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"SENSITIVITY ANALYSIS OF MANNING'S COEFFICIENT ON THE WATER LEVELS OF A FLOOD MODEL"

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Resumen

Los parámetros y características de los modelos matemáticos introducen ruido. Por consiguiente, es recomendable llevar a cabo un análisis de sensibilidad cuando se construyen modelos o previo a su uso. Este estudio analizó la sensibilidad de los niveles de agua (generados por el paquete hidrodinámico 1D de MIKE-11) al coeficiente de rugosidad de Manning. Un tramo de 5 km del Río Santa Bárbara en el Sur del Ecuador (el cual tiene un largo historial de inundaciones) y su información relacionada, fueron seleccionados para examinar la sensibilidad de los niveles de agua simulados, al coeficiente de Manning. Se empleó un enfoque de Monte Carlo, y los resultaros sirvieron para evaluar la robustez del modelo hidrodinámico 1D. El análisis mostró sensibilidad a los cambios en el coeficiente de Manning, con una diferencia de hasta 1.02 m entre los niveles de agua máximos mínimos. Sin embargo, los resultados del mapeo de inundaciones revelaron diferencias casi imperceptibles en la extensión de las áreas inundadas. Los hallazgos muestran que los valores promedio del coeficiente de Manning, según lo recomienda la literatura, pueden ser usados con confianza para estimar mapas de peligro de inundación para ríos de montaña similares en la región interandina.

Palabras clave: Simulación de inundaciones, Modelo hidráulico 1D, MIKE-11, Coeficiente de Manning, Análisis de sensibilidad, Monte Carlo

Abstract

The parameters and characteristics of mathematical models introduce noise. Consequently, conducting a sensitivity analysis when building models or prior to their use, is recommended. This study assessed the sensitivity of the water levels (generated by the 1D hydrodynamic MIKE-11 package) to Manning's roughness coefficient. A 5-km reach of the Santa Barbara River in Southern Ecuador (which has a long history of flooding), and its related data, were selected to examine the sensitivity of simulated water levels to Manning's n. A Monte Carlo approach was employed, and the results served to evaluate the robustness of the 1D hydrodynamic model. The analysis showed sensitivity to changes in Manning's coefficient, with a difference of up to 1.02 m between the maximum and minimum water levels. Nevertheless, the results of flood mapping delineation revealed almost unnoticeable differences in the extent of flooded areas. The findings show that the average values of Manning's n, as recommended in the literature, can be used with confidence to estimate flood hazard maps for similar mountain rivers in the Inter-Andean region.

Keywords: Flood simulation, 1D hydraulic model, MIKE-11, Manning's coefficient, sensitivity analysis, Monte Carlo

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1. Introduction

River flow modeling faces numerous challenges. Among them are the following: the effect of solid flow, changes in channel morphology, flow through bridges and structures, the coupling of hydrologic and hydraulic models, the reduction of computational efforts (Bladé, Cea & Corestein, 2014), the specification of model parameter surfaces (Hardy, Bates, & Anderson., 1999), and dealing with limited historical records (Gichamo, Popescu, Jonoski, & Solomatine., 2012). There are many sources of uncertainty in hydrodynamic modeling, most of which have been extensively analyzed and discussed in the literature (Dimitriadis et al., 2016), such as the effect of input data, model parameters, and model structure (Di Baldassarre, 2012; Willems, 2012; Papaioannou, Loukas, Vasiliades & Aronica, 2016). Key hydraulic variables are inflow, channel and floodplain slope, and friction resistance (i.e. Manning´s coefficient) (Dimitriadis et al., 2016). The non-linear interactions among these parameters can generate additional variations in model performance, which are hard to quantify and may vary depending on the methods used for sensitivity analysis (Pappenberger, Beven, Ratto & Matgen, 2008). Manning's coefficient introduces uncertainty in the estimation of water discharge (Wohl, 1998; Fread, 1989), and since field survey data is oftentimes used to approximate its value, it is one of the most difficult parameters to calculate (Dimitriadis et al., 2016). Besides, different models present different levels of sensitivity to this parameter (Dimitriadis et al., 2016), and previous studies reported that it contributes to most of the total model's uncertainty (Tayefi, Lane, Hardy, & Yu., 2007).

Diritriadis et al. (2016) stated that uncertainty decreases with increasing slope, roughness, and discharge. On the other hand, Wohl (1998) found that channels with slopes ranging from 0.001 to 0.006 and low roughness values, showed a higher variation in Manning than channels with slopes ranging from 0.026 to 0.111. The Santa Barbara River has an average slope of 0.0025; therefore, a higher variation in Manning is most likely expected.

Furthermore, wave celerity is influenced by changes in Manning's coefficient, and more vegetated areas have been found to reduce wave celerity (Anderson, Rutherfurd & Western, 2006), and to diminish flood extent.

Vegetation is the most important feature that affects Manning´s n, and it generates higher flow resistance in case of flooding, which is why its influence on flooding has also been considered by Fread (1989), among other authors. Generally, vegetation is taken into account by weighting the averages of different land cover types and by assigning roughness estimates within the ranges established by Chow (1959) (see Anderson et al., 2006; Wong, Freer, Bates, Sear & Stephens, 2014; Falter et al., 2016). Furthermore, as stated by Ferguson (2010), Manning's n is very sensitive to variations in discharge (Ferguson, 2010). And so, the understanding of the relationship between Manning's n and water depth, might help evaluate how a model reacts to these changes (Lenhart, Eckhardt, Fohrer & Frede, 2002), and how calibration with relatively low discharge values (from historical records) can benefit the prediction of extreme events (which accounts for model performance) (Horritt & Bates, 2002).

Sensitivity analysis (from here on denoted as SA) is a useful tool to better understand model performance and to reduce uncertainty (Pappenberger et al., 2008), since SA evaluates to what extent uncertainty in the model's output can be attributed to uncertainty in the model's input (Iooss & Lemaître, 2015). SA is performed by keeping all parameters constant while varying a single parameter (Lenhart et al., 2002). For this purpose, a Monte Carlo (from here on referred to as MC) sampling approach is one of the most widely used techniques (Weichel, Pappenberger & Schulz, 2007; Dimitriadis et al., 2016). Other methodologies exist, such as using replicated Latin hypercube sampling, which relies on MC Sampling (Hall, Tarantola, Bates & Horritt, 2005; Pappenberger et al., 2008), or global sensitivity methods such as screening or variance decomposition methods (Iooss & Lemaître, 2015). The performance of hydraulic models depends also on the equations used, the numerical scheme, the geometric spatial discretization, the boundary conditions, and terrain roughness (Bladé et al., 2014), where Manning's coefficient is proportional to roughness (Wohl, 1998). According to Pappenberger et al. (2008), boundary conditions and channel roughness are the main parameters influencing maximum water levels in the river.

Hydraulic modeling is generally performed using 1D or 2D models. According to Di Baldassarre (2012), "as the dimension of a model increases, the bias tends to decrease, whereas the uncertainty tends to increase". More dimensions also involve a greater computational burden (Bladé et al., 2014; Hunter, Bates, Horritt, & Wilson., 2007), which limits the application of models with a higher number of dimensions, and some authors claim that the differences in uncertainties attributed to different types of models are less important than the uncertainty caused by an input parameter; so simplified models are sometimes just as convenient (Dimitriadis et al., 2016; Papaioannou et al., 2016). There are four main types of model dimensions used for modeling floods: 1-D, quasi 2-D, 2-D, combined, and 3-D.

In Quasi 2-D models, floodplains are treated as storage reservoirs or as 1D flood branches linked to the main channel (in MIKE-11, for example). These models are appropriate when broad floodplains are present and secondary flow from the channel to the floodplains is important (Timbe, 2007). On the other hand, 2D models represent the river as a mesh of polygonal cells to characterize topography, and 3D models are not very common since they require very complex meshes (Bladé et al., 2014). Additionally, combined models couple 1D and 2D models, and are considered a good alternative for complex geometries (Tayefi et al., 2007).

1D models are based on the following assumptions: Flow is one-dimensional, pressure has a hydrostatic distribution, vertical accelerations are negligible, streamline curvature is small, the bottom slope of the channel is small, Manning's equation describes resistance effects, water is incompressible and homogeneous, water flow is parallel to the river channel and perpendicular to each cross-section, water level, and velocity are constant at each cross-section (Bladé et al., 2014), and water level is the same in the river and floodplains (Timbe, 2007). Certain authors (e.g. Jung, Merwade, Yeo, Shin, & Lee.,2013) have obtained good results when using 1D models, while others, such as Tayefi et al. (2007) argue that 1D models are not the best option for places with complex topography. In the present study, a 1D model was preferred for the hydraulic modeling of the Santa Barbara River in southern Ecuador, a river with a long history of flooding. Since the floodplains are not significantly wider than the river, a 1D approach can be taken, where flow occurs in a stream-wise direction (Horritt & Bates, 2002; Falter et al., 2016).

The river was represented in the form of lines perpendicular to flow, which contain a series of points; these lines correspond to the cross-sections (Aronica, Bates, & Horrittt., 2002). The model employed the Saint-Venant equations, which are "a system of partial differential equations that model gradually varied, unsteady flow" (Moussa, 1996), and are generally used for flood routing (Dimitriadis et al., 2016). According to Timbe (2007), this is a suitable approach when the floodplain and the river are not separated by dikes or embankments, and when the floodplains are not very wide.

The Santa Barbara River is located in an urban area typical of the inter-Andean region, and human settlements, as well as infrastructure, exist on the floodplains, mainly on the left bank (the right river bank does not yet have consolidated settlements), which renders the area even more prone to flood risk. Flood modeling studies are scarce in the study region and no methodological guide exists for its application despite the fact that flooding takes place every couple of years, especially near the Velasco Ibarra Bridge (SENAGUA, 2014). The specific objective of this work was to determine a 1D model's sensitivity to floodplain and channel roughness coefficients, using MIKE-11 as the modeling tool, and by varying Manning's n values within the ranges recommended by Chow (1959). This research is also in line with previous hydraulic studies by SENAGUA (2014), which used the HEC-RAS package to assess the vulnerability to flooding in a 10 km reach of the Santa Barbara River. HEC-RAS, like the MIKE-11 modeling kit, solve the 1D Saint-Venant equations. Besides, this model can be easily implemented given its low computational burden, and since all necessary input parameters are available; furthermore, it is appropriate for performing the required MC simulations intended for this research. This region lacks flood study in general because of the low availability of economic resources and scarce historical records. Discharge data for two return periods (20- and 50-year flood events) was used, and the effect of inundation levels on the delineation of flooded areas was also calculated. Average stage values were estimated with 90% confidence intervals.

2. Materials and Methods

2.1. Study site

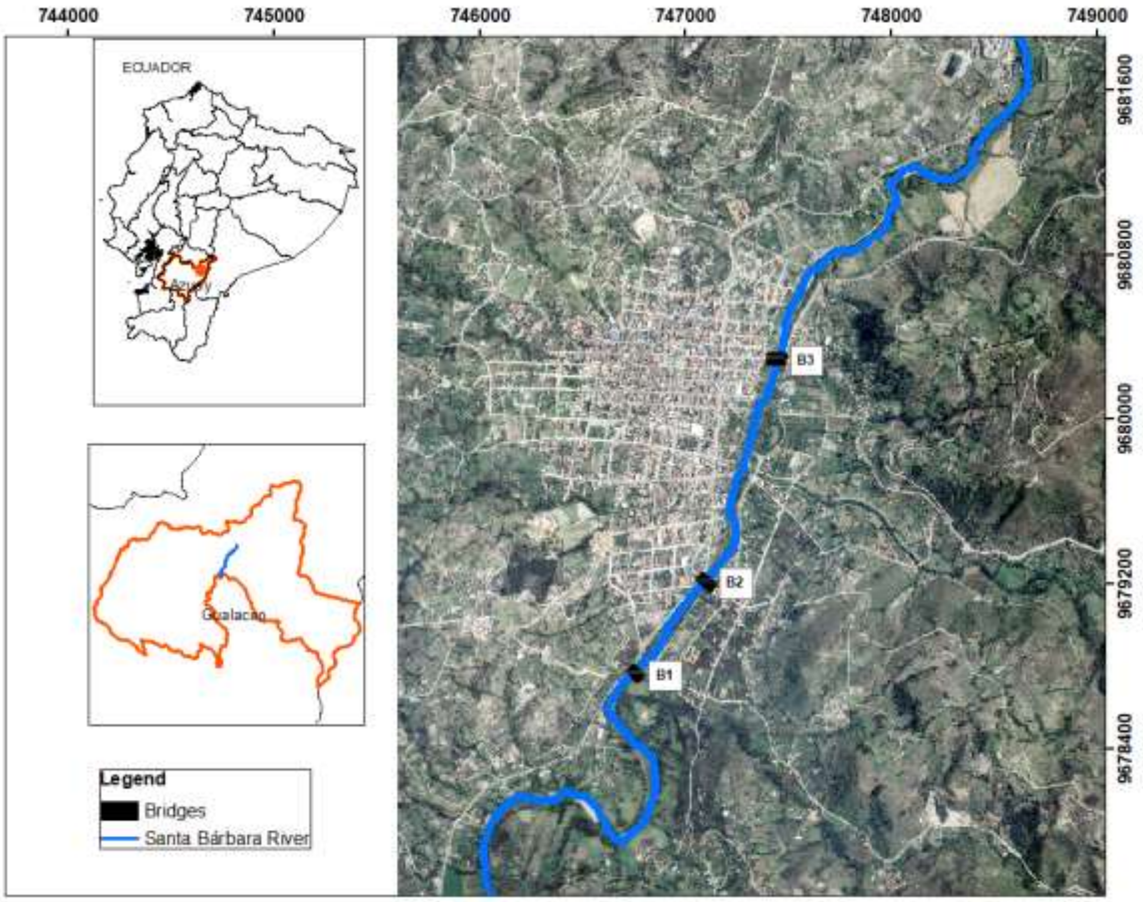

Figure 1. The study area, the location of the river reach and bridges.

The study region (fig. 1) comprises a 5 km long reach of the Santa Barbara River, which flows through Gualaceo's city center. This mountain river is located in the East-central region of the Azuay province and belongs to the Paute River Basin, which generates 50% of the electric power demand of Ecuador (Yadaicela, 2011). There are three bridges along the reach located at chainages 822 m (B1: Chacapamba), 1386 m (B2: Jaime Roldós), and 2544 m (B3: Velazco Ibarra), respectively. The site has an altitude of 2230 m. a.s.l. (Campozano, Tenelanda, Sanchez, Samaniego & Feyen, 2016), and a 14 ºC yearly average temperature (Mora & Willems, 2011). The precipitation regime is bimodal, and the average annual rainfall is 820 mm (Campozano et al., 2016), which is characteristic of the inter-Andean regime

(Ochoa, Campozano, Sánchez, Gualán & Samaniego, 2015). Floods which caused the river to overflow strongly impacted the urban area, and the city of Gualaceo has been affected by these events with a recurrence of 2 to 4 years (SENAGUA, 2014); for instance, flooding occurred on June 2007, April and July 2011, July 2013, and on July 2017.

2.2. Data availability

The following data were available: water discharges for the 20- and 50-year return periods, estimated from flood frequency analyses of historical instantaneous maximum discharge data, a 3 m resolution digital elevation model, contour lines obtained from SIG TIERRAS, 474 surveyed river cross-sections, and estimated Manning coefficients for every cross-section (SENAGUA, 2014). Table 1 presents the discharge boundary conditions for the two recurrence intervals.

Table 1. Discharge boundary conditions (BC) for the river reach

Recurrence interval (years)	Flow (m^3/s)		
	Upstream	Left tributary	Right tributary
20	667.36	16.49	44.67
50	805.94	19.92	53.94

The Manning coefficient for every cross-section corresponds to the weighted values obtained as a function of the approximate percentages of the five dominant land cover types (forest, crops, scrub, grass, and bare soil) in the left and right banks. These values were calibrated by using the floodplain's and channel's roughness as free parameters against observed flooded areas of recent inundation events. Table 2 presents the ranges of variation in Manning's coefficient for the dominant vegetation types, as defined by Chow (1959). These ranges (upper and lower limits) were used for SA, to select random n values and for computing the floodplain's Manning weighted values. Also, random values were selected for the main channel.

Table 2. The lower and upper limits of Manning's n values and the calibrated values for the dominant land cover types in the Santa Barbara River reach.

Land cover type	Lower limit	Upper limit	Calibrated value
Forest	0.08	0.12	0.1
Crops	0.025	0.045	0.035
Scrub	0.07	0.16	0.1
Grass	0.025	0.035	0.03
Impermeable (paved)	0.012	0.014	0.013
Bare Soil	0.02	0.04	0.03
Main river channel	0.03	0.05	0.035

2.3. Model implementation

The 1D MIKE-11 hydrodynamic model, which employs numerical methods to solve the state flow equations (DHI, 2002; Alam, Willems & Alam, 2014), was implemented in the 5 km Santa Barbara River reach. This package can use different flow descriptions: dynamic, diffusive, and kinematic wave. We used the dynamic wave description because it preserves the dynamic behavior of the system (Alvarado, Schwanenberg, Hatz, & Brinkmann, 2013). Furthermore, MIKE-11 assumes a linear variation between each time step, as well as instabilities in bridges and structures, and uses the energy equation to determine the discharge and backwater profile at bridges; it also accounts for friction losses using the Manning's formula (DHI, 2002). The numerical scheme uses a 6-point Abbot finite difference to solve the continuity and momentum equations as well as the advection-dispersion equations (DHI, 2002). The continuity and momentum equations are presented in equations 1 and 2, respectively.

Equation 1. Continuity equation

$$\frac{\delta Q}{\delta \mathrm{x}} + \frac{\delta A}{\delta \mathrm{t}} = \mathrm{q}$$

Equation 2. Momentum equation

$$\frac{\delta Q}{\delta t} + \frac{\delta(\frac{Q^2}{A})}{\delta x} + gA\frac{\delta h}{\delta x} + \frac{gQ|Q|}{C^2 AR} = 0$$

where, Q is discharge, A the flow area, q the lateral inflow, h the stage above datum, C the Chezy resistance coefficient, R the hydraulic or resistance radius, and α the momentum distribution coefficient.

As stated by Moussa (1996), even though the reliability of a model can be affected by the use of finite difference schemes, these numerical methods are recommended whenever the inputs and outputs are significant. An initial simulation was performed in MIKE-11 for unsteady flow conditions, and the results of this simulation were then used as the initial condition for the MC analysis, so as to improve stability when executing the model. In MIKE-11, the type of model is defined first (i.e. hydrodynamic, advection-dispersion, sediment transport, etc.), and then the input data such as the river network geometric data, initial conditions (stage and discharge), cross-section data, boundary conditions (inflow discharge upstream and stage downstream), and hydrodynamic parameters. In this research, the MIKE 11 model was implemented using the same data (i.e. cross-sections, Manning's coefficients) and conditions from previous work in HEC-RAS (SENAGUA, 2014). Only some hydrodynamic parameters (e.g. time step) were adjusted to discard numerical instabilities. The simulation results, along with the previously calibrated Manning values, were used as the reference model for comparing the SA results.

2.4. *Sensitivity analysis*

Prior to running the SA simulations, an R code was implemented for automation purposes since MIKE-11 is not able to randomly replace Manning's n in the main cross-section file; a uniform distribution in the minimum-maximum range (Table1) was used. Each file contained two different randomly-weighted averaged Manning coefficient values (left and right floodplains), and a random n value for the river channel, per cross-section. The script was used to generate 600 cross-section files per flood event since prior analyses have shown that at least 600 simulations are needed. Each file contained 186 cross-sections. After each simulation, result files were imported into MIKE-View in order to extract water level tables for each flood event (600 tables per event). The water levels computed by MIKE-11 correspond to the hypothetical water elevations that would be reached if sufficient room was available in the channel; it does not calculate the extent of flooding. A hydrodynamic hotstart condition was specified in order to define a starting water level in the channel since this condition provides better stability when running the model. The time step for the analysis was 10 seconds. After every simulation, the processed water level tables for each flood event (600 tables per event) were extracted for plotting and analyzing the results.

Three normality tests were performed on the data (Shapiro-Wilk, Jarque Bera, and Adjusted Jarque Bera) for determining the best method to measure spread. The spread of the data has been used for regionalized sensitivity analysis (Pappenberger et al., 2008). Afterwards, inundation extent and flooded areas were calculated by means of the *"Flood from stream water surface elevation"* Arc Hydro toolbox extension of ArcGIS. The input data were the following: the river thalweg polyline, the rasterized lowest points of the stream at each cross-section with the corresponding water level data from MIKE-11, and a 3 m. resolution DEM, which directly influences the accuracy of flood hazard mapping (Ward et al., 2015). This tool works by projecting point water surface elevations on a raster, based on the provided topography from the DEM.

Lastly, bootstrapping was performed to evaluate how trustworthy the 600 simulations were for computing the median/mean water levels. This technique resamples the data in order to create a greater number of samples; in our case, water level data were sampled with replacement. Bootstrapping calculates confidence intervals for a sample statistic (the median was used in this study), which helps validate the results (Pappenberger et al., 2008; Carpenter & Bitchel, 2000).

3. *Results and Discussion*

The overall aim of this study was to assess the sensitivity of Manning's coefficient on the computation of water levels and flood mapping using a 1D hydraulic model. Figures 4 and 5 present an overview of water level results (600 MC simulations) along the river reach for the 20- and 50-year return period flood events. As can be seen in both figures, the water level data obtained after performing the MC simulations varied significantly in response to changing Manning´s coefficient values, variations between the maximum and minimum water levels are of up to 1.02 m for the 20-year flood event and up to 0.941 m for the 50-year flood event. There are also differences of up to 0.693 m and 0.744 m with respect to the reference values for the 20 and 50-year flood events, respectively. As expected, the bridges produce a backwater effect upstream of these structures during flood events.

The results show that the water level inundation data are not normally distributed, as confirmed by three normality tests: the Shapiro-Wilk, the Jarque Bera, and the Adjusted Jarque Bera tests (Table 3). Since all p-values are very close to zero, the null hypotheses that support normality of the data can be rejected. The distribution of the data for the two flood events was examined at three representative points along the river reach: at 1100.12, 1545.81, and 2999.67 m., since greater variations are observed at these locations. Figures 2 and 3 show the histograms and box plots (maximum/minimum, 90th percentiles, and median) for these locations, which confirm the results of the normality tests.

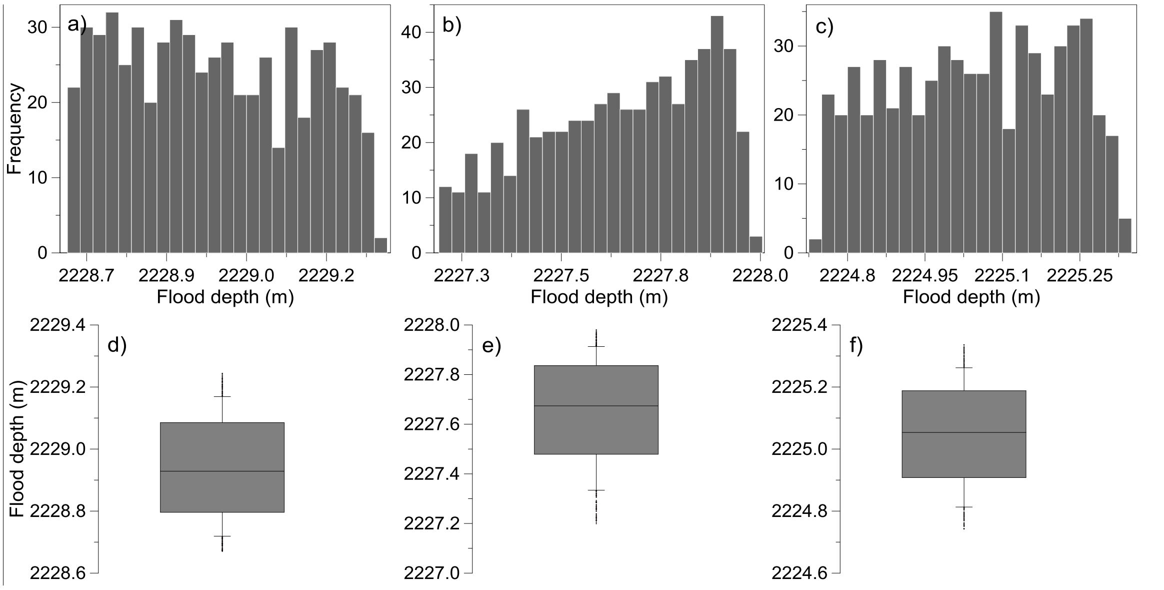

Figure 2. Data distribution for the 20-year flood event at the following distances: 1100.12 m (a, d), 1545.81 m. (b, e), 2999.67 m (c, f).

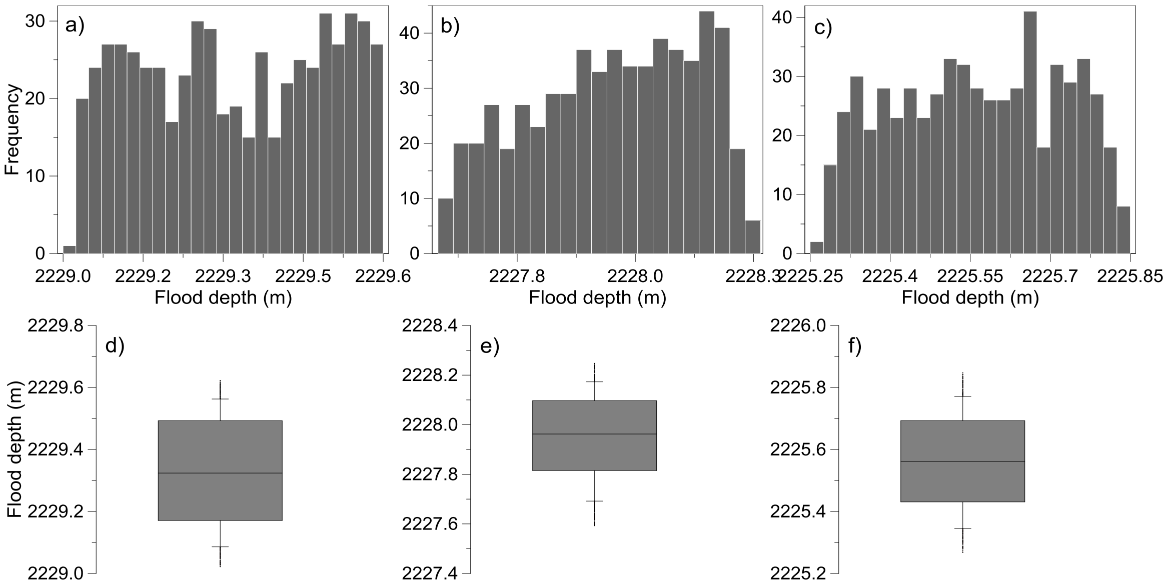

Figure 3. Data distribution for the 50-year flood event at the following distances: 1100.12 m (a, d), 1545.81 m. (b, e), 2999.67 m (c, f).

Table3. Results of the normality tests

Distance (m)	Shapiro-Wilk		Jarque Bera		Adjusted Jarque-Bera	
	TR20	TR50	TR20	TR50	TR20	TR50
1100.12	W = 0.019204, p-value < 2.2e-16	W = 0.019279, p-value < 2.2e-16	X-squared = 8999000, df = 2, p-value < 2.2e-16	X-squared = 998800, df = 2, p-value < 2.2e-16	AJB = 9225 100, p-value < 2.2e-16	AJB = 9225 000, p-value < 2.2e-16
1545.81	W = 0.020505, p-value < 2.2e-16	W = 0.020157, p-value < 2.2e-16	X-squared = 8993900, df = 2, p-value < 2.2e-16	X-squared = 994300, df = 2, p-value < 2.2e-16	AJB = 9220000, p-value < 2.2e-16	AJB = 9220 300, p-value < 2.2e-16
2999.67	W = 0.019806, p-value < 2.2e-16	W = 0.019765, p-value < 2.2e-16	X-squared = 8996700, df = 2, p-value < 2.2e-16	X-squared = 8996400, df = 2, p-value < 2.2e-16	9222800, p-value < 2.2e-16	AJB = 9222500, p-value < 2.2e-16

The arithmetic mean could not be used as a suitable central tendency measure because the data is not normally distributed; therefore, the median, which better represents the data when the distribution is skewed, was estimated. For defining confidence intervals, the 90% quantiles were calculated, as they provide a good measure of spread (Subramani & Kumarapandiyan, 2012; Di Baldassarre, 2012). Percentiles were used in other works to illustrate the range of variation of different erosion scenarios in flood modeling (Wong et al., 2014).

In figures 4 and 5 it can be noted how the medians of the modeled water levels deviate from the reference model, with a maximum distance of 0.259 m. for the 20-year flood event, and a maximum distance of 0.423 m for the 50-year flood event. Both graphs illustrate that the model is indeed sensitive to variations in Manning (the difference in water levels is clearly visible). In contrast, at and upstream of the bridges, the differences are much smaller since hydraulic structures control the flow (they reduce flow area), and Manning's coefficients have little effect on the computation of water levels.

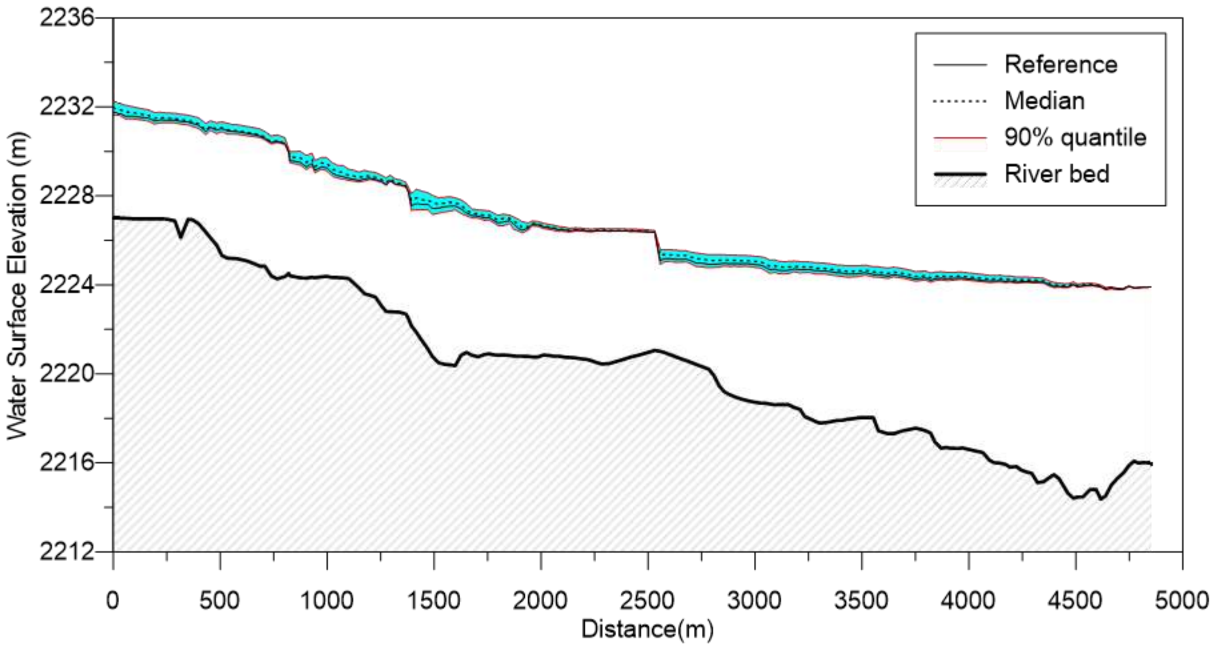

Figure 4. Surface water levels with respect to the streambed for the 20-year flood event: median, reference, maximum, minimum, and 90% water level quantiles for the 600 MC simulations.

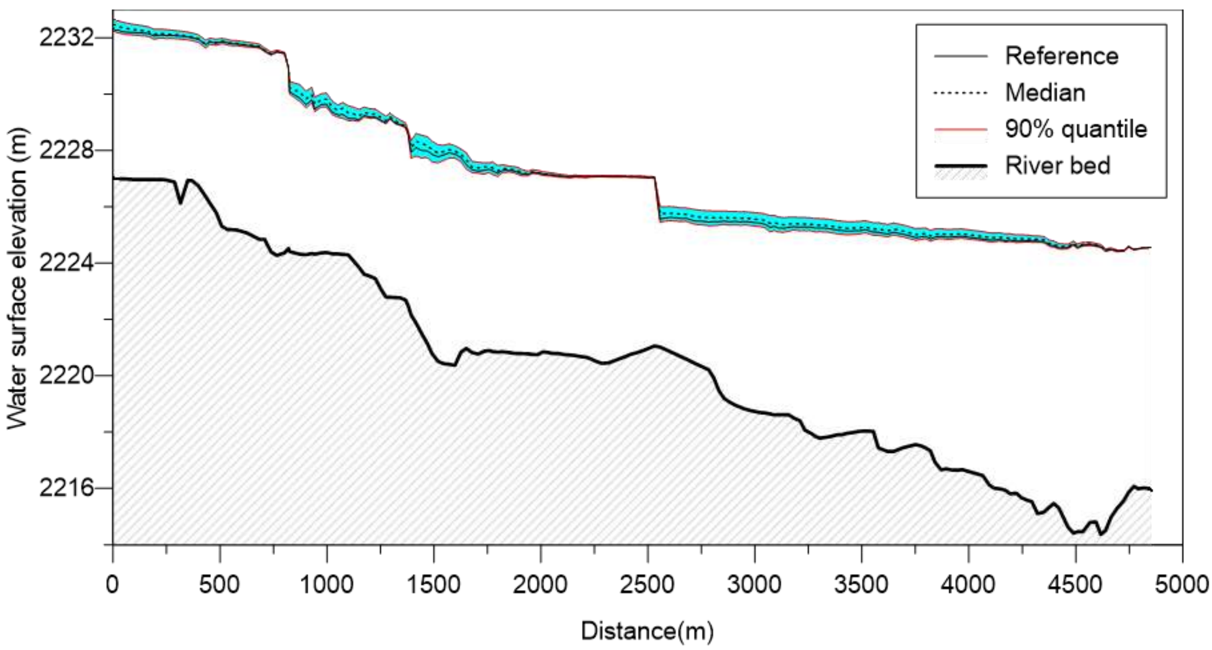

Figure 5. Surface water levels with respect to the streambed for the 50-year flood event:

median, reference, maximum, minimum, and 90% water level quantiles for the 600 MC simulations.

Figures 6 and 7 compare the flooded map areas obtained with the median, the 90th percentiles, and the reference model, for the 20- and 50-year flood events, respectively. MIKE-11's hydraulic results indicate that the model is sensitive to changes in Manning's coefficient, with regards to water levels, which differs from other studies in which variations in Manning's coefficient within a specified range resulted in minor variations in water levels (Tayefi et al., 2007). In terms of flood mapping, changes in Manning's coefficient are not as noticeable (Figures 6 and 7), most likely due to the typical topographic characteristics of the Inter-Andean region, consisting of narrow floodplains and steep upland slopes. The total inundation areas are shown in Table 4. The results indicate small differences among flooded areas, and these variations decrease with increasing recurrence intervals.

Table 4. Inundated areas in hectares for the 20- and 50-year flood events.

Modeled parameter	The 20-year flood event	The 50-year flood event
Reference model	109.62	127.13
Lower 90% quantile	104.53	124.99
Median	115.53	130.04
Upper 90% quantile	122.62	134.57

Because the means and medians calculated with bootstrapping (1000, 2000, 5000, 10000, 20000, 30000, 40000, and 50000 resamplings) prove to be the same as the sample statistics (no difference up to the fifth decimal place), this fact strengthens the trustworthiness of the calculated statistics (i.e. the median) with the 600 MC runs. This is especially true of the median, which represents the data in a more accurate fashion. However, due to the fact that all sensitivity analyses present a certain degree of uncertainty (Pappenberger et al., 2008), precaution ought to be taken when interpreting the results. In this work, no more than 600 simulations were considered because of time constraints, but according to the analysis performed, a greater number of simulations would not have provided markedly better results.

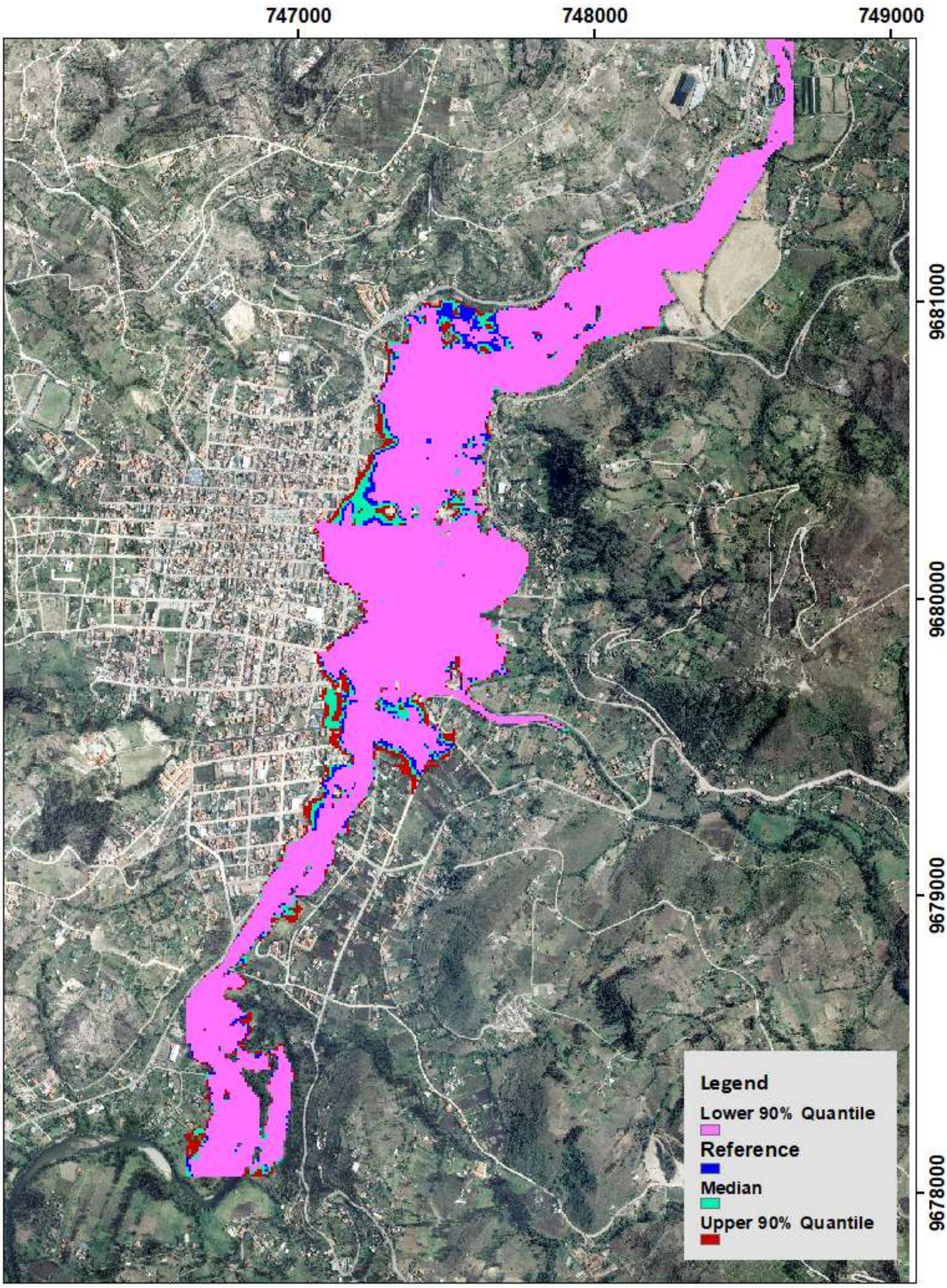

Figure 6. Inundated areas for the 20-year flood event: lower quantiles (blue), medians (cyan), upper quantiles (red), and reference (purple).

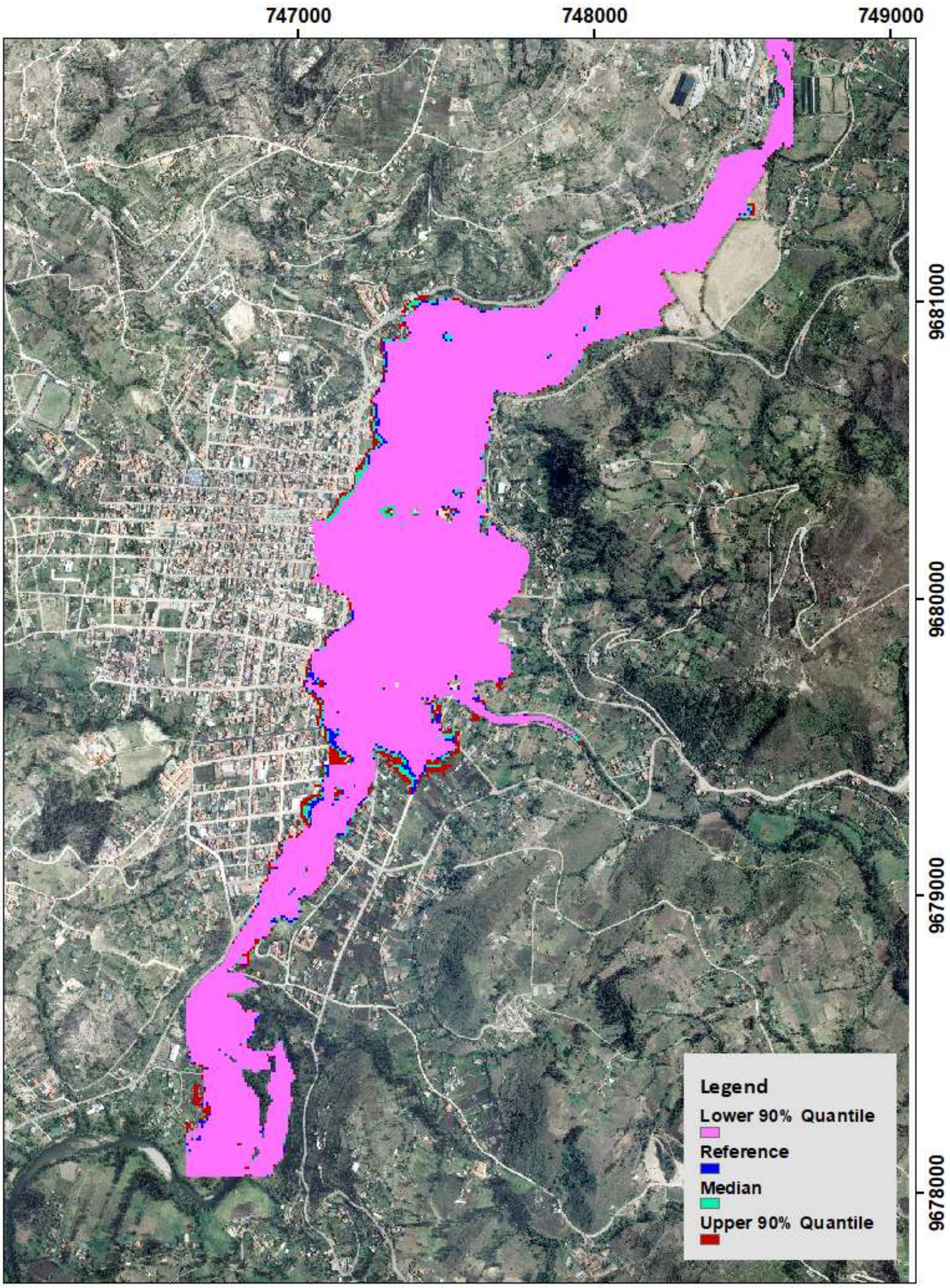

Figure 7. Inundated areas for the 50-year flood event: lower quantiles (blue), medians (cyan), upper quantiles (red), and reference (purple).

On the flood extent maps for each flood event (Figs. 6 and 7), the same spatial pattern is displayed, and an expansion of the flood wave after the second bridge is clearly visible, which is most likely due to a locally flatter terrain. Urbanization could further increase the risk of flooding due to the impermeable areas, which impede infiltration (e.g. housing, paved roads, etc.) and thus increase runoff. The flooded area starts narrowing down after the last bridge, as it moves farther away from the densely urbanized zone. As can be seen in the flood maps, the reference maps are very close to the lower quantiles, but the median and upper quantile maps are also very similar. So the calibration of Manning's coefficient in the hydraulic model does not necessarily provide better results on flood delineation.

Overall, obtaining flooded areas and comparing model performance is very important to assess different flood scenarios and for better addressing flood risk management, especially since changes in flood patterns due to climate change are uncertain, despite the fact that climate change is nowadays a very important contributor to flooding (Alam et al., 2014). In future research, it would also be interesting to compare the results obtained with MIKE-11 with those of a 1D and 2D coupled model.

4. Conclusions

The issue of flooding in the Santa Barbara River has recently initiated a significant shift towards flood risk management. The present study suggests that sufficient knowledge, as well as reliable data, exist for predicting the extent of floods and for taking timely precautions to reduce and even prevent material losses. The analysis also revealed that calibration efforts can be possibly disregarded in the future for similar conditions in mountain rivers of the Inter-Andean region since the recommended average Manning's coefficients from the literature can be used with confidence. The 600 simulations seem to yield sufficient and accurate results, which would be particularly useful in developing nations were data and economic resources are scarce. Additionally, since variations in Manning's n produced significant responses in water levels, screening sensitivity analysis methods could be employed to determine which variables produce the greatest amount o variation in the model's output.

In the future, it would be interesting to compare the simulation results with data from appropriate imagery or radar altimetry, and it would be advantageous to validate the model with remote sensing data. There is still a lot to be accomplished in terms of flood modeling and flood risk assessment in the area, but the mapping and evaluation of different flood scenarios as well as performing further evaluations with respect to the reliability of the statistical data, can provide important contributions to optimize resources and to develop flood preventive measures such as a flood warning system.

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