Columbia Water Center
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Climate Informed Global Flood Risk Assessment

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Executive Summary

Floods associated with severe storms are a significant source of risk for property, life and supply chains. Regional flood risk changes over time due to changes in land use, flood mitigation, infrastructure development, and climatic factors. **Global assessments of flood risk are challenging since they need to account for changing local and global factors, and due to limited high-resolution data on key causal factors**. Traditional approaches to flood risk assessment are typically indexed to an instantaneous peak flow event at a specific recording gage on a river, and then extrapolated through hydraulic modeling of that peak flow to the potential area that is likely to be inundated. However, **property losses tend to be determined as much by the *duration* of flooding as by the depth and velocity of inundation**. The existing notion of a flood return period based on just the instantaneous peak flow rate at a stream gage consequently needs to be revisited, especially for floods due to persistent rainfall (>30-day duration) as seen in Thailand, Pakistan, the Ohio and the Mississippi Rivers, France, and Germany in the last decade. Such floods may relate to slowly changing climate conditions, especially in the tropical oceans, e.g., related to the El Nino Southern Oscillation (ENSO) and the Madden-Julian Oscillation (MJO).

Quantifying how the flood risk in a region changes over time in response to climate conditions can improve risk characterization, insurance pricing and actuarial management.

This white paper summarizes some of the work from the Columbia Global Flood Initiative. Innovative statistical methods for local and global flood risk estimation through the integration of key topography, climate data and spatial concordance were developed to provide a robust platform for the best possible risk estimates for actuarial and portfolio analysis. The Columbia Global Flood Tool consists of two technological innovations that can be adopted both in data abundant locations and in data sparse locations for assessing the flood potential and developing the regional risk estimates, as well as their evolution in time. A Hierarchical Bayesian Methodology is developed for multi-site estimation of flood risk under both stationary and non-stationary assumptions. This model can be used directly with streamflow in data abundant regions. Parallel to this model, we have developed a framework that embeds several statistical and physical modeling techniques from rainfall to runoff to estimate the flood risk in a region. This framework can be used in data sparse regions through globally available climate data. We have demonstrated the application of this Tool for a suite of 6 regions across the world where recent mega-floods have led to concerns, as part of a project with AIG.

Grand Challenges

Recent mega-floods in Thailand, Pakistan, Queensland, the Midwestern US, India, China and Europe have led to heightened interest in risk assessment for floods. In some cases, such as Thailand and the Mississippi River, the efficacy of the flood control projects and their operation was called into question. Areas that were not previously considered a major risk had industrial infrastructure inundated by flooding, leading to substantial global supply chain effects in addition to direct loss of use of assets[1]. It is interesting to note that several of these floods were associated with multiple, recurrent events that led to flooding durations of 30 to 170 days. The 2011 Thailand flood was "rated" as a 30-year event based on the peak flow, but the sequence of tropical cyclones and rainfall events over the 116 days of flooding appears to be unprecedented. The risk of such events has not been formally considered in past analyses. ***A lesson that emerges is that flood risk analysis may need to consider the risk of different types of floods, rather than just be indexed to the instantaneous peak flow in a river, associated with a single extreme rainfall event.***

Meteorologists have considered intensity-duration-frequency (IDF) curves for extreme rainfall in a region for different durations. Typically storm durations from 1 hour to 72 hours are considered, and the rainfall totals associated with each duration for specified return periods are estimated. Hydrologists and transportation system managers often use the IDF curves together with assumptions as to antecedent soil moisture conditions (AMC) from prior rainfall in a watershed to assess or update flood risk from an event. Moreover, this approach assumes a stationary climate and typically a single curve interpolated from rain gauges in the area is applied for the catchment. The extreme events are assumed to be time and space independent. ***There is little to no literature on how to estimate and link the probability of persistent rainfall over 30 to 120 days that leads to high AMC in the region, their spatial dependence structure, and the probability of an extreme rainfall event over a few days, as a basis for projecting the risk of mega-floods in a region.***

It is now understood that the events related to persistent and recurrent rainfall (e.g., due to repeated waves of tropical moisture every 5 to 7 days in the Ohio river basin in 2011, or due to repeated tropical cyclones and rainfall in Thailand and Queensland in 2011), appear to correspond to the persistence of specific global climate patterns, that may be identifiable from

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[1] Haraguchi, M., & Lall, U. (2015). Flood risks and impacts: A case study of Thailand's floods in 2011 and research questions for supply chain decision making. International Journal of Disaster Risk Reduction, 14, 256-272.

global, historical data fields, and also from climate models that project future conditions[2]. ***An exploration of these patterns and their predictability has great promise for improving estimates of mega-floods through the development of a joint probability density for both the rain associated with the AMC and the event precipitation attributes.*** Of course, linking these to the nature of atmospheric and ocean circulation mechanisms that control these precipitation systems will be the only credible way to generate and verify projections under future climate changes. A central question is how the precipitation mechanisms may change in the future, and since the current climate models do a poor job of reproducing precipitation statistics, focusing on mechanism change is an important goal for credible projections.

Ultimately, one is interested in assessing flood risk for specific assets at risk within the region for which policies are to be written, or whose disruption (e.g., transportation networks) would result in business disruption or loss of use claims. Ideally, one would like to be able to geo-reference a location of interest and have a ready look up table for the potential exposure of flood risk at that location. Factors that complicate such an assessment include the need to model the hydraulics of flow in river channels and through a developed urban area; the operation and condition of flood control infrastructure; and data limitations add to these factors. In the US, Australia and in Europe, 100-year and 500-year flood plain zoning maps that effectively place a particular property in a specific risk category are developed. However, despite the large expense of developing these maps, their accuracy at the property level is low (e.g., uncertainty estimates on the FEMA maps often lead to non-discrimination between the 100- and 500-year floodplains as marked), there is no consideration of changing climate factors or of inundation duration, and the hydraulic analyses are typically linked to a single steady-state flow. The re-rating of Sacramento’s flood protection to be only at the 77-year level in early 2000 by FEMA, relative to the 500-year level protection estimated at the time of design in the 1960s, reflects the dramatic changes in assessed risk that can occur due to changes in the baseline climate. Assessing how the operation of the reservoir and dike system will mitigate this risk is also very difficult for an outsider. ***Given these concerns, how a global flood risk product should best approach local risk estimation and refinement to those conditions emerges as a challenge.***

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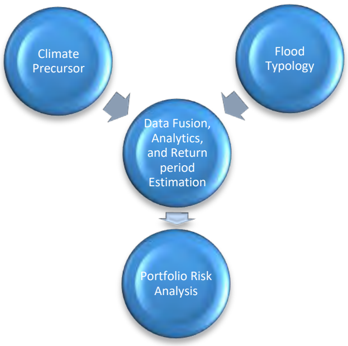
[2] Nakamura, J., Lall, U., Kushnir, Y., Robertson, A. W., & Seager, R. (2013). Dynamical structure of extreme floods in the US Midwest and the United Kingdom. *Journal of Hydrometeorology*, 14(2), 485-504.

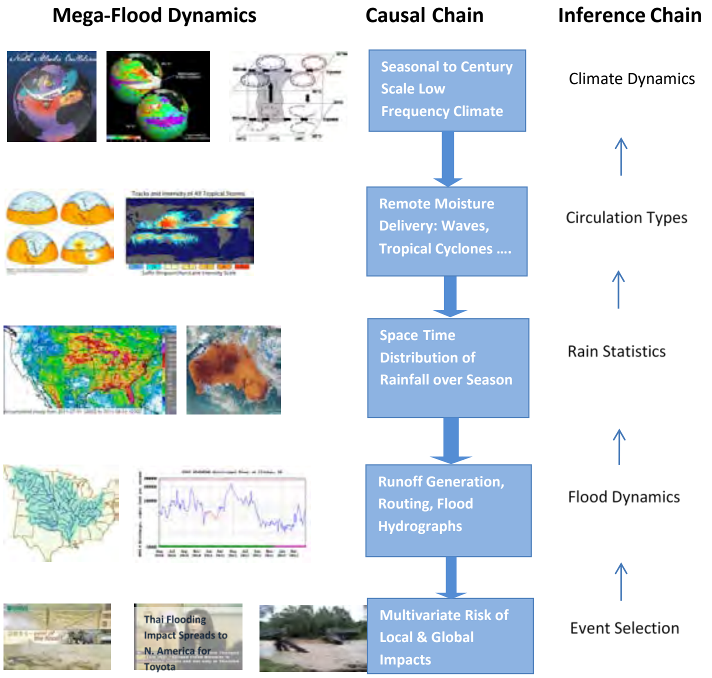
The Global Flood Risk Estimation Process



Columbia's Global Flood Initiative Innovations

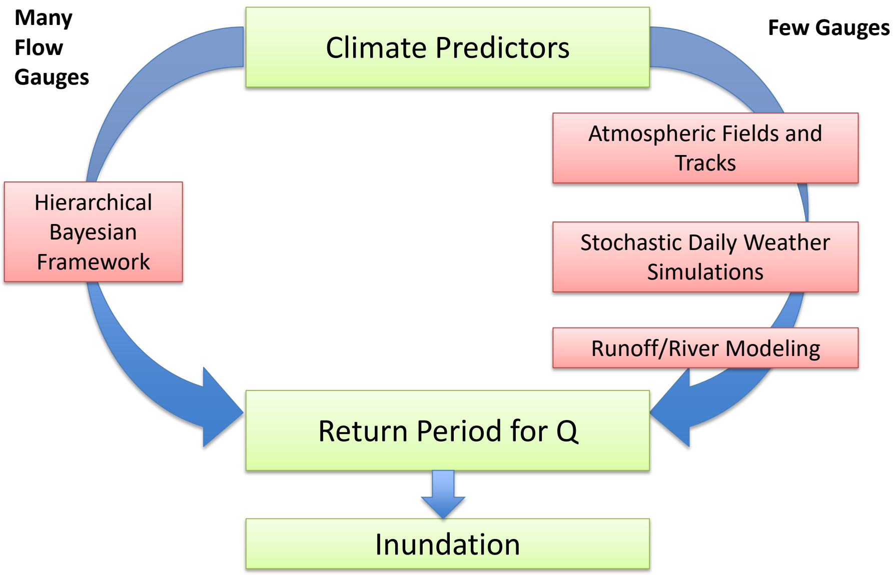
We have developed a stochastic modeling strategy that integrates the above factors into a comprehensive risk assessment tool with uncertainty estimation and the capacity to simulate risk under changing climate conditions, preserve spatial correlation for portfolio risk analysis, and to perform automatic updates as additional local or global information becomes available.

The general conceptual structure for a climate informed global/local flood risk assessment is illustrated in Figure 1. The approach breaks significantly from any existing product in making explicit the dependence of the likelihood or frequency and intensity of extreme regional floods on a causal chain of ocean-atmosphere processes whose slow variation and regime-like changes translate into significant and persistent changes in the probability of major floods in large regions of the world. For instance, the same climate



conditions led to nearly concurrent drought/heat wave in Russia and floods in Pakistan and Western China. Similarly, the Ohio River, Missouri River and Upper Mississippi River floods and associated spring/summer tornadoes in 2011 were marked by the February-June seasonal evolution of the same persistent climate pattern. The moisture for these large floods was funneled into the region of interest through specific, anomalous circulation patterns. An understanding and mapping of these factors into a ***dynamic risk*** framework is important for establishing a process by which flood risk could be systematically updated reflecting changing climate conditions, whether due to human influence, or as part of the natural cycles of climate variation. Dynamic risk implies that in addition to a nominal return period for a flood event in a region, one also estimates the probability of occurrence of such an event over a specified future period (season, year or decade). Given a variety of tools to map the causal chain illustrated, the question becomes how best to use the data for probabilistic inference.

The overall framework we built is a two-way technological capability that can be implemented both in data-abundant or data-sparse locations. Most traditional approaches for flood risk estimation start with at-site rainfall or streamflow records and simulate a relatively short history from which peak flows in a river are established and their return period is estimated. Our approach is quite different and is based on (a) a Hierarchical Bayesian modeling approach for multi-site estimation of flood risk and (b) a causal probabilistic network, with nonparametric method of statistical rainfall modeling integrated with a physically-based runoff modeling system.



Hierarchical Bayesian Framework for Flood Estimation: Traditionally, extreme value analysis pursues the estimation of a relationship between the process variable (either annual maximum series or peak of a threshold) and its probability of exceedance. Regionalization has typically been based on classical statistics where parameters are mostly assumed stationary in time and space and their associated uncertainties are usually neglected or based on normality assumption. Typical models include Gumbel distribution[3] or more recently the Generalized Extreme Value (GEV) distribution[4]. While such approaches address a specific component of the modeling extreme values of a place-based issues, we depart from these to develop a unified modeling capability that can address the multiple layers of complexity of fitting appropriate multivariate data distributions, estimating the model parameter uncertainties, spatial extensions and aggregation and temporal trends using Hierarchical Bayesian Models. The model and parameter uncertainties and trends can be fully incorporated into outputs and information from different sources (stations, locations) can be used to shrink those uncertainties and improve the model reliability.

Causal Network Framework for Flood Estimation: Many river basins/watersheds are either ungaged or have very sparse streamflow gaging networks. There are substantial differences for rainfall-runoff characteristics as a function of the degree of urbanization, the channel geomorphology, drainage density and channel sinuosity, and the associated pattern of topographic relief. Typical hydraulic and hydrologic models attempt to parameterize these features case by case, and often these parameters are either not calibrated (referred to similar settings) or calibrated at a few locations and then extrapolated. In a statistical flood risk modeling context, given a spatio-temporal rainfall field, it should be possible to evaluate the potential inundation statistics conditional on the broadly available data on surface conditions, as represented in the digital elevation and surface cover fields. We developed such a model that permits multi-scale regionalization of flood potential in a river basin using local information, given stochastic realizations of potential rainfall sequences. This consists of synthetic hydrologic modeling over the watershed attribute class to derive the appropriate probability distributions. Historical inundation maps, where available for the events considered, will provide a basis for both model calibration/validation, and for developing a “risk envelope” for the assets of interest in the river basin. Any analysis involving asset risk will be dependent on the quality and quantity

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[3] Hershfield, D. M., 1961: Rainfall frequency atlas for the United States for durations from 30 minutes to 24 hours and return periods from 1 to 100 years. Technical Paper 40, U.S. Weather Bureau, Washington, D.C.

[4] Katz RW, Parlange MB, Naveau P., 2002: Statistics of extremes in hydrology. Adv Water Resour 25(8–12):1287–1304. doi: 10.1016/S0309-1708(02)00056-8.

of data that Customer provides the Vendor. **We now have a global hydrologic model developed at multiple scales that can be used to support these analyses.**

Global Flood Toolkit

We piloted the toolkit at six sites to develop and test selected methods for subsequent global application for river flooding. Instead of just producing a 100-year flood map, as is traditionally done, the goal was to also to estimate the uncertainty in the return period at a location, to link climate predictors to the extreme floods, to look at the spatial and temporal structure of floods, and their causes.

Specific tasks were as follows:

1) We tested the feasibility of using a chain of weather simulations to rainfall-runoff models to inundation models using globally available data sources to establish synthetic series of potential flooding at any location of interest.
2) We tested the feasibility of using Bayesian Statistical Models with observed time series as well as model-generated series to estimate return periods at the sites of interest and also their potential variation given some climate indicators.
3) We considered a broader set of flood measures than is usually done so that subsequent analyses of flood losses can be better informed by attributes beyond the peak flow/inundation level.
4) We developed exploratory work on the global spatial coincidence in extreme rainfall/flood events and its implication for portfolio risk.

A summary of some of the key lessons and challenges are as follows:

1. A multivariate daily weather (Precipitation, Tmin, Tmax, Wind) generator that can preserve space and time dependence of these variables was developed and demonstrated successfully at all sites. It can condition on a few selected climate variables. The data used were gridded global products, and also re-analysis products from climate models. The model is invariant to the spatial resolution of the data, and can be applied at river basin scales.
    a. Application for future climate scenarios (climate change as well as oscillatory components such as ENSO, and next 5-to-10-year scenarios) with downscaling from appropriate variables is feasible, but needs to be developed and tested.
    b. Potential applications to heat and wind indices are possible, but have not been tested.

  c. Linkage with the Bayesian model and trend analyses for scenario development still needs to be done.

2. The VIC model, which is used extensively for continental and global hydrologic modeling, was selected and modified to include 1-d kinematic wave routing to test its capabilities for producing reasonable flood flow simulations. The results varied by region of application, and did not lead to a clear understanding of where and when this approach linked to the weather generator will work well. We are now considering deep learning and transfer learning models as an alternative to VIC.
    a. Global datasets were available to constrain VIC parameters from past work, and these were used. In terms of future applications this is a plus, as it provides a prior data set that can be readily used.
    b. VIC is a continuous simulation model, unlike HEC-RAS or other event-based models, and the hope was that this will allow us to better model complex flooding events that have long duration and are composed of multiple events, such as the Thailand, Indus, Queensland and Mississippi floods.
    c. No uncertainty analysis on VIC was done formally, and there was limited effort at calibration of VIC parameters to sites. DEM’s and rainfall at different resolutions were explored and the change in results was noted. Sensitivity to model resolution and its impact in different settings requires formal exploration.
    d. Simple inundation models consistent with those used in other global flood modeling efforts were implemented with mixed results, and a formal inundation model from AIG was finally used. This required significant calibration effort on a site-by-site basis.
    e. Automatic calibration methods need to be implemented for VIC or an alternate rainfall-runoff model (which could be event based), conditional on “features” of the watershed for which data is readily available. This algorithm would also need to provide an automatic sensitivity and uncertainty analysis.
    f. Dams and levees were neglected for proof of concept of the modeling chain. This limits the modeling capabilities in many regions of interest, and the role of dams and levees needs to be considered in the rainfall-runoff model, whether it is physics based or using deep learning.
3. The Hierarchical Bayesian Modeling was restricted to peak annual flow series at a set of streamflow gauges or nodes where VIC outputs are monitored, and focused on demonstrating whether scaling related to drainage area and selected climate predictors

can be used to develop an appropriate multivariate flood return period prediction system for a region.

   a. For Brazil locations, both nested in a river basin and across basins, skill in prediction was demonstrated and inundation maps were provided.
   b. For other locations (USA, Thailand, Germany), the approach was able to reduce the uncertainty in flood quantile estimates over traditional methods (local and regional) of flood frequency analysis. The use of climate information (observed or from GCM outputs) for non-stationary prediction of flood quantiles and risk was not fully explored for these locations. The limited exploration did not demonstrate significant predictive utility from the linear models used.
   c. Integration with the weather generator-rainfall runoff model needs to be explored.
   d. Extension to flood volume and duration needs to be done.
   e. Regionalization strategy considering homogeneity of causal mechanism and associated scaling or model structure needs to be developed as a semi-automatic algorithm for global application.

4. Exploratory work was done on spatial concordance and scaling for extreme rainfall events to understand the potential for a portfolio risk product.
   a. As the duration of an event increases, the potential for multiple events with large spatially contiguous area to happen globally in the same season or year increases.
   b. Scaling relations for rainfall duration, amount and area are found suggesting possible applications to portfolio risk estimation if indexed directly to rain. Similar explorations with streamflow duration and area flooded were conducted and show similar results.
   c. Linkage to AIG assets still needs to be done, and the toolbox for doing this using rainfall is now available.
   d. Multi-hazard spatial analyses especially for climate driven phenomena – e.g., ENSO – can be developed as an extension linked directly to AIG assets

Future Directions

Global Climate Predictors for Large Scale Floods

The mechanisms for floods can vary, even in a given location. The spatial and temporal structure of rainfall associated with an extreme flood may depend on the antecedent atmospheric processes including prior events that deposited snow or rain. To develop a climate informed strategy, we need to identify the main mechanisms associated with the extreme floods and how the frequency, intensity and spatial expression of these mechanisms is manifest. This is important for credible forecasts of the potential for future extreme floods, conditional on key climate variables. These atmospheric processes can be classified depending on the latitude, continentality, season and other factors, such that a global strategy for climate prototyping in the flood context results. Our goal here is to make progress towards a strategy for climate-based flood return periods, and as a byproduct inform the risk of extreme climate events that are associated with extreme rainfall, wind and flooding. Thus, mechanisms that lead to tornadoes, rainfall and floods or extreme wind and rain can be studied in a unified way conditional on climate. Initial work in this direction has shown significant promise at lead times of one to 3 months.

For mega-floods, we believe that tropical moisture delivery into the region of interest is important, since in most cases local moisture sources are not large enough to deliver the sustained moisture needed for the associated rainfall event. Thus, the identification and modeling of features such as atmospheric rivers and tropical cyclones associated with the flood events is important. During the first phase, we focused on developing the links and algorithms that can use the identified climate precursors as inputs. In the second phase, *we propose to develop a comprehensive database of the global climate predictors that modulate the large-scale floods*. There are several well identified climate modes that operate from intra-seasonal (Madden-Julian Oscillation) to multi-decadal scales (Atlantic Multidecadal Oscillation) that have been shown to influence the seasonal and longer-term expression of the key circulation patterns prevailing worldwide. Climatic indices of these modes have been developed and recorded both for global factors (e.g., ENSO: NINO3.4 index), hemispheric (e.g., MJO indices), and regional (e.g., the EAWR pattern over Europe). We are now exploring machine learning methods for automatic identification of global and regional prediction schemes. Key steps involved in this process are the following:

a) Break down rain/flood events by the type of mechanism.
b) For each mechanism, e.g., frontal storm (or rain on snow), we would seek to parameterize the key attributes, e.g., speed, direction, pressure drop and the central pressure, as a joint distribution and explore how these interact with basin topography to determine the impact on flows and the convergence in the drainage network.
c) Consequently, it would be possible to build time series simulation models of these indices to represent the inter-annual and decadal variability and how these modes interact with within season variability. We would develop a space-time wavelet-based

model to provide global predictors in a given latitude band using appropriate variables from GCM simulations (re-analysis or scenarios).

d) Explore the simulations from GCMs or machine learning models for seasonal forecasts and also for the next 5-10 years to see if certain models can do a good job of simulating the key mechanisms identified and link this to the stochastic simulation models we develop.

Stochastic Modelling for Flood Risk Estimation

In a statistical flood risk modeling context, given a spatio-temporal rainfall field, it should be possible to evaluate the potential inundation statistics conditional on the broadly available data on surface conditions, as represented in the digital elevation and surface cover fields. We developed such a model during the pilot phase that permits multi-scale regionalization of flood potential in a river basin using local information, given stochastic realizations of potential rainfall sequences. The stochastic rainfall scenarios reproduce well, the key attributes with appropriate intensity-duration-frequency and spatial expression, hence provided a basis for conditioning basin hydrologic attributes for flood risk assessment. For the future, we propose the extension of the Stochastic Model to generate near-term (5 – 10 years) Climate Scenarios and Forecasts for a dynamically updating Regional Flood Risk Scoring.

Global Scale

Leveraged Product from Phase I

The current weather generator is tailored to take as inputs, the principal components of the atmospheric pressure fields for simulating climate informed rainfall, temperature and wind scenarios for any given location globally. Simulations of the climate variables from the previous task relevant to each mechanism will be used to drive the previously developed models.

Statistical Forecasts of Floods

We propose to directly map the global climate predictors from the previous task for the region of interest, statistically to the flood risk. This way, if we know the state of current and projected indicator there is a quick early warning tool for season ahead risk in different parts of the world.

Automatic Trend and Climate Sensitivity Identification for Extremes

We propose to develop a Bayesian model for nonstationarity (predictors could be CO2/Temperature/Time, ENSO, PDO) using a multilevel pooling approach where the trend coefficients are partially pooled to single Normal distribution or mixture distribution to discover clustering in extremes, including possible covariance across locations and predictors[5].

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[5] Gelman, A., and J. Hill, 2007: Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge University Press.

Urban Floods

Develop a general modeling framework for integrating multiple sources of information such as rain gauge data, radar information and climate scenarios into spatio-temporal fields for extreme rainfall events and simultaneous flood risk estimation. We are well placed to obtain high resolution radar and remote sensing data and explore the urban flood issues. It may be necessary to do event-based modeling rather than continuous modeling at the urban scale, linked to specific types of events with high resolution time and space data. Product focus will be on the simulation of blended radar-gauge rainfall fields at 15 min or hourly resolution using Bayesian model[6].

Uncertainty Analysis using Bayesian Approach

The goal is to improve uncertainty analysis by both formally modeling the parameter uncertainties and reducing them using regional information, and to integrate across the different modeling streams. Some ideas we intend to explore are as follows:

a) Extension of past work to directly consider precipitation attributes as well as GCM outputs (e.g., sea level pressure, wind field, rainfall forecasts, etc.) as predictors for the model based on scaling relationships. For instance, can we use 1, 3, 5, 30-day precipitation in each sub-basin as a predictor of the flood flow, duration and volume at the sub-basin outlet, and still explore the scaling relationships as part of it. Here, the model could be built using the VIC outputs of these variables, accounting for the bias and uncertainty in VIC simulations, or built directly from the rain and flow data or GCM rainfall forecasts. For the latter case, it could give us a way to predict at ungaged locations, where rain data is available.

b) Focus directly on extremes and not modeling the full annual max flow distribution – i.e., consider a GPD style model rather than LN or GEV. Identify predictors associated with extremes regionally and then use them to predict the events. This would include prediction of the number of events to be expected above some threshold in a given year or season in a region. Possibly shift directly to a mixture model that uses different mechanisms inferred from atmospheric data, and then builds a hydrologic or statistical model for the terrain and infrastructure response. Pick all events of the mechanism that exceed some threshold and map those to flood flows, then normalize probabilities to annual.

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[6] Rahill-Marier, B., Devineni, N., Lall, U., & Farnham, D. (2013, December). Multivariate Bayesian Models of Extreme Rainfall. In AGU Fall Meeting Abstracts (Vol. 2013, pp. H43N-05).

c) Extension to global scale -- can we parameterize the key basin attributes -- topography, drainage network density, soils etc. and see if we can build a model in a highly resolved area and apply to locations where the data on flow in particular is poor or non-existent - the key here is to identify attributes that could work globally and are still dependent on climate so we could do climate informed simulations.

Bibliography on related Floods and Climate Research

1. Armal, S., Devineni, N., Krakauer, N.Y., & Khanbilvardi, R. (2020). Simulating precipitation in the Northeast United States using a climate-informed K-nearest neighbour algorithm. *Hydrological Processes*, 34: 3966– 3980.

2. Armal, S., Devineni, N., & Khanbilvardi, R. (2018). Trends in extreme rainfall frequency in the contiguous United States: Attribution to climate change and climate variability modes. *Journal of Climate*, 31, 369 - 385.

3. Devineni, N., Lall, U., Xi, C., & Ward, P. (2015). Scaling of extreme rainfall areas at a planetary scale. Chaos: *An Interdisciplinary Journal of Nonlinear Science*, 25(7), 075407.

4. Farnham, D. J., Doss-Gollin, J., & Lall, U. (2018). Regional extreme precipitation events: Robust inference from credibly simulated GCM variables. *Water Resources Research*, 54(6), 3809-3824.

5. Hamidi, A., Devineni, N., Booth, J., Hosten, A., Ferraro, R., & Khanbilvardi, R. (2017). Classifying urban rainfall extremes using weather radar data: An application to the Greater New York Area. *Journal of Hydrometeorology*, 18, 611 - 623.

6. Haraguchi, M., & Lall, U. (2015). Flood risks and impacts: A case study of Thailand's floods in 2011 and research questions for supply chain decision making. *International Journal of Disaster Risk Reduction*, 14, 256-272.

7. Jain, S., & Lall, U. (2001). Floods in a changing climate: Does the past represent the future?. *Water Resources Research*, 37(12), 3193-3205.

8. Khalil, A. F., Kwon, H. H., Lall, U., Miranda, M. J., & Skees, J. (2007). El Niño–Southern Oscillation–based index insurance for floods: Statistical risk analyses and application to Peru. *Water Resources Research*, 43(10).

9. Kwon, H. H., Brown, C., & Lall, U. (2008). Climate informed flood frequency analysis and prediction in Montana using hierarchical Bayesian modeling. *Geophysical Research Letters*, 35(5).

10. Lall, U., Devineni, N., & Kaheil, Y. (2015). An empirical, nonparametric simulator for multivariate random variables with differing marginal densities and nonlinear dependence with hydroclimatic applications. *Risk Analysis*, 36, 57 - 73.

11. Lima, C. H., & Lall, U. (2010). Spatial scaling in a changing climate: A hierarchical bayesian model for non-stationary multi-site annual maximum and monthly streamflow. *Journal of Hydrology*, 383(3-4), 307-318.

12. Lima, C. H., Lall, U., Troy, T. J., & Devineni, N. (2015). A climate informed model for nonstationary flood risk prediction: Application to Negro River at Manaus, Amazonia. *Journal of Hydrology*, 522, 594-602.

13. Lima, C. H., Lall, U., Troy, T., & Devineni, N. (2016). A hierarchical Bayesian GEV model for improving local and regional flood quantile estimates. *Journal of Hydrology*, 541, 816-823.

14. Lima, C. H., AghaKouchak, A., & Lall, U. (2017). Classification of mechanisms, climatic context, areal scaling, and synchronization of floods: the hydroclimatology of floods in the Upper Paraná River basin, Brazil. *Earth System Dynamics*, 8(4), 1071-1091.

15. Lu, M., Lall, U., Schwartz, A., & Kwon, H. (2013). Precipitation predictability associated with tropical moisture exports and circulation patterns for a major flood in France in 1995. *Water Resources Research*, 49(10), 6381-6392.

16. Merz, B., Kreibich, H., & Lall, U. (2013). Multi-variate flood damage assessment: a tree-based data-mining approach. *Natural Hazards and Earth System Sciences*, 13(1), 53-64.

17. Nakamura, J., Lall, U., Kushnir, Y., Robertson, A. W., & Seager, R. (2013). Dynamical structure of extreme floods in the US Midwest and the United Kingdom. *Journal of Hydrometeorology*, 14(2), 485-504.

18. Najibi, N., Mazor, A., Devineni, N., Mossel, C., & Booth, J. (2020). Understanding the spatial organization of simultaneous heavy precipitation events over the conterminous United States. *Journal of Geophysical Research: Atmospheres*, 125, e2020JD033036.

19. Najibi, N., Devineni, N., Lu, M., & Perdigao, R. A. (2019). Coupled flow accumulation and atmospheric blocking govern flood duration. *Nature partner journal (npj) Climate and Atmosphere*, 2, 19.

20. Najibi, N., & Devineni, N. (2018). Recent trends in the frequency and duration of global floods. *Earth System Dynamics*, 9, 757 - 783.

21. Najibi, N., Devineni, N., & Lu, M. (2017). Hydroclimate drivers and atmospheric teleconnections of long duration floods: An application to large reservoirs in the Missouri River Basin. *Advances in Water Resources*, 100, 153 - 167.

22. Orton, P. M., Conticello, F. R., Cioffi, F., Hall, T. M., Georgas, N., Lall, U., ... & MacManus, K. (2020). Flood hazard assessment from storm tides, rain and sea level rise for a tidal river estuary. *Natural hazards*, 102(2), 729-757.

23. Sankarasubramanian, A., & Lall, U. (2003). Flood quantiles in a changing climate: Seasonal forecasts and causal relations. *Water Resources Research*, 39(5).

24. Schlef, K. E., Moradkhani, H., & Lall, U. (2019). Atmospheric circulation patterns associated with extreme United States floods identified via machine learning. *Scientific reports*, 9(1), 1-12.

25. So, B. J., Kim, J. Y., Kwon, H. H., & Lima, C. H. (2017). Stochastic extreme downscaling model for an assessment of changes in rainfall intensity-duration-frequency curves over South Korea using multiple regional climate models. *Journal of Hydrology*, *553*, 321-337.
26. Sun, X., Lall, U., Merz, B., & Dung, N. V. (2015). Hierarchical Bayesian clustering for nonstationary flood frequency analysis: Application to trends of annual maximum flow in Germany. *Water Resources Research*, 51(8), 6586-6601.
27. Sun, X., & Lall, U. (2015). Spatially coherent trends of annual maximum daily precipitation in the United States. *Geophysical Research Letters*, *42*(22), 9781-9789.
28. Ward, P. J., Kummu, M., & Lall, U. (2016). Flood frequencies and durations and their response to El Niño Southern Oscillation: Global analysis. *Journal of Hydrology*, 539, 358-378.
29. Wu, Y., Lall, U., Lima, C. H., & Zhong, P. A. (2018). Local and regional flood frequency analysis based on hierarchical Bayesian model: application to annual maximum streamflow for the Huaihe River basin. *Hydrology and Earth System Sciences Discussions*, 1-21.