Flood analysis comparison with Probability Density Functions and a stochastic weather generator (#103363)

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Flood analysis comparison with Probability Density Functions and a stochastic weather generator

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Flood forecasting has become an essential component of hydrology and natural disaster management due to the increasing frequency and severity of extreme hydrological events driven by climate change. This study compares two methodologies for predicting flood events in Morelia, Mexico: one using theoretical distribution functions and another employing stochastic weather generators. The methodology integrates maximum runoff results for different recurrence intervals into a hydraulic model of the drainage network, using both the Soil Conservation Service Curve Number (SCS-CN) method and a multivariate stochastic model (MASVC). Hydrodynamic modeling with HEC-RAS, incorporating two-dimensional shallow water equations, was used to simulate flood inundation areas. The study reveals that while both modeling approaches similarly replicate the system's behavior, they produce different water levels due to variations in maximum flow values. The stochastic model tends to generate higher maximum water levels. High-resolution Digital Elevation Models (DEMs) and land use data were crucial in improving the accuracy of the hydraulic simulations. Findings indicate that unregulated urban growth in flood-prone areas significantly exacerbates the impact of flooding. The generated hazard maps and flood simulations provide valuable tools for urban planning and decision-making, highlighting the need for strategic interventions to mitigate flood risks. This research underscores the importance of integrating advanced modeling techniques in flood risk management to enhance the precision and reliability of flood forecasts.

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Abstract

Flood forecasting has become an essential component of hydrology and natural disaster management due to the increasing frequency and severity of extreme hydrological events driven by climate change. This study compares two methodologies for predicting flood events in Morelia, Mexico: one using theoretical distribution functions and another employing stochastic weather generators. The methodology integrates maximum runoff results for different recurrence intervals into a hydraulic model of the drainage network, using both the Soil Conservation Service Curve Number (SCS-CN) method and a multivariate stochastic model (MASVC). Hydrodynamic modeling with HEC-RAS, incorporating two-dimensional shallow water equations, was used to simulate flood inundation areas. The study reveals that while both modeling approaches similarly replicate the system's behavior, they produce different water levels due to variations in maximum flow values. The stochastic model tends to generate higher maximum water levels. High-resolution Digital Elevation Models (DEMs) and land use data were crucial in improving the accuracy of the hydraulic simulations. Findings indicate that unregulated urban growth in flood-prone areas significantly exacerbates the impact of flooding. The generated hazard maps and flood simulations provide valuable tools for urban planning and decision-making, highlighting the need for strategic interventions to mitigate flood risks. This research underscores the importance of integrating advanced modeling techniques in flood risk management to enhance the precision and reliability of flood forecasts.

Introduction

In recent decades, flood forecasting has become a critical component of hydrology and natural disaster management. The increasing frequency and severity of extreme hydrological events, primarily due to climate change, highlight the need to enhance the precision and reliability of forecasting systems. The ability to accurately and timely forecast flood events is essential to reduce property loss, protect vital infrastructure, and prevent human casualties (Papaioannou et al., 2021).

Flood forecasting is a multidisciplinary field combining information from meteorology, hydrology, geography, and computer science, among other disciplines. Progress in these areas has led to more advanced forecasting models and methods. However, natural systems have variability and uncertainty, and human-environmental interactions are complex. These significant challenges have not yet been solved (Chahinian et al., 2023).

Adopting emerging technologies such as artificial intelligence, machine learning, and big data has opened new ways for flood risk analysis and modeling (Karyotis et al., 2019; Mosavi et al., 2018). These approaches promise improvements in the ability to predict floods by enabling the processing of large volumes of data and the identification of complex patterns imperceptible to traditional methods (Falconer et al., 2009). In addition, the increasing availability of high-resolution data obtained through satellites and other remote sensing offers unprecedented opportunities to improve flood forecasts' accuracy and spatial resolution (Munawar et al., 2022).

Methods based on Machine Learning are, without a doubt, among the most analyzed in recent years. This type of methodology includes Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Multilayer Perceptron (MLP), Artificial Neural Networks (ANNs), Wavelet Neural Networks (WNN), and Support Vector Machines (SVM), among others.

Choubin et al. (2016) analyzed precipitation prediction using three models: multiple linear regression (MLR), MLP, and ANFIS, using large-scale climate signals as inputs. Effective climate indices were selected through principal component analysis and cross-correlation to predict the standardized precipitation index (SPI) in the Maharlu-Bakhtegan basin, Iran. The results indicated that the MLP model outperformed the MLR and ANFIS models, suggesting a nonlinear relationship between climate signals and precipitation, making nonlinear methods more effective for predicting the analyzed area.

Gessang and Lasminto (2020) propose using ANN and a weather forecasting API for flood prediction and mitigation in a sub-basin of Indonesia. The research highlights how the precipitation intensity in this area can cause significant increases in river water levels, leading to flooding. ANN was used to predict rainfall and, together with the curve method (CN) of the United States Soil Conservation Service (USSCS), calculate maximum runoff, demonstrating the usefulness of these models in flood risk management.

Hernández-Bedolla et al. (2023) present a multivariate and multisite stochastic model, MASVC, designed to estimate maximum runoff in non-measured basins. The study highlights how precipitation influences the determination of runoff at different time scales and uses a stochastic approach to generate synthetic precipitation sequences, preserving spatial and temporal variability in daily, monthly, annual, and extreme values. The model was evaluated in the Rio Grande watershed of Morelia, Mexico. It showed its effectiveness by contrasting its results with conventional probability density functions and providing a more dependable approximation of peak surface runoff.

Several factors prevent the successful application of various flood analysis and prediction technologies in operational practice despite the numerous methods that exist for this purpose. These include the need for comprehensive and accurate historical datasets, understanding local river and rainfall dynamics, and integrating heterogeneous models and data into cohesive and reliable operating systems (Perera et al., 2020).

Despite the progress of the methods that predict flood events using maximum rainfall from distribution functions as an input, these are still the most widely used methods. Thus, this study compares two hydraulic models in the main rivers of Morelia, Mexico. One model uses flows derived from theoretical distribution functions; the other uses synthetic flows derived from stochastic models. This comparison aims to assess an alternative option to the current methods for forecasting and evaluating urban flood events.

Materials & Methods

Case study

Morelia, the largest and most populous urban area in Michoacán, Mexico, is characterized by its significant population and complex fluvial network. The city has a fluvial network of fifteen perennial tributaries, shown in Figure 1 and the object of analysis in this work. The Rio Grande is the city's main river channel, collects the runoff generated in the area, and is regulated upstream by the Cointzio dam.

Morelia is prone to frequent floods from overflowing rivers, which directly impact houses and disrupt residents' daily lives. For instance, in 2018 a severe storm caused injuries, inundations in homes, landslides, and wrecked vehicles. Today, floods are perceived as having only negative consequences and as disasters that inflict harm, sometimes irreparable. These impacts are aggravated by the expansion of cities naturally prone to flooding, such as near rivers and streams.

Methodology

The proposed methodology utilizes maximum runoff results for various recurrence intervals within the hydraulic model of Morelia City's drainage network. It also incorporates scenarios created with the daily MASVC (Hernández-Bedolla et al., 2023). Moreover, the HEC-RAS model was adjusted to obtain the flood areas based on topographic studies and changes in the Manning roughness coefficients (Demir & Keskin, 2020; Yalcin, 2020). The methodology is illustrated in Figure 2.

Surface runoff

Surface runoff was calculated using two types of methodology. One method was the Probability Density Functions with The Soil Conservation Service Curve Number (PDF-SCS-CN), which is used to estimate runoff from small-to-medium-sized watersheds SCS-CN method (AL-Hussein et al., 2022; Ansori, 2023; Sathya et al., 2023). The other method was the stochastic weather generator, which applied the MASVC-SCS-CN approach. The MASVC is a multivariate stochastic model that uses lag one autoregressive multivariate parameters. It consists of two modeling phases. The first phase models the occurrence of precipitation (wet-dry), and the second phase estimates the amount of precipitation on a daily scale. Then, the maximum precipitation values are extracted, and the runoffs are computed using the SCS-CN method.

Flood inundation

Hydrodynamic model HEC-RAS is used to model rivers (one-dimensional), flood areas (two-dimensional), channels, drains, and dams (Açıl et al., 2023; Bharath et al., 2021; Bush et al., 2022; Goswami et al., 2023; Namara et al., 2022; Ongdas et al., 2020). HEC-RAS calculates the depth of inundation and velocity based on floodwater discharge hydrographs (Hydrologic Engineering Center, 2009). HEC-RAS was applied for the two-dimensional hydraulic model and was solved by the 2-D shallow water equations. The solution method for both equations was by volume finite differences. The unsteady differential form of the mass conservation equation is (Equation 1).

$$r = \frac{\partial H}{\partial t} + \frac{\partial (hu)}{\partial x} + \frac{\partial (hv)}{\partial y} \qquad [1]$$

Where r is the source/sink term, H is the surface elevation (m); t is the time, hu and hv are the flow in x and y (m^2s^{-1}); HEC-RAS recently incorporates fully 2-D shallow equations (Costabile et al., 2020). The shallow water equations are presented in the following equations.

$$\frac{\partial p}{\partial t} + \frac{\partial}{\partial x}\left(\frac{p^2}{h}\right) + \frac{\partial}{\partial y}\left(\frac{pq}{h}\right) = -\frac{n^2 pg\sqrt{p^2+q^2}}{h^2} - gh\frac{\partial H}{\partial x} + pf + \frac{\partial}{\rho \partial x}(h\tau_{xx}) + \frac{\partial}{\rho \partial y}(h\tau_{xy}) \qquad [2]$$

$$\frac{\partial q}{\partial t} + \frac{\partial}{\partial x}\left(\frac{pq}{h}\right) + \frac{\partial}{\partial y}\left(\frac{q^2}{h}\right) = -\frac{n^2 pg\sqrt{p^2+q^2}}{h^2} - gh\frac{\partial H}{\partial y} + qf + \frac{\partial}{\rho \partial x}(h\tau_{xy}) + \frac{\partial}{\rho \partial y}(h\tau_{yy}) \qquad [3]$$

Where p and q are hu and hv, (m^2s^{-1}); n is the Manning's roughness coefficient (s $m^{-1/3}$), g is the gravity acceleration (ms^{-2}), ρ is the water density (kg m^{-3}), τ_{xx}, τ_{yy}, and τ_{xy} are the components of the stress tensor and f is the Coriolis parameter (s^{-1}). We propose the diffusive wave algorithm to select boundary conditions and response times. In this case, the inertial terms of the equation are neglected.

The Eulerian Shallow Water equation (EM-SWE) was the calibration solution method. This method utilizes the momentum-conservative discretization assuming local conservation of momentum about control volume centered on all cell face $(V \cdot \nabla)u_N$ (Hydrologic Engineering Center, 2021).

$$[(V \cdot \nabla)\mathrm{u}_N]_f \approx \left(\frac{1}{h}[\nabla \cdot (hVu_N - u_N \nabla \cdot hV)]\right)_f \qquad [4a]$$

$$[(V \cdot \nabla)\mathrm{u}_N]_f \approx \frac{\alpha_f^L}{\overline{h}_f A_{L}} \sum_{k \in K(L)} Q_{i,k}^{-}\left(V_k^u \cdot n_f - u_{N,f}\right) + \frac{\alpha_f^R}{\overline{h}_f A_{R}} \sum_{k \in K(L)} Q_{R,k}^{-}\left(V_k^u \cdot n_f - u_{N,f}\right) \qquad [4b]$$

Where $h_i = \Omega_i / A_i^W$; $Q_{\overline{i,k}}$ is the minimum value of inflow at face k to cell i $s_{i,k}$, Q_k, 0; A_k is the face vertical area; A_L is the left cell horizontal area, A_R is the right cell horizontal area, V_j is the cell average current velocity vector V_k^u is V_L for $u_{N,k}$ major than cero and is V_R for $u_{N,k}$ less than zero; n_f is the face-normal unit vector.

DEM and land use

The quality of flood modeling depends on the topographic information. A hybrid mesh was used, combining a gridded DEM dataset with 5m of resolution from the National Institute of Statistics and Geography (INEGI, https://www.inegi.org.mx/temas/topografia/) and more detailed 0.5 m data from a specific topographic study to improve the accuracy in rivers. The land use data was obtained from INEGI (https://www.inegi.org.mx/temas/usosuelo/), and field visits to the rivers were conducted to determine the Manning coefficient (n).

Boundary conditions

Two-dimensional modeling was done with flexible and triangular meshes. The meshes gave more detail in the rivers due to a high-accuracy topographic survey (Muñoz et al., 2022; Ontowirjo et al., 2023). For the flood areas, a regular grid with a 5-meter resolution was proposed for roads, as well as for urban and rural areas. Boundary conditions describe how water behaves at the model domain's boundaries, including different conditions at the model edges (Hydrologic Engineering Center, 2009). Upstream boundary conditions are needed at the upstream end of all reaches that do not connect to other reaches or storage areas. Hydrographs were assigned upstream of each sub-basin studied. ~~Hydrographs corresponding to various return and historical periods were assigned upstream of each sub-basin studied.~~ For the downstream boundary condition, the normal depth option was chosen for the HEC-RAS model (Hydrologic Engineering Center, 2021).

Simulation and calibration

The process of calibrating the hydraulic model is based on the different steps described below. 1) Simulation of the entire study area to identify the simulation times and potential flooding zones near the streams and rivers. 2) Simulation of the diffusive wave algorithm to generate the first flood from historical rainfall data. 3) Calibration using the EM-SWE by changing the Manning roughness coefficient and field visits to perform mesh refinement. 4) Validation of the results from the actual flooding for a specific date. 5) Generation of floods from different return periods and results from MASVC-SCS-CN and PDF-SCS-CN.

Results and Discussion

The city of Morelia often experiences floods due to the excess water in the urban drains that are part of the city's structure. In order to analyze the flooding problem accurately, a high-resolution (5m) Digital Elevation Model (DEM) of the city is needed. This study used 9 DEMs provided by INEGI (Instituto Nacional de Estadística y Geografía (INEGI), n.d.) to create a Digital Surface Model (DSM) that reflects the city's structure. This DSM allowed us to locate the potential channels that could form when the drains overflow.
However, the DSM has a limitation in that it does not account for vegetation. Vegetation can lower the hydraulic capacity of waterways, raising the flood risk. Bathymetric data on the river network was obtained from CONAGUA (2016) to obtain a comprehensive topographic model of the urban area. This data was combined with the MDE of the urban layout to create a complete topographic model. The final topographic model enabled the precise identification of the city's location, depth, and areas prone to flooding.

The hydraulic simulation was performed with the HEC-RAS version 6.3 program. This software applies the two-dimensional shallow-water equations of diffusion waves and lets the user select the best solution method.

Shallow water equations are a set of mathematical equations that capture the movement of water in open channels. These equations can simulate different hydraulic phenomena such as floods, drinking water flows, and wastewater, which is why they were applied in this study.

The hydraulic model covers a 34.74 km² area, split into 751,641 cells and 871,976 nodes. The cells have varied sizes depending on the area, with large-scale cells in areas away from the channels (10m) and small cells in the channels (2m) and structures (1m). This variable size enhances the calculation process without losing detail in critical areas. The model includes 170 structures, such as bridges, gates, and culverts. These structures reflect the actual topography of the area and allow the water flow around them to be modeled.

The hydraulic model requires 17 boundary conditions. Of these, 16 are water inlets, represented by the hydrographs of each tributary, and one is an outlet located in the final section of the Rio Grande outside the city. This configuration enables the flow within the study area to act naturally, conforming to the terrain's topography. Figure 3 shows the position of boundary conditions in the model.

A comparative analysis was used to obtain the hydrographs for the water inlets. Two methods were applied: the best-fit probability function (Sánchez-Quispe et al., 2021) and stochastic models (Wright et al., 2020). Both methods were used to estimate design storms.

The hydrographs for the modeling were derived from the maximum flows suggested by Hernández-Bedolla et al. (2023). The model input hydrographs, 15 in total, were produced using the HEC-HMS software. The constant flow of the Cointzio dam was based on its historical discharges.

Figure 4 shows that the use of stochastic models results in consistent maximum flows, regardless of the methodology (PDF-SCS-CN or MASVC-SCS-CN) used, because these models are uniform over time and reduce the uncertainty caused by the significant variation of using a best-fit distribution function, which changes between basins and seasons.

Manning's roughness coefficient is critical for hydraulic simulation as it influences the flow speed. For instance, higher roughness coefficients typically indicate more resistance and slower flow velocities. Satellite images were used as a basis for this. Ven Te Chow (1959) states that this coefficient can be derived from land cover. However, the Manning coefficients were verified to ensure the parameter's accuracy in the system's hydraulic performance. This involved field visits and topographic surveys.

The data gathered enabled the identification of areas with comparable features of land cover and soil type. Each zone was given a distinct roughness coefficient. Figure 5 illustrates the spatial variation of these coefficients.

Different return periods (2, 10, 50, 100, 200 and 500 years) were used for hydraulic simulations. These simulations revealed four zones of natural flooding (Figure 6). This information is essential for deciding the city's urban growth, as these areas are prone to flooding.

The input data inevitably creates variation in the depths produced on the flood surfaces depending on the model used, but the flood areas are clearly defined, as shown in Figure 7. This variation in the depths produced does not significantly affect the flood surface. It keeps us safe since the hydraulic behavior of the system in the study area is well-defined.
Both modeling approaches (distribution functions and stochastic models) similarly replicate the system's behavior; however, they yield different water levels due to the varying maximum flow values each model generates. These differences result from the different maximum flow values that each model creates. In general, stochastic models generate higher maximum water levels, as Table 2 shows.

Conclusions

All cities, particularly those prone to natural hazards like flooding, must address the challenges posed by unregulated urban growth. By occupying natural flood areas, economic and social losses pose a severe threat, which becomes a vital issue for governments.
The findings of this study highlight the necessity of using hydraulic models as essential tools in urban planning and decision-making to mitigate impacts on existing urban centers. Assessing natural hazards and their effects, such as rainfall that causes floods, is a complicated task that requires rigorous analysis, as done in this research. Decreased uncertainty in areas with limited data gives more confidence to the decisions that need to be made, as well as analyzing and generating a critical evaluation to avoid overestimating the effects of floods.
A crucial task in decision-making is the generation of hydraulic models that simulate the flow behavior. Therefore, it is essential to be careful when creating the model. It is important to verify every aspect involved in the physical and hydraulic model. Two-dimensional hydraulic models accurately simulate the flow behavior as it happens. The generation of hazard maps, such as those for flooding, helps identify the areas where urban development should be avoided because they are in areas prone to flooding, such as the natural floodplains of the river network of Morelia.
The hazard maps produced in this study can help to identify strategic locations for hydraulic works that can help mitigate the impacts of flooding in the urban area of Morelia. By analyzing different return periods, the maps clearly show the recurrent flood zones that should be prioritized for intervention. The flood maps can also be helpful for future work in developing warning systems that can link rainfall events with the historical floods generated.

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References

Açıl, A., Aydın, A., Eker, R., & Duyar, A. (2023). Use of UAV Data and HEC-RAS Model for Dimensioning of Hydraulic Structures on Forest Roads. *Croatian Journal of Forest Engineering*, *44*(1), 171–188. https://doi.org/10.5552/crojfe.2023.1701

AL-Hussein, A. A. M., Khan, S., Ncibi, K., Hamdi, N., & Hamed, Y. (2022). Flood Analysis Using HEC-RAS and HEC-HMS: A Case Study of Khazir River (Middle East—Northern Iraq). *Water (Switzerland)*, *14*(22). https://doi.org/10.3390/w14223779

Ansori, M. B. (2023). FLOOD HYDROGRAPH ANALYSIS USING SYNTHETIC UNIT HYDROGRAPH, HEC-HMS, AND HEC-RAS 2D UNSTEADY FLOW PRECIPITATION ON-GRID MODEL FOR DISASTER RISK MITIGATION. *International Journal of GEOMATE*, *25*(107). https://doi.org/10.21660/2023.107.3719

Bharath, A., Shivapur, A. V., Hiremath, C. G., & Maddamsetty, R. (2021). Dam break analysis using HEC-RAS and HEC-GeoRAS: A case study of Hidkal dam, Karnataka state, India. *Environmental Challenges*, *5*. https://doi.org/10.1016/j.envc.2021.100401

Bush, S. T., Dresback, K. M., Szpilka, C. M., & Kolar, R. L. (2022). Use of 1D Unsteady HEC-RAS in a Coupled System for Compound Flood Modeling: North Carolina Case Study. *Journal of Marine Science and Engineering*, *10*(3). https://doi.org/10.3390/jmse10030306

Chahinian, N., Alcoba, M., Dembélé, N. dit J., Cazenave, F., & Bouvier, C. (2023). Evaluation of an early flood warning system in Bamako (Mali): Lessons learned from the flood of May 2019. *Journal of Flood Risk Management*, *16*(3). https://doi.org/10.1111/jfr3.12878

Choubin, B., Khalighi-Sigaroodi, S., Malekian, A., & Kişi, Ö. (2016). Multiple linear regression, multi-layer perceptron network and adaptive neuro-fuzzy inference system for forecasting precipitation based on large-scale climate signals. *Hydrological Sciences Journal*, *61*(6), 1001–1009. https://doi.org/10.1080/02626667.2014.966721

Chow, V. Te. (1959). *Open-channel hydraulics* (McGraw-Hill, Ed.).

CONAGUA. (2016). *Actualización del estudio para el control de avenidas en el sistema Río Grande-río Chiquito de la presa Cointzio a su desembocadura al lago de Cuitzeo*.

Costabile, P., Costanzo, C., Ferraro, D., Macchione, F., & Petaccia, G. (2020). Performances of the new HEC-RAS version 5 for 2-D hydrodynamic-based rainfall-runoff simulations at basin scale: Comparison with a state-of-the art model. *Water (Switzerland)*, *12*(9). https://doi.org/10.3390/W12092326

Demir, V., & Keskin, A. Ü. (2020). Obtaining the manning roughness with terrestrial-remote sensing technique and flood modeling using FLO-2D: A case study Samsun from Turkey. *Geofizika*, *37*(2), 131–156. https://doi.org/10.15233/gfz.2020.37.9

Falconer, R. H., Cobby, D., Smyth, P., Astle, G., Dent, J., & Golding, B. (2009). Pluvial flooding: New approaches in flood warning, mapping and risk management. *Journal of Flood Risk Management*, *2*(3), 198–208. https://doi.org/10.1111/j.1753-318X.2009.01034.x

Gessang, O. M., & Lasminto, U. (2020). The flood prediction model using Artificial Neural Network (ANN) and weather Application Programming Interface (API) as an alternative effort to flood mitigation in the Jenelata Sub-watershed. *IOP Conference Series: Materials Science and Engineering*, *930*(1). https://doi.org/10.1088/1757-899X/930/1/012080

Goswami, G., Prasad, R. K., & Kumar, D. (2023). Hydrodynamic flood modeling of Dikrong River in Arunachal Pradesh, India: a simplified approach using HEC-RAS 6.1. *Modeling*

Earth Systems and Environment, *9*(1), 331–345. https://doi.org/10.1007/s40808-022-01507-2

Hernández-Bedolla, J., García-Romero, L., Franco-Navarro, C. D., Sánchez-Quispe, S. T., & Domínguez-Sánchez, C. (2023). Extreme Runoff Estimation for Ungauged Watersheds Using a New Multisite Multivariate Stochastic Model MASVC. *Water (Switzerland)*, *15*(16). https://doi.org/10.3390/w15162994

Hydrologic Engineering Center. (2009). *HEC-GeoRAS GIS Tools for Support of HEC-RAS using ArcGIS® User's Manual*. www.hec.usace.army.mil

Hydrologic Engineering Center. (2021). *HEC-RAS User's Manual*. www.hec.usace.army.mil/confluence/display/RASUM/

Instituto Nacional de Estadística y Geografía (INEGI). (n.d.). *INEGI*. Retrieved January 3, 2024, from https://www.inegi.org.mx/app/geo2/elevacionesmex/

Karyotis, C., Maniak, T., Doctor, F., Iqbal, R., Palade, V., & Tang, R. (2019). Deep learning for flood forecasting and monitoring in urban environments. *Proceedings - 18th IEEE International Conference on Machine Learning and Applications, ICMLA 2019*, 1392–1397. https://doi.org/10.1109/ICMLA.2019.00227

Mosavi, A., Ozturk, P., & Chau, K. W. (2018). Flood prediction using machine learning models: Literature review. In *Water (Switzerland)* (Vol. 10, Issue 11). MDPI AG. https://doi.org/10.3390/w10111536

Munawar, H. S., Hammad, A. W. A., & Waller, S. T. (2022). Remote Sensing Methods for Flood Prediction: A Review. In *Sensors* (Vol. 22, Issue 3). MDPI. https://doi.org/10.3390/s22030960

Muñoz, D. F., Yin, D., Bakhtyar, R., Moftakhari, H., Xue, Z., Mandli, K., & Ferreira, C. (2022). Inter-Model Comparison of Delft3D-FM and 2D HEC-RAS for Total Water Level Prediction in Coastal to Inland Transition Zones. *Journal of the American Water Resources Association*, *58*(1), 34–49. https://doi.org/10.1111/1752-1688.12952

Namara, W. G., Damisse, T. A., & Tufa, F. G. (2022). Application of HEC-RAS and HEC-GeoRAS model for Flood Inundation Mapping, the case of Awash Bello Flood Plain, Upper Awash River Basin, Oromiya Regional State, Ethiopia. In *Modeling Earth Systems and Environment* (Vol. 8, Issue 2, pp. 1449–1460). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/s40808-021-01166-9

Ongdas, N., Akiyanova, F., Karakulov, Y., Muratbayeva, A., & Zinabdin, N. (2020). Application of hec-ras (2d) for flood hazard maps generation for yesil (ishim) river in kazakhstan. *Water (Switzerland)*, *12*(10), 1–20. https://doi.org/10.3390/w12102672

Ontowirjo, B., Fathurrahman, I., Ramadhan, M. V., Zahriani, A., Zahra, M., & Wahyudi, H. (2023). LiDAR DEM and HEC-RAS On-Grid Rainfall Hydrograph Model for Irrigation System. *IOP Conference Series: Earth and Environmental Science*, *1198*(1). https://doi.org/10.1088/1755-1315/1198/1/012023

Papaioannou, G., Vasiliades, L., Loukas, A., Alamanos, A., Efstratiadis, A., Koukouvinos, A., Tsoukalas, I., & Kossieris, P. (2021). A flood inundation modeling approach for urban and rural areas in lake and large-scale river basins. *Water (Switzerland)*, *13*(9). https://doi.org/10.3390/w13091264

Perera, D., Seidou, O., Agnihotri, J., Mehmood, H., & Rasmy, M. (2020). Challenges and Technical Advances in Flood Early Warning Systems (FEWSs). In *Flood Impact Mitigation and Resilience Enhancement*. IntechOpen. https://doi.org/10.5772/intechopen.93069

Sánchez-Quispe, S. T., Navarro-Farfán, M. del M., & García-Romero, L. (2021). Methodology for processing meteorological and hydrometric data at basin level. In *CIERMMI Women in Science T-XVI Engineering and Technology Handbooks*. https://doi.org/10.35429/H.2021.16.107.145

Sathya, A., Thampi, S. G., & Chithra, N. R. (2023). Development of a framework for sand auditing of the Chaliyar River basin, Kerala, India using HEC-HMS and HEC-RAS model coupling. *International Journal of River Basin Management*, *21*(1), 67–80. https://doi.org/10.1080/15715124.2021.1909604

Wright, D. B., Yu, G., & England, J. F. (2020). *Six Decades of Rainfall and Flood Frequency Analysis Using Stochastic Storm Transposition: Review, Progress, and Prospects*.

Yalcin, E. (2020). Assessing the impact of topography and land cover data resolutions on two-dimensional HEC-RAS hydrodynamic model simulations for urban flood hazard analysis. *Natural Hazards*, *101*(3), 995–1017. https://doi.org/10.1007/s11069-020-03906-z

Figure 1

River network of the city of Morelia

Own elaboration by means of QGIS 3.18.

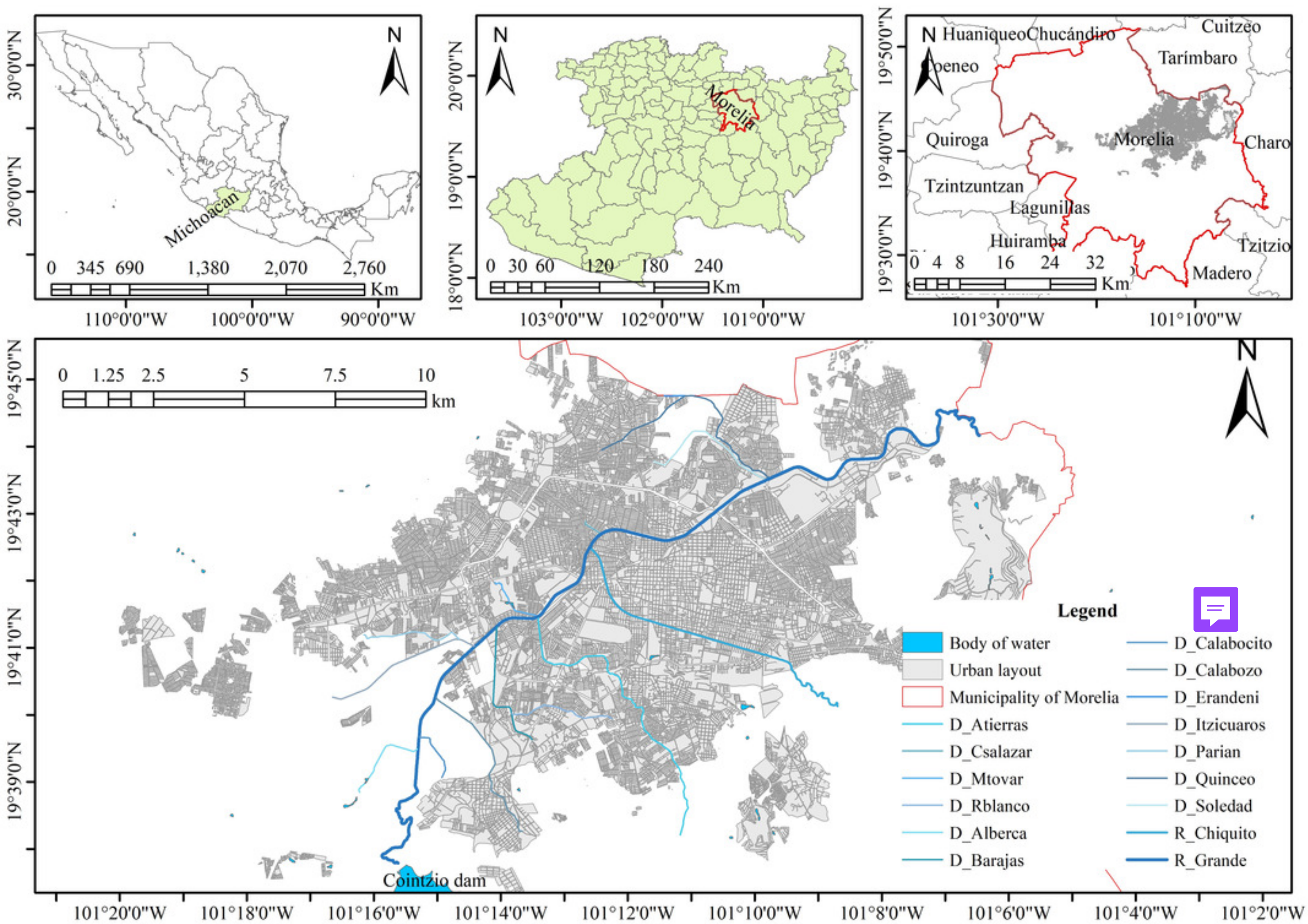


Figure 2

Proposed methodology

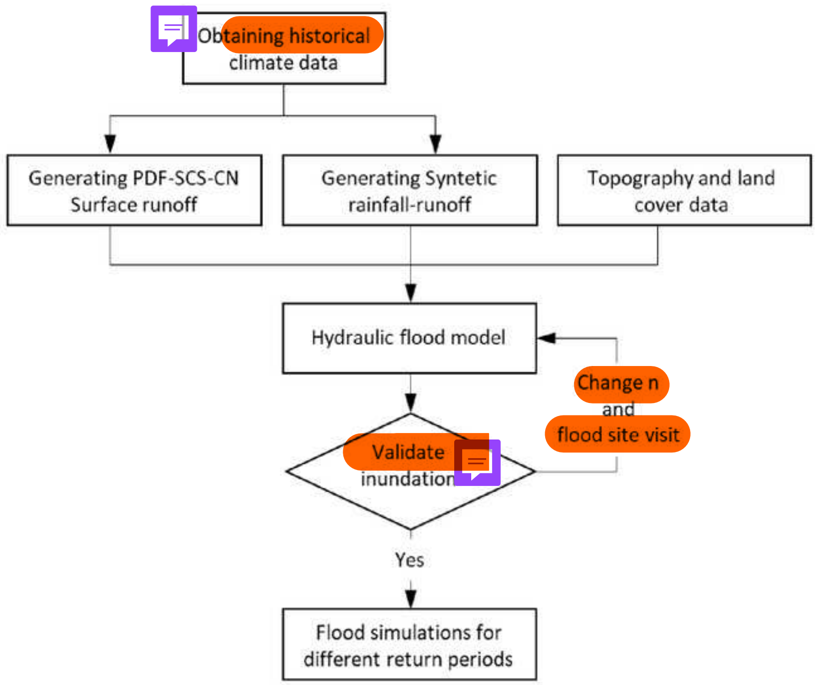

Obtaining historical
climate data
Generating PDF-SCS-CN
Surface runoff
Generating Syntetic
rainfall-runoff
Topography and land
cover data
Hydraulic flood model
Change n
and
flood site visit
Validate
inundation
Yes
Flood simulations for
different return periods

Figure 3

Boundary Conditions for the Hydraulic Model

Own elaboration by means of QGIS 3.18.

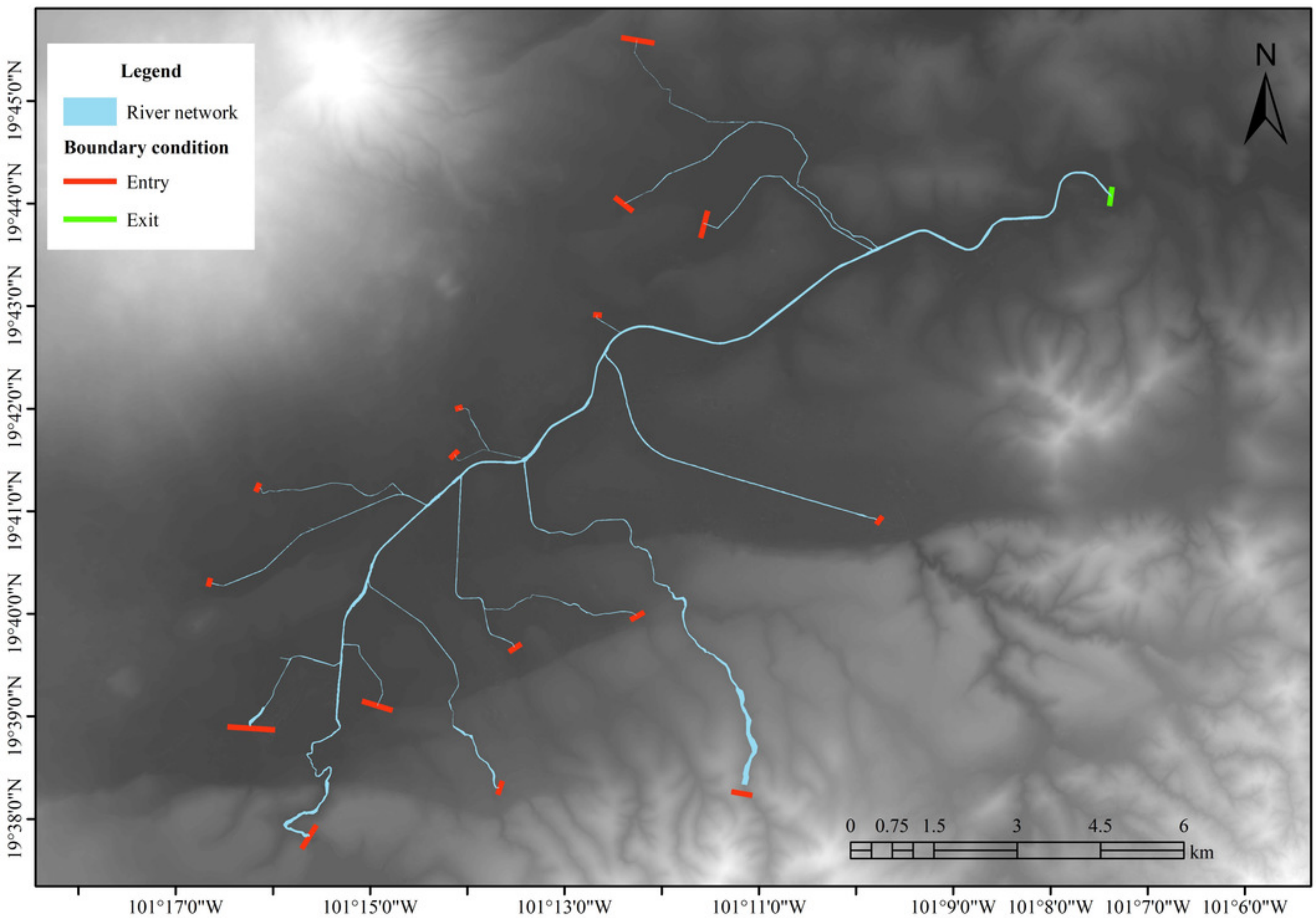


Figure 4

Peak runoff flows resulting from the precipitation events in the microbasins of the study, MASVC-SCS-CN, and PDF-SCS-CN generated in Hec-HMS. a) Itzicuaros drain, b) Quinceo drain, c) Chiquito river, and d) Arroyo de tierras drain

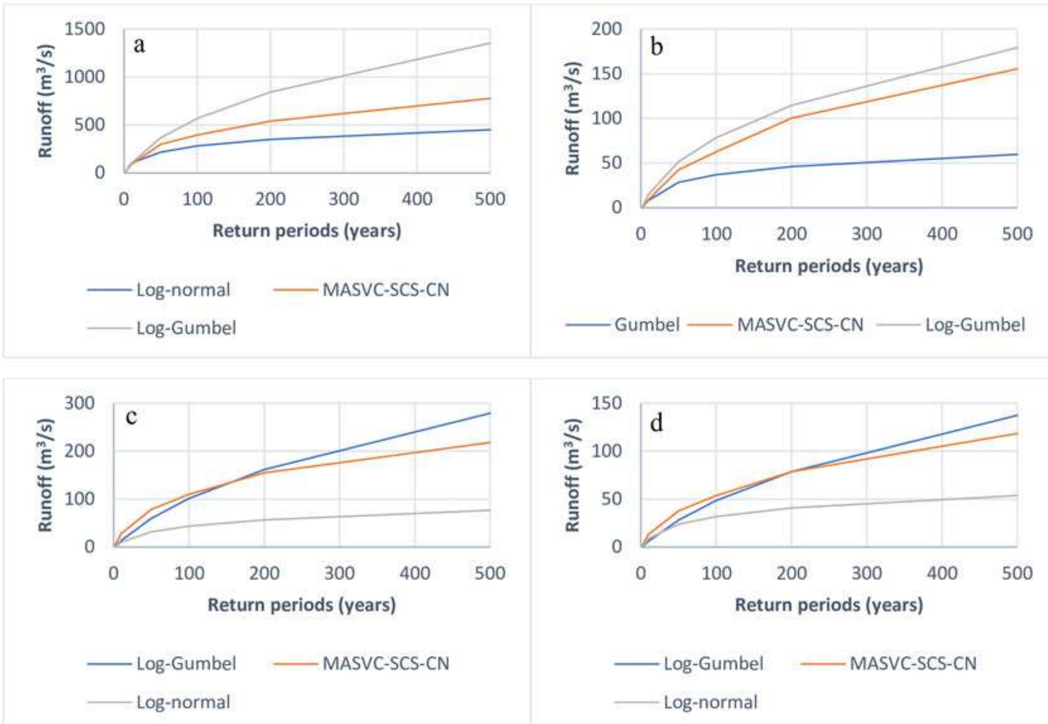

a
Runoff (m³/s)
1500
1000
500
0
0
100
200
300
400
500
Return periods (years)
Log-normal
MASVC-SCS-CN
Log-Gumbel
b
Runoff (m³/s)
200
150
100
50
0
0
100
200
300
400
500
Return periods (years)
Gumbel
MASVC-SCS-CN
Log-Gumbel
c
Runoff (m³/s)
300
200
100
0
0
100
200
300
400
500
Return periods (years)
Log-Gumbel
MASVC-SCS-CN
Log-normal
d
Runoff (m³/s)
150
100
50
0
0
100
200
300
400
500
Return periods (years)
Log-Gumbel
MASVC-SCS-CN
Log-normal

Figure 5

Manning's roughness coefficients per zone

Own elaboration by means of QGIS 3.18

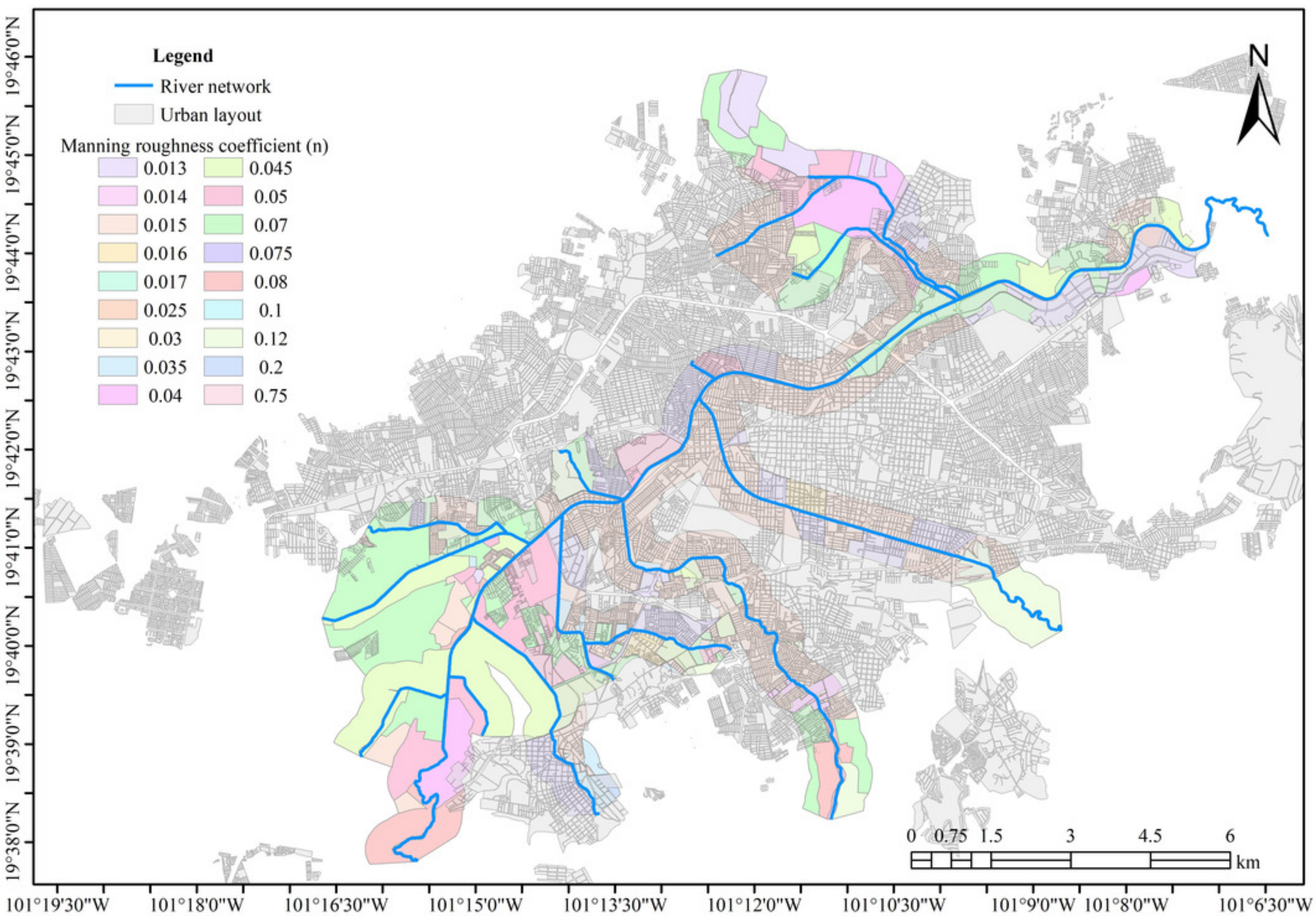


Figure 6

Natural floodplains of the river network

Own elaboration by means of QGIS 3.18

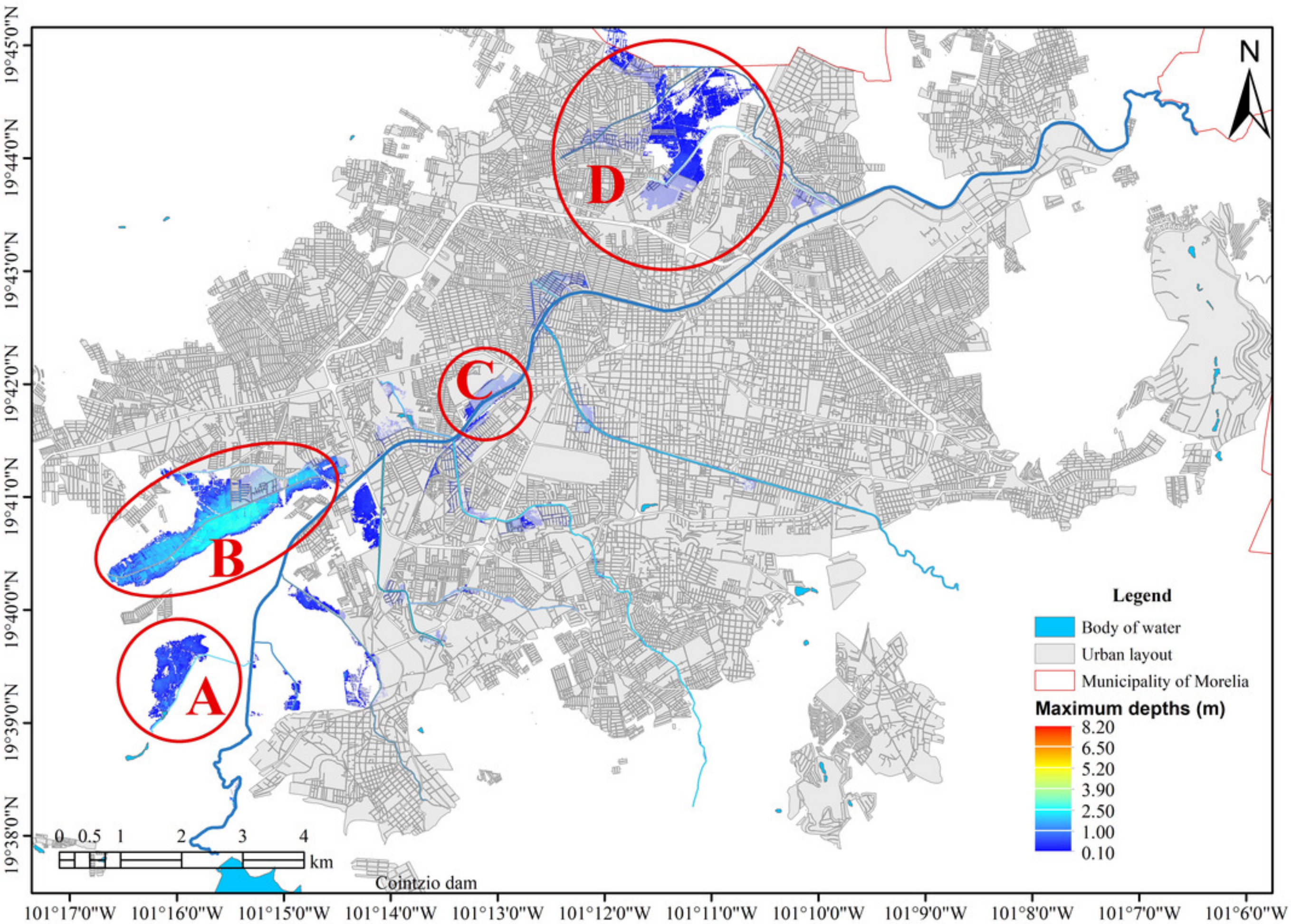
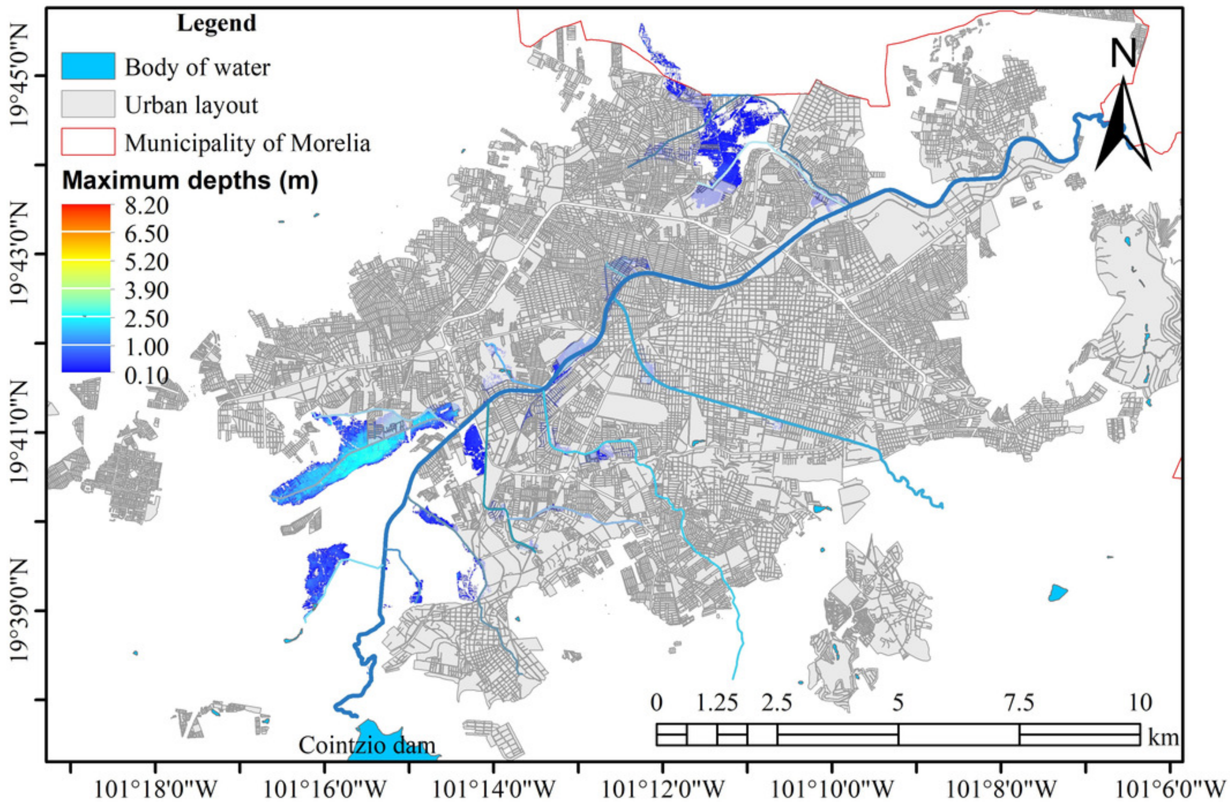


Figure 7

Hydraulic simulation for 100 and 200-year return periods, respectively, where flood zones are shown

Own elaboration by means of QGIS 3.18


Legend
Body of water
Urban layout
Municipality of Morelia
Maximum depths (m)
8.20
6.50
5.20
3.90
2.50
1.00
0.10
N
0 1.25 2.5 5 7.5 10
km
Cointzio dam
19°45'0"N
19°43'0"N
19°41'0"N
19°39'0"N
101°18'0"W
101°16'0"W
101°14'0"W
101°12'0"W
101°10'0"W
101°8'0"W
101°6'0"W

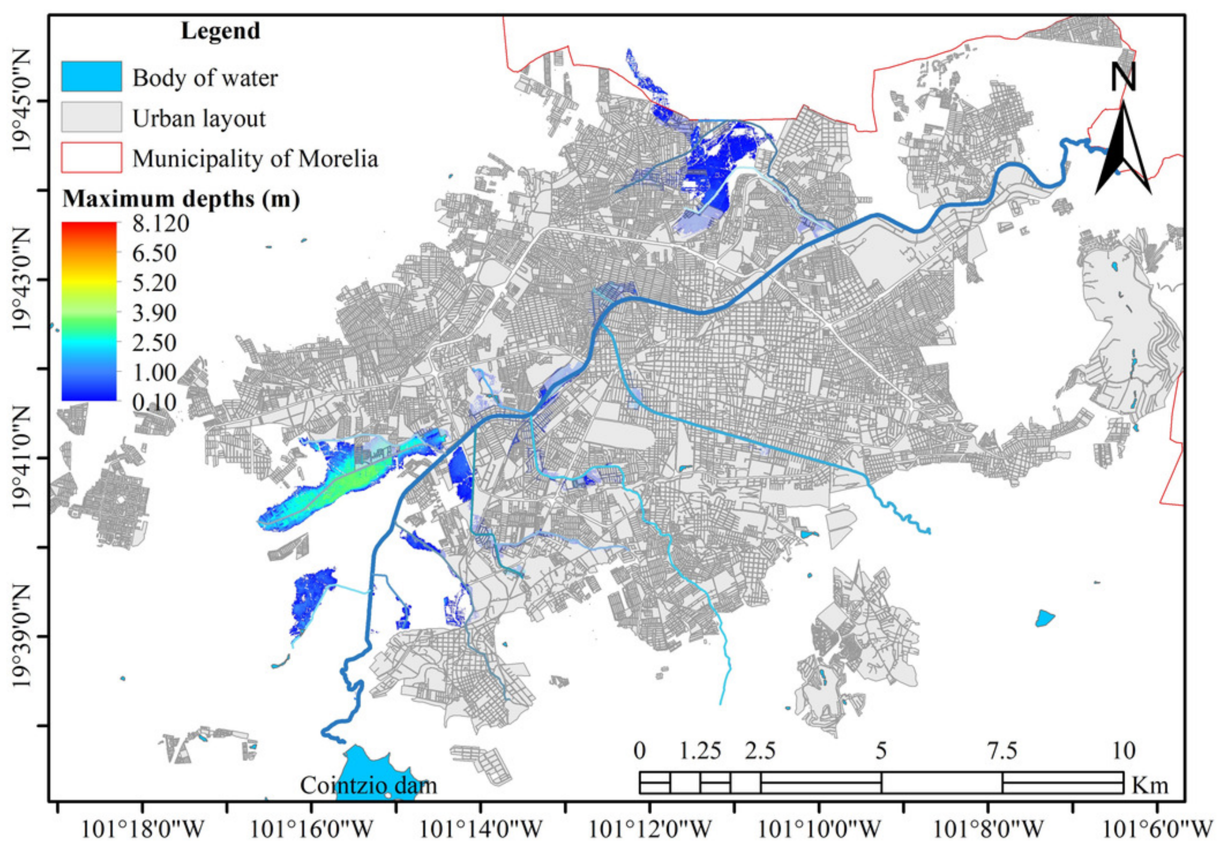

Legend
Body of water
Urban layout
Municipality of Morelia
Maximum depths (m)
8.120
6.50
5.20
3.90
2.50
1.00
0.10
N
0 1.25 2.5 5 7.5 10
Km
Cointzio dam
19°45'0"N
19°43'0"N
19°41'0"N
19°39'0"N
101°18'0"W
101°16'0"W
101°14'0"W
101°12'0"W
101°10'0"W
101°8'0"W
101°6'0"W

Table 1(on next page)

River Network of the city of Morelia

River Network of the City of Morelia				
Name	ID	Channel length (km)	Total ΔH (m)	Average S (%)
R. Grande	01	29.35	12.144	0.04
Alberca	02	2.41	4.34	0.18
Calabocito	03	1.53	2.63	0.17
Calabozo	04	4.90	106.74	2.18
Itzícuaros	05	4.40	0.62	0.01
Parían	06	2.90	12.01	0.41
Barajas	07	3.78	10.35	0.27
Arroyo Blanco	08	2.96	37.69	1.27
Arroyo de Tierras	09	9.09	246.12	2.71
Mora Tovar	10	1.69	8.46	0.50
Río Chiquito	11	9.24	104.11	1.13
Carlos Salazar	12	0.57	17.54	3.06
Soledad	13	4.03	1.16	0.03
Quinceo	14	6.60	9.00	0.14
Erandeni	15	3.52	62.16	1.77

Table 2(on next page)

Maximum Depth level reached in flooding areas

Method	Tr	Average maximum depth (m)			
		a	b	c	d
Distribution f.	2	0.35	0.32		
Stochastic		0.37	0.32		
Distribution f.	10	0.43	0.95		0.18
Stochastic		0.38	0.85	0.21	0.19
Distribution f.	50	0.56	1.37	0.69	0.23
Stochastic		0.57	1.69	0.74	0.29
Distribution f.	100	0.65	1.62	0.73	0.29
Stochastic		0.68	2.01	0.91	0.38
Distribution f.	200	0.77	2.02	1.15	0.35
Stochastic		0.68	2.01	0.91	0.38
Distribution f.	500	1.06	2.18	1.76	0.42
Stochastic		1.53	2.78	2.11	0.64