydrodynamic simulation for each of the 31 selected
23 hydrographs, which resulted from the utilisation of the rainfall-runoff model using as input
24 the WRF multi-physics ensemble output. The illustrated flood map summarises the 31
25 different possibilities of the inundation area that could result from the characterisation of
26 precipitation with the WRF model. Each of these flood maps can also be associated to a
27 probability enabling the representation of a probabilistic flood map, shown in the figure. This
28 allows the identification of the areas highly vulnerable to flooding from this event.
29 Additionally, **Fig. 8b** introduces the infrared SPOT satellite image of the 12th of November
30 2009, which is used for comparison against the produced flood maps derived from running
31 the 31 hydrographs as inputs in the 2D model. Notably, in the numerical results, the blue area
32 identifies the region of the domain that is most likely to be flooded (90%), the comparison of

1 this area with the observed inundation in the satellite image, show a good skill of the model
2 chain at reproducing the registered flood in the study area.

3 Despite the variability in the estimated peak discharge utilised as input in the different
4 hydrodynamic runs, inundation results show similar affected areas in all realisations (only
5 with small differences in its size). This is verified in the results shown in **Fig. 9a**, where the
6 relationship between peak discharge of the 31 hydrographs, is plotted against the size of the
7 maximum-flooded area. The distribution of points in this graph clearly indicates that although
8 there are differences in the estimated peak flow (see histogram in **Fig. 9b**), in most cases the
9 resulting size of the inundated area is similar. Histogram plot shown in **Fig. 9c** indicates a
10 clear concentration numerically derived flooded areas with a size larger than 130 km². Indeed,
11 the mean value of the maximum-flooded estimated area is 138.94 km², while the standard
12 deviation is 16.09 km².

13 These results support that the hydraulic behaviour in all hydrodynamic simulations was
14 indeed very similar, regardless of the peak discharge of the hydrograph. It is reflected that this
15 may be the result of induced hydrodynamics by a valley-filling flood event, which is
16 identified with the relatively high floodplain area-to-channel-depth ratios in all simulations.
17 Hence, all possible hydrographs generated with the hydrological model show similar levels of
18 lateral momentum exchange between main channel and floodplain. For this reason, the
19 predictive performance of all hydrodynamic simulations used to reproduce the inundation
20 extent appears to be good (see **Table 5**).

21 The estimation of several error metrics in these results was performed using binary flood
22 extent maps, where the comparison is based on the generation of a contingency table, which
23 reports the number of pixels correctly predicted as wet or dry. From this, measures of fit such
24 as: BIAS, False Alarm Ratio (FAR), Probability of Detection (POD), Probability of False
25 Detection (POFD), Critical Success Index (CSI) and the True Skill Statistics (TSS) are
26 estimated. **Table 5** introduces the results for all 31 members and error metrics. Clearly, there
27 is little variability in the performance of the model for each of the runs, showing that there has
28 been a small propagation of the error to the flood map. The ensemble average of these
29 quantities is also illustrated in the last column of the table, where values of BIAS=1.013,
30 FAR=0.189, POD=0.819, POFD=0.180; CSI=0.686 and TSS=0.639 are reported. As noted
31 before, these results indicate an apparent good skill of the model chain at reproducing the
32 flood extension, due to the incidence of this extreme event. It should be borne in mind,

1 however, that some misclassification errors may also be included in the observed flooded area
2 due to specular reflections that may classify some wet vegetation as water or open water as
3 dry land. In consequence, flood extent maps should be used with caution in assessing model
4 performance (Di Baldassare, 2012). This is particularly true during high-magnitude events
5 where the valley is entirely inundated, such as the case study of this investigation where small
6 changes in lateral flood extent may produce large changes in water levels.

7 In this sense, it has been argued that flood extent maps are not useful for model assessment
8 (Hunter et al., 2005) and high water marks are more useful to evaluate model performance.
9 Unfortunately, for the case study information of inundation depths was not available. Despite
10 this fact, a further revision of simulated inundation depths is also carried out. For this, 10
11 points distributed within the numerical domain are selected. These are illustrated by the
12 coloured dots in **Fig. 10**, along with the values of mean water depth in all the 31 simulations
13 (red solid line). In all cases, a high variability in the estimated inundation depth on the
14 floodplain is depicted (with values varying between 1.5 and 3m). This result supports that in
15 the case of valley-filling flood events, there is a higher sensitivity to errors in the vertical
16 dimension of the flood.

17 In one hand, this demonstrates that the geomorphological characteristics of the site (e.g. low-
18 lying area, smooth slopes in the river channel and floodplain) are dominant in the accurate
19 determination of the magnitude of an inundated area, regardless of the peak discharge. This
20 implies that for this type of rivers and when predicting inundation extent, it may be more
21 important to have a good characterisation of the river and floodplain (e.g. high quality field
22 data and a LiDAR derived DEM), than a good characterisation of the rainfall-runoff
23 relationship.

24 Current approaches to flood mapping, have pointed out that in order to produce a
25 scientifically justifiable flood map, the most physically-realistic model should be utilised (Di
26 Baldassarre et al., 2010). Nevertheless, even with these models the amount of uncertainty
27 involved in the determination of an affected area is important and should be quantified.

28

29 **4 Discussion and Conclusions**

30 Flood risk mapping and assessment are highly difficult tasks due to the inherent complexity of
31 the relevant processes, which occur in several spatial and temporal scales. As pointed out by

1 Aronica et al. (2013), the processes are subject to substantial uncertainties (epistemic and
2 random), which emerge from different sources and assumptions, from the statistical analysis
3 of extreme events and from the resolution and accuracy of the DEM used in a flood
4 inundation model. By acknowledging that all models are an imperfect representation of the
5 reality, it is important to quantify the impact of epistemic uncertainties on a given result.

6 The utilised methodology was comprised of a Numerical Weather Prediction Model (NWP), a
7 distributed rainfall-runoff model and a 2D hydrodynamic model. Thus, the numerical
8 framework contains several sources of uncertainty at every level of the model cascade
9 (meteorological, hydrological and hydrodynamic). The quantification of uncertainty was only
10 carried out at the meteorological and hydrological levels of the model chain; from which non-
11 behavioural ensemble members were removed based on the fit with observed data. In
12 contrast, at the hydrodynamic level, the numerical model was setup in a deterministic way
13 following recommendations of published guidelines for a good representation of the case
14 study, more specifically with regards to the selected spatial resolution, boundary conditions
15 and roughness values (see Asselman et al. 2008). This was done as uncertainties at this level
16 have been mainly ascribed to issues with model implementations and definition of free
17 parameters (Beven et al. 2011). This enabled the assessment of uncertainty and its
18 propagation, from a modelled rainfall event to a predicted flooded area and depth.

19 At the meteorological level, a multi-physics ensemble technique was utilised to evaluate the
20 generation of epistemic uncertainties (designed to represent our limited knowledge of the
21 processes generating precipitation in the lower troposphere). While in the hydrological model
22 a multi-response validation was implemented by means of the definition of six sets of
23 plausible parameters from past flood events. This was done in order to reduce the
24 dimensionality of the parameter calibration problem (see Gupta et al., 2009). This procedure
25 was preferred over a GLUE analysis (e.g. Pedrozo-Acuña et al., 2015), as the investigation
26 was aimed to understand the propagation of uncertainty along the model chain.

27 It should be borne in mind that it is not easy to disaggregate the many sources of uncertainty
28 within the model cascade. Thus, it is necessary to make assumptions about how to represent
29 uncertainty. Therefore, the assessment of hydro-meteorological model performance at the
30 three levels is carried out through the estimation of skill scores.

31 **Fig. 11** presents a summary of the propagation of two well-known error metrics, BIAS (top
32 panel) and NSC/TSS (bottom panel). These metrics were selected, as they enable a direct

1 comparison of their values at each of the stages within the model cascade. In both metrics, the
2 evolution of the confidence limits is illustrated by the size of the bars. Their evolution from
3 the meteorological model to the hydrological model, show an aggregation of meteorological
4 uncertainties with those originated from the rainfall-runoff model. However, the skill is
5 considerably improved from a mean value of 0.65 in the meteorological model, to 0.793 in the
6 hydrological model. In the last stage of the model chain (hydrodynamic model), the
7 confidence limits of the results, show an apparent improvement in model skill. However, it
8 should be noted that this may be ascribed to the complex aggregation of errors in valley-
9 filling events, which is verified in the observed sensitivity of the simulated inundation depths.
10 The mean value of the skill is reduced to TSS=0.639. The results provide an useful way to
11 evaluate the hydro-meteorological uncertainty propagation within the modelling cascade
12 system.

13 BIAS and NSC/TSS error metrics ([Fig. 11](#)) revealed discrepancies between observations and
14 simulations throughout the model cascade. For instance, an increase in the NSC from the
15 rainfall to the flood hydrograph it implies that the hydrological model is more sensitive (wider
16 uncertainty bars) to its main input (precipitation) than the WRF model is to the set of micro-
17 physics parameterisations. On the other side, the uncertainty bounds in the hydrological
18 model imply a high sensitivity of hydrographs to both, errors from the meteorological model
19 and its numerical setup with free parameters (amplifying the uncertainty). This is observed in
20 the spaghetti plot shown in [Fig. 6a](#), where large uncertainty bounds were identified. In order
21 to reduce errors from the interaction of uncertainties coming from both models, these bounds
22 were reduced with the selection of 31 hydrographs that comply with Cor>0.7 and NSC>0.6
23 (see [Fig.6b](#)). It is reflected that the estimated error in the meteorological model may reflect a
24 spatial scaling issue (comparing observations from rain gauges to simulations at the meso-
25 scale).

26 Results concerning predictions of inundation extent indicate an apparent good skill of the
27 model chain at reproducing the flood extension. The propagation of uncertainty and error
28 from the hydrological model to the inundation area revealed that is necessary to assess model
29 performance not only for flood extension purposes, but also to estimate inundation depths,
30 where results indicate a higher variability (e.g. increase in the error). This last modelling step
31 is quite important given the consequences for issuing warning alerts to the population at risk.

1 The similar magnitude in inundation extents of all numerical results indicated the
2 predominance of a valley-filling flood event, which was characterised by a flooded area
3 strongly insensitive to the input flood hydrograph. While this can be explained by the limited
4 effect that the volume overflowing the riverbanks and reaching the floodplain will have on the
5 maximum inundation area, the difference between the observed and the simulated flooded
6 area remains important (TSS=0.639).

7 It should be pointed out, that this methodology contains more uncertainties that were not
8 considered or quantified in the generation of flood extent maps for this event. Results showed
9 that a large amount of uncertainty exists in the NWP model, and such uncertainty can
10 be propagated and aggregated at the catchment level. Members of the ensemble were shown to
11 differ significantly in terms of their cumulative precipitation, spatial distribution, river
12 discharge, inundation depths and areas. The evolution of skill within the model cascade shows
13 a complex aggregation of errors between models, suggesting that in valley-filling events
14 hydro-meteorological uncertainty has a larger effect on inundation depths than that observed
15 in estimated flood inundation extents.

16 It is advised that in the future, attention should be given to the assessment of hydro-
17 meteorological uncertainty in a similar numerical framework applied to catchments with
18 different morphological setting. The assessment of the error propagation within the model
19 cascade is seen as a good step forward, in the communication of uncertain results to the
20 society. However, as shown in this work, an improvement in model prediction during the first
21 cascade step (rainfall to runoff) can be reverted during the second cascade step (runoff to
22 inundation area) with important consequences for early warning systems and operational
23 forecasting purposes. Finally, the proposed numerical framework could be utilised as a robust
24 alternative for the characterisation of extreme events in ungauged basins.

25

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31

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3 Table 1. Ensemble members defined for the multi-physics WRF ensemble

Ensemble member	Micro-Physics	surface layer physics	Cumulus physics	Feedback /sst_update	RMSE	NSC	Cor	Bias	Criteria NSC >0.3, Cor >0.8
1	WSM5	5-Layer TDM	Kain-Fritsch Eta	off/off	445.23	-0.25	0.94	0.44	reject
2	WSM5	5-Layer TDM	Kain-Fritsch Eta	off/on	262.73	0.44	0.97	0.98	select
3	WSM5	5-Layer TDM	Kain-Fritsch Eta	on/off	250.51	0.49	0.97	1.01	select
4	WSM5	5-Layer TDM	Kain-Fritsch Eta	on/on	257.35	0.43	0.97	1.05	select
5	WSM5	5-Layer TDM	Betts-Miller-Janjic	off/on	502.47	-0.65	0.97	0.28	reject
6	WSM5	5-Layer TDM	Betts-Miller-Janjic	on/on	520.58	-0.77	0.97	0.25	reject
7	WSM5	Noah	Kain-Fritsch Eta	off/off	233.04	0.42	0.96	1.18	select
8	WSM5	Noah	Kain-Fritsch Eta	off/on	236.14	0.33	0.96	1.24	select
9	WSM5	Noah	Kain-Fritsch Eta	on/off	359.11	0.17	0.90	0.56	reject
10	WSM5	Noah	Kain-Fritsch Eta	on/on	245.31	0.41	0.96	1.12	select
11	WSM5	Noah	Betts-Miller-Janjic	off/off	486.26	-0.49	0.98	0.33	reject
12	WSM5	Noah	Betts-Miller-Janjic	off/on	486.02	-0.49	0.97	0.34	reject
13	WSM5	Noah	Betts-Miller-Janjic	on/off	535.00	-0.82	0.97	0.23	reject
14	WSM5	Noah	Betts-Miller-Janjic	on/on	543.78	-0.87	0.96	0.23	reject
15	Thompson	5-Layer TDM	Kain-Fritsch Eta	off/off	216.70	0.60	0.97	1.09	select
16	Thompson	5-Layer TDM	Kain-Fritsch Eta	off/on	236.64	0.50	0.97	1.15	select
17	Thompson	5-Layer TDM	Kain-Fritsch Eta	on/off	238.89	0.57	0.96	0.97	select
18	Thompson	5-Layer TDM	Kain-Fritsch Eta	on/on	275.24	0.50	0.96	0.89	select
19	Thompson	5-Layer TDM	Betts-Miller-Janjic	off/on	571.49	-1.15	0.96	0.16	reject
20	Thompson	5-Layer TDM	Betts-Miller-Janjic	on/off	572.27	-1.14	0.95	0.16	reject
21	Thompson	5-Layer TDM	Betts-Miller-Janjic	on/on	502.47	-0.65	0.97	0.28	reject
22	Thompson	Noah	Kain-Fritsch Eta	off/off	238.06	0.38	0.96	1.25	select
23	Thompson	Noah	Kain-Fritsch Eta	off/on	234.03	0.48	0.97	1.13	select

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1 Table 2. Error Metrics in the estimation of precipitation by members of the multi-physics ensemble (blue rows
 2 indicate the stations located within the Tonalá catchment)

Station No.	Root-Mean Square Error (RMSE) and Normalised RMSE per Station considering Ensemble average												<Nor_RMSE> %
	Multi-physics ensemble member												
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	
30167	210.26	96.56	144.62	104.42	106.84	76.31	160.48	129.88	101.03	210.95	164.85	86.80	13.96
27003	544.34	578.19	564.46	474.81	427.30	516.95	458.25	484.05	568.20	572.30	385.17	479.47	35.13
27007	234.90	246.00	198.01	135.27	129.43	207.93	126.51	197.32	246.90	328.28	132.09	191.81	19.44
27015	96.68	129.89	151.02	194.33	235.76	179.69	152.06	152.60	118.97	116.87	260.49	188.20	24.01
27074	173.37	211.87	191.22	197.46	78.94	148.88	174.92	247.65	187.98	207.39	123.09	157.21	17.19
27073	227.47	201.91	228.62	256.39	281.38	245.68	186.21	219.36	159.34	147.79	247.69	223.88	46.46
27075	87.04	119.26	104.10	100.82	151.17	64.92	76.45	147.30	85.75	105.68	52.14	68.67	10.72
27076	140.53	160.28	141.95	124.03	108.33	130.53	191.75	162.59	226.04	236.09	129.78	150.84	17.14
27077	89.10	113.42	83.60	225.48	252.24	207.73	254.20	282.40	110.77	83.93	203.01	192.86	30.57
27039	333.50	204.36	197.48	295.84	302.19	261.39	264.08	321.66	172.86	152.14	257.59	430.63	73.28
27054	123.18	30.77	45.28	113.16	119.18	77.41	106.84	112.68	118.83	127.43	110.06	106.67	34.75
27060	70.69	56.23	59.51	33.42	40.13	30.04	78.07	93.80	88.46	80.36	56.73	66.31	19.88
27024	160.33	137.81	140.76	120.58	127.54	73.57	148.27	136.47	145.12	167.79	153.26	151.87	85.04
27084	68.72	71.32	54.58	53.56	106.93	65.65	61.06	72.31	61.46	62.96	50.14	50.92	19.02
7365	172.91	117.44	103.02	252.03	139.79	163.49	301.52	216.38	179.67	129.71	271.88	210.11	24.52
27011	143.70	162.77	143.61	107.82	77.55	86.15	128.03	143.69	106.59	116.49	86.81	81.27	106.83
27036	81.46	60.69	27.36	61.69	19.14	35.64	23.58	45.89	22.13	40.23	39.22	55.55	12.04
27008	158.85	72.82	74.96	131.34	134.94	100.16	102.82	149.97	66.67	79.36	97.87	254.33	19.68
												Average {Rel_RMSE} catch.	23.14
												Average {Rel_RMSE} all	33.87

Station No.	BIAS per Station and Ensemble Average												<BIAS>
	Multi-physics ensemble member												
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	
30167	0.71	0.90	0.81	1.07	1.12	0.99	0.80	0.85	0.91	0.71	1.23	1.06	0.93
27003	0.51	0.48	0.50	0.58	0.62	0.54	0.59	0.57	0.49	0.49	0.66	0.58	0.55
27007	0.72	0.71	0.79	0.91	0.91	0.78	1.13	1.26	0.73	0.61	0.90	0.80	0.85
27015	1.21	1.32	1.40	1.50	1.61	1.46	1.37	1.37	1.24	1.21	1.68	1.48	1.40
27074	0.82	0.76	0.79	0.78	1.08	0.86	0.81	0.71	0.80	0.77	0.88	0.83	0.82
27073	1.74	1.65	1.74	1.83	1.91	1.80	1.58	1.70	1.47	1.44	1.80	1.72	1.70
27075	0.92	0.85	0.88	0.88	1.20	0.96	0.90	0.80	0.89	0.86	0.98	0.93	0.92
27076	0.86	0.82	0.86	0.91	0.95	0.89	0.79	0.84	0.73	0.71	0.89	0.85	0.84
27077	1.12	1.17	1.10	1.48	1.54	1.44	1.54	1.60	1.20	1.14	1.42	1.40	1.35
27039	2.41	1.87	1.84	2.26	2.29	2.11	2.13	2.36	1.73	1.64	2.09	2.84	2.13
27054	1.89	1.08	1.24	1.82	1.87	1.54	1.76	1.81	1.84	1.91	1.79	1.77	1.69
27060	1.42	1.33	0.72	1.08	1.20	1.05	1.47	1.57	1.54	1.49	1.32	1.39	1.30
27024	3.34	2.96	3.03	2.76	2.88	2.07	3.16	2.98	3.11	3.45	3.17	3.17	3.01
27084	1.32	1.35	1.17	1.23	1.61	0.78	1.27	1.36	1.27	1.29	1.07	1.01	1.23
7365	1.43	1.20	1.09	1.63	1.32	0.72	1.78	1.55	1.43	1.26	1.68	1.51	1.38
27011	3.57	3.91	3.55	2.93	2.33	2.49	3.33	3.58	2.91	3.09	2.56	2.45	3.06
27036	1.36	1.25	1.09	1.28	0.97	1.15	0.95	1.20	1.06	1.16	1.15	1.24	1.15
27008	1.37	1.07	1.05	1.29	1.31	1.20	1.21	1.35	0.99	0.93	1.19	1.62	1.22
												Average {Rel_RMSE} catch.	0.94
												Average {Rel_RMSE} all	1.42

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1 Continuation of Table 2. Error Metrics in the estimation of precipitation by members of the multi-physics
 2 ensemble (blue rows indicate the stations located within the Tonalá catchment)
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Station No.	Nash-Sutcliffe Coefficient per Station and Ensemble average												<NSC>	
	Multi-physics ensemble member													
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12		
30167	0.72	0.94	0.87	0.93	0.93	0.96	0.84	0.89	0.94	0.72	0.83	0.95	0.88	
27003	0.16	0.05	0.09	0.36	0.48	0.24	0.40	0.33	0.08	0.07	0.58	0.34	0.26	
27007	0.70	0.67	0.78	0.90	0.91	0.76	0.91	0.79	0.66	0.41	0.90	0.80	0.77	
27015	0.88	0.78	0.70	0.50	0.27	0.57	0.70	0.69	0.81	0.82	0.11	0.53	0.61	
27074	0.84	0.76	0.80	0.79	0.97	0.88	0.84	0.67	0.81	0.77	0.92	0.87	0.83	
27073	-0.27	0.00	-0.28	-0.61	-0.94	-0.48	0.15	-0.18	0.38	0.46	-0.50	-0.23	-0.21	
27075	0.94	0.89	0.91	0.92	0.82	0.97	0.95	0.83	0.94	0.91	0.98	0.96	0.92	
27076	0.87	0.83	0.86	0.90	0.92	0.88	0.75	0.82	0.65	0.62	0.89	0.85	0.82	
27077	0.82	0.70	0.84	-0.17	-0.46	0.01	-0.48	-0.83	0.72	0.84	0.05	0.15	0.18	
27039	-4.41	-1.03	-0.90	-3.26	-3.44	-2.32	-2.39	-4.03	-0.45	-0.13	-2.23	-8.02	-2.72	
27054	-0.46	0.91	0.80	-0.23	-0.36	0.42	-0.10	-0.22	-0.36	-0.56	-0.16	-0.09	-0.03	
27060	0.60	0.75	0.72	0.91	0.87	0.93	0.51	0.29	0.37	0.48	0.74	0.65	0.65	
27024	-7.99	-5.64	-5.93	-4.08	-4.69	-0.89	-6.68	-5.51	-6.36	-8.84	-7.21	-7.06	-5.91	
27084	0.67	0.64	0.79	0.80	0.20	0.70	0.74	0.63	0.73	0.72	0.82	0.82	0.69	
7365	0.50	0.77	0.82	-0.07	0.67	0.55	-0.54	0.21	0.45	0.72	-0.25	0.25	0.34	
27011	-16.74	-21.76	-16.72	-8.99	-4.17	-5.38	-13.08	-16.74	-8.76	-10.66	-5.47	-4.67	-11.09	
27036	0.61	0.78	0.96	0.78	0.98	0.93	0.97	0.88	0.97	0.91	0.91	0.82	0.87	
27008	0.60	0.92	0.91	0.72	0.71	0.84	0.83	0.64	0.93	0.90	0.85	-0.03	0.73	
												Average {Rel_RMSE} catch.	0.63	
												Average {Rel_RMSE} all	-0.63	

Station No.	Correlation Coefficient per Station and Ensemble average												<Cor>	
	Multi-physics ensemble member													
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12		
30167	0.99	0.99	0.99	0.97	0.98	0.99	0.99	0.99	0.99	0.97	0.98	0.98	0.99	
27003	0.95	0.96	0.97	0.97	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.98	
27007	0.98	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.95	0.98	0.97	0.97	
27015	0.97	0.96	0.97	0.94	0.93	0.95	0.95	0.95	0.94	0.94	0.93	0.94	0.95	
27074	0.98	0.98	0.98	0.98	0.99	0.98	0.99	0.98	0.98	0.98	0.99	0.99	0.98	
27073	0.95	0.96	0.95	0.94	0.94	0.94	0.92	0.92	0.91	0.92	0.94	0.94	0.94	
27075	0.98	0.98	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	
27076	0.98	0.98	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.96	0.97	0.97	0.97	
27077	0.96	0.95	0.96	0.96	0.95	0.96	0.95	0.95	0.97	0.97	0.95	0.96	0.96	
27039	0.95	0.95	0.94	0.93	0.94	0.94	0.94	0.94	0.95	0.95	0.94	0.93	0.94	
27054	0.91	0.96	0.94	0.93	0.93	0.94	0.91	0.91	0.92	0.91	0.90	0.93	0.93	
27060	0.96	0.97	0.97	0.96	0.97	0.97	0.95	0.95	0.96	0.96	0.97	0.96	0.96	
27024	0.91	0.93	0.92	0.90	0.91	0.95	0.89	0.90	0.89	0.89	0.94	0.94	0.91	
27084	0.91	0.91	0.92	0.94	0.92	0.95	0.92	0.91	0.92	0.92	0.93	0.93	0.92	
7365	0.93	0.93	0.94	0.92	0.94	0.97	0.91	0.92	0.91	0.92	0.91	0.92	0.93	
27011	0.94	0.94	0.95	0.93	0.95	0.96	0.89	0.93	0.91	0.92	0.91	0.91	0.93	
27036	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	
27008	0.97	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.97	0.96	0.96	0.96	0.96	
												Average {Rel_RMSE} catch.	0.97	
												Average {Rel_RMSE} all	0.95	

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6 Table 3. Flood events in the Tonala River used in the calibration process of free parameters in the hydrological
7 model, along with computed error metrics.

Event	Max Q (m ³ /s) Obs.	Λ	F _s	F _o	Max Q (m ³ /s) Calc.	NSC	Cor	Bias
2001	577.98	0.2	0.1	0.9	584.79	0.529	0.764	1.112
2005	589.25	0.4	0.6	0.9	609.87	0.812	0.907	1.043
2007	538.50	0.2	1.8	0.9	543.87	0.483	0.780	0.902
2008	597.35	0.4	1.8	0.9	823.04	0.155	0.861	0.983
2009	1262.57	0.8	1.8	0.9	1424.56	0.910	0.962	0.942
2011	545.40	0.9	1.6	0.9	597.08	0.413	0.721	1.051

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1 Table 4. Error metrics in the estimation of river discharge by the rainfall-runoff model using 6 parameter sets and
 2 12 members of the multi-physics ensemble (those selected are shown in bold with NSC>0.6 and Cor>0.7).

Member No.	WRF Member	Hydrological Parameters	NSC	Cor	Bias
1	M1	2001	0.733	0.884	0.852
2	M2	2001	0.074	0.973	1.529
3	M3	2001	-0.035	0.974	1.564
4	M4	2001	-0.511	0.975	1.686
5	M5	2001	-0.638	0.441	1.485
6	M6	2001	-0.223	0.961	1.593
7	M7	2001	-0.192	0.961	1.579
8	M8	2001	-0.043	0.959	1.537
9	M9	2001	0.064	0.958	1.504
10	M10	2001	0.245	0.971	0.525
11	M11	2001	-1.503	0.944	1.832
12	M12	2001	-0.752	0.954	1.710
13	M1	2005	0.639	0.901	0.742
14	M2	2005	0.404	0.977	1.414
15	M3	2005	0.318	0.978	1.449
16	M4	2005	-0.077	0.977	1.569
17	M5	2005	-0.545	0.366	1.368
18	M6	2005	0.181	0.968	1.478
19	M7	2005	0.200	0.968	1.465
20	M8	2005	0.321	0.966	1.422
21	M9	2005	0.408	0.966	1.389
22	M10	2005	-0.081	0.960	0.426
23	M11	2005	-0.909	0.951	1.717
24	M12	2005	-0.264	0.961	1.595
25	M1	2007	0.376	0.914	0.601
26	M2	2007	0.761	0.978	1.244
27	M3	2007	0.711	0.979	1.278
28	M4	2007	0.444	0.976	1.395
29	M5	2007	-0.440	0.261	1.191
30	M6	2007	0.633	0.974	1.306
31	M7	2007	0.647	0.974	1.293
32	M8	2007	0.722	0.973	1.251
33	M9	2007	0.771	0.972	1.219
34	M10	2007	-0.508	0.952	0.322
35	M11	2007	-0.129	0.959	1.539
36	M12	2007	0.340	0.969	1.420
37	M1	2008	0.240	0.922	0.547
38	M2	2008	0.837	0.978	1.186
39	M3	2008	0.797	0.978	1.220
40	M4	2008	0.570	0.974	1.337
41	M5	2008	-0.479	0.209	1.132
42	M6	2008	0.741	0.976	1.248
43	M7	2008	0.753	0.976	1.235
44	M8	2008	0.813	0.975	1.194
45	M9	2008	0.851	0.975	1.161
46	M10	2008	-0.720	0.945	0.276
47	M11	2008	0.079	0.962	1.481
48	M12	2008	0.495	0.972	1.361
49	M1	2009	-0.036	0.838	0.494
50	M2	2009	0.819	0.978	0.882
51	M3	2009	0.899	0.977	0.907
52	M4	2009	0.649	0.963	1.286
53	M5	2009	0.060	0.811	0.580
54	M6	2009	0.839	0.959	0.849
55	M7	2009	0.883	0.959	0.890
56	M8	2009	0.896	0.954	0.929
57	M9	2009	0.890	0.950	0.928
58	M10	2009	-1.233	0.972	0.209
59	M11	2009	0.638	0.938	1.236
60	M12	2009	0.885	0.946	1.042
61	M1	2011	-0.247	0.949	0.396
62	M2	2011	0.938	0.970	1.019
63	M3	2011	0.930	0.971	1.052
64	M4	2011	0.819	0.964	1.168
65	M5	2011	-0.662	0.055	0.955
66	M6	2011	0.890	0.978	1.133
67	M7	2011	0.899	0.979	1.120
68	M8	2011	0.931	0.979	1.079
69	M9	2011	0.945	0.978	1.047
70	M10	2011	-1.136	0.931	0.195
71	M11	2011	0.433	0.967	1.364
72	M12	2011	0.738	0.976	1.246
<Ensemble average of selected members>			0.793	0.965	1.113

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Table 5. Error metrics in the estimation of river discharge by the hydrodynamic model using the 31 members of the multi-physics ensemble.

Error metrics	Comparison of flooded areas between numerical results from running ensemble members vs. Observed																													<Ensemble average>		
	Ensemble Member																															
	M1	M13	M26	M27	M30	M31	M32	M33	M38	M39	M42	M43	M44	M45	M50	M51	M52	M54	M55	M56	M57	M59	M60	M62	M63	M64	M66	M67	M68	M69	M72	
BIAS	0.903	0.838	1.084	1.099	1.119	1.120	1.094	1.078	1.056	1.021	1.092	1.089	1.096	1.051	0.902	0.915	0.891	0.820	1.020	0.982	0.872	1.056	1.004	0.982	0.995	1.047	1.040	1.028	1.016	1.005	1.092	1.013
FAR: False Alarm Ratio	0.148	0.120	0.215	0.217	0.283	0.210	0.216	0.212	0.209	0.217	0.216	0.215	0.152	0.207	0.148	0.154	0.139	0.137	0.193	0.155	0.133	0.206	0.187	0.178	0.182	0.204	0.201	0.225	0.192	0.187	0.216	0.189
POD: Probability of Detection	0.770	0.737	0.851	0.861	0.849	0.849	0.858	0.849	0.836	0.751	0.857	0.854	0.848	0.833	0.769	0.775	0.751	0.810	0.823	0.845	0.756	0.847	0.816	0.807	0.814	0.833	0.831	0.821	0.821	0.818	0.857	0.819
POFD: Probability of False Detection	0.124	0.094	0.217	0.222	0.187	0.187	0.220	0.214	0.205	0.186	0.220	0.219	0.186	0.203	0.124	0.131	0.185	0.185	0.184	0.066	0.108	0.266	0.175	0.163	0.168	0.199	0.195	0.186	0.182	0.175	0.220	0.180
CSI : Critical Success Index	0.679	0.670	0.690	0.695	0.711	0.711	0.694	0.691	0.685	0.709	0.693	0.692	0.710	0.685	0.679	0.679	0.706	0.654	0.687	0.708	0.677	0.620	0.687	0.687	0.690	0.686	0.687	0.619	0.688	0.688	0.693	0.686
True Skill Statistics	0.645	0.643	0.634	0.639	0.621	0.662	0.638	0.636	0.631	0.660	0.637	0.636	0.661	0.631	0.645	0.643	0.615	0.601	0.639	0.659	0.648	0.660	0.641	0.644	0.640	0.634	0.636	0.610	0.640	0.642	0.637	0.639

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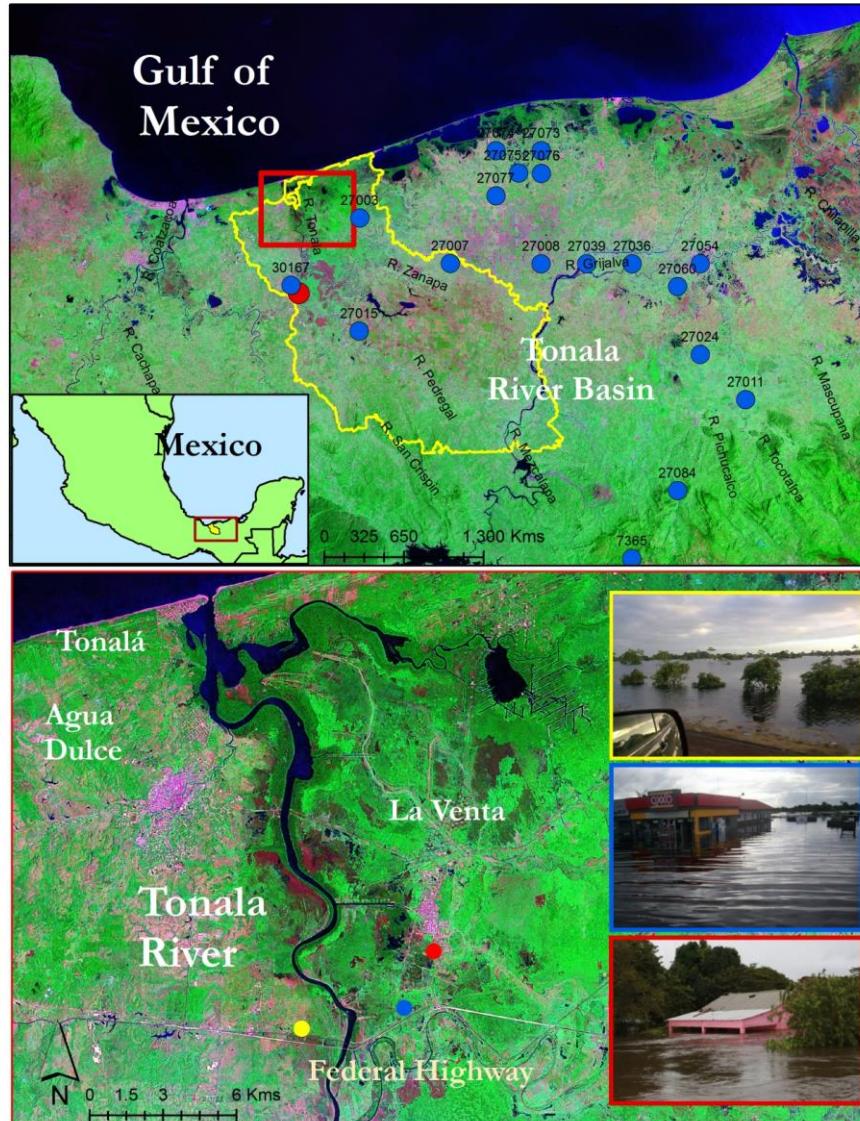


Figure 1. Top panel: Location of the Tonala River basin in Mexico, blue line represents the boundary limits of the catchment; blue dots illustrate the location of weather stations; red dot: streamflow gauge. Bottom panel: zoom of the study area and photographs of observed impacts; yellow, blue and red dots represent the location at which photos were taken.



Figure 2. Numerical setup of the WRF with a nested domain covering Mexico. Domain 1: 25km resolution; Domain 2: 4km resolution; the orange region illustrates the Tonalá catchment.

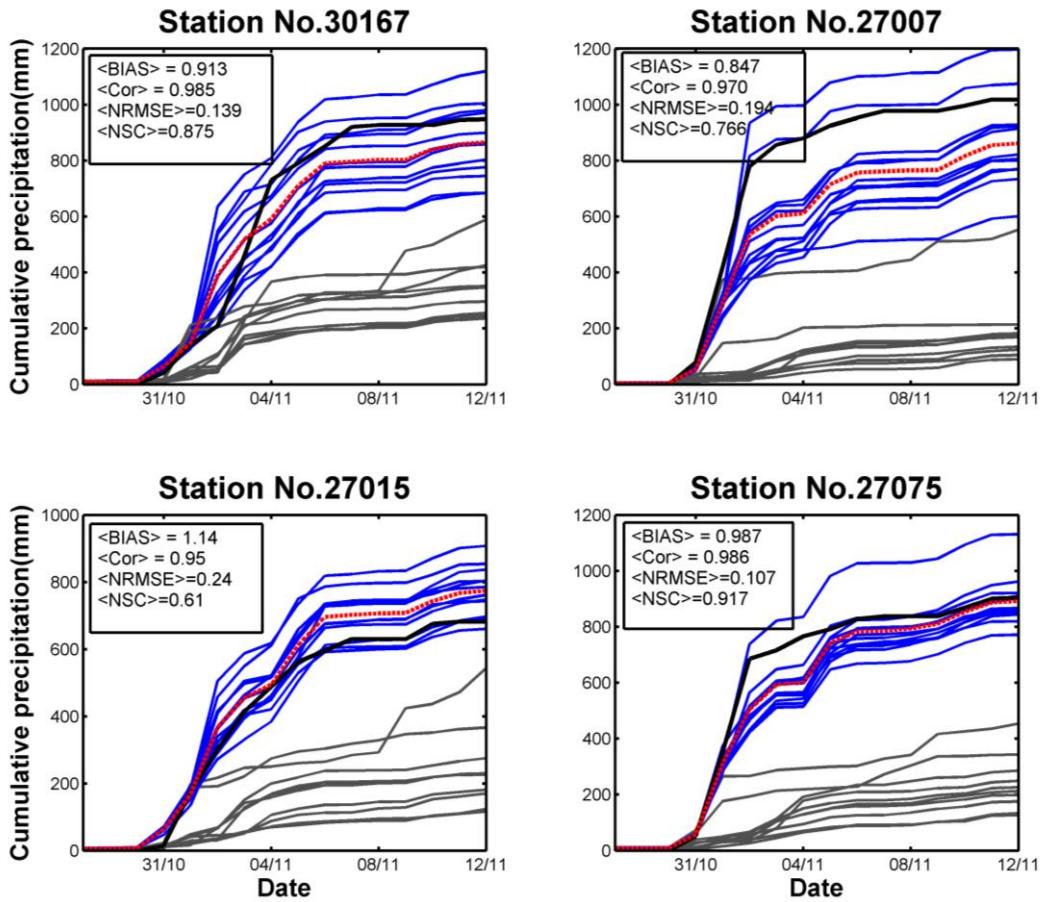
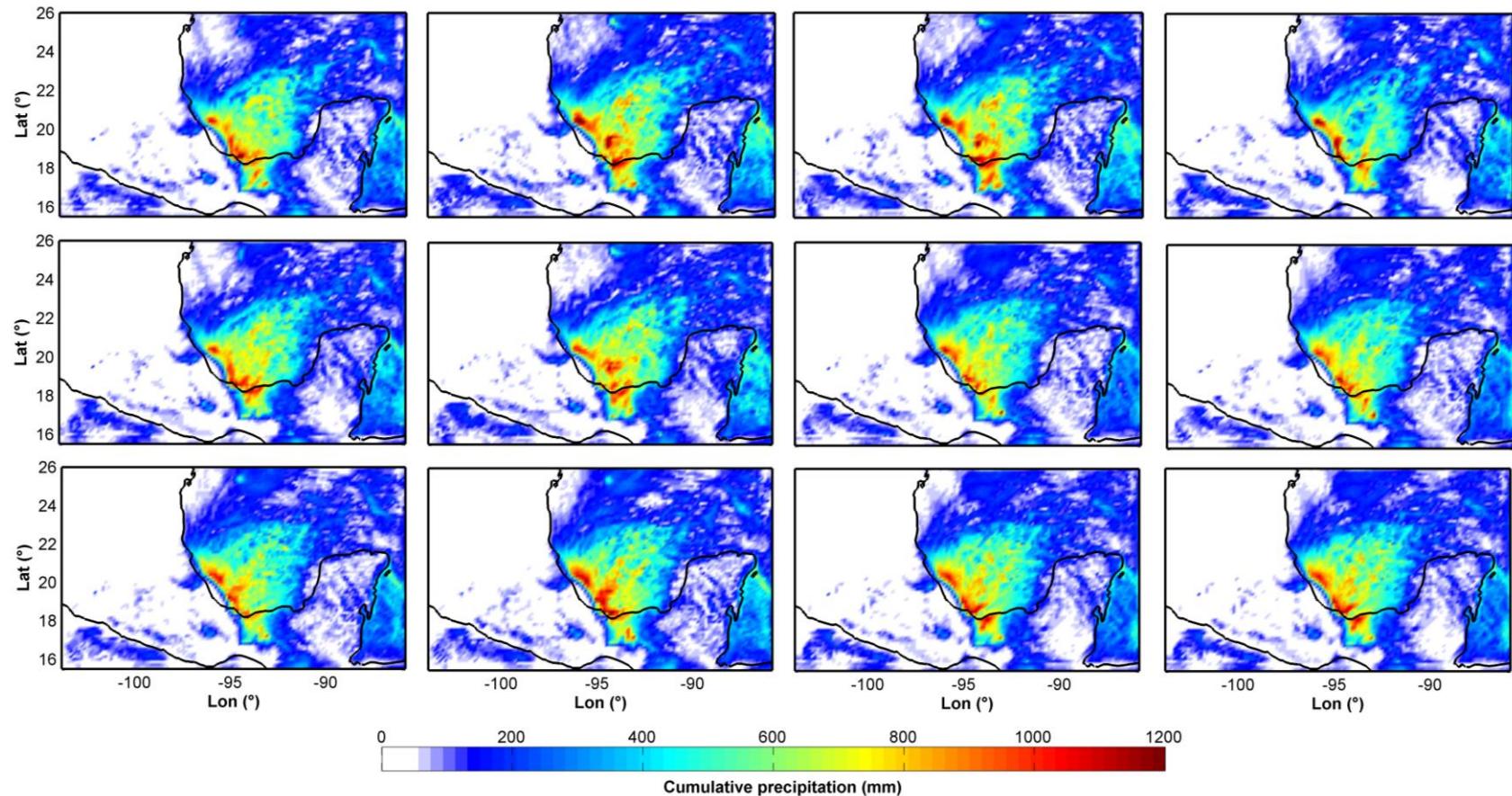


Figure 3. Comparison of cumulative precipitation estimated by the 23 model runs of the WRF multi-physics ensemble. Blue solid line: selected members with $NSC > 0.3$; grey solid line: disregarded members with $NSC < 0.3$; red dotted line: mean of the selected 12 members; black solid line: measurements at each of the four weather stations from 27th October 2009 to 12th November 2009.

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3 **Figure 4.** Cumulative precipitation fields estimated by the WRF model using the selected 12 members of the multi-physics ensemble (27th
4 October 2009 – 12th November 2009).

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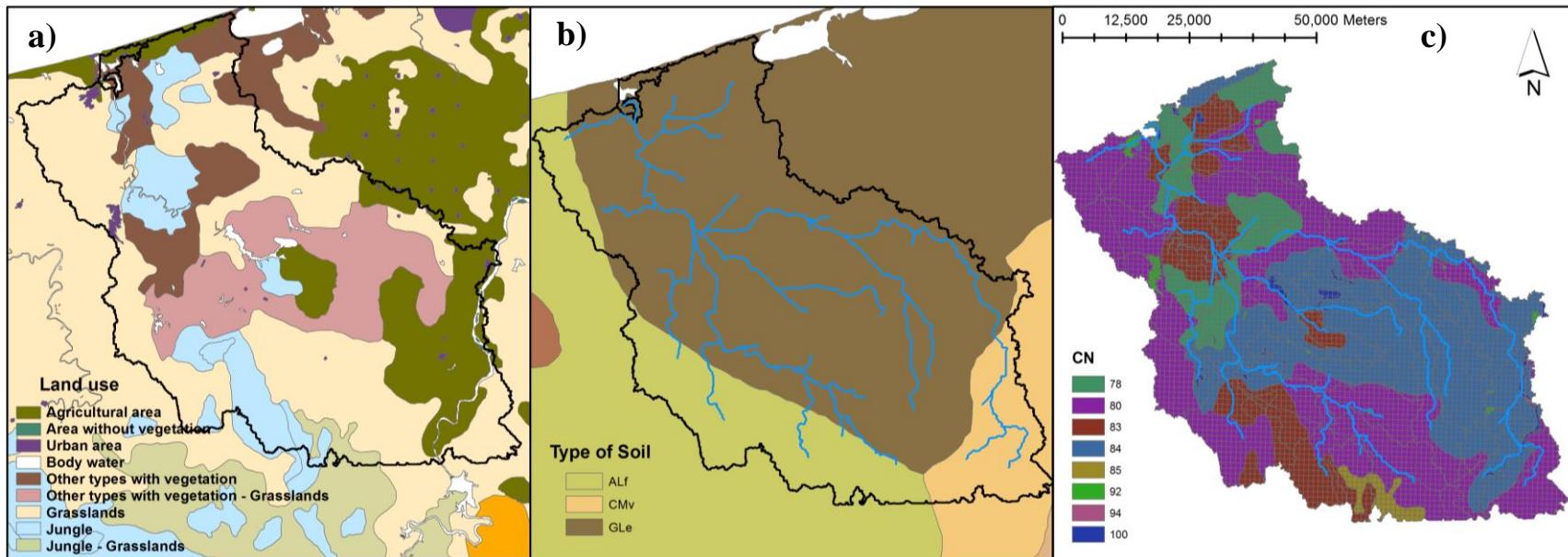
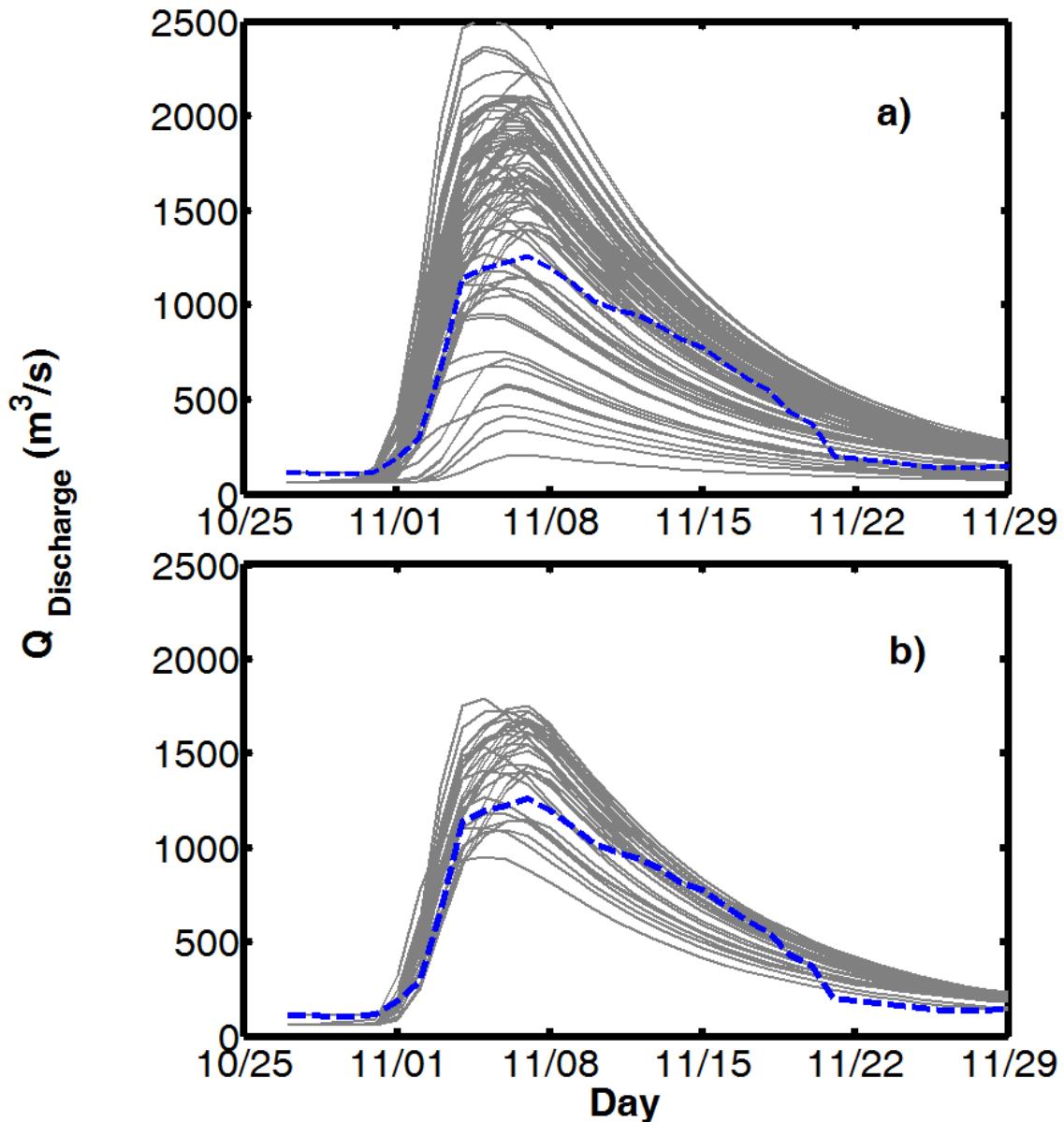
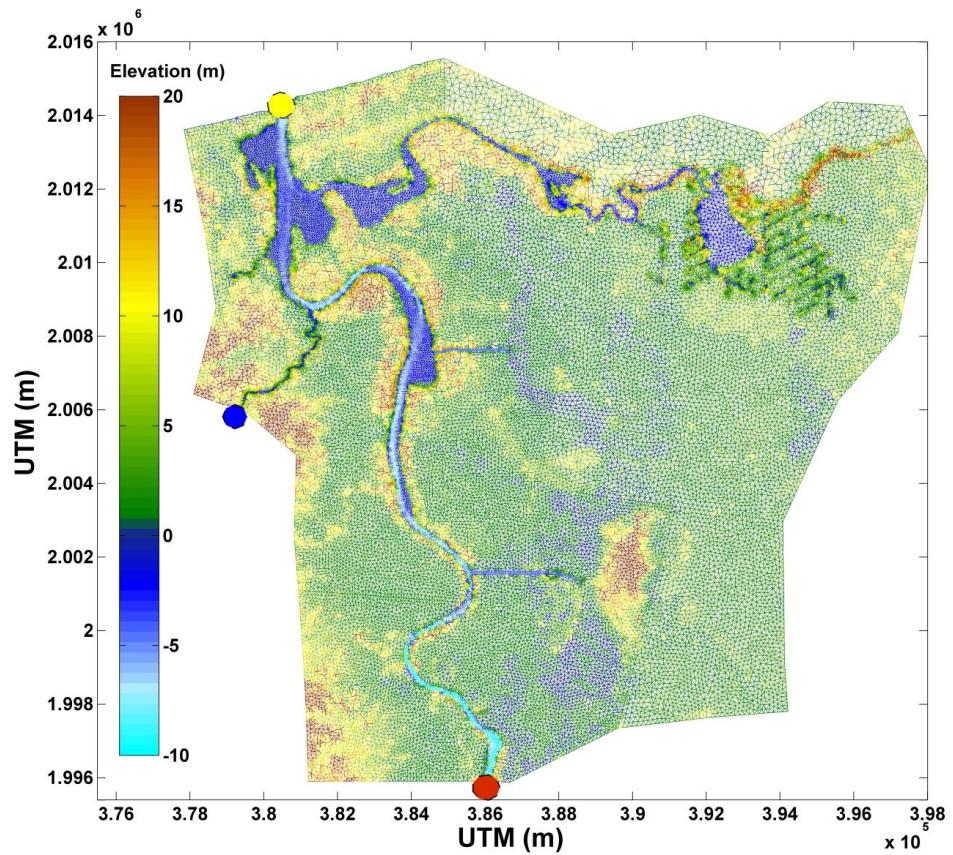


Figure 5. Input data parameters in the hydrological model; a) Land use; b) Pedology; c) River network, curve number and grid.



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Figure 7. Model domain along with the numerical mesh and elevation data in the study area;
Boundary conditions are represented by blue dot: Agua Dulcita river; red dot: input
hydrograph; yellow dot: river-mouth.

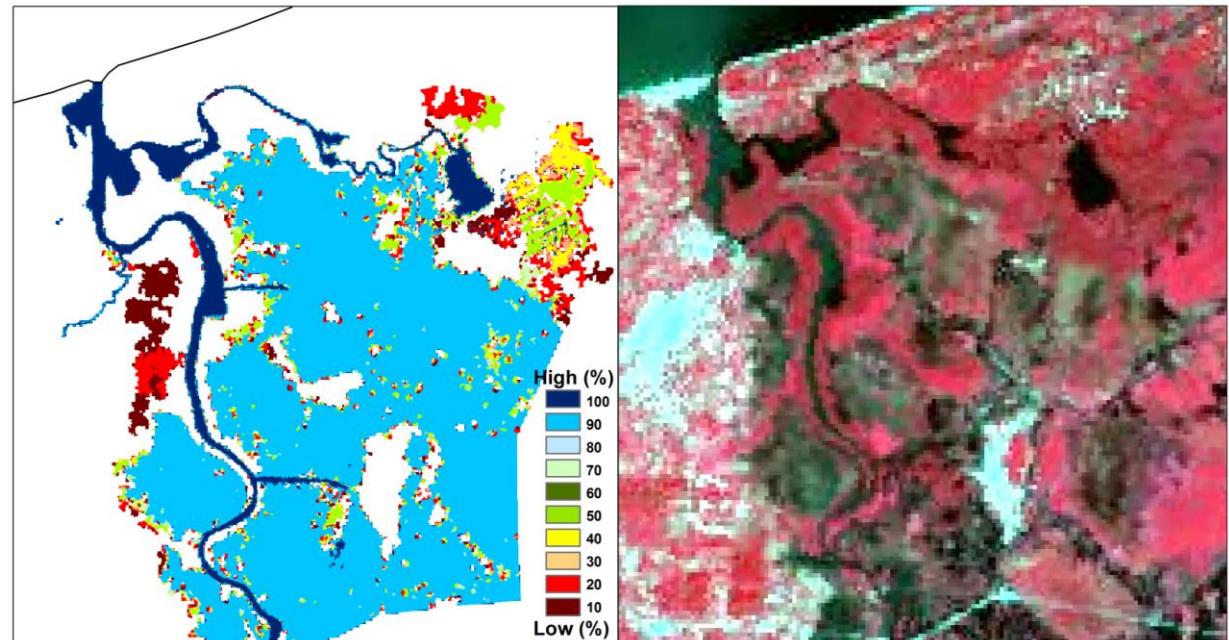
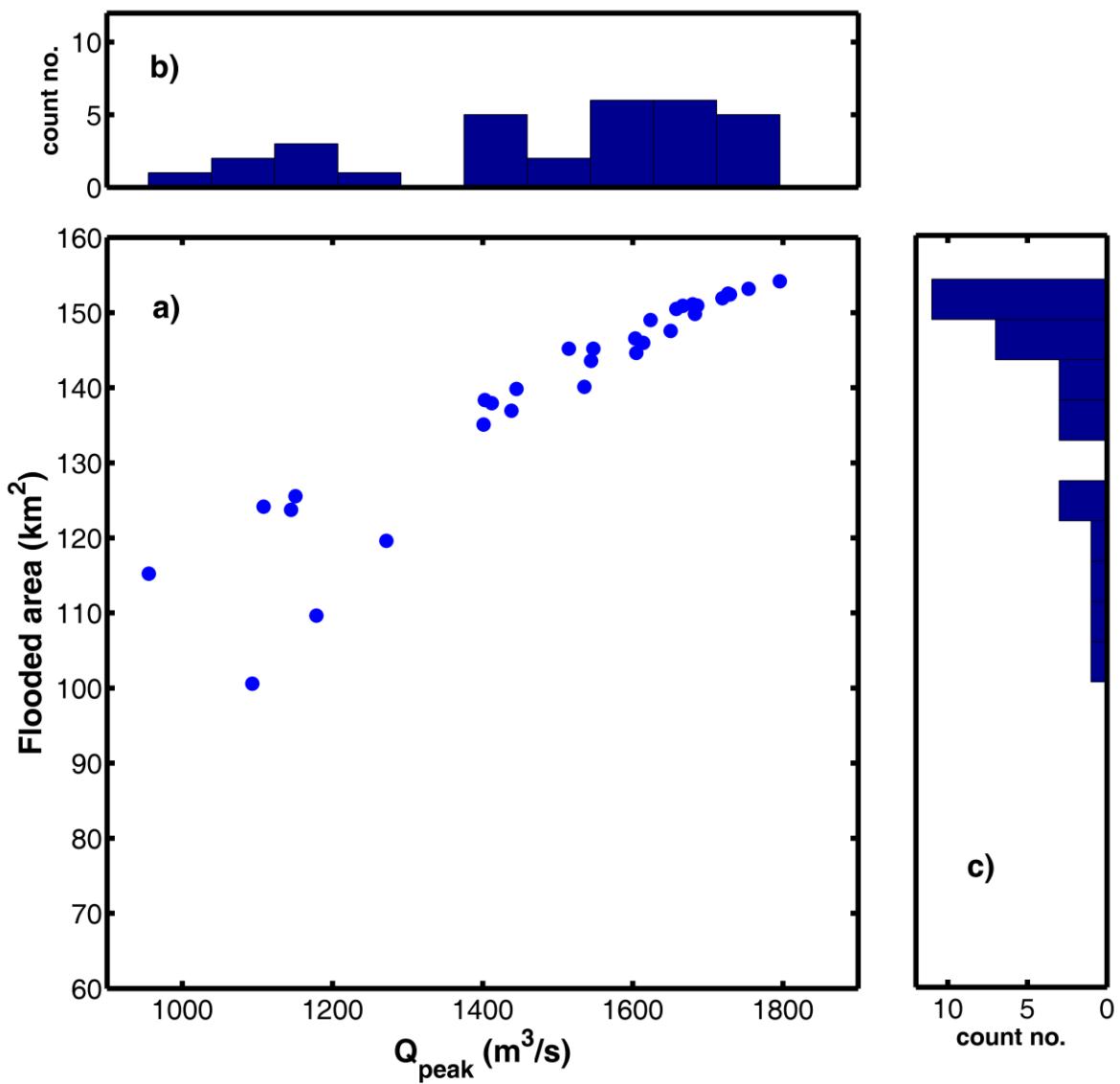


Figure 8. Data vs. model comparison of flood extent; a) Probabilistic flood map derived from the ensemble runs with the hydrodynamic model; b) Infrared SPOT image corresponding to the 15th November 2009.



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Figure 9. a) Maximum-flooded area vs. peak discharge estimated for all 31 hydrodynamic
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simulations of the 2009 flood event; b) Histogram of peak discharges; c) Histogram of
 estimated size of maximum-flooded area.

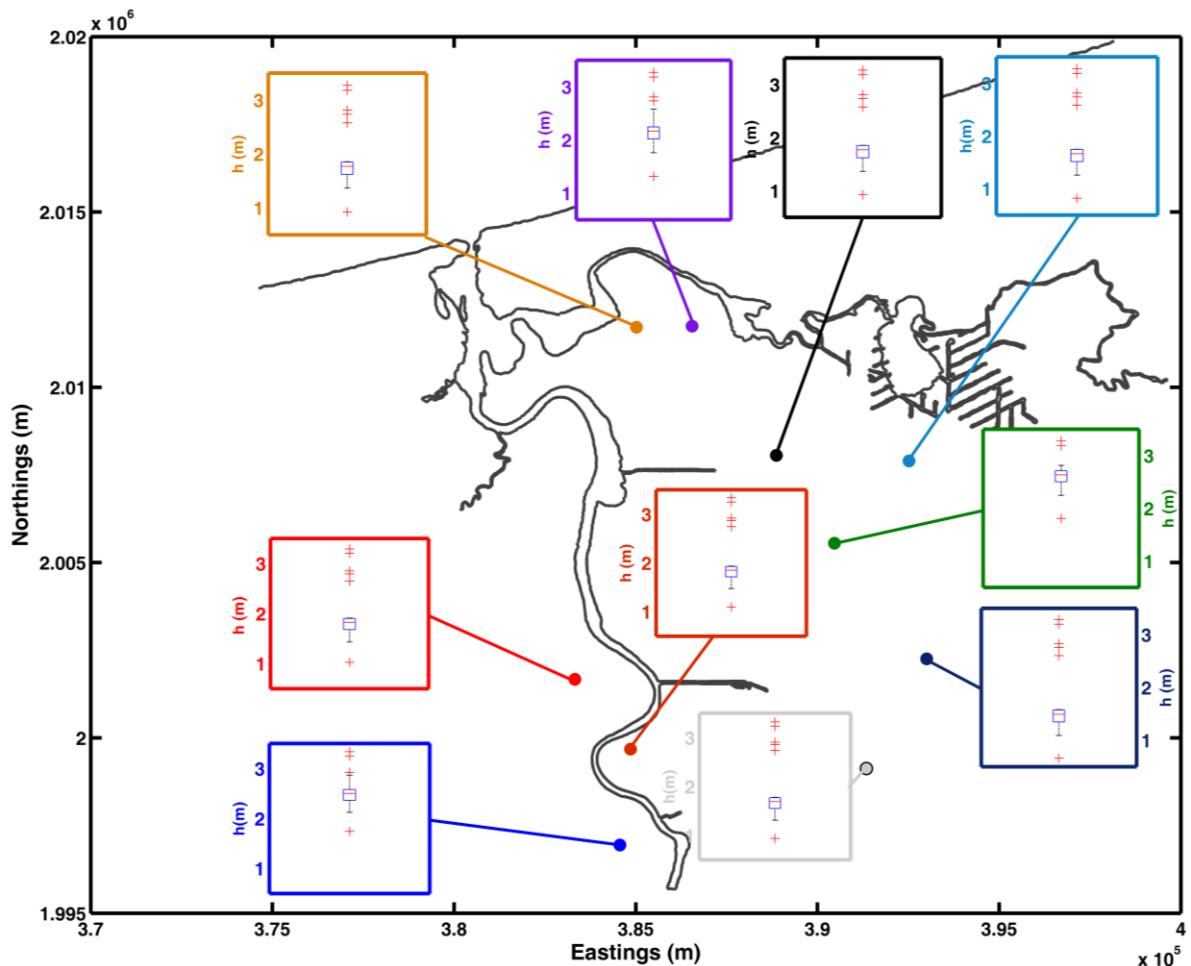
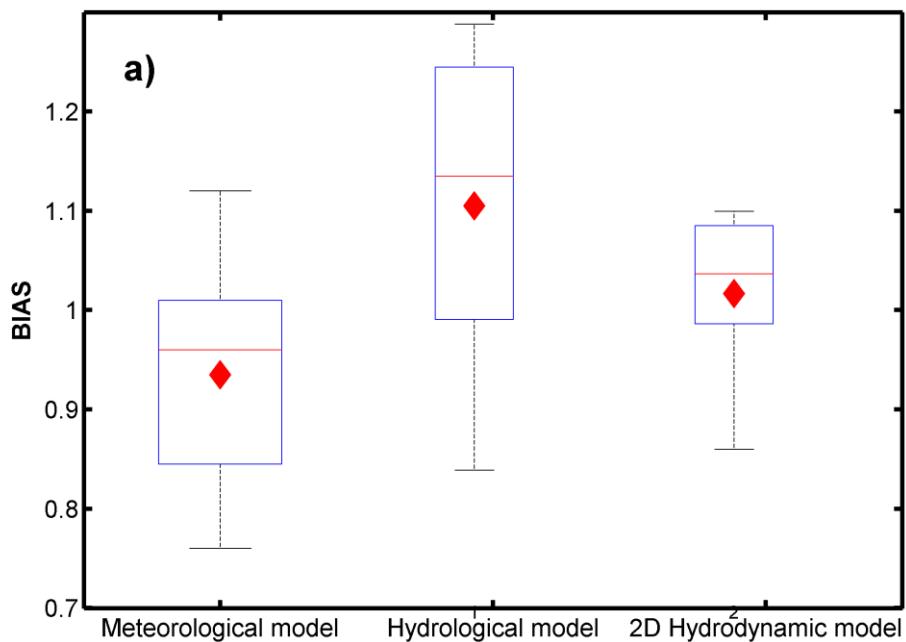


Figure 10. Estimated maxima inundation depths at different locations within the floodplain. Red line represents the median. Bars correspond to the standard deviation. Upper and lower limits of the box are the values of the 25th and 75th , respectively. Crosses depict outliers.

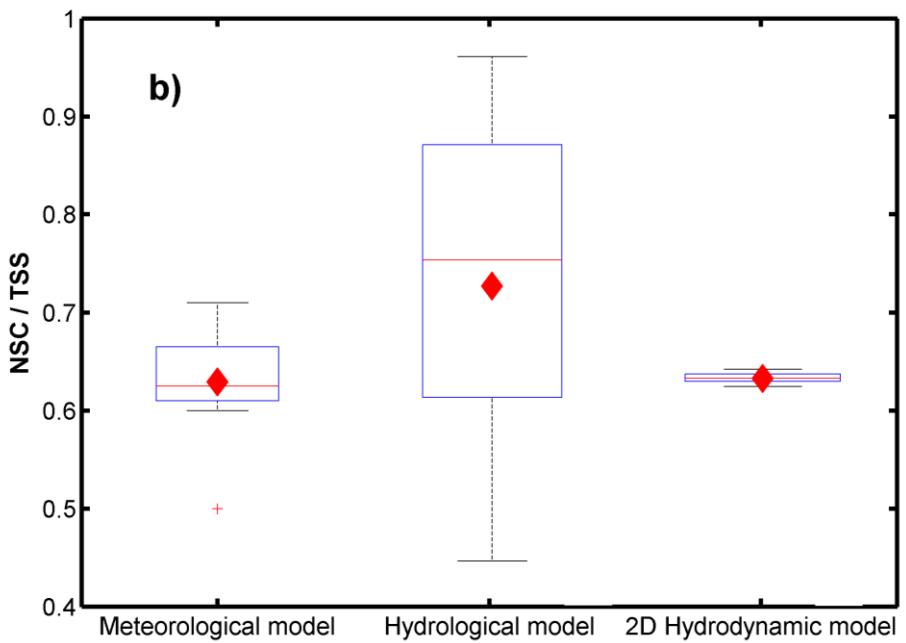
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BIAS propagation within the model cascade



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Skill evolution within the model cascade



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5 **Figure 11.** a) BIAS and b) Skill propagation within the model cascade (meteorological-
6 hydrological-hydrodynamic); diamonds: corresponding ensemble mean value.