Can We Model Floodplain Inundation Patterns in Data-Scarce Areas?

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ABSTRACT

This paper proposes a methodology to model floodplain inundation patterns in data-scarce areas by using global remote sensing data. In particular, MODIS data are used for hydraulic model (HEC-RAS) calibration and validation purposes which is coupled with Geographic Information System (GIS) to map flood extent areas, while NASA's SRTM is used to describe floodplain topography. The Fogera floodplain (the upper Blue Nile in Ethiopia) is used as an example application to illustrate the methodology. To this end, parameter and input uncertainty is explicitly taken into account and visualized via probabilistic floodplain maps of the ensemble simulation. In view of that, model performance, reliability, and predictive uncertainties are critically discussed. This approach revealed that a better characterization and visualization of the flood hazard. Also, the study investigates the impact of land-use changes on floodplain inundation patterns using a SWAT modeling system and the propagation of this land-use change in flood inundation patterns is seen again via probabilistic flood maps. This helps planners to use remote sensing data to model and monitor flooding.

Keywords: Floodplain modeling, , Flood hazard, HEC-RAS, Remote sensing; SWAT, Uncertainty.

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1. INTRODUCTION

Flooding is a usual process, which may lead to disastrous consequences if it overlaps with the occurrence of a susceptible object (Hiben Mehari G and G. Tesfa-Alem). Nowadays, this situation is happening often in Africa at an alarming rate and noticeably causing flood-related fatalities as well as economic losses as reported by Padi, *et al.*, (2011). Indeed consistent methods are needed to perform flood damage estimates to formulate an early warning system and all possible ways of living with the flood. However, no comprehensive data and guides are available to deal with the situation easily (Di Baldassarre and Uhlenbrook, 2012). For instance, a flood catastrophe may arise when human settlements accord with extreme rainfall events, an upswing of water stages, or dam breaks (Hiben Mehari G and G. Tesfa-Alem). Thus, the occurrence and severity of flood disasters depend mainly on the topography, climate, rainfall distribution, watershed, economy, and land use of a certain region (Bronstert, 2003;Douben, 2006;De Wrachien,*et al*., 2011). According to Barredo (2007) and Di Baldassarre and Uhlenbrook (2012) the significance of floods is self-evident that flood disasters account for about a third of all-natural disasters in terms of their number and associated economic losses. In Ethiopia, nonstop land use/cover changes endorsing flooding have been allied with the absence of proper land use planning, poverty and unmanageable land use management (Moges,*et al.*, 2010).

This study aims at assessing the significance of remote sensing data at supporting our ability to deal with the extreme consequences of recent catastrophic flood events in Ethiopia and future research agenda that have highlighted that flood risk prevention still needs to be improved to reduce human losses and economic damages caused by flood disasters. These studies proved that, hydrologic and hydraulic models are powerful tools for supporting flood risk management and lowland development. Floodplain mapping, in particular, is a focus of many researchers and practitioners, and it is a successful measure to prevent new human settlements in flood-prone areas and raise the awareness of living with floods (Cuny, 1991;Venkatachary, *et al*., 2001). However, it is becoming difficult to develop hydraulic models and produce flood risk/ mitigation planning maps due to the unavailability of hydrological and topographical data. According to Tarekegn, *et al.*(2010) on the same study area of this research there was a critical discussion on how to improve the Digital Abbreviations should be defined in parentheses the first time Elevation Model (DEM) uncertainty from freely available remote sensing data that was obtained from ASTER product. However, still the discussion had concerns about the newly introduced uncertainties associated with the correction of the DEM. These were the reconstruction of the river terrains and the integration of the results into the raster DEM using the Inverse Distance Weighting (IDW) interpolation technique. In addition to this, the study reported that the simulated area of the flood extent couldn't capture the area of flood extent obtained from the 2006 MODIS product (Fig.1) for different reasons. This posed different questions. One might be argue that MODIS images have high errors caused by large-scale wetting of the land surface by direct rain (Tarekegn, *et al.*, 2010). And other may say the contribution of the ungauged flows is uncertain as reported by Wale, *et al*. (2009). The study indicated that the detailed assessment of effects of ungauged catchments requires installing of additional stream gauges in the area, and alternatively observed stream flows can be extrapolated to ungauged catchments using a regionalization theory. Also, some other papers studying on this area (Merwade, *et al.*, 2008) state that the effects of high water levels of Lake Tana are observed up to a distance of 13 km upstream from the lake what indicates that back-waters effects from Lake Tana play a role in the flooding patterns. Therefore, these techniques might be improved by introducing a probabilistic approach to compensate for the uncertainties coming from different sources of uncertainty. To this end, this research deals with the hydrological and hydraulic modeling of the Fogera floodplain system in Ethiopia, with a focus on the usefulness of the current growth in availability of globally and freely available remote sensing data for the production of probabilistic floodplain maps under different sources of uncertainty. In particular, parameter and input uncertainty is explicitly taken into account, as it is well known that hydraulic models are affected by different significant sources of uncertainty (Merwade, *et al*., 2008;Di Baldassarre, *et al*., 2009; Tarekegn,*et al*., 2010). Therefore, this study deals with an uncertainty-based approach to produce probabilistic floodplain maps of data-scarce areas as an example application in the upper Blue Nile (Ethiopia). Therefore, this case study is considered as a more adequate approach to visualize flood hazards via probabilistic flood maps. Furthermore, the study also aims at coupling the hydrological and hydraulic models by performing scenarios of land-use change in the hydrological model and sees its effect via a probabilistic map from hydraulic models. This is also directly related to the adaptation to land-use change and be able to see how the system behaves under these different adaptation options.

Finally, yet importantly, this paper describes and compares the merits and demerits of the deterministic and probabilistic approaches for the floodplain mapping techniques and evaluation process. Accordingly, the research is in favor of the probabilistic approach as one can't be sure of the system behavior and what's going on in the process.

2. MATERIALS AND METHODS

2.1. Study Area

The study was performed in the Blue Nile sub-basin (a major source of the Nile River) around Lake Tana (Fig.1). The major rivers draining to the lake are Gilgel-Abay, Magech, Ribb, and Gumera. The Gilgel-Abay flows in the north direction to the lake, the Magech flows to the south through the floodplains of Dembya, and the Ribb and the Gumera flow through the Fogera floodplains. The test site is the Fogera floodplain on 29 and 35 km of the Ribb and Gumara rivers respectively. For this test site, NASA's SRTM topography and airborne imagery of the Dartmouth Flood Observatory (DFO) are used. DFO provides a MODIS image for the 2006 prolonged flood event experienced in the area (Fig.1) and this image is used for the model calibration and validation process. It is vital to note that this flooded area (Fig. 1) cannot be well-thought-out error-free. For example, Schumann, *et al.*, (2009) analyzed the uncertainty of flood extent maps derived from satellite imagery and proved the necessitate to shift from deterministic binary (wet/dry) maps to probabilistic inundation maps. Thus, this paper aims to argue and analyze the main source of observation uncertainty to perform a possible paradigm shift to represent the flooding extent maps in data scares areas.

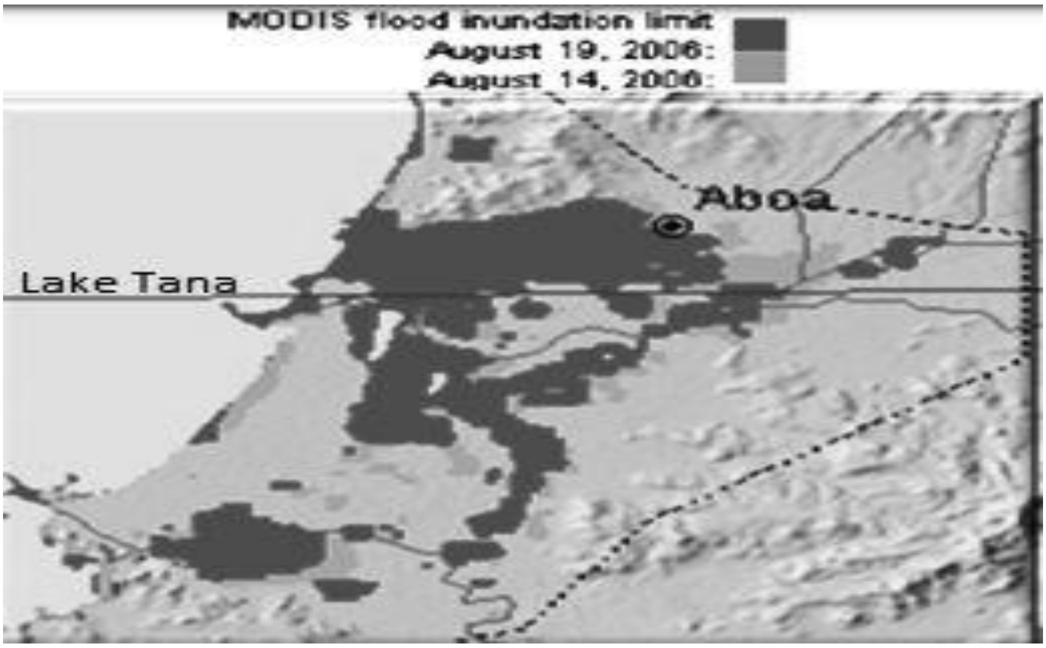

Figure 1: The Fogera floodplains from MODIS satellite imagery 2006 [Source: http://www.dartmouth.edu/~floods/2006174 Nile.html]

3. DATA USED

3.1. Flood inundation modeling

This study uses, HEC-RAS a one-dimensional hydraulic model which is capable of simulating the water surface profile of steady and unsteady flow in natural and artificial channels that solves De Saint-Venant equations with an algorithm based on the Preissmann implicit four-point finite scheme (Preissmann, 1961). The selection of 1D or 2D model depends on the purpose of the study and the dimension of the model. A 2D model that solves other complex equations will bring about more data and parameter uncertainties. It is vital to eliminate various sources of uncertainties if the research purpose is to assess the applicability of SRTM DTM to support global flood mapping. Furthermore, a 1D model is far more efficient than a 2D model when computation time is a key issue, particularly for large-scale models. While applied to waterway floodplains where 1D flow is Principal, HEC-RAS can produce results with a level of accuracy analogous to 2D models (M. S. Horritt and Bates, 2002). HEC-RAS is capable of making, in the same way, good predictions of the inundated area as 2D model, whether calibrated against hydrometric data or flood extent of another event, compared with LISFLOOD-FP (a raster-based inundation model) and TELEMAC-2D (a distributed model solves 2D shallow water equations of free surface flow) (M. S. Horritt and Bates, 2002). In the same way, simulation of steady-state has fewer uncertainties of input data than unsteady state simulation. In view of the fact that steady-state only regard as one value of peak discharge at the upstream boundary. It will symbolize the magnitude of this flood event and at the same time reduce uncertainties brought by the time series of unsteady state. For that reason, this study simulates the steady flow state using a 1D HEC-RAS model.

3.2. Model Calibration (2006 Flood)

We need models to make qualitative and/or quantitative predictions. In this regard, model calibration plays a key role in building a model. In view of that in August 2006, the Ribb and Gumara Rivers experienced a significant flood event (Fig.1). The return period for such an event was estimated with an exceedance probability of 2 years from the flood frequency analyses. The model was calibrated by comparing the flood extent of each cross-section with the high water marks (from MODIS) in the aftermath of the August 2006 flood event (Fig.1). Different sets of Manning's n values are tested to get the best fit model. Given the homogeneous characteristics of the river reach, the potentially distributed Manning's n value was limited to one value for the channel and one for the floodplain (Di Baldassarre, *et al*., 2009). These values are ranged from 0.02 to 0.06 with an interval of 0.01 for the channel, and from 0.06 to 0.16 with an interval of 0.02 for the floodplain. Therefore, there are 35 different combinations of Manning's n values and 35 simulations were made to find the optimal combination of Manning's coefficient (Fig.2). Apparently, those unrealistic Manning's n sets of which the one on the main channel is larger than the one on floodplain would be eliminated. This is due to the consensus that the roughness of the riverbed is smaller than that of the floodplain since flow scours the riverbed almost all the time to make it smooth. Then, this makes the Manning's n on the channel to be smaller than floodplains.From the context of model performance as stated by Werner (2004) where one model is evaluated against another based on the objective function set for model evaluation. This is because of the uncertainty approach where there are different model results and are evaluated based on a certain criterion known as the objective function. This can be set according to the purpose of the study. In this particular research mean absolute error (MAE) and Nash & Sutcliffe coefficient (Ns) are set as the evaluating criteria. In addition to this, performance is predominantly viewed from the concept of model reliability and this reliability can be articulated as the reciprocal to predictive uncertainty (Werner, 2004). The results indicate that the calibration of the roughness parameter which together with the geometry is considered to have the most important impact on predicting inundation extent, and flow characteristics. Manning's roughness coefficients for the Gumara and Ribb rivers (Fogera floodplain) cannot be measured explicitly and must be determined through calibration. The idea of parameter uncertainty analysis estimation method (Fig.2) is involved in this study in the quantification of the uncertain parameters and their propagation throughout the model in predictions of the inundation patterns. Therefore, calibrating Manning coefficient model packages focus basically on improving the performance of the model. One may pose a question about how this work could be successful, but the answer is simple and tricky because the overall importance and meaning of calibration are to match up the model result with the benchmark (in this case satellite imagery from MODIS) through all possible ways. In other words, calibration is the art of diplomacy between the model result and the benchmark by reducing all the possible sources of uncertainty associated with the model. Hence, in this case, study the idea of calibration of the Manning coefficient is done based on the principles and notions of improving the reliability of the model by reducing the uncertainties in the model using an expert judgment of all possibilities. Understanding of such uncertainty is very essential and update to improve flood forecasting, floodplain mapping, and in general flood management. The simulations of the hydraulic model are evaluated based on different sets of Manning coefficients and run accordingly. At each model run, the result is evaluated against the MODIS imagery of flood extent to meet the objective function to minimize the error and be able to produce a representative flood extent map by trying all the possible solution and this exhaustive search is done for the Ribb and Gumara rivers.

3.3. Model Validation (2006 Flood)

Model validation is an essential part of the model development. It ensures that the model meets its intended requirements in terms of the methods employed and the results obtained. The ultimate goal of model validation is to make the model useful in the sense that the model addresses the right problem, provides accurate information about the system being modeled, and makes the model actually used. In general, the process is akin to developing a legal case in which a preponderance of the evidence is compiled about why the model is a valid one for its purported use. Accordingly, satellite imagery has also been found for the same year of a flood event, on a different day on the 19^{th} of August 2006, from MODIS. This imagery is used for a model validation process. Consequently, the area of the flood event was digitized (Fig.5) to compare with the model result of the flood event on the 19^{th} of August 2006 using the same optimal parameter set used during the model calibration process. Therefore, this may increase the reliability of model prediction and revealed a good result with Nash & Sutcliffe coefficient (Ns) = 0.71 which was 0.76 during model calibration. Hence, this validation helps to a better understanding of the model's capabilities, limitations, and appropriateness for addressing a range of important questions as well as in the case of models that contain elements of human decision making, validation becomes a matter of establishing credibility in the model.

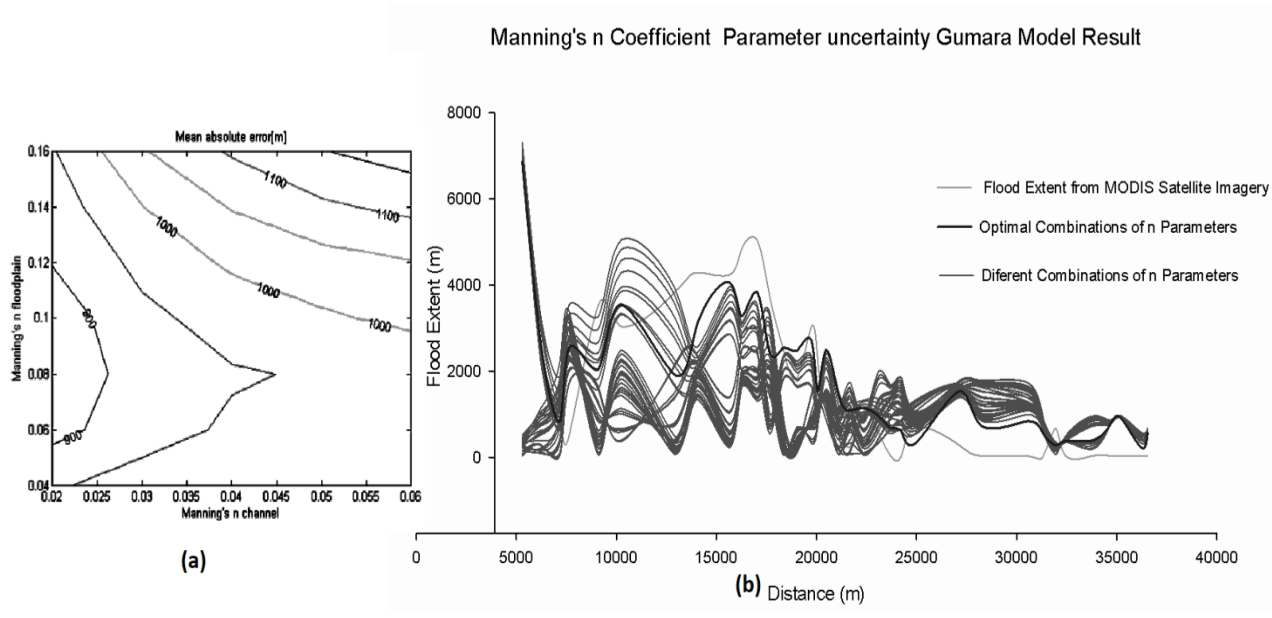

Figure 2: MAE of different combinations of Manning coefficient (a) and Parameter uncertainty of the model calibration process of the Gumara river (b*)*

4. MATERIALS AND METHODS

4.1. Deterministic floodplain mapping

The deterministic approach is the most commonly used method of assessing flood risk based on predicting the magnitude and extent of the 1- in 100-years or 200-years flood event. Though potentially very useful to engineers, this information can mislead planners and developers into assuming that areas outside these limits are risk-free and vice versa i.e. overestimating. This study presents an outline methodology and an operational framework for assessing floodplain mapping, and is analyzed and discussed by comparing deterministic and probabilistic approaches using hydrodynamic numerical solutions. In a deterministic approach, flood inundation maps show the flood extent without consideration of the inherent uncertainties associated with the modeling exercise. Where such information is lacking, inadequate, or simply ignored, and inappropriate development is allowed to take place within the floodplain, the consequences, sooner or later, are inevitable. Therefore, it is unknown how these uncertainties are transferred and propagated to the inundation map (Merwade, *et al.*, 2008). In this research, the deterministic approach is achieved by using the uncertain measured flow data. And this data is calibrated with different possible sets of Manning's n coefficient and finally took the model parameter with least MAE equal to 852m and highest Ns equal to 0.76. Fig.4a illustrates the application of deterministic floodplain mapping to the 1-in-100 year flood inundation map at the Gumara river. But how reliable are estimates of return periods for such events when records of peak discharge are generally of much shorter duration when the climatic regime may be changing, and when catchment plays in developing improved procedures for flood risk assessment to support the planning process? In general, the deterministic approach is based on the assumption that the model fully represents the physical behavior of the river. In this particular case study, the deterministic approach is overestimating the flood area as compared to the evaluation criteria of MODIS flood event of 2006 and it also represents one blackish (Fig.4a) color which is not informative to give an area of priorities and emphasis. From the point of view of optimal design of engineering solutions, it is not an appropriate or more certain way of model evaluation. And this evaluation is done based on the uncertain data measured from the ground which was calibrated and validated against the uncertain satellite imagery of MODIS 2006. Therefore, this approach lacks the certainty of the model either by over or underestimating the model result. Because basically the design of engineering solutions implies maximum utility with list cost. And this approach doesn't fit with this solution because of the highest uncertain data set in the area.

4.2. Probabilistic floodplain mapping

This section describes a comprehensive way of describing the inherent risks or problems from all possible sources in describing the physics in a system. In particular, this study is dealing with the uncertainty-based approach to represent the floodplain mapping to the 1-in-100 year flood event at the Ribb and Gumara rivers. To achieve this approach in describing the hydraulic behavior of river and flood dynamics, simplified models are typically favored, as they consent to a large number of simulation runs to entirely explore the whole parameter space. As in the case of this study, HEC-RAS model is used. In this study the ensemble simulation (Fig.3a) endeavors at evaluating and weighing the model performances when uncertainty is considered. And then the performance is weighed up by analyzing how inflow uncertainties propagate through the model. The basis for choosing inflow as the main source of uncertainty is that generally speaking, inflow is one of the most second important factors that affect hydraulic model results (Pappenberger, *et al.,* 2007). The first most important factor typically is the Manning's n on the channel and floodplain. In view of the fact that the influence of Manning's n on channel and floodplain has been analyzed during model calibration and model validation, the second most important factor inflow data uncertainty is considered here. Moreover, the design flood is very uncertain since it is evaluated based on the measured data by statistical methods. At the very beginning, there are uncertainties in the measured data due to low measuring instruments accuracy, careless surveyors, lack of education, not understanding of data importance, etc. Following, there are also uncertainties in the statistical methods. Taken as a whole, the design flood uncertainty will be augmented by the two sources of uncertainties mentioned above. The ensemble simulation is performed (Fig.4a) using the HEC-RAS model calibrated and validated against the 2006 flood event. Hence, a Monte Carlo Simulation sampling technique (Fig.4a) based on the generalized likelihood uncertainty estimation (GLUE) framework is chosen as a tool to analyze uncertainty. For that reason, 200 inflow discharges are generated according to a normal distribution (Fig.4a). The normal distribution with lower and upper bounds is assumed to present the variation of inflow discharge. They are calculated by ± 20% and these 200 single-value discharges were fed as the upstream boundary condition for a steady-state ensemble simulation. Other configurations of the original model which have been calibrated against the 2006 flood event have remained the same. For both the Ribb and the Gumara model, 200 water profiles are simulated. Among the 200 simulated results, the water profiles of the 5^{th} through 95^{th} percentile results will be chosen for further analyses of their water profile. The model gives results in each cross-section (Fig4a). These are the 200 values of flood extent which are the results of each simulation. These data sets are sorted from small to large and the first and last 5 values are eliminated. Thus, 90 values that represent 5% to 95% percentile are obtained where several parameter sets can turn out equally for good model predictions. The level of uncertainty in model predictions can also be controlled by rejecting poorer simulations (MS Horritt, 2006). The steps to produce the probabilistic maps that take account of the comprehensive nature of a system for proxy using HEC-RAS and GIS application are described below from 1 through 10.

1. Set all outputs of hydrological models of the flood event of 2006, Q_{100}, and scenarios under land-use change
2. Make a Monte Carlo simulation/sampling technique of each hydrological model result in step 1 (Fig.4b)
3. Feed the results of step 2 into the hydrodynamic model to make an ensemble simulation under input uncertainty.
4. Compare the flood extent result of step 3 with the satellite imagery and evaluate the model performance (M_p) of each simulation. (Fig.5)

$$M_p = \frac{MAE_{min}}{MAE}, if\ MAE = 0\ then\ M_p = 1 \quad (1)$$

Model performance

Where MAE $_{(min)}$ is the flooded area predicted by the model with the minimum mean absolute error, MAE is the predicted mean absolute error of each simulation; M_p is the model performance to give weights for each run. After a large number of runs, different Model performances are obtained and their corresponding flood maps are produced. Before these maps were combined, each map has to be assigned weights that represent the likelihood. This approach is based on the generalized likelihood uncertainty estimation (GLUE) framework (Aronica,*et al.*, 2002). This weight, L_i, ranged from 0 to1, is formulated by the equation below:

$$L_i = \left[\frac{M_{pi} - \min(M_{pi})}{max\ (M_{pi}) - min\ (M_{pi})}\right] \quad (2)$$

Model performance weight

5. Give weights for each simulation based on step 4 (Fig. 4b). This will be an attribute to give higher weight (L_i) to the best simulation/model performance of the ensemble simulation. Therefore, there

will not be an equal likelihood for the probabilistic map to be reproduced. After this, the weights are normalized (L_{in}) using the following formula.

$$L_{in} = \left[\frac{M_{pi} - \min(M_{pi})}{max\ (M_{pi}) - min\ (M_{pi})}\right] * \left[\frac{n}{\sum_{i=1}^{n} M_{pi}}\right] \quad (3)$$

Weight normalized

Where L_{in} is normalized weights, max (M_{pi}) and min (M_{pi}) are the maximum and a minimum measure of fit found throughout the ensemble and n is several simulations. It can be seen from the equation above that the bigger the measure of fit, which means the more accurate the prediction, the bigger the weight will be assigned to the simulation. After obtaining the weight for each simulation, the focus will be set on the flood situation for each cell, and the weighted average flood state for each cell will be made:

$$C_j = \frac{\sum_{i=1}^{n} L_{in} * W_{ij}}{\sum_{i=1}^{n} L_{in}} \quad (4)$$

Weighted average for each cell

Where C_j is an indication of weighted average flood state for j^{th} cell, W_{ij} is the flood situation for j^{th} cell in simulation i, which is $W_{ij} = 0$ for not been inundated and $W_{ij} = 1$ for been inundated. And C_j is ranged from 0 to 1, which represents the likelihood of flood state of a particular cell for a typical flood event.

6. Produce an inundation map for each ensemble simulation
7. Reclassify the inundation maps in step 6
8. Multiply each reclassified maps by their corresponding weight (L_{in})
9. Sum up all the maps in step 8
10. Finally stretch all the summed up maps between 0 through 100 to make a probabilistic map of that particular event (Fig.5b).
11. Repeat steps 1 through 10 to reproduce probabilistic maps of different land-use scenarios.

The white grids present places which are least probable (dry) in this flood event, whereas black grids show places that have a high probability to be inundated (up to 100%). The more blackish the color the higher probability a grid will be inundated as shown in Fig. 5b.

5. RESULTS AND DISCUSSION

In this particular study, the probabilistic approach gave a smaller area of inundation. This is basically because of the weights introduced for each 200 number of ensemble simulations used to illustrate the applicability of the probabilistic approach in improving the model performance by reducing the uncertainties and be able to produce 200 deterministic inundation maps of the 200 runs. After this, the 200 maps are multiplied by their corresponding weights, in this case, those poorer simulations with the weight equal to zero according to the formulas for model performance in this study are discarded. And other poorer simulations get lesser weights. Accordingly, they get less inundation area. Therefore, these inundation areas are based on the objective function set to evaluate model performance. As you can see in the flooded area of the two maps (fig5), you see the area which was fully inundated in the case of deterministic which was not observed from satellite imagery was discarded during the probabilistic approach. In general, the finding of this study is to show those areas which are highly probable to be flooded get blackish and vice versa. Then, the area of inundation of probabilistic approach to be higher or lesser than the deterministic depends on the model performance. In this case study, it looks to be lesser but still the whitish color might also be inundated but with less probability so, this tells which area should be more prioritized. Therefore, this approach is quite convincing from the point of view of engineering solutions in minimizing risk and cost-effectiveness.

5.1. Land use change scenarios

Different factors affect runoff generation. One is the meteorological factor such as, rainfall intensity, rainfall amount, rainfall duration, and distribution over the drainage basin, the direction of storm movement, and secondly, are climatic conditions that affect evapotranspiration such as temperature, wind, relative humidity, and so on. Thirdly is the physical characteristics that affect the runoff generation, based on vegetation cover, soil type, drainage area, basin shape, elevation, topography, drainage network patterns, ponds, lakes, reservoirs, sinks, in the basin which prevent or delay runoff from continuing downstream. In addition to this, human activities can also greatly contribute to the runoff generation as part of land-use change. As the number of human inhabitant increases the interventions also increase, and as more development and urbanization occurs, most of the natural landscape is replaced by impervious surfaces such as houses, roads that reduce infiltration into the ground and accelerate runoff to the ditches and streams. Accordingly, the following different scenarios of land-use change are developed to see the effect of land-use change in the study area

(Table 1). This study also aims at reproducing the probabilistic inundation maps under land-use change. These are the flow results under adaptation to the environment for Q_{100} via the SWAT modeling system. To this end, a Monte Carlo sampling technique is used to sample 200 normal distributed values ±20% peak flow of each scenario. This is the same as the technique used before the Land-use update (LUP). And these all are set as an upstream boundary condition to perform simulations under different adaptation options. The following Table1 shows the targets set for each scenario as well as the result of model simulation under adaptation to the environment or land-use change. Figure 3 below shows sample flow results under the adaptation option of scenario B of the Gumara River. As Figure 3 shows the expansion of dry land in the basin that takes place according to scenario B resulted in substantial increases in the mean monthly discharge of around 40% for wet months while during the summer discharge decreased up to 35%.This adaptation option possibly to happen if the likelihood of land-use change is happening in the area. Therefore, this land-use change can be also tuned for further study to any other options or proposals of governmental bodies.

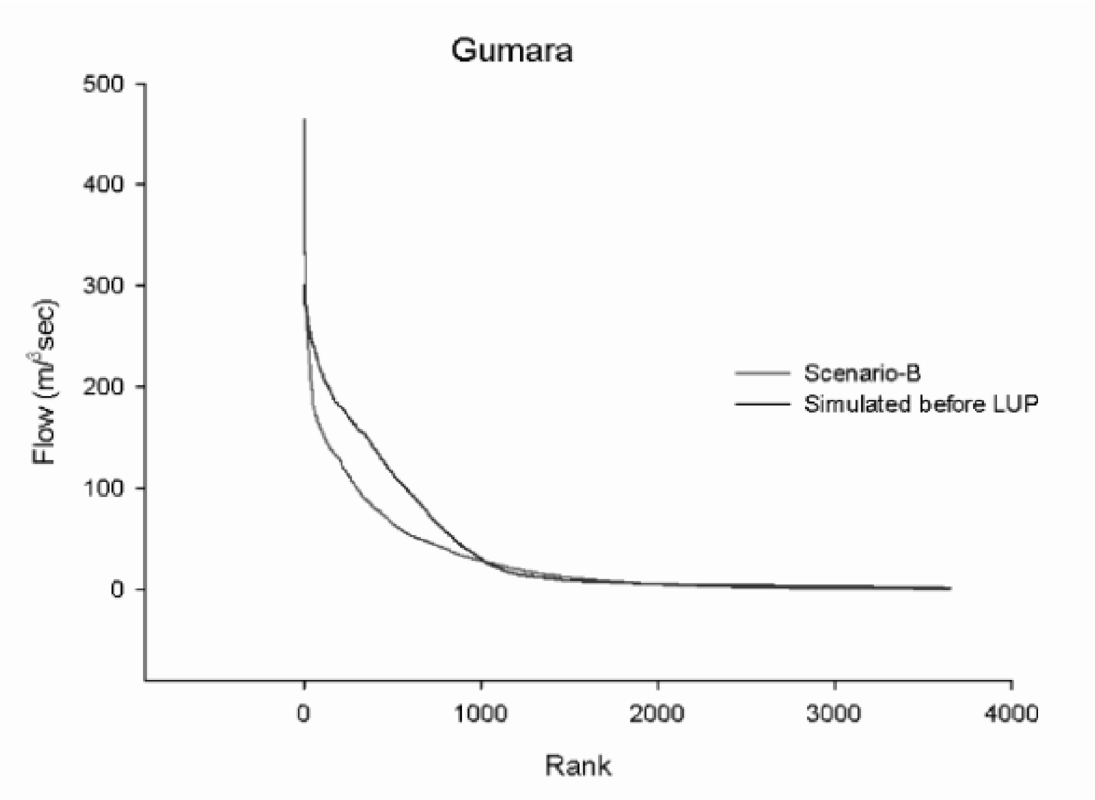

Figure 3: Extremes ranking independently

Tabel-1 Land use change evaluation criteria and scenario result

Percentage of Area Change for Every Land Use%		scenarios results					
Scenarios	Description	Ribb river			Gumara river		
		Q_{100} before LUP	Q_{100} Peaking factor	Q_{100} after LUP	Q_{100} before LUP	Q_{100} Peaking factor	Q_{100} after LUP
A	Expansion of agricultural land by 20%	305	1.8	555	574	1.3	746
B	Expansion of dry land by 20%	305	1.6	488	574	1.2	689
C	Expansion of urban land by 20%	305	2.4	730	574	1.9	1090

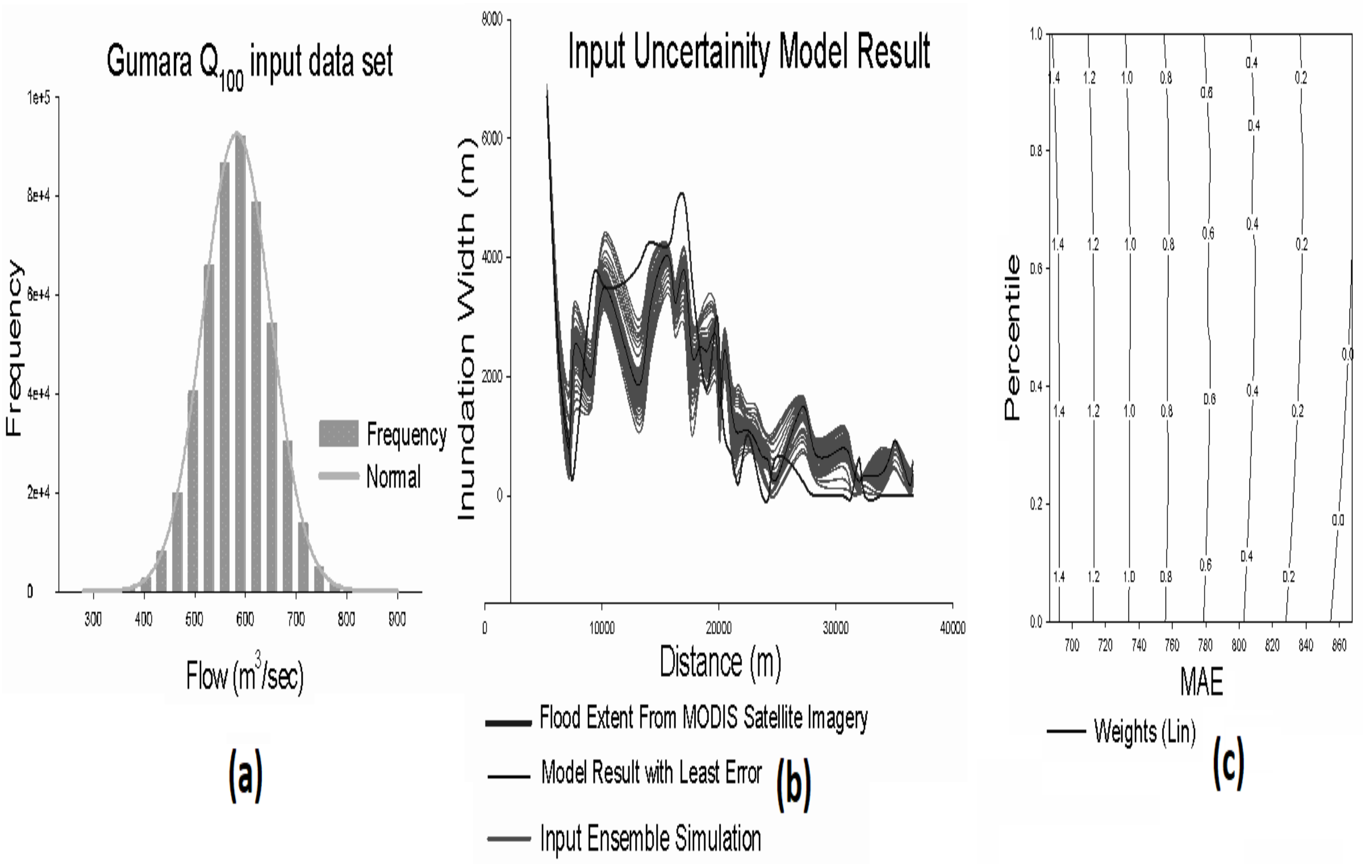

Figure 4: the normalized weights according to the model performance (c) of the ensemble simulation of the normal distribution of flow uncertainties (b) so as to produce the probabilistic map of the study area that enables to capture the uncertainties associated with the input data (a)

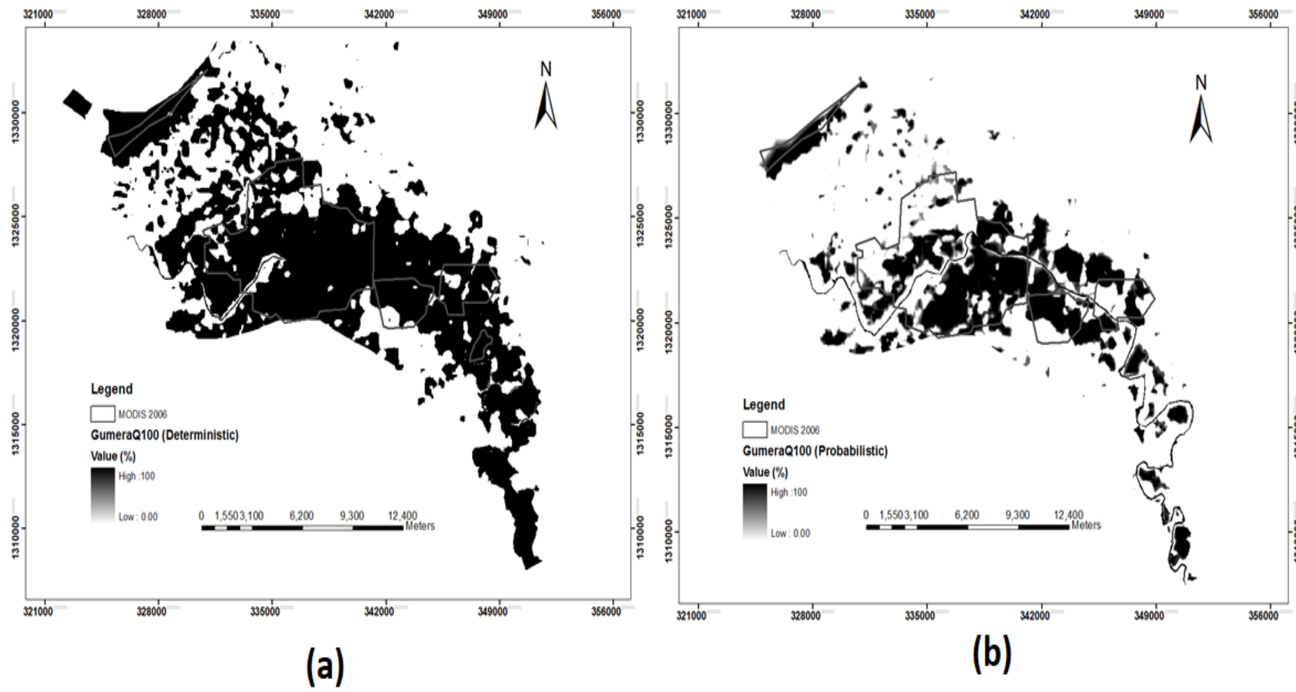

Figure 5: Comparisons of the deterministic (a) and probabilistic (b) floodplain maps of Q_{100} of the Gumara River

Application of the complementary procedures for floodplain mapping to the same test site enables a decisive dialogue about the merits and demerits of deterministic and probabilistic approaches to deriving flood extent maps. Hypothetically visualizing flood hazard in a probabilistic base is more apt than deterministic, since deterministic predictions of inundation extents and design floods, which use the solitary unsurpassed fit model and best estimate peak discharge, might misrepresent the uncertainty and reduce the reliability in the modeling process and give a spuriously accurate result (K.J. Beven and Freer, 2001; Bates, 2004; K. Beven, 2006). Basically, the idea of a deterministic approach is according to the analogous once the hydraulic model is calibrated and/or validated using historical data, then it can produce a correct flood map of different magnitude. However, this consensus is very questionable. In actuality, quite a lot of studies such as (Aronica, *et al.*, 1998; M. S. Horritt and Bates, 2002;Romanowicz and Beven, 2003; M. S. Horritt, *et a*l., 2007; Di Baldassarre, *et al.*, 2009b) have shown that flood inundation models are not necessarily much up with their objectives to give good predictions when they are evaluated against flood events different from those used in a calibration process. Therefore, a flood inundation model, calibrated on a historical event, may give a poor forecast of a synthetic design event. In contrast, probabilistic approaches have a high possibility to give a better forecast, as they assume the use of multiple behavioral models in the forecast, rather than a single best-fit model (Bates, 2004; Stephens, *et al.*, 2012)(Fig.5). This work has limitations for not using flood marks ground data which is not common in Ethiopia. So, if such data are used a better result will be expected. And, such an approach is recommended for further studies.

6. CONCLUSIONS

Flooding is a serious issue in the study area where it happens almost every year. The current climate and land-use changes seem to have also played some role in the frequency of flooding in the area. One of the main tasks of this study was to evaluate how important/useful are the globally and freely available remote sensing data (SRTM, MODIS) in developing countries. The application of SRTM DTM with HEC-RAS, HEC-GeoRAS, and GIS for producing a probabilistic map was found to be a good and time-saving technique for the reason that simulations in HEC-RAS is very fast and the overall MAE is decreased from 852m of deterministic to 702m and Ns from 0.76 to 0.86 of the probabilistic approach. This is because the weights given to each simulation under uncertainty of input data set (Fig.5). Thus, it discarded those poorer simulations of their performance. This can be visualized from Fig.5. Furthermore, this approach has significant relevance in giving information for decision makers to give more emphasis and priorities for highly susceptible areas of flooding. This is because of the uncertainty-based approach of weighting each simulation.

Furthermore, this study also indicated that seasonality (wet and dry seasons), special distributions of rainfall, and soil and land cover heterogeneity are a source of errors in hydrological models. Therefore, this analogous may lead to the significance of developing a seasonal parameterization technique of model building. Thus, each simulation of the year is divided into two and then two parameter sets are obtained for each dry and wet period.

After the development of a well-calibrated SWAT model which produced a reasonably good performance (Ns up to 0.75) taking into account the concept of the distributed model during the simulation period. To this end, a new land-use update was performed. The new module introduced in SWAT 2009 achieved this new land use update. While doing this, the percentage difference of the discharge response before and after the land use update of the specific date was assumed as the percentage increase or decrease of the flood frequency analyses. Therefore, if the current land use is changed to the new updated one then the discharge of Q_{100} of the flood frequency is multiplied by a factor (found by comparing simulations before and after land-use change) and these reproduces a new Q_{100} for that specific land use (scenario) and see its effect via floodplain maps.

In general, flood risk mitigation is vital in developing countries. In the case of Ethiopia, reducing flood risk is dependent upon alleviating poverty, and vice versa. Lack of food reduces human beings' competence to cope with disasters, stresses, and shocks. In addition to this, it means that unnecessary costs are not invested in areas with less probability of flood exceedance and vice versa. Hence, this research will contribute to the efforts being undertaken in the country for achieving the disaster prevention and protection policy of the government in Ethiopia and as a tool for the developing countries with data-scarce environment.

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