ASSESSING THE EXPOSURE OF CRITICAL INFRASTRUCTURE AND OTHER ASSETS TO THE CLIMATE INDUCED FAILURE OF AGING DAMS IN THE U.S.

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ABOUT THIS REPORT:

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FINAL REPORT FOR THE GLOBAL RISK INSTITUTE (GRI)

PAULINA CONCHA LARRAURI AND UPMANU LALL

FOREWORD

Aging dams and levees, in combination with an increasing frequency of climate extremes pose an unprecedented risk to communities around the world. The financial risk associated with the failure of such assets is unmapped, due in part to the complexity of the chain of events triggered by the failure of a major dam or levee, and of the difficulty of estimating the probability associated with such a failure. In this report, we explore **how the causal chain of the communities and critical infrastructure at risk can be quantified using dams as an example. We outline the nature of this challenge**, given the existing methodologies, data availability, and gaps in dam risks assessments, **and propose a framework for a rapid screening of the changing probabilities of catastrophic failure of aging dams and the assets subsequently at risk**.

The situation in the USA is of particular concern[1]. There is a very large inventory (>90,000) of aging dams with a median age of nearly 60 years, compared to a nominal design life of 50 years. At least 1680 of these dams are considered to pose a high hazard of failure, and may require over $70 billion in repairs[a]. Often bridges, major roads and rail networks, electric power generation and transmission facilities, municipal water and wastewater treatment and distribution systems, solid waste handling facilities, commercial establishments, hospitals, warehousing and distribution centers, airports, riverine navigation facilities and population centers risk being flooded if one of these dams were to fail. Dam failures have occurred in recent years during persistent rainfall events. Fortunately, most of these have been small dams[2,b], whose failure has had a modest impact. However, there have been some notable close calls. In February 2017 the Oroville Dam in California, the tallest dam in the USA, experienced a failure of the main and emergency spillways following a persistent period of rainfall that filled the reservoir. The flow over the spillways was 5-10% of the design flow, and the spillway failure was ascribed to "long-term systemic failure" reflecting inadequate design and maintenance[c]. Over 200,000 people were evacuated as a precautionary measure anticipating dam failure, and the cost of repair has exceeded $1.1 billion. Concerns to 650 other dams in California have subsequently been voiced[d]. A similar situation evolved in Houston in August 2017, when the US Army Corps of Engineers (USACE) saved the Addicks and Barker dams from imminent overtopping and potential failure, through an emergency release of water in the middle of the night during hurricane Harvey. The USACE, which owns these dams, had identified much earlier that the dams built in the 1940s, had a "risk of catastrophic failure", and may be "critically near failure" even under normal operations, and were listed as extremely high risk in 2009. Funds had been authorized for repairs which were not completed at the time of the hurricane[e]. There are over 7,000 dams listed as hazardous in Texas, of which these two have been repeatedly identified as high risk[f]. Formal dam safety risk analyses are conducted by the USACE and other organizations, but a very small fraction of the US inventory of dams has been processed in this way. Given the rather limited number of dams of high profile that have been analyzed, the task of prioritizing and assessing the potential economic disruption that dam failures could cause in the USA, especially as climate extremes become more intense and frequent is daunting.

[a] https://www.sacbee.com/news/california/water-and-drought/article193151499.html
[b] https://www.weather.gov/media/publications/assessments/SCFlooding_072216_Signed_Final.pdf
[c] https://www.sacbee.com/news/california/water-and-drought/article193151499.html
[d] https://www.courthousenews.com/creaky-leaky-dams-among-biggest-risks-to-california-audit/
[e] https://weather.com/storms/hurricane/news/houston-dams-harvey-addicks-barker, https://www.hydroreview.com/2016/03/02/corps-designates-addicks-and-barker-dams-extremely-high-risk/#gref
[f] https://www.houstonpublicmedia.org/articles/news/2016/03/07/139872/texas-has-thousands-of-bad-dams-two-in-houston-deemed-extremely-high-risk/

The objectives of the work reported here were to:

(1) Identify the risk pathways associated with climate induced failure of aging dams
(2) Assess and demonstrate strategies for the rapid quantification of these risks using publicly available data sources in the USA
(3) Develop and demonstrate an approach for the rapid identification of assets at risk if a dam were to fail
(4) Recommend an approach for how a national assessment of dam failure risk could be performed and updated on a regular basis with a focus on portfolio risk

Our approach intends to provide a preliminary ranking of the priority areas of concern and can be generalized to other countries. **An intended application is for a portfolio level risk analysis by investors, asset managers, and insurance providers**. It is not intended to be a rigorous dam failure risk analysis at each of the 90,000 locations. The USACE typically invests over 2 years in a detailed study at a single site, at a considerable expense. They own 700 dams, about 50% of federally owned dams, and target only their dams for analysis. The vast majority of US dams are privately owned or owned by state and municipal agencies, and detailed risk analyses are typically not available. In 2015, the USACE estimated that to fix all dams in their portfolio that need repair would cost $24 billion, and take 50 years at the current funding rate[g]. Our approach is patterned after their methodology but is not as exhaustive given the resources available.

Using dams in the Cumberland River Basin as an example, we provide a framework to quantify the causal network of the climate and age-induced changing risk of dam failures, and prioritize different dams or regions in terms of potential financial impact. This provides the foundation for a comprehensive national risk estimation and prioritization effort for financial and other mitigation actions.

The first part of this report focuses on the trigger events of dam failures. Using probabilistic models, we assess the spatial and temporal patterns of extreme rainfall and stream flow events that could trigger the overtopping failure of a single dam or the cascading failure of a series of dams within a region. The failure probability varies with time, due to (1) inter-annual and decadal climate variability; (2) anthropogenic climate change; (3) the changing free capacity of a dam due to sedimentation; and (4) the fragility of a dam due to age and type of construction material. An approach to the estimation of these probabilities as a measure of risk was developed.

A challenge with the estimation of a dam's probability of failure is the lack of readily available data on the main parameters that may induce failure. In particular, data related to the design and operation of a dam such as elevation time series, discharge-elevation curves, and storage-area curves are not included in national dam inventories available to the public. Historical inflow data (stream flows and precipitation) may also be limited or discontinuous. Future climate projections made by ocean-atmosphere general circulation models (GCMs) are known to have large biases and uncertainty especially for precipitation projections. For the dams included in our test case, we found that there is an increasing trend in the number of events that could lead to overtopping. As well storage loss due to sedimentation may be shifting the return periods assumed for critical dam storage elevations (e.g. the probability of being at the top of the flood storage elevation), which increases the probability of overtopping as even smaller, more recurrent flood volumes can exceed the remaining free storage.

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[g] https://www.usace.army.mil/Media/Fact-Sheets/Fact-Sheet-Article-View/Article/590578/dam-safety-facts-and-figures/

The second part focuses on the quantification of damages in the event of a failure. A detailed regional analysis was performed to shed light on the kinds of financial impacts that may emerge as a concern, and for which public data was available. **We find that the 100 and 500-year flood plains usually considered for insurance purposes would likely be overwhelmed by a dam break for several river miles below the dam, and that current dam hazard classifications do not give visibility to the different types of hazards that each of them poses. In our case study, all the dams were classified as High Hazard, yet the financial impacts of the failure of each of them were strikingly different**.

We highlight that at this point, there is no clear understanding of the scale of the economic disruption that would be caused by the dam failures consequent to climate induced triggers. While we are able to provide a preliminary approach to trigger probability quantification, and the mapping of the vulnerability of critical infrastructure, population centers, and toxic waste sites to flooding from dam failure, **the resources available have constrained our ability to develop and test a strategy for the aggregate financial risk faced by the USA nationally or regionally from such failures. An approach to address this challenge would require a quantification of both the life and property losses as well as the supply chain effects and larger scale propagation of the loss of regional services. Linkages to economic and valuation models that would allow such a quantification are still needed, and would constitute a contribution to the narrative on climate change impacts, as well as on the national investment needs for aging infrastructure.**

Contents

INTRODUCTION

A changing climate presents us with the potential for more frequent and more intense precipitation extremes and hence an increasing risk for floods and droughts. Dams and levees have been used as one of the measures for flood control, and dams are also used for buffering drought risks. The large, US portfolio of dams now has a median age that exceeds its design life, and the state of maintenance of the vast majority of the dams is a concern. Consequently, there is concern over the potential failure of one or more of these dams through the dual threat of climate change and increasing fragility. There is no comprehensive research on understanding this risk, or of its financial implications for industry, communities or government across the USA. The potential probability of failure of dams is not established. Neither is the potential impact of the failure in terms of the value of the loss of services provided by the dam, or the downstream impacts on asset, population and reconstruction needs, or the cascading impact across the national and regional economy. The research presented here represents the first effort to develop an approach in this direction. We focus primarily on an identification of methods for the rapid quantification of the trigger probability for dam failure, and of the critical infrastructure that would be impacted if the dam fails. The approach developed is exemplified for the Cumberland region in the USA, and suggestions for its extension, and inclusion in a financial loss estimation strategy are indicated as key research directions.

The physical conditions of dams and the environment surrounding them experience changes over time, which translate into changes in the functionality and safety of the dams. For example, development in flood plains, and changes in land use can increase runoff peaking and volume [1,3], and sediment buildup reduces dam storage capacity [4,5]. These changes can lead to an increased risk of dam overtopping. Climate variability and change, and faulty designs heighten the risk of failure [6,7]. Therefore, the exposure of populations and infrastructure networks to floods and dam failures changes dynamically [8]. Our framework takes into consideration these time dependent changes. Figure 1 is a representation of the changing nature of the probabilities and consequences of dam failures, including how we address each of these variables. The product of the estimated probabilities and consequences is the changing financial risk.

For the probability estimation we rely on climate models, historical precipitation, temperature, and streamflow data, siltation surveys, and information on the dam operation. For the estimation of the assets at risk we use publicly available dam break and consequence tools developed by the US Army Corps of Engineers (USACE) and FEMA, and national infrastructure datasets. The Decision Support System for Infrastructure Security Lite (DSS-WISE™Lite)[9] is used to simulate dam failures to estimate the inundated area and the affected population. The building inventories and depth-damage curves in FEMA's Hazard-US (HAZUS) software are used to estimate the direct financial losses. Other national databases of critical infrastructure are also used in the analysis. The AHP method is applied to obtain the dam hazard ranks considering seven criteria shown in Figure 1 as C1 to C7.

We provide context on the pressing situation of dams in the United States, which originally motivated this research. However, the framework we present can be applied to dams in other geographies.
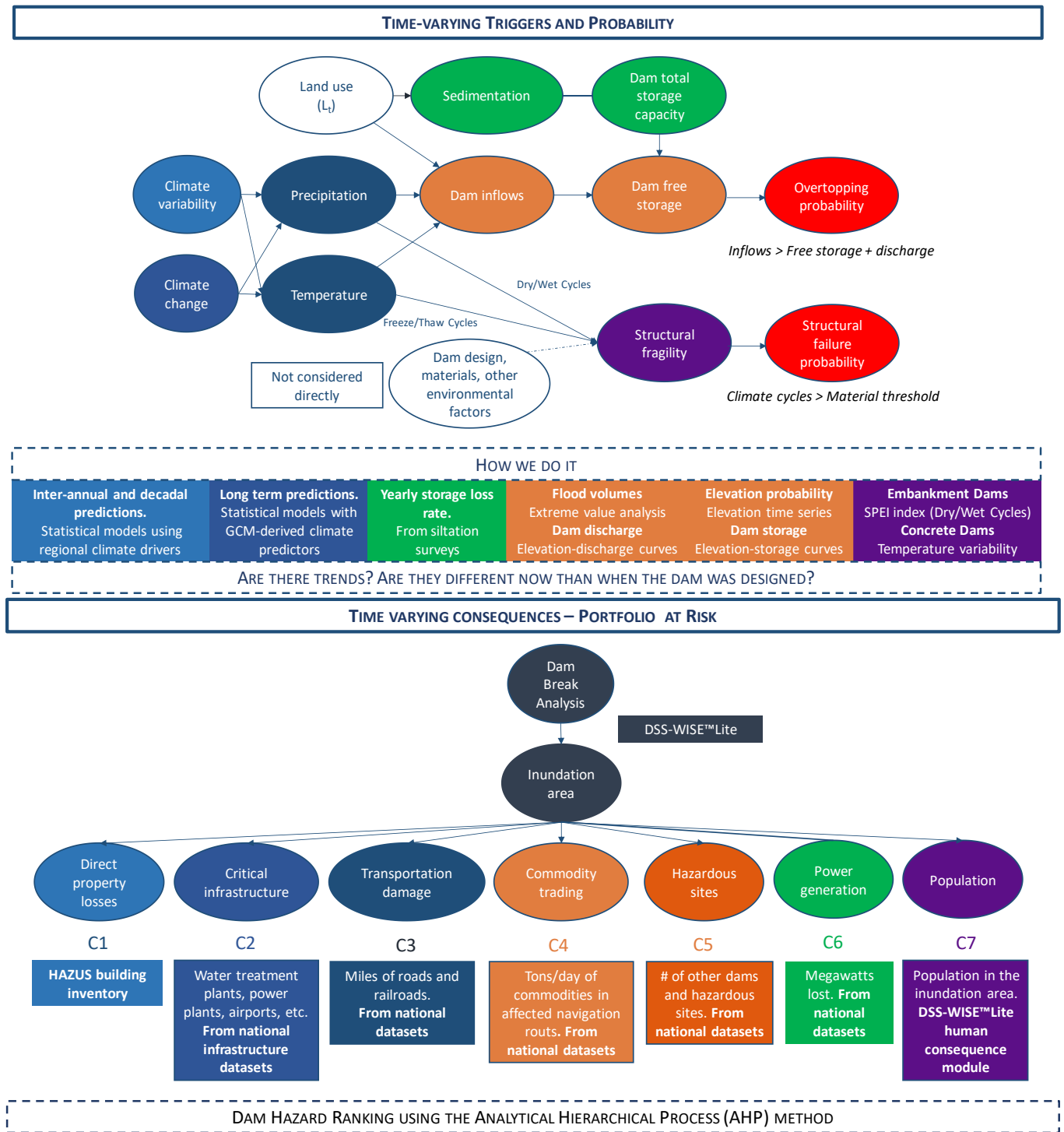
TIME-VARYING TRIGGERS AND PROBABILITY

Land use (L_t)

Sedimentation

Dam total storage capacity

Climate variability

Precipitation

Dam inflows

Dam free storage

Overtopping probability

Inflows > Free storage + discharge

Climate change

Temperature

Dry/Wet Cycles

Freeze/Thaw Cycles

Not considered directly

Dam design, materials, other environmental factors

Structural fragility

Structural failure probability

Climate cycles > Material threshold

HOW WE DO IT

Inter-annual and decadal predictions. Statistical models using regional climate drivers	**Long term predictions.** Statistical models with GCM-derived climate predictors	**Yearly storage loss rate.** From siltation surveys	**Flood volumes** Extreme value analysis **Dam discharge** Elevation-discharge curves	**Elevation probability** Elevation time series **Dam storage** Elevation-storage curves	**Embankment Dams** SPEI index (Dry/Wet Cycles) **Concrete Dams** Temperature variability

ARE THERE TRENDS? ARE THEY DIFFERENT NOW THAN WHEN THE DAM WAS DESIGNED?

TIME VARYING CONSEQUENCES — PORTFOLIO AT RISK

Dam Break Analysis

DSS-WISE™Lite

Inundation area

Direct property losses	Critical infrastructure	Transportation damage	Commodity trading	Hazardous sites	Power generation	Population
C1	C2	C3	C4	C5	C6	C7
HAZUS building inventory	Water treatment plants, power plants, airports, etc. **From national infrastructure datasets**	Miles of roads and railroads. **From national datasets**	Tons/day of commodities in affected navigation routs. **From national datasets**	# of other dams and hazardous sites. **From national datasets**	Megawatts lost. **From national datasets**	Population in the inundation area. **DSS-WISE™Lite human consequence module**

DAM HAZARD RANKING USING THE ANALYTICAL HIERARCHICAL PROCESS (AHP) METHOD

Figure 1 Proposed framework to assess the probability and consequences of dam failures.

In the United States there are over 85,000 dams with an average age of 57 years in the National Inventory of Dams (NID) [10]. **The risks and challenges posed by aging dams in the country are widely acknowledged** (ASCE, 2017; Ho et al., 2017; Imbrogno, 2014; see also timeline in Figure 2). There have been on average 10 dam failures per year in the U.S. from 1848 to 2017, but since 1984 the average failure rate has increased to 24 per year, mostly in dams less than 15 meters tall [2]. The Associated Press released a report in 2019[13], which identified more than 1,680 dams in the U.S. as being in poor or in unsatisfactory condition. There are currently no publicly available analyses of the estimated financial and other risks that would be posed by the failure of these dams, or of their susceptibility to failure considering how the climate has changed relative to the data available when these dams were designed 50 to a 100 years ago.

Multiple dams in the U.S. do not comply with the current design flood standards because they were built when long precipitation records were not available. Perhaps as a consequence of this, the number of dam overtopping incidents far exceed structural failure in the United States [11,14]. About 1/3 of dam failures occur by overtopping [15], often times due to inadequate spillway capacity. Large dams intended for flood control were designed to withstand very large precipitation events but with changes in flood return periods, their design may not guarantee safety anymore [16]. It was estimated that the probability of hydrologic failure will increase for most dams in California by 2100 [7], and this is without considering reduced storage capacity due to sedimentation. The historical 1 in 100-year flood event is projected to shift towards smaller return periods in many regions of the U.S*.* (Maurer et al., 2018; Vogel et al., 2011; Wobus, 2017).

NYT Feb 2011	**NYT Feb 2017**	**NYT Nov 2019**
"More than 4,400 dams are considered susceptible to failure, according to the Association of State Dam Safety Officials"	Failure of Oroville Dam Spillway 70 dams failed in South Carolina between 2015-2016 due to heavy rains.	California spent $1.1 billion repairing the Lake Oroville spillway Associated Press report of risky dams Failure of the Spencer Dam in Nebraska
$51 billion needed to rehabilitate dams nationwide	**$60 billion** needed to rehabilitate dams nationwide	**$70 billion needed** to repair and modernize the nations dams

Figure 2 Recent progression of the state of dams in the United States (some reported in the New York Times, NYT).

Sediments reduce reservoir storage and can block water intakes and outlet structures, which translate into reductions of water supply reliability and flood control, and increase the risk of dam overtopping. Most reservoirs in the U.S. and around the world have been designed with a sediment design life (i.e. around 100 years for the Bureau of Reclamation and USACE dams), which means *that as sediment increases reservoir performance decreases* [21], so the overall benefit of a dam decreases [4]. However, for most dams, sediment loading projections assumed stationary environmental conditions. Changes in land use, and climate may modify sedimentation rates over the life of the dam [22].

Increased sediment deposition in dams is recognized as a growing problem in the US. The US Army Corps of Engineers (USACE) is developing strategies to inform the prioritization and data collection to assess the impacts and severity of future sedimentation in the reservoirs they operate through their project "Enhancing Reservoir Sedimentation Information for Climate Preparedness and Resilience" (RSI). This includes sharing reservoir

siltation survey data with the Reservoir Sedimentation Database (RESSED) database maintained by the US Geological Survey (USGS). Siltation surveys are needed to evaluate the rate of storage loss per year but budget constraints limit the location and frequency in which they are carried out. RESSED contains siltation surveys for more than 2,000 dams in the U.S., however there are more than 90,000 dams in the country.

To give a perspective of the problem, the storage loss percentage was obtained from RESSED for 87 dams spread across the U.S. that included siltation surveys. Because surveys are not done frequently, we assumed that the storage loss rate is constant over the years so we divided the storage loss percentage by the number of years between the start of operation and the survey year and called it the yearly storage loss rate (SLR). The median SLR value in the sample was 0.12 %. Figure 3 shows an estimation of the number of dams with storage loss greater than 20% and 10% in 2020 and by 2040 based on the median SLR. **More than 21,000 dams in the U.S. may have a loss of storage greater than 10% by 2040-** the map is not comprehensive because many dams do not have the start of operation date (e.g. many dams in Texas).
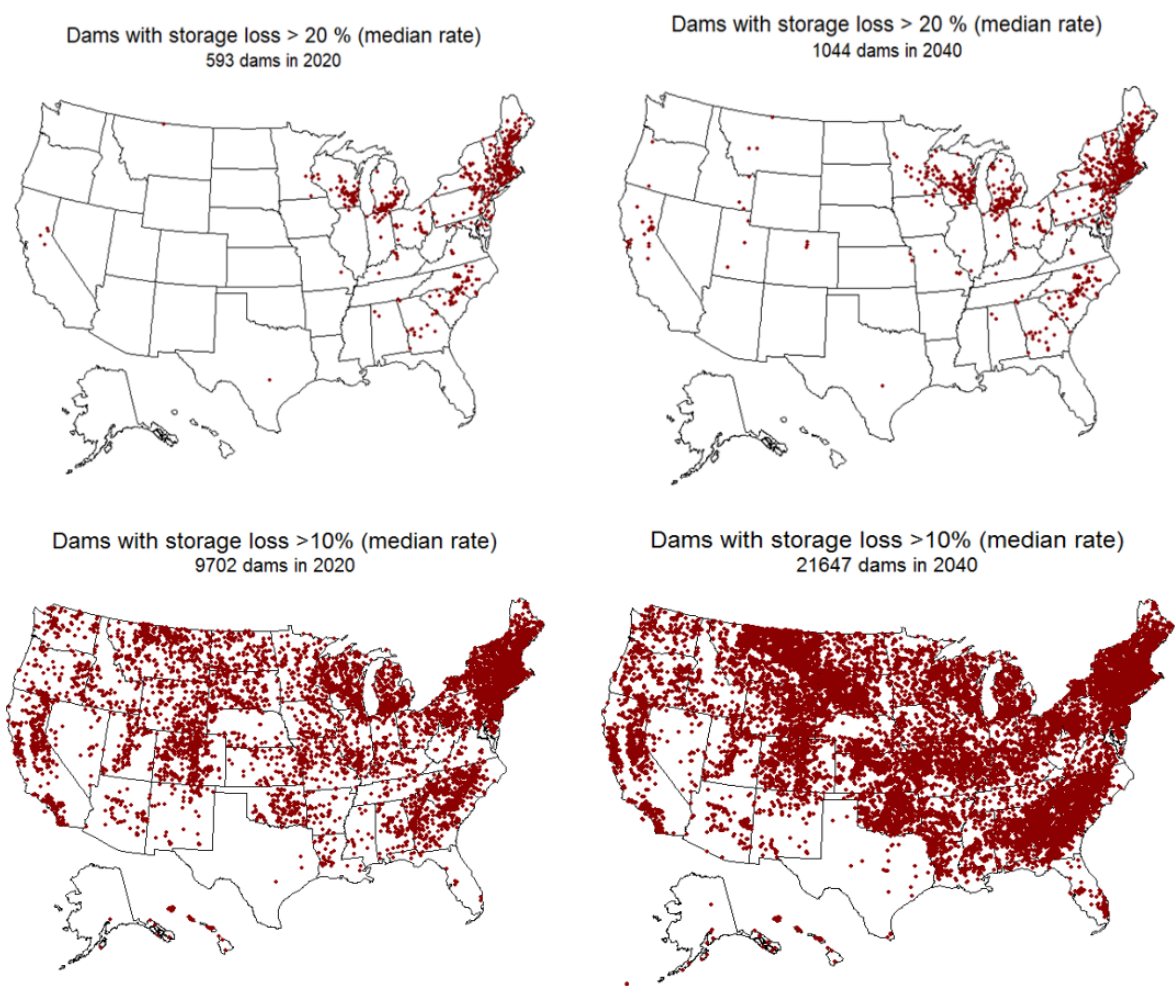

Figure 3 Estimate of the number of dams with storage loss greater than 10 and 20% assuming the median SLR. Only dams with reported year of construction are shown. Using the 2018 National Inventory of Dams in 2020

The Federal Emergency Management Agency (FEMA) oversees the National Dam Safety Program and the Federal Guidelines for Dam Safety, which encourage dam owners and regulators to employ strict safety

standards. However, **each state has the responsibility over the regulations, inspection, permitting, and enforcement of the non-federally owned dams located within its boundaries** (excluding Alabama, which does not have a dam safety program), **and there is great variability in staffing and quality of the dam safety programs across states** [1]. For example, Missouri performs safety inspections on only about 650 of its more than 5,000 dams because state law exempts all dams that are under 35 feet, used for agricultural purposes or that are regulated federally. Texas has similar exemptions and around 45% of its dams are exempted as a result. Federal agencies operate only 5% of the reservoirs found in the NID, and more than half of the dams in the country belong to private entities. The Association of State Dam Safety Officials estimated that it would cost US$64 billion to rehabilitate all federal and non-federal dams, and the U.S. Army Corps of Engineers estimated $25 billion is needed just to address deficiencies in the dams they operate [12]. The concerns over dam safety are real. Lakes are being drained in Texas to repair old dams [23], and in Oregon aging dams and dam failure concerns have led to community activism to raise funds for repairs because federal and state funding are scarce. In 2019 FEMA's National Dam Rehabilitation Program had a grant pool of $10 million for all dams classified as high hazard potential in the U.S. [24]; the repair of one of Oregon's dams alone is estimated at $80 million [25].

Given the budgetary and personnel constraints, a method to prioritize funding allocation that accounts for the likelihood and consequence of dam failures is required to ensure improvements in dam safety where it is most needed.

Dam hazard classifications based on probable loss of life, and social and economic disruptions (not related to the probability of failure) exist in the U.S. but variations among federal agencies and states make it difficult to develop a consistent national assessment of dam hazards [26,27]. The NID includes hazard classifications for the dams, but each state and federal agency reports the classifications according to their own metrics. Additionally, flood risk mapping and dam hazard assessments are dynamic endeavors and require continuous updating. This is demonstrated in the growing number of high hazard potential dams in the U.S. propelled by changes in land use and development downstream of the dams; currently there are approximately 15,627 in this category as per the NID [10]. However, it is unclear to us, whether the assessments to change a dam hazard classification comprehensively examine the current state of the dams (siltation, concrete and foundations), or of downstream ecosystems, population and critical infrastructure exposed, and updates related to the increasing intensity and persistence of precipitation under climate change.

There are insurance mechanisms to cover flood losses. In the US, flood insurance rate maps (FIRMs) determine the cost of flood insurance through the National Flood Insurance Program (NFIP) managed by FEMA. NFIP considers the 1 in 100 year flood return period as base to delineate flood areas [28]. FEMA's guidance for flood risk analysis and mapping recommends the inclusion of dam flood risk information in flood risk maps as best practice [29], but this is voluntary. **The damages of dam failure could potentially be much greater the 1 in 100-year flood area in the NFIP but FIRMS, although available throughout the U.S., do not consider dam failure**. In the section of financial loss estimation, we provide an example of the estimated damages in the 1 in 100-year flood zone and 1 in 500-year flood zone with and without including a dam failure in Nashville, TN, showing that the inundation area would be greater in the event of a failure.

FEMA's periodic updates to flood risk maps typically cost over $2 million per county, so comprehensive analyses of dam break induced flooding and impacts that cover the more than 85,000 dams, in over 3,000 counties across the country would be quite expensive (>$6 billion). A national flood risk update would most likely highlight the need for significantly higher additional investments for risk mitigation to cover just the most critical

locations. If nothing is done, and some of the largest dams failed, in addition to the loss of life, large damages may occur to downstream critical infrastructure (e.g., other dams, electric power plants and transmission infrastructure, highways, bridges, water and wastewater treatment plants), whose repair and replacement costs would emerge as an issue. The lack of a comprehensive analysis of this risk, and its securitization mechanisms, is a considerable concern as the confluence of the increasing fragility of the dams, and the increasing risk of high precipitation events, manifests as a higher probability of failure and downstream impact.

CASE STUDY

The U.S. Army Corps of Engineers (USASE) managed dams in the Cumberland River Basin (CRB) were used as a case study to illustrate the application of the framework. The CRB extends in parts of Kentucky and Tennessee. The ten largest dams in the CRB are operated by the USACE as an integrated system, and their main purposes are flood control, electricity generation, and recreation. Elevations along the location of these dams range from 4,150 feet in the eastern headwaters to 302 feet at the Ohio River confluence [30].

The configuration of the system of dams is shown in Figure 4. Wolf Creek Dam, Dale Hollow Dam, Center Hill Dam, and J Percy Priest Dam are arranged in a parallel configuration (i.e. there are no upstream dams), while Cordell Hull, Old Hickory, Cheatham, and Barkley dams are in series (i.e. there are dams upstream from them). The configuration of the dams' system is relevant in the assessment of cascading failure as explained in the next section "Probability of Failure".
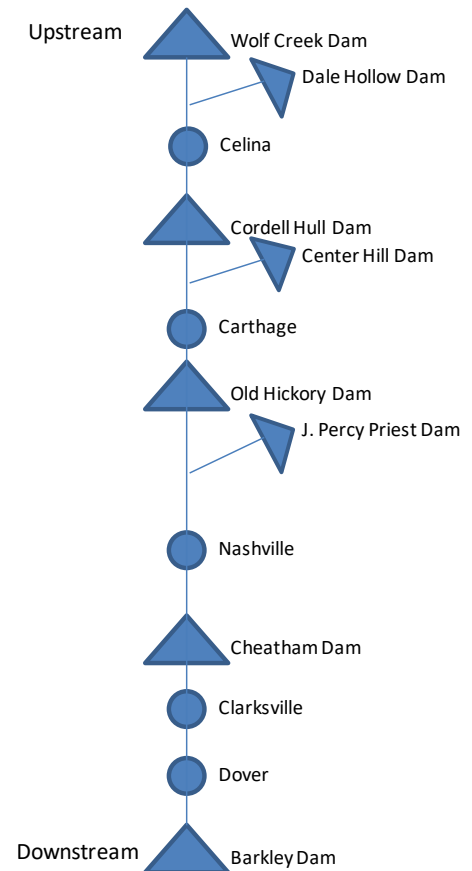

Figure 4 Diagram of USACE dams in the Cumberland River Basin.

PROBABILITY OF FAILURE

Our proposed approach for estimating the probability of dam failure considers its time-varying nature conditional on inter-annual and decadal climate variability and anthropogenic climate change, diminishing dam capacity due to sedimentation, and the structural fragility of the dam due to age and type of construction material (Figure 5). Simple functions were developed to show how each of these variables may be changing, and how they affect the reliability of a dam as it ages.
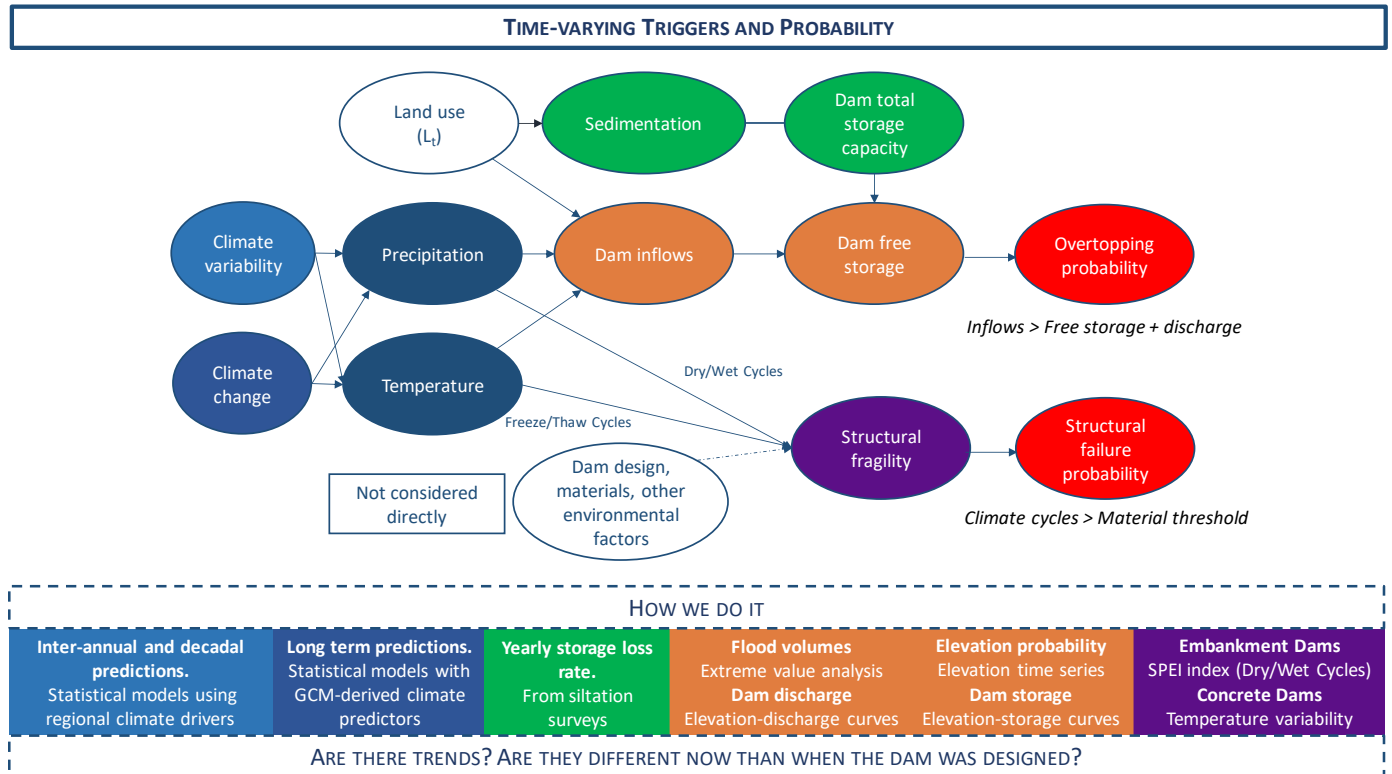

Figure 5 Framework to assess the probability of failure.

CLIMATE AND THE RISK OF OVERTOPPING: REVIEWING PAST METHODS AND CURRENT TRENDS

Hydrologic risk is defined as the risk of failure from overtopping, which happens when inflows exceed the free storage and discharge capacity of a dam.

Prior to 1950, design standards for the hydrologic safety of dams in the U.S. were mainly based on judgment and experience [31]. In the decades after, hydrologic design criteria for dam safety have generally been based on local flood-frequency analyses (FFA) or on a single (and static) "maximum" event called the probable maximum precipitation (PMP) or the probable maximum flood (PMF) [32,33]. The FFA, PMP or PMF **design approaches assume that the probability of dam failure by overtopping remains constant for the duration of the design life** (i.e. it is stationary).

Recently there has been much debate about the idea that the assumptions of stationary climatic baselines for dam design and operation may no longer be appropriate for long term projections of climatological parameters [34,35]. It is argued that long-term climatic trends, river regulation, changes in runoff due to land use or other climate feedbacks, and sedimentation may make this assumption invalid [6,35,36].

A variety of techniques have been developed to account for changes in the probability of flood events [35]. One common approach is to use bias-corrected downscaled precipitation projections from global circulation models (GCMs), and hydrologic models to generate streamflow [7,18,37,38]. However, these projections have many shortcomings[39], potentially resulting in underestimations of future peak floods[36,37]. It has been proposed to use the large-scale climate circulation variables that GCMs are able to predict better to obtain regional extreme precipitation events, rather than obtaining the precipitation events directly from the GCM[39]. The use of statistical approaches with time varying parameters has also been proposed to allow changes in the flood distribution, either using the trend or large scale climate variables as covariates [40]. Overall, **this is an evolving field and there is still no consensus on the use of stationary (constant probability) or nonstationary (changing probability) assumptions for infrastructure design** due to the uncertainty around them, unless obvious trends have been detected [35,41]. The design of more flexible infrastructure (shorter time scale projections) has been suggested as the way to deal with the uncertainty of future climate[42]. To this day, the concepts of design life level and reliability are still the recommended design principles by government agencies[36].

We want to emphasize the relative importance of including short term or long term climate risks depending on the investment life or the operational life of dams. Inter-annual and decadal climate variability that can be identified and predicted is suitable for shorter term investment or design life, while anthropogenic climate change, which is expected to alter the occurrence of extreme events, informs longer time scales[42], albeit with greater uncertainty.

Probability of Overtopping

1. Review regional drivers, models, and trends of flood events.

2. Compare the return periods of extreme streamflow events using all the data currently available and the data available before a dam was built.

3. Do trend analysis for the streamflow. Analyze the relationship between precipitation and extreme stream flows.

4. Estimate storage losses due to sedimentation.

5. Obtain the probability of overtopping (hydrologic risk) accounting for sedimentation losses.

6. Estimate proxies for fragility

Understanding the underlying mechanisms and trends of regional extreme precipitation and floods is important to inform the spatial and temporal variation of the risk of overtopping of multiple dams simultaneously. Statistical climate models can help predict future conditions, and depending of the time scale needed, different models and predictors may apply.

In our example we review two models developed for the Ohio River Basin (where the Cumberland River Basin, our test case, is located) related to the drivers and future projections of extreme precipitation and streamflow [39]. One is intended for predictions of anthropogenic climate change, and the other assesses the probabilities of having very wet or dry regional conditions using historical data exclusively, representing inter-annual and decadal variability[43]. Similar models can be developed for other regions.

The Ohio River Basin has a history of recurrent large flooding events that have had high human and financial costs. The floods are generally associated with persistent, or heavy precipitation events, and snowmelt, and in less degree to changes in land use. Springtime extreme streamflow is driven by a persistent and strong circulation called the Bermuda High, which forces anomalous moisture transport from the gulf of Mexico and Tropical Atlantic[39]. To analyze the regional exposure to extreme precipitation days, Farnham et al., (2018) define an event as the days that at least 4 of the 15 sub-regions in the basin experience extreme precipitation (greater than the daily 99th percentile) and quantify the probability of such days conditional on five climate indices. They use 1950 to 2005 as historical period, and 2006-2100 for future projections, and their Bayesian model propagates the parameter estimation uncertainties to the future simulations (longer time, more uncertain).

Farnham et al., (2018) compare the results of their model with the common approach of bias corrected GCMs for precipitation and show how using the GCM-derived indices yield better results. **Overall, an increase in regional extreme precipitation days in the flood season** (March-April-May) is projected (Figure 6), **which are closely related to extreme stream flows in the region (taking the Ohio River Basin as a whole). This is to show that the probability of having multiple dam failures within the same river basin may increase in the long term.**
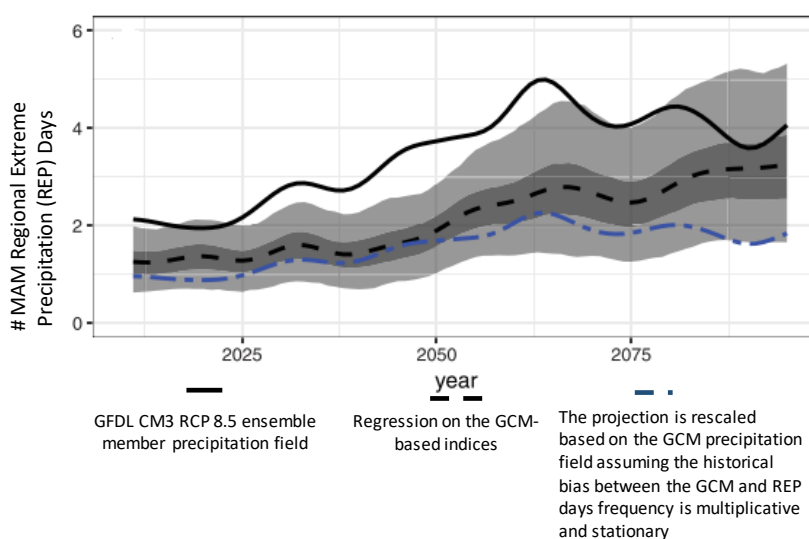

| GFDL CM3 RCP 8.5 ensemble member precipitation field | Regression on the GCM-based indices | The projection is rescaled based on the GCM precipitation field assuming the historical bias between the GCM and REP days frequency is multiplicative and stationary |

Figure 6 Projections of regional extreme precipitation days in the Ohio River Basin.
Adapted from Farnham et al., (2018)[39] with permission from the authors.

In another model (Amonkar et al, 2020)[43] used streamflow gages from the Ohio River Basin to study the streamflow characteristics on a river basin scale. Site specific annual maximum streamflows were converted to binary values if they exceeded the 90th quantile, and aggregated across the river basin as count exceedance data. With their model, they estimate the average occurrence of Wet and Dry years in any 10-year period and the maximum persistence length of Wet and Dry years across a 30-yr period (Figure 7). This model is based purely on historical streamflow data. Models such as this could be used to update the likelihood of extreme precipitation events in the next year or 10 years and hence update the probability of dam failure, and the consequent prioritization of action or financial risk mitigation strategies.
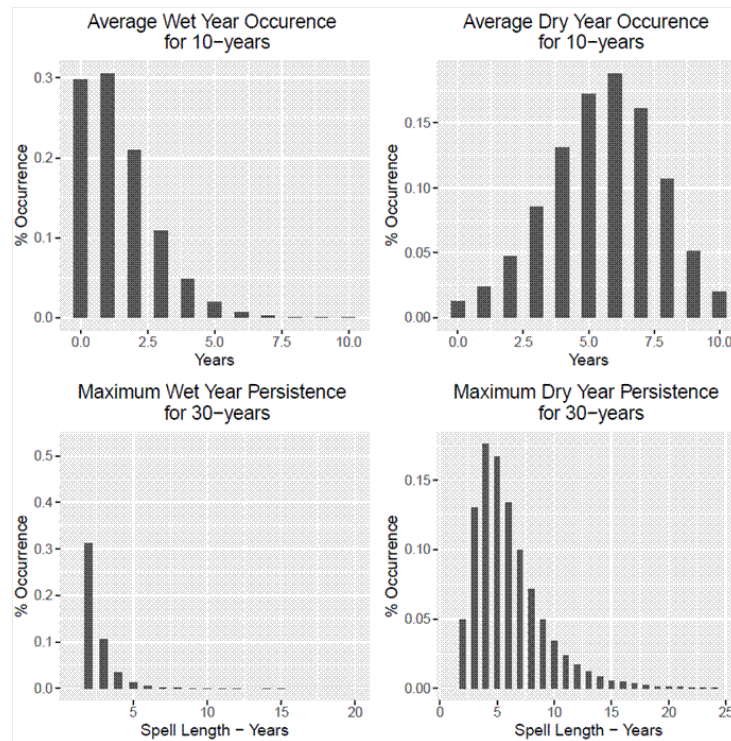
Figure 7 Occurrence and persistence of wet and dry years in the Ohio River Basin. Used with the permission of the authors

These models help understand the extreme streamflow characteristics and future projections at a basin scale. In the next section we review the streamflow characteristics at the location of a dam to assess if extreme inflows have changed from the time the dam was designed. We then show how the probability of overtopping can be updated to reflect changes in streamflow sediment, and other environmental conditions affecting the stability of the dam materials.

Overtopping probability analysis part I: Changes in flood event recurrence

The first step is to analyze if the return flood probability has changed from the time the dam was designed and built to the present. This is to see if we can expect significant variations in the flow in the rest of the analysis. The log Pearson type III distribution was the recommended distribution for extreme flow analysis around the time when the majority of dams in the U.S were built, so we use it to compare the return periods fitting streamflow data pre-dam and post-dam. The U.S. Geological Survey (USGS) provides streamflow data from gages across the country and it can be retrieved with the programming language R using a package called dataRetrival.

We used Wolf Creek Dam as an example with data from an operations manual[44] but we want to note that assumptions were done in the reservoir discharges and elevations, so the results obtained throughout are for illustration purposes and do not necessarily resemble how the reservoir is actually managed. We retrieved the stream flow data available from before Wolf Creek Dam started operating (1940 to 1952). The mean daily stream flows of USGS gages in tributary streams

OVERTOPPING EMBANKMENT DAM. INFLOW EXCEEDS OUTFLOW

Image from: DAM-BREAK FLOOD MODELING/MAPPING USING DSS-WISE™ LITE:STEP-BY-STEP INTRODUCTION WITH HANDS-ON EXERCISES, One-Day Short Course, Module 2, September 13, 2018, Washington State Convention Center, Seattle, WA

contributing to the total dam inflow were added (examples of USGS gage locations for Wolf Creek Dam in Figure 8). In some cases, imputations were done using rank correlations with other upstream gages to complete the total streamflow time series.
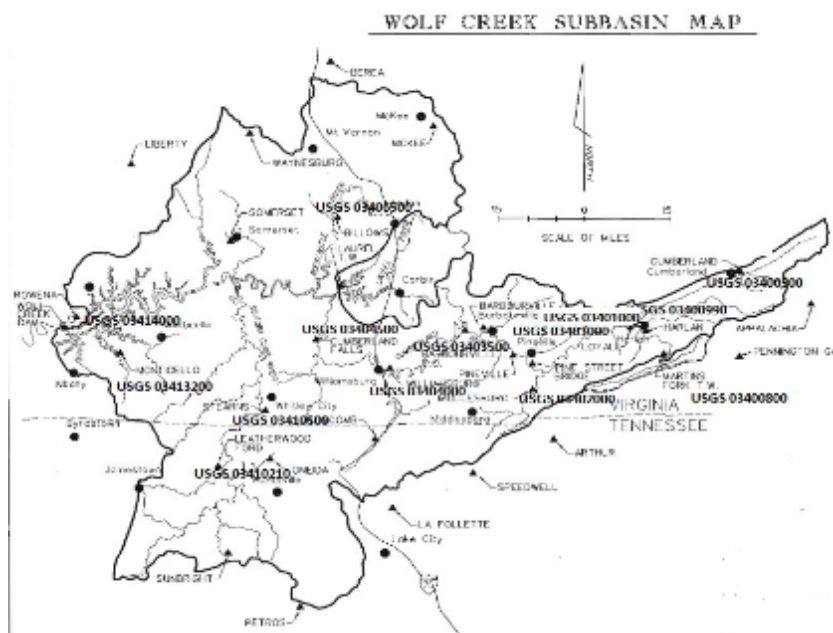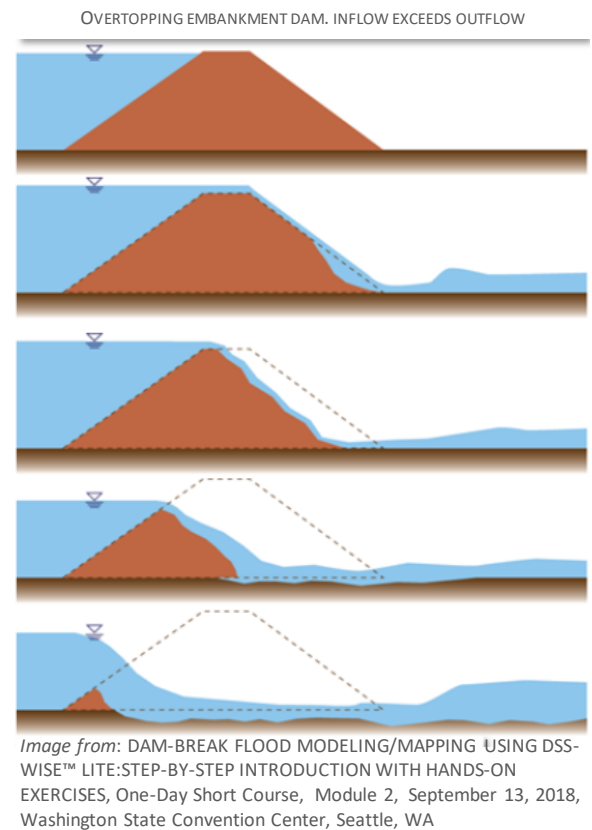

Figure 8 USGS streamflow gages in the Wolf Creek Dam subbasin [44].

We fit the annual maximum of the resulting daily mean streamflow values with a log Pearson type III distribution (Figure 9 left). We did the same using the time series available now (Figure 9 right) and **the 100 year return flood is 2% larger considering the whole time series; the 200 year return flood estimate is 5% larger.**
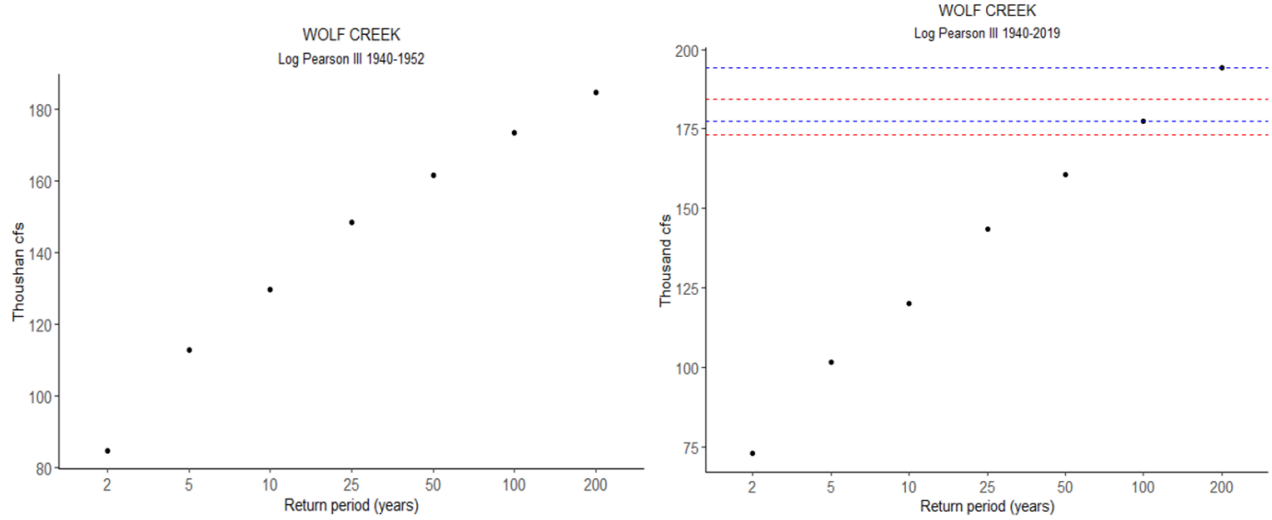

Figure 9 Return periods with log Pearson type III distributions. The dotted red lines on the right figure are the flow values corresponding to the 100 year and 200 year return periods in the distribution of the left.

The next step is to fit the streamflow data to a more suitable distribution to assess the probability of overtopping, since we are interested in flood events exceeding a threshold value, which can occur more than once in a given year (as opposed to the log Pearson III distribution that uses only annual maxima), given that there can be substantial damages resulting from the second or third largest floods in extremely wet years [34]. Partial duration series rather than peak annual floods are more suitable in such cases and the Generalized Pareto (GP) distribution [45], is commonly used to obtain the return periods. The GP has three parameters: scale (β), shape (ξ), and location (u, also known as the threshold). The cumulative density function is given by:

$$F_u(x) = P(X - u \le x | X > u) = F_{\xi,u,\beta}(x) = \begin{cases} 1 - \left(1 + \dfrac{\xi(x-u)}{\beta}\right)^{-\frac{1}{\xi}}, & \xi \neq 0 \\ 1 - \exp\left(-\dfrac{x-u}{\beta}\right) & , \xi = 0 \end{cases}$$

where $\beta > 0$. When $\xi > 0$ the Pareto distribution is applied, and when $\xi = 0$ it simplifies to the exponential distribution.

The daily mean streamflow threshold (u) for the partial duration series was defined as the 1 in 2-year flood (i.e. the median of the annual series of maximum daily streamflows). During wet spells, several consecutive days can exceed the threshold so the events are not independent. We considered independent flood spell events as those that have a minimum of 8 consecutive days below the threshold in between them. We obtained the volumes as cfs-day of each flood spell by accumulating the flows in days that exceeded u and taking the maximum of the accumulated volume. Then the flood volume events exceeding u (referred as F_V) were fitted to a GP distribution. The exceedance probabilities and return periods of F_V can be assessed with the density distribution (example for Wolf Creek in Figure 10).
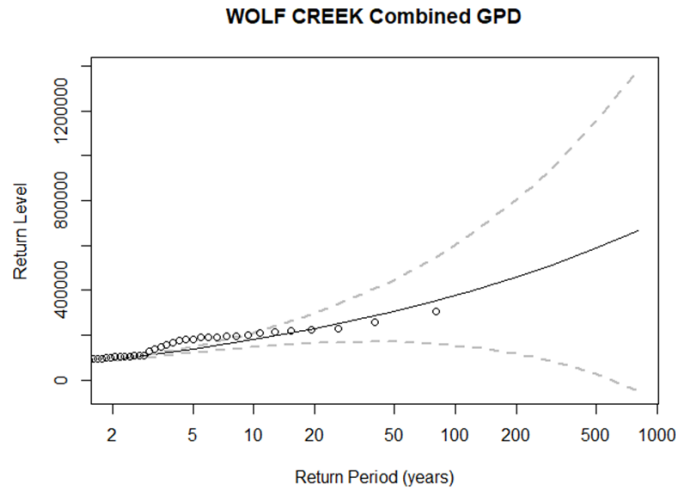
WOLF CREEK Combined GPD

Figure 10 $F_{V\,time}$ return periods for Wolf Creek

Overtopping probability part II: Trend analysis

The next step is to do a trend analysis to assess if the frequency and magnitude of F_V events are increasing in the region. This can be done in different ways but here we use the Mann Kendall test to analyze the trend of the number of events exceeding u in one year. We also do locfit regressions of the events exceeding u per year (coded as 1 if there were exceedances in that year and 0 if there were not) with time and CO_2 as predictors.

None of the gages/total streamflow series in the Wolf Creek example showed a significant trend with the Mann Kendall test. A change in trend was evident when CO_2 emissions was used as the predictor (with CO_2 emmissions datataken from the Primary Mauna Loa CO_2 Record available at Scripps; Keeling et al., n.d.), taking off after 380 ppm. So for future estimations of streamflow return periods, CO_2 can be used as a covariate to introduce the trend in the β and u parameters of the GP distribution.

Precipitation – F_V analysis.

Another way to predict changes in the future return period of F_V, is to use precipitation predictions based on the relationship between precipitation and F_V. The precipitation- F_V dynamic can be approximated with detailed hydrology models or simplified versions. Decadal precipitation predictions can be obtained from probabilistic models and longer term precipitation projections can be estimated from climate-driven models using GCM derived global circulation predictors, as discussed in the Climate Drivers and Regional Extreme Events section.

Overtopping analysis part III: Sedimentation

As dams fill with sediment, the available storage is reduced (a diagram of a generic dam configuration is provided below for clarity). Dams that have controlled discharges may have a lower hydrologic risk due to sedimentation provided that outlets are not blocked with sediments. This is because dam managers maintain the dam level at safe conditions. However, **the frequency of reaching flood level in a dam (this is a high level in the dam) may increase, which can increase the probability of overtopping.** In dams that do not have a controlled

discharge, the effect of sedimentation increases the risk of overtopping as the dam fills and less volume can be contained, plus the potential outlet blockage.
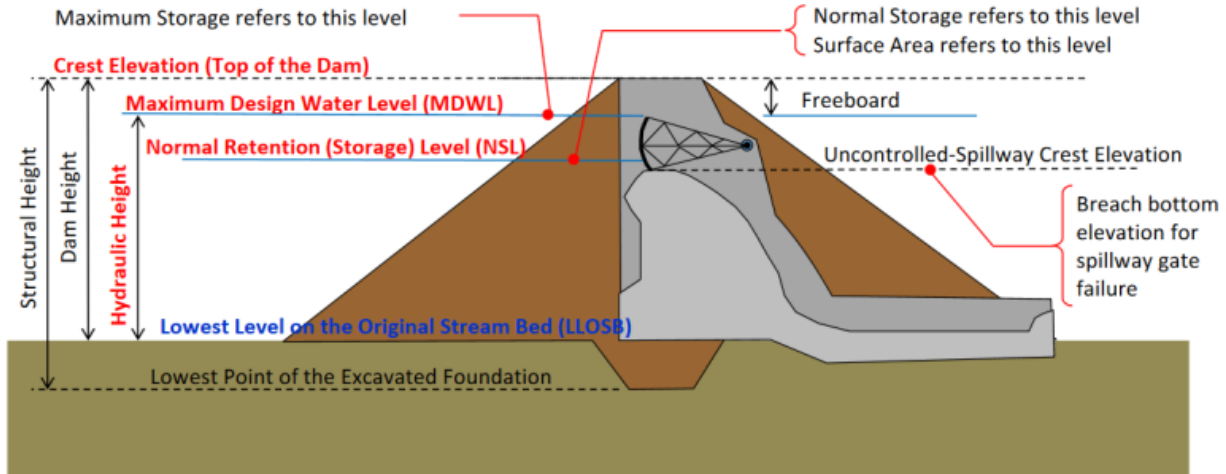
Dam diagram. Taken from: DAM-BREAK FLOOD MODELING/MAPPING USING DSS-WISE™ LITE:STEP-BY-STEP INTRODUCTION WITH HANDS-ON EXERCISES, One-Day Short Course, Module 2, September 13, 2018, Washington State Convention Center, Seattle, WA

The probability of reaching or exceeding a given reservoir elevation is key when analyzing the risks of overtopping; this defines the probability distribution of the free storage. Reservoir elevation curves can be used to assess the probability of overtopping or the probability of reaching the spillway crest, which can result in erosion. In these curves, the volume than can be stored at each elevation is known, allowing for the calculation of the available storage volume V_{diff} as the difference of the volume at the maximum elevation of the dam $V(e_{dam})$ and the volume at a defined elevation $V(e_S)$:

$$V(e_{dam}) - V(e_S) = V_{diff}$$

The effect of sediment buildup can be included in the analysis of the probability of overtopping by updating the dam elevation-storage curves using estimates of storage rate loss. Then the probability of reaching a "dangerous" dam elevation given inflows to the reservoir is updated.

In our example, Wolf Creek's elevation-storage curves and elevation-discharge curves included in the operation manual were done in 1949 and the dam started operating in 1951. A yearly storage loss rate was estimated with data from siltation survey of 87 dams across the U.S (RESSED database, also explained in the introduction). We took the median (0.12%/year), Q25 (.09%/year), and Q75 (0.25%/year) of the SLR across the country. Considering this SLR and the age of the dam, the current storage in 2020 could be between 6.5- 18% smaller than the original. We take the median value using a SLR of 0.12% to adjust the initial elevation=storage curves showing how for the same elevation, there is less storage now and how the storage will be affected by the time the dam is 100 years old in 2051 (Figure 11). Therefore, the probability of being at flood elevation has shifted and will keep increasing as more sediment is deposited.
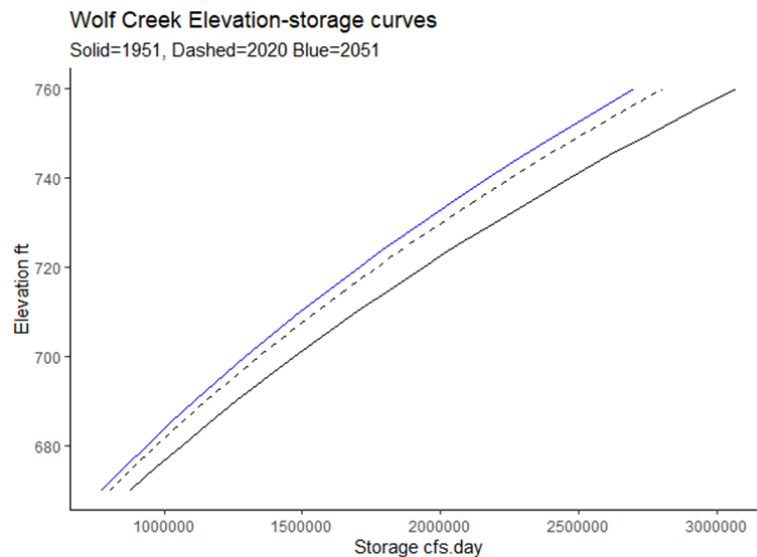
Figure 11 Elevation-Storage curves in 1948 and estimated in 2020 and 2051 adjusting for sedimentation.

If the time series of reservoir elevations is not available, we can simulate them with the elevation-storage curves, the daily inflows, and the elevation-discharge curves. A threshold exceedance analysis then follows (as the one done for F_V) to obtain the elevation return periods. In our example we set the threshold as the initial elevation for the flood control pool (i.e. the top of the hydropower pool). The resulting elevation return periods with the 2020 elevation-storage curve are shown in Figure 12. Note that we had to make some assumptions regarding the discharges and inflow so the curve likely underestimates the reservoir levels at each return period, but the purpose of the example is to illustrate how to apply the methodology.
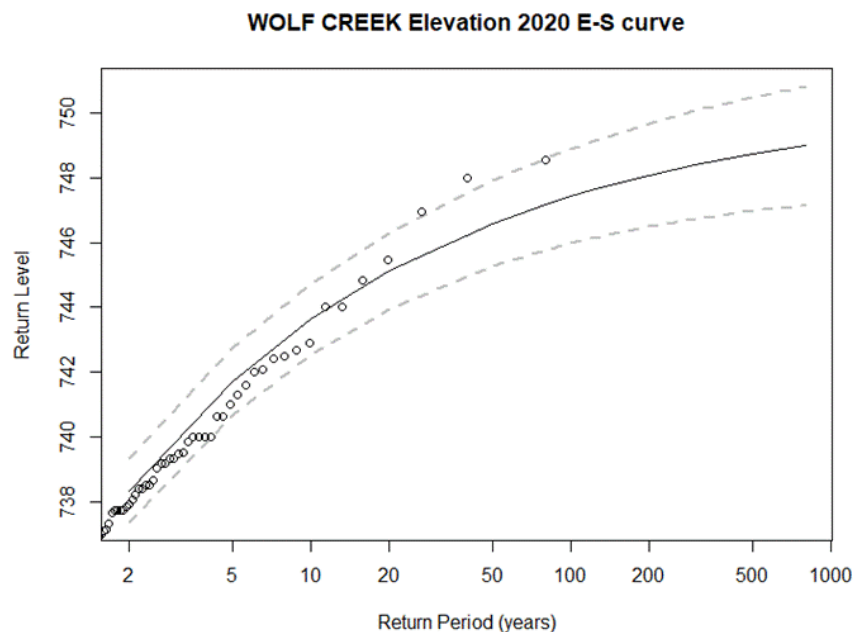

Figure 12 Elevation return periods obtained with the estimated daily inflows, and the updated elevation-storage curve.

Overtopping analysis part IV: Probability

Now we combine the return inflow volumes F_V, the elevation return periods, and the available storage at V_{diff} at different dam elevations to estimate the probability of overtopping.

The probability that inflow F_V equals or exceeds the available storage V_{diff} considering the discharge of the spillway, gates and other outlets at the defined initial elevation $D(e_s)$ (obtained from elevation-discharge curves) is given by:

$$P(F_V \geq V_{diff} + D(e_s))$$

So one can compute the minimum F_V needed to exceed $V_{diff} + D(e_s)$ at different elevation scenarios (e_s) and assess the probability of exceedance using the cumulative density function of F_V previously obtained. In our Wolf Creek example, this leads us to the return periods for shown in Figure 13 (we want to clarify that this is an example and many assumption were made for the dam discharges). Note that the return periods will be higher when the initial elevation is lower because the dam has more free storage available and therefore F_V needs to be larger to exceed the capacity.

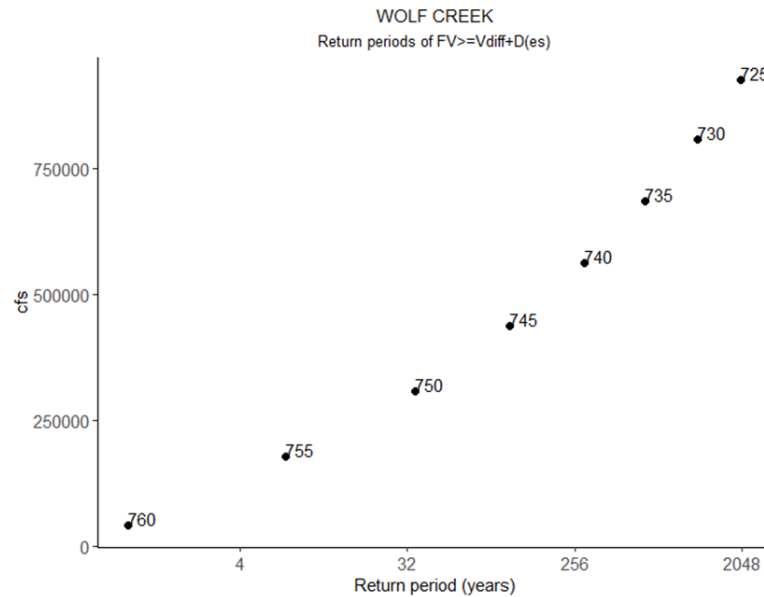**WOLF CREEK**
Return periods of FV>=Vdiff+D(es)

Figure 13 Return periods for $F_V \geq V_{diff} + D(e_s)$ at selected starting elevations.

The risk of failure quantifies the likelihood of experiencing a failure at least once in a given period of time (usually evaluated using the design life of the dam). The risk of failure R is related to a return period T, and is described as[47]:

$$R = 1 - (1 - p)^n = 1 - q^n = 1 - (1 - 1/T)^n$$

where n = design life of the dam, p is the probability of exceedance and q is the non-exceedance probability[47] . The return period T (or the probability of exceedance) does not depend on the life of the structure, but R does. For example, the chance of having at least one event in 30 years for the 1 in 100-year flood (p=.01) is 1-(1-.01)[30], which equals 26% chance. We calculate the probability of exceeding V_{diff} at different reservoir levels at least once in a

period *n*. In the example we take *n* as 72 years (current age of the dam) and 100 years (common design life). The results are plotted in Figure 14. This can help determine the water level maintained in the reservoir.
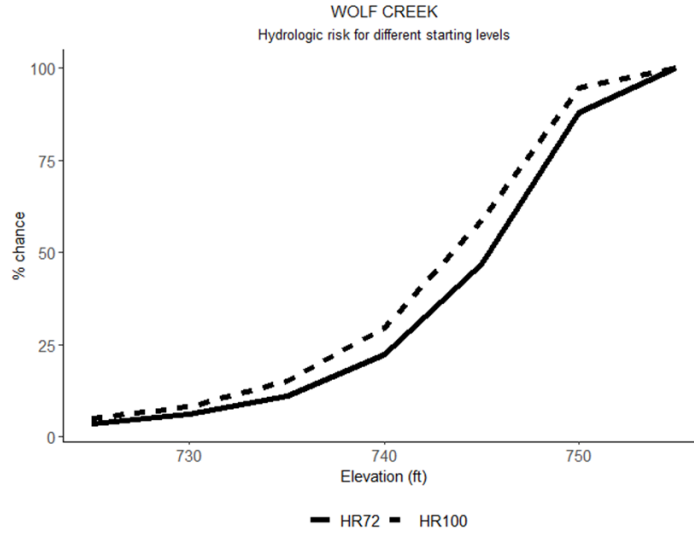

Figure 14 Hydrologic Risk in % of design life=72 and 100 (R72 and R100 respectively) considering changes in sedimentation.

We can also estimate the joint probability of $F_V \geq V_{diff} + D(e_s)$ and the dam being at elevation (e_s). These events are likely not independent as a very wet season may cause the dam to already be at high levels when the F_V occurs but for simplification here we treat them as such. The joint exceedance probability is given by the multiplication of the probability of exceedance of the elevation and the inflow:

$$p = P\left(e_s \cap F_V \geq V_{diff} + D(e_s)\right) = P(e_s) * P(F_V \geq V_{diff} + D(e_s))$$

We consider the same *n* periods as in Figure 14 and the elevation probability distribution from Figure 12. The resulting hydrologic risk is a lot smaller when the elevation probabilities are considered, since the probability of being at high reservoir elevations is very small (Figure 15).
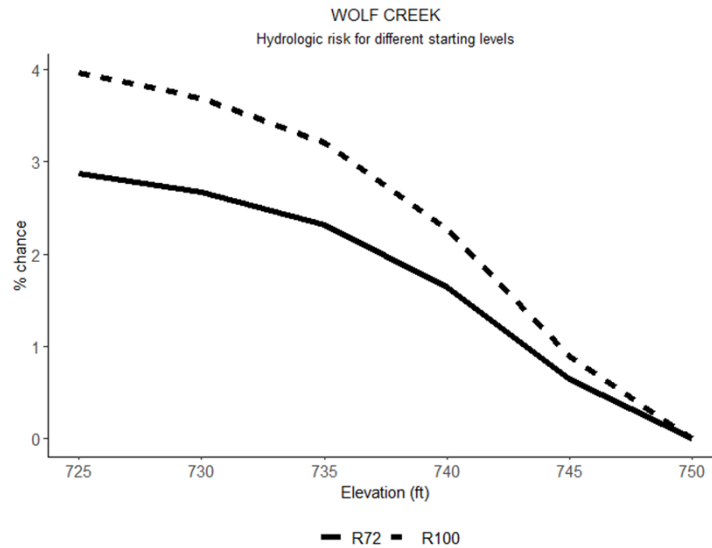

Figure 15 Hydrologic risk accounting for the probability of the elevation
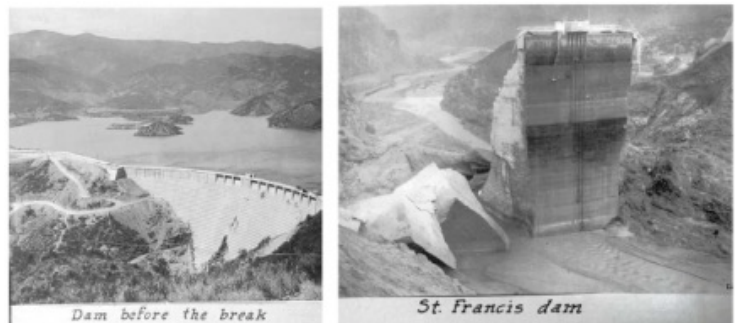
Risk analysis part V: Structural Fragility

Dam structures can deteriorate as the properties of their materials and their foundations change over time[48]. As the dam weakens, there will be a time when it is unable to withstand static, flood induced, or earthquake loadings [49]. The structural characteristics of a dam depend on the material of construction and design, and are affected by physical and chemical environmental processes.

In general, dams are classified as embankment dams or concrete dams. Embankment dams are made mainly of rock and soil and have lower construction costs than concrete dams but they are more likely to fail by overtopping[11]. As the dam overtops, the material erodes until there is complete failure. These dams are also prone to seepage, piping, and internal erosion, all of which involve complex mechanisms. Insufficient drainage, corrosion of outlet pipes, deformation and settlement of the materials, surface erosion, loss of strength due to improper compacted fill or

Concrete Arch dam failure. Image from: DAM-BREAK FLOOD MODELING/MAPPING USING DSS-WISE™ LITE:STEP-BY-STEP INTRODUCTION WITH HANDS-ON EXERCISES, One-Day Short Course, Module 2, September 13, 2018, Washington State Convention Center, Seattle, WA

cycles of wetting and drying/freezing and thawing (i.e. leading to cracking and slope instability), vegetation, and animal activity can all lead to structural failure. Internal erosion is the most common aging scenario for the foundation of earth and rockfill dams, and it is a process that may remain undetected for a long time without the proper monitoring [50].

Concrete dams can be gravity, arch, or buttress dams. Regardless of the type of concrete dam, their stability highly depends on the strength of the concrete (which can deteriorate as the dam ages) and on the strength and stability of the foundation and abutments. For concrete dams, failure by overtopping means sliding or overturning of the whole structure due to erosion of the abutments and foundation [11]. Several phenomena can result in structural failure and their characterization is not trivial. Failure probability in these cases can be a function of multiple variables such as the dam's height and width, the material of construction, the slope, the foundation type, and many others. The failure models can be quite complex and specific for the different structural failure modes.

A fragility analysis would therefore entail access to very detailed information for each dam, which is out of the scope of the general framework proposed for a preliminary identification of risky dams. However, considering that wet-dry and freezing-thawing cycles are potential stressors for the structural integrity of embankment and concrete dams respectively [50–52], and that climate information is available, **we created a simple index based on historical climate data and in future climate scenarios to represent structural fragility** related to these cycles. Ice expands about 9 percent upon freezing, causing forces of up to 30,000 lb/in^2, which is sufficient to crack concrete if it is not protected against this action [52]. Dry-wet cycles can affect seepage behavior in

embankment dams. Severe droughts can originate cracks, which become channels of infiltration into the dam during the wet cycle. This increases the chances of internal erosion and reduces dam stability [51]. A rapid drawdown of a reservoir can result in failure[51]. **Therefore, we take the number of freeze-thaw cycles (F/T) and the number of wet-dry cycles (W/D) as a proxy for the probability of having structural deterioration in concrete and embankment dams respectively.**

The earliest concretes used in dams failed in about 50 to 100 F/T cycles (dams constructed unitl about 1945); modern frost resistant concrete normally withstands more than 1,000 cycles of F/T [52]. **We consider the probability of experiencing more than 100 F/T cycles in the design life of a concrete dam if it was built prior to 1945 and 1000 cycles if it was built after that.** This probability could change due to climate change, so GCM temperature projections, which are known to be more accurate than precipitation projections, can be used. In embankment dams, the threshold is related to the number of wet-dry cycles (W/D). Wet-dry cycles in seepage analyses are normally defined as the process from dry to saturated and from saturated to dry[53], where the saturation refers to the material of construction. With increasing number of wet-dry cycles, irreversible damage accumulates in the material, resulting in degradation of physical and mechanical properties[53].

Wet-Dry Cycles

To estimate the W/D cycles we use the Standardized Precipitation Evapotransporation Index (SPEI), which takes into account both precipitation and potential evapotranspiration in determining drought [54]. The SPEI can be used for determining the onset, duration, and magnitude of droughts. The average value of the SPEI is 0, and the standard deviation is 1. SPEI values <-1 indicate a condition of drought, the more negative the value the more severe the drought; values >1 indicate more humid conditions compared to normal. When the SPEI has a value between -1 and +1 the situation is identified as normal. In Figure 16 we use -1.5 and 1.5 to indicate extreme wet or dry periods in the 12-month SPEI index.
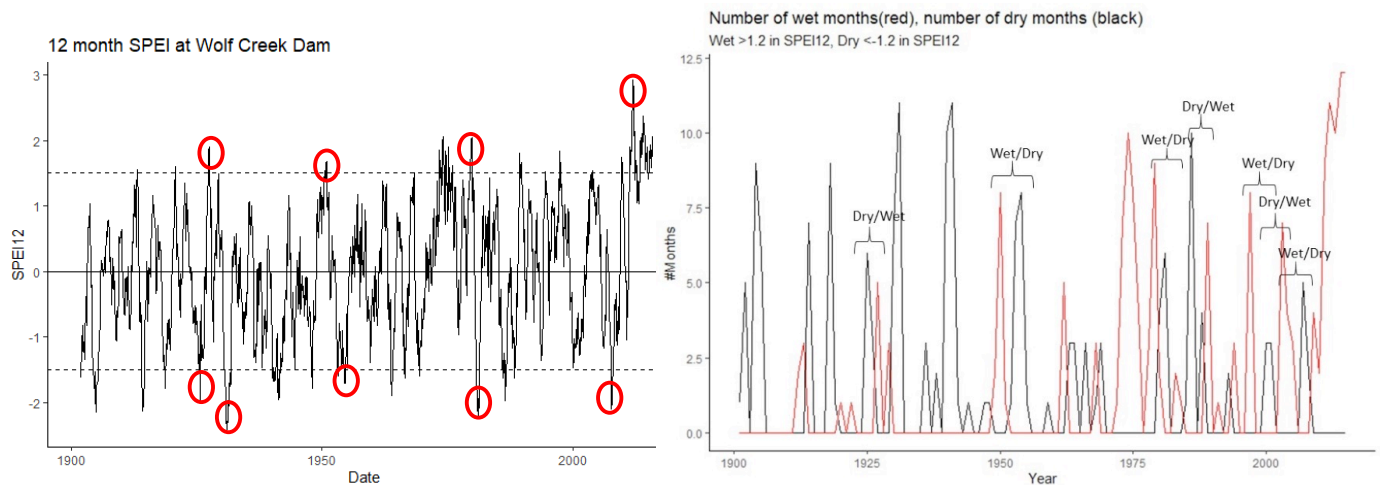
Figure 16 12-month SPEI index at Wolf Creek Dam (left). The horizontal dashed lines indicate drought conditions or above normal wet conditions. Number of months per year in wet or dry conditions (right). Data was retrieved for Wolf Creek Dam from http://spei.csic.es/database.html#p1.

We calculate the probability of W/D cycles as the ratio of the number of times conditions switch from wet to dry or dry to wet in the period of record, considering dry as SPEI12< -1.2 and wet as SPEI12 > 1.2

In the example, the probability of experiencing a W/D cycle (dry-wet plus wet-dry occurrences) in any given year is 12% taking the whole dataset. If only the years after 1950 are considered, the probability increases to 13.8% showing an increase in the frequency of such events. The dam has experienced 9 W/D cycles in its operating lifetime (with different intensity of drought and wet conditions). The probability of experiencing at least one more event in the next 10 years is 77%, so it is very likely that the dam will be exposed to more W/D cycles in its remaining operating life. **Any new event can potentially lead to a dam failure, unfortunately we don't have the data to calculate the conditional probability of failure given that there was a W/D cycle, but at least obtaining this probability helps compare exposure across different dams.**

Freeze-Thaw cycles

The frequency of F/T cycles, and therefore their probability of occurrence, can be obtained from temperature datasets and GCM temperature projections. The process is the same as for W/D cycles but in this case, the exceedance event that matter is to surpass 1,000 F/T cycles in the life of the structure [52].

In our example, daily temperature was obtained from the ERA Interim Reanalysis available at KNMI (https://climexp.knmi.nl/start.cgi) and temperature anomalies were retrieved from the NOAA Global Surface Temperature Dataset. The temperature has an upward trend in the last 25 years (Figure 17), and the area does not experience F/T cycles (temperatures do not go near or below freezing), so there is no risk of structural fragility due to this failure mode. As for the W/D cycles, obtaining this probability
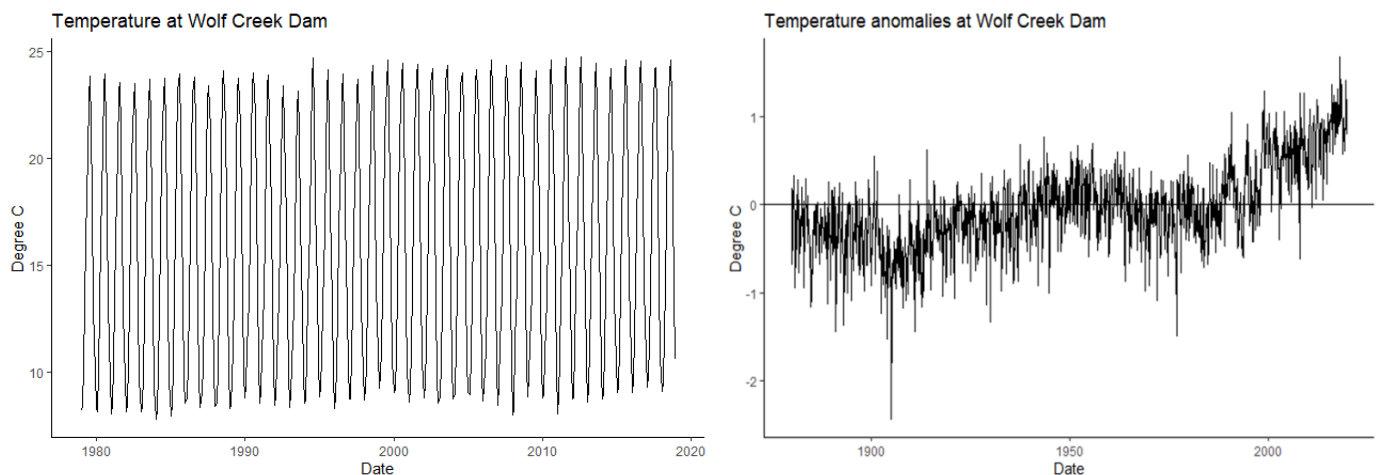
Figure 17. Temperature from ERA Interim Reanalysis-left. Temperature anomalies from NOAA Global Surface Temperature Dataset-right

W/D cycles are likely correlated with flood events so their joint probability should be considered for more in detailed analyses.

Overtopping analysis part VI: Portfolio Risk

As explained in the Climate drivers and regional extreme events section, many dams located within a region may experience extreme climate events simultaneously. Therefore, the probability and consequences of their joint failure need to be considered in a portfolio risk assessment.

Dams that are in parallel (i.e. there are no other dams upstream from them), may or may not experience an overtopping event simultaneously, with a certain probability. For such dams, the probability of two or more experiencing an overtopping event can be derived based on regional precipitation and streamflow data, and used with the potential probability of failure by overtopping, to assess the joint probability distribution of failure of multiple such dams. For example, for two dams A and B in parallel in the same region, treated as non-independent events the probability that both of them fail is given by:

$$P(A \cap B) = P(A|B) * P(B)$$

For dams in series, the conditional probability of overtopping of the downstream dam, given that one or more of the upstream dams has failed (or not) is needed. So for dams A and B that are in series the probability that A fails given that B fails (A is downstream of B) is given by:

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

Once these probabilities are estimated, all the potential failure pathways in the portfolio can be examined, and the probability and the potential loss associated with each pathway can be scored to derive a probability weighted measure of portfolio risk. Within the portfolio, the network links that contribute the highest expected loss can be identified. The framework for quantify losses is reviewed in the next section. Assessing the financial consequences of dam failures

ASSESSING THE FINANCIAL CONSEQUENCES OF DAM FAILURES

In this section we review approaches to quantify the potential financial consequences and damage to critical infrastructure caused by dam failures, and describe the proposed methodology with examples of dams located in the Cumberland River Basin. We propose seven decision criteria encompassing the direct economic losses including dam replacement costs, potential damages to critical infrastructure such as power plants, electric substations, wastewater treatment plants, roads, railroads, navigation routes, and facilities containing hazardous materials, and the population affected (Figure 18). The framework uses publicly available dam break and consequence tools developed by the US Army Corps of Engineers and FEMA, and national infrastructure datasets. In particular, we use the Decision Support System for Infrastructure Security Lite (DSS-WISE™Lite) to estimate the inundated area, and FEMA's Hazard-US (HAZUS) software to estimate the direct financial losses.

We also show how the inundation area from a dam failure can exceed the flood insurance rate maps (FIRMS) estimated 1 in 100-year and 1 in 500 year event floods.

The application of the framework could be the creation of a national dam hazard map to complement FIRMS and allow the identification of "hot spots" beyond the current dam hazard classifications using the analytic hierarchical process (AHP) as a ranking method.
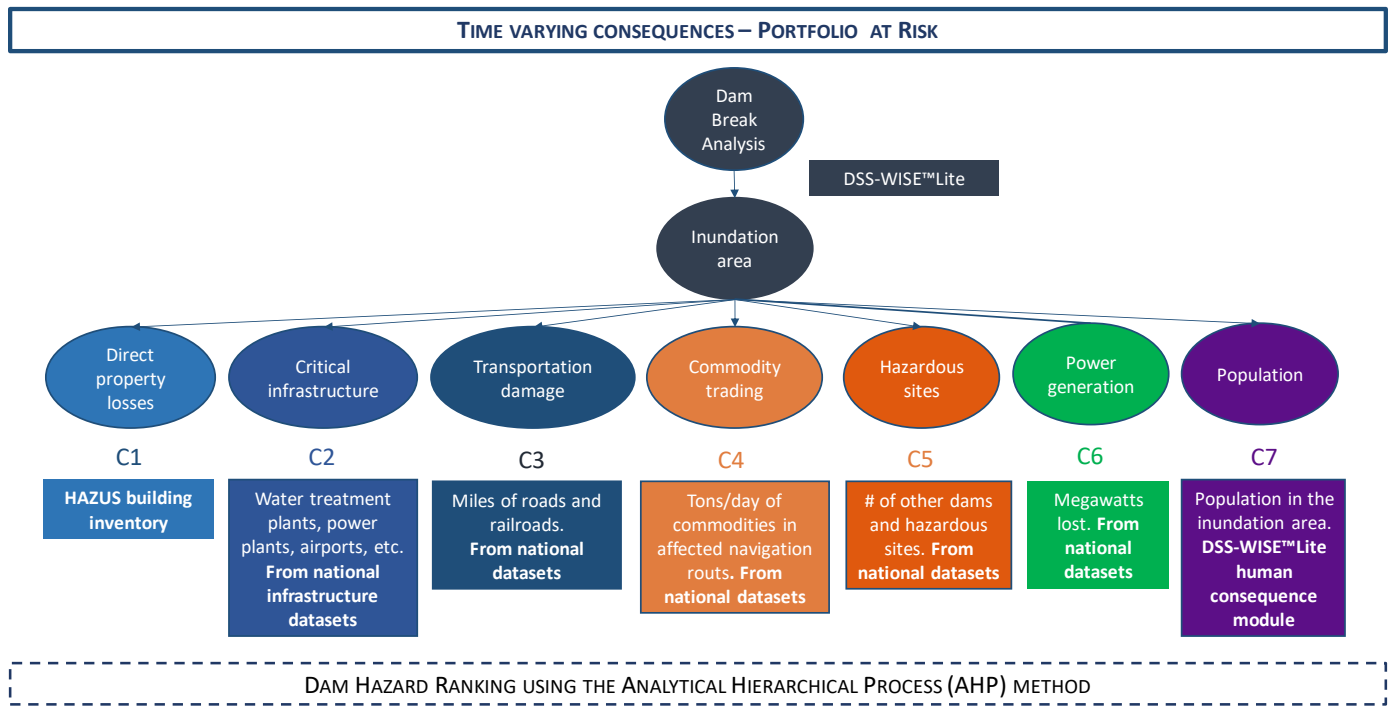
DSS-WISE™Lite

Direct property losses	Critical infrastructure	Transportation damage	Commodity trading	Hazardous sites	Power generation	Population
C1	C2	C3	C4	C5	C6	C7
HAZUS building inventory	Water treatment plants, power plants, airports, etc. **From national infrastructure datasets**	Miles of roads and railroads. **From national datasets**	Tons/day of commodities in affected navigation routs. **From national datasets**	# of other dams and hazardous sites. **From national datasets**	Megawatts lost. **From national datasets**	Population in the inundation area. **DSS-WISE™Lite human consequence module**

DAM HAZARD RANKING USING THE ANALYTICAL HIERARCHICAL PROCESS (AHP) METHOD

Figure 18 Risk analysis: Assessing the consequences of failure

DAM HAZARD CLASSIFICATION INCLUDING FINANCIAL AND INFRASTRUCTURE RISKS

In general, the characterization of probable loss of human life in dam hazard classifications is clearer than the potential economic losses and critical infrastructure damage. This is partially due to the accessibility to demographics data and because loss of life is an immediate priority in hazard classifications (as it should be). However, the financial impacts of a dam failure can be quite significant, and these are heightened in extreme events, as other critical infrastructure can fail. In October 2015, South Carolina (SC) experienced an estimated 1 in 500 year storm event [55], and 36 small dams failed as a result of the storm [56]. The subsequent flooding due to the storm and dam failures resulted in 19 deaths, the closure of all highways in Columbia, and the closure of 120 km of the critical north-south Interstate 95 highway that connects the east coast of the US. Nearly 30,000 people were without power and damage losses were estimated at US$1.5 billion [56].

Multi-criteria decision analysis (MCDA) techniques have been proposed to improve dam hazard classifications, since they can include variables expressed in different units (monetary, impacted population, damaged infrastructure, etc.)[57–59]. MCDA models rank decision options based on a set of evaluation criteria and the importance of each criterion is represented by weights usually elicited from experts or stakeholders [60], and summarized in a decision matrix. The weighted sum method (WSM) is a simple and often used MCDA technique [61,62], where a score is calculated multiplying the performance criteria value by the criteria weight and all the weighted scores are added. Criteria weight assignment often relies on expert opinion[57] and a sensitivity analysis is needed to test for rank reversal. The analytic hierarchy process (AHP)[63] is the most popular MCDA technique in the academic literature for dam risk ranking [59], integrating quantitative and qualitative measures, and personal preferences in performing decision analyses. This technique is similar to WSM, but AHP uses the relative importance of the alternatives in terms of each criterion to hierarchically structure single or multi-dimension decision making problems [57].

Our framework uses AHP for dam hazard ranking using seven criteria (Figure 18). AHP requires normalized performance values so the data is transformed into dimensionless values, and summarized into a decision matrix. The performance values are normalized vertically so the elements of each column in the decision matrix add to one. The decision matrix is organized in j columns (criteria) and i rows (dams). The normalized matrix (n.m) was obtained as follows:

$$n.m = \frac{\min(x_j) - x_{ij}}{\min(x_j) - \max(x_j)}$$

where j is a criterion and i is a dam. This way the dams that score higher in the criteria have a higher normalized score. For the weighted matrix, the weights across the criteria need to add to one. We used the following criteria and assigned equal weight to each of them:

C1-DIRECT ECONOMIC LOSSES - Includes the depreciated replacement costs of residential, industrial, commercial, government, religious, and agricultural infrastructure, and the dam replacement cost.

C2 -ECONOMIC RISK OF INFRASTRUCTURE – Number of utilities with damages greater than 40% including wastewater treatment plants (WWTP), power plants (PP), Airports (Air), and electric substations (ES).

C3-MILES OF MAJOR ROADS AND RAILROADS – Obtained from national datasets. This estimation does not consider the inundation depth.

C4-TONS/DAY OF COMMODITIES IN AFFECTED NAVIGATION ROUTES – obtained from national datasets.

C5- NUMBER OF OTHER DAMS AND SITES WITH POTENTIAL HAZARDOUS WASTE defined under the Resource Conservation and Recovery Act (RCRA) referred as RCRA sites.

C6 -AFFECTED POWER GENERATION IN MEGAWATTS – obtained from national datasets.

C7-AFFECTED POPULATION – obtained from the human consequence module included in DSS-WISE™Lite.

We acknowledge that there are some known issues with AHP and all MCDA methods, related to the uncertainty in the weights assigned, the independence of the criteria, and rank reversal issues [64,65]. MCDA requires sensitivity analyses of the weights, but they generally involve systematically varying one parameter over their entire range while keeping the others constant; therefore the combined effects of different parameters cannot be determined [65]. Weights are normally assigned by experts and decision makers.

Criteria estimation

Inundation area

First we need to estimate the inundation area of a dam failure and the depth at different points. There are many software products available to do this [27,66]. In the U.S., the Hydrologic Engineering Center River Analysis System (HEC-RAS) and the more recent DSS-WISE™Lite are popular publicly available tools to do such analyses. HEC-RAS requires detailed inputs and expertise but it is more flexible and accurate than DSS-WISE™Lite, however, DSS-WISE™Lite is much faster [67]. In the framework presented here, DSS-WISE™Lite is used to estimate the dam inundation

areas and losses because it is more appropriate for our scope, which requires the analysis of multiple dams where limited information is available. DSS-WISE™Lite was developed by the National Center for Computational Hydroscience and Engineering at the University of Mississippi on behalf of USACE [68].

A downside of using DSS-WISE™Lite is that it does not allow modelling cascading failures so we could not include them in our framework. However, an approximation of potential overtopping of downstream dams was included in the hazard characterization by counting the dams that are located within the inundation area of a failed upstream dam. This could also inform the probability of failure of dams in series discussed in the failure probability section. For sequential dam failure FEMA's guidance recommends that the hazard potential classification of the upstream dam must be as high as or higher than any downstream dams that could fail as a result of the upstream dam's failure. However, there are cases where both upstream and downstream dams are classified as High hazard just based on the potential population affected, so the risk of the cascading failure is not visible.

The starting dam pool elevation in the example dam break simulations is the top of flood pool level (i.e., the dam is at capacity). Consistent with the overtopping scenario, we would like to simulate a starting condition of flood stage downstream of the dam but this is not currently possible in DSS-WISE™Lite, as it only simulates sunny day failures. The tool does not simulate backwater either. Therefore, **the resulting inundation area is a conservative estimation in situations when a region is at flood stage prior to the failure**. Two types of failures were modeled: sudden and complete failure labeled as S1, and partial failure using parameters for breach formation from empirical equations[69] labeled as S2.

Losses

To calculate the direct economic losses (C1) we used infrastructure datasets and depth-damage curves included in the software HAZUS. HAZUS is a publicly available model developed by FEMA to estimate the financial consequences of floods at the census block level, but it is computationally intensive[70]. Given the national scale we want to achieve, we extracted building databases and depth-damage curves contained in HAZUS, and performed the loss analysis externally using the programming language R to speed up the process.

HAZUS has a nation-wide inventory of buildings, referred as general building stock or GBS. The database has many assumptions; for example, exact locations of the buildings in HAZUS' GBS are unknown, and buildings are uniformly distributed at the census block level, but it is the best available at a national scale. The database contains the depreciated infrastructure replacement cost in million USD, allowing the estimation of direct losses depending on inundation extent and depth using depth-damage curves. The results presented in our direct loss criteria C1, are point estimates in million dollars aggregated by occupation type: residential, commercial, industrial, education, government, and religious.

C1 also includes dam replacement costs, and these were approximated with a function of cost-storage used for hydroelectric dams,[71] assuming USD$ 1,294 per acre-ft. We acknowledge that the cost approximation per storage volume is highly uncertain, but this gives indication of the order of magnitude of the costs for replacing the dams.

The infrastructure percent damage estimations in criterion C2 (economic risk of infrastructure) consider the lower bound of inundation depth from DSS-WISE. The number of utilities with damages greater than 40 % characterize infrastructure with high potential financial losses. Criteria C3 to C6 do not take into account

inundation depths and the reported numbers only consider the number of locations, electricity generation capacity, and commodities transported that could be affected because they are within the inundation zone. For C3 and C4, the losses related to interruptions in commodity trading can be roughly estimated with data from the commodity flow survey (CFS) collected periodically by the US Census Bureau in cooperation with the Bureau of Transportation Statistics, US Department of Transportation [72]. This analysis cannot differentiate exactly by the name of the damaged road or railway nor includes damage related to inundation depth, but it serves as a coarse estimate of what is at stake for transportation in a region.

Test Case Results

Hazard Classifications

In the example, the failure of J Percy Priest Dam scores higher across the criteria because of its proximity to the city of Nashville (Figure 4), however some criteria such as the dam replacement cost, impacted megawatts, and the presence of dams within the inundation area are higher for other dams (results shown in Figure 19).

The final hazard ranking in descending order is J Percy Priest, Center Hill, Cordell Hull, Old Hickory, and Dale Hollow Dam, assuming equal weights for the criteria. This ranking is sensitive to the chosen weights and a sensitivity analysis on the weights could be performed.

Analysis of losses using FIRMs (1 in 100 years and 1 in 500 years) and Percy Priest failure in Nashville

The objective of this analysis was to put into perspective the differences in damages and insurance needs included in the flood inundation rate maps (FIRMs) and those resulting from a dam failure. In the example, we constrained the analysis to the boundaries of Nashville's Urban Service Districts for comparison purposes, given that it is the largest urban area in the test case region. The infrastructure within the FIRMs (1% and 0.2% return floods) in Nashville was compared with the inundation area of Percy Priest's Dam failure *plus* the FIRMs areas. This analysis only considers the C2-C6 consequences. The flood insurance rate maps obtained for Kentucky did not include flood depth for most of the areas, so in this crude comparison we only take into account the number of facilities within the inundation zone without estimating damages as a function of inundation depth. It is evident from the results in Table 1 that the potential damage in electricity supply, WWTPs and losses associated to commodity trading in impaired navigation routes could be much greater than the FIRM maps alone. The exposure of RCRA sites, electric substations, and damaged miles of major roads and railroads is also greater. The commodity most impacted would be coal (Table 2), which in turn could affect other sectors. This shows that damages incurred by the failure of Percy Priest dam would be greater than those considered in the FIRM zones, which could likely be uninsured.
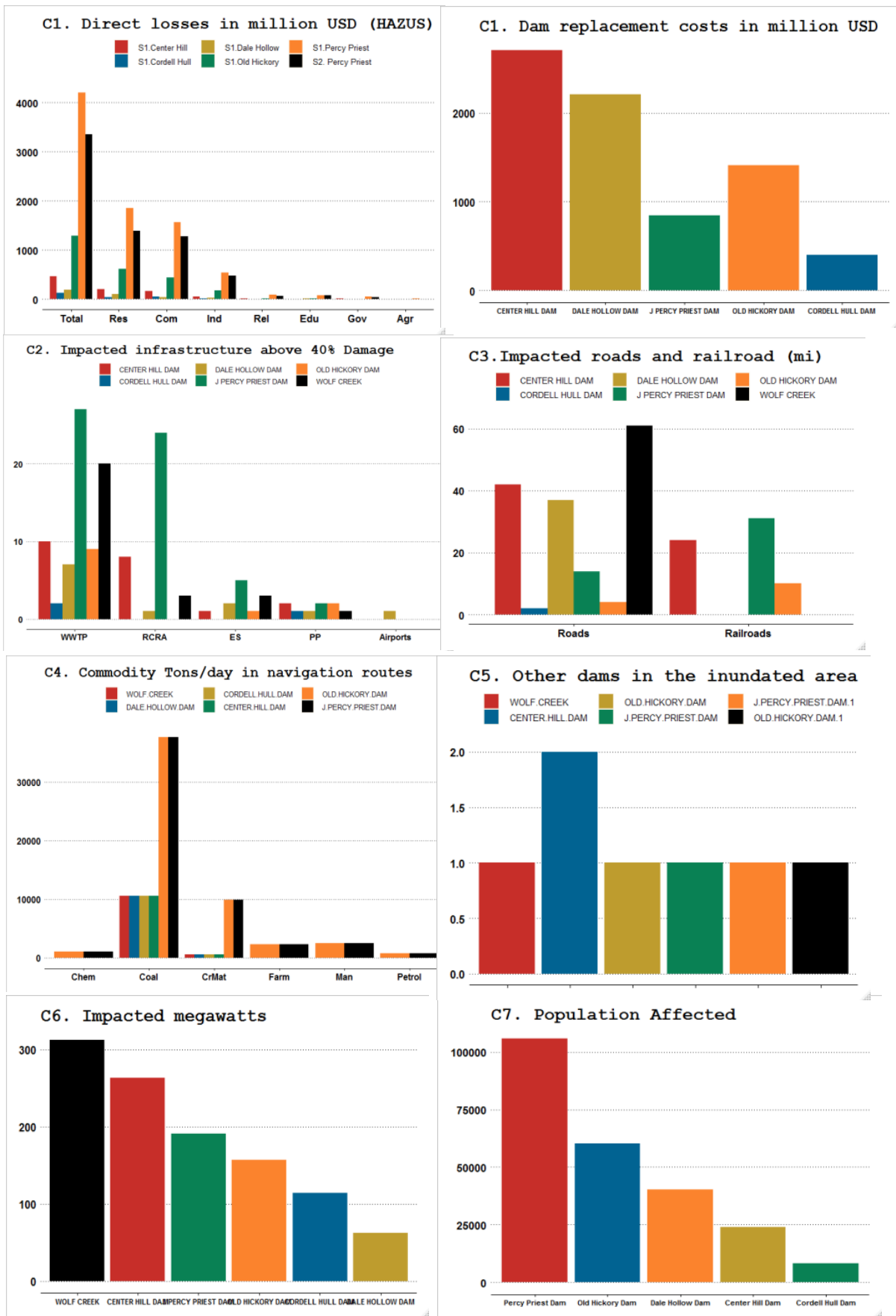
Figure 19 Consequence estimation results

Table 1 Infrastructure affected in Nashville in different inundation scenarios

Inundation Extent	MWs	WWTPs	Roads (mi)	ES	Railroad (mi)	RCRA sites	Tons/day in Navigation route
DFIRM 100 year flood	0	16	2.3	6	6	1	0
DFIRM 100 year flood	0	28	4.3	12	14	4	0
DFIRM 100 year flood and Percy Priest Dam	33.8	52	7.8	14	20	6	53,987
DFIRM 500 year flood and Percy Priest Dam	33.8	54	8.4	16	21	6	53,987

*MWs=Megawatts, WWTPs=Wastewater treatment plants, ES=Electric substations, RCRA=hazardous sites

Table 2 Commodities (in ton/day) transported in the affected navigation routes in Nashville in case of failure of Percy Priest.

Coal	Petrol	Chem	CrMat	Man	Farm	Mach
37,674.6	724.5	1,020.1	9,864.4	2,466.0	2,236.8	0.4

*Chem=Chemical materials, CrMat=Construction materials, Farm=agricultural products, Man=Manufactured goods

> **In this section we presented a framework to estimate some of the financial and social consequences of a dam failure and showed how they can be larger than those considered in the flood insurance rate maps or FIRMs.**
>
> **In the next section we discuss how other indirect losses could be quantified and included in the estimation of regional financial risk of dam failures**.

ASSESSING FINANCIAL RISK

During the course of the project, we were able to provide a foundation as well as example applications for how dam failure risk could be quantified, and potential asset and life loss risks identified using publicly available sources of data. Time and personnel resource constraints prevented us from integrating the results into a regional financial risk estimation strategy. **The process pursued for impact assessment does provide a basis for the direct loss assessment in the event of a dam failure. However, it does not yet consider indirect economic impacts, through for instance, the loss of transportation or energy or water infrastructure, or the closure of areas due to the spread of toxic waste from repositories in the flood plain to downstream communities and ecosystems**. Such impacts can be, in theory, assessed through regional economic models subject to shocks. The development of such models for climate change impact analysis has been pursued to an extent [73–76]. However, specific risk factors related to hazards are typically resolved at a rather macro level, and may be grossly underestimated. In a sense**, our work to date provides an approach for the bottom up generation of information as to hazards that could be used in such integrated assessment models.**

Significant uncertainties are associated with the dynamics of climate, the presentation of climate hazards, and the manner in which they are manifest. Consequently, a bottom up consideration of such hazards in economic analyses is rare. However, it is also clear that the short and long term financial effects of hazards and their climate dependence need to be properly considered to quantify the dual effects of aging infrastructure on changing

regional populations and economies. **As climate adaptation efforts advance, having a prioritized approach to regional investment and renewal, and to appropriate financial risk mitigation strategies will emerge as a priority. We are keen to advance our work in this direction and extend the foundation and examples developed in this report to present an economic and financial risk modeling strategy in this regard.**

NEXT STEPS (TO EXTEND THE CURRENT PROJECT)

MODEL DEVELOPMENT:

The basic building blocks for a model that could estimate direct losses from dam failure were developed and tested in the project. The extension of these into **a comprehensive catastrophe model that could provide a stochastic catalog of loss for use with parametric financial instruments for risk management or for traditional insurance type of applications** is now feasible, and this is an application we are interested in pursuing.

Most of the existing research on the indirect impacts of natural disasters builds on the predictions of input-output (I-O) and computable general equilibrium (CGE) models. In both cases, a multi-sectoral accounting approach is utilized that builds a matrix for money flows across different sectors of the economy for perturbations of the state of any one of the sectors. For the I-O models the coefficients of such matrices are calibrated to historical data and are time invariant, representing static production functions, and attempt to predict how damages in one sector will propagate through production and trade to other sectors. The CGE models are similar but consider stable demand and supply functions and predict how the price, supply and demand across sectors may evolve. **In our view such models are useful to get a directional estimate of the potential indirect impact, but are not well suited for the dynamic impact of hazards.**

CLIMATE EXTREMES	DAM FAILURE	REGIONAL FINANCIAL EXPOSURE	

ANALYSIS OF EXTREME EVENTS RETURN PERIODS	PROBABILITY	DIRECT FINANCIAL LOSSES	ECONOMIC LOSS PROPAGATION TO DIFFERENT SECTORS/ CASCADING EFFECTS
Regional climate models	Dam characteristics, age, sedimentation rate, operational data, maintenance, current physical conditions	Infrastructure replacement costs (including dam reconstruction), elevation-damage curves	Model money flow:
Precipitation and temperature data	INUNDATION AREA	Agriculture losses	Input-output models (I-O)
Streamflow data/ dam inflows	Dam characteristics, dam break inundation model (very time consuming)	INDIRECT FINANCIAL LOSSES FROM:	Computable general equilibrium models (CGE)
	CASCADING DAM FAILURE/ FAILURE OF MULTIPLE DAMS IN THE REGION	Transportation interruption: supply chains, jobs, tourism, etc. Loss of dam services Power cuts Water/wastewater cuts Release of toxic materials	Bayesian networks to assess uncertainty and risk propagation Scenario analysis of economic development Cost of inaction

Given the temporal dimensions of the hazard and the subsequent economic re-adjustment, **systems dynamics models, in conjunction with a Bayesian structure for information and uncertainty flow could provide a novel approach to propagating a risk framework associated with dam failure risks into the economy**. The intention would be to **include both the dimensions of hazard induced loss, and economic growth in selected sectors that benefit from reconstruction and relief activities**. An interesting speculation in this regard is the degree to which the hazard could induce a transition to a radically different form of infrastructure, e.g., a destruction of a thermo-electric power plant may stimulate replacement by renewable solar or wind generation facilities, which in turn require very different quantities of water, transmission, energy storage and technical labor markets. Likewise, regional economic development plans could be stimulated or adversely impacted by the hazard. **The bottom up approach to information propagation at the regional scale, with an appropriate consideration to external linkages could then provide a paradigm for Integrated Assessment Modeling in the context of Climate Change Adaptation.**

DATABASE DEVELOPMENT:

We would like to develop the necessary databases to build a platform to map the changing risk profiles associated potential dam failures across the United States, using the bottom-up framework presented in this report, and expanding it to the comprehensive catastrophe model escribed previously. Below is the data needed, data available, and gaps that we have detected:

Data needed for probability estimation

- *Dam inflows-* Inflows can be approximated with the contributing streamflow using USGS gage data. This is a time-consuming process and there might be many missing data points in the streamflow time series. Large scale hydrology models such as VIC can also be used but the generated streamflow carries large uncertainty and does not consider the impact of regulated flows.

- *Dam operational data such as elevation (or storage) time series, storage-elevation curves, and discharge-elevation curves*. This is needed to estimate the return period of the elevations. Operational data may be available in operations manuals of dams managed federally (such as the ones managed by USACE), and obtaining them is a time-consuming process. Operations data of private dams is harder if not impossible to obtain and several assumptions need to be made.

- *Storage rate loss due to sedimentation*. Can be coarsely estimated with the RESSED database. For dams already included in the database, storage loss can be more accurately estimated.

- *Climate models* – Regional climate models of precipitation and temperature can be obtained from the literature or developed for regions where they are not available. These models can be medium term (i.e. yearly and decadal) or based on GCM projections to account for climate change. The identification and development of such models for the whole U.S. is needed.

- *Maintenance, inspections, and overall conditions of dams*. The NID has related information but it is not released to the public due to safety concerns. The Associated Press did a study revealing that the conditions of thousands of dams across the U.S. are unsatisfactory but the data was not released when requested.

Data needed for consequence estimation

- *Critical infrastructure locations, capacity, and population served*. Data from different sources needs to be compiled, and there is great variability in the information provided from each source. Also, there are some significant data gaps at the national level; for example, there is no national database of drinking water utilities so it needs to be created. Estimations of the demand (where applicable), population served, and most importantly, *functions to translate their interruption to indirect economic losses are needed to feed into the economic loss models discussed previously*.

- *Dam services*. Currently the NID has information for the primary purposes and other uses of dams but there is no data about the users or beneficiaries of the dam services (e.g. volume of water for public supply, industries, type of industry, and agriculture). For hydroelectric dams, the electricity generating capacity is included in the NID database but not who is served (i.e. if it is industry, what type of industry, domestic, etc.). Some dams have studies about the economic benefits provided by the dams, but are mostly related to flood control. Having more detailed information on the users and dam services demand would help estimating the indirect losses in case of failure.

- *Locations of hazardous sites, volume, and toxicity of the materials contained.* There is information about the locations of hazardous sites as defined by the RCRA, but the volumes and toxicity of the materials contained is not available nationwide. *Information on health and environmental impact and their translation into indirect economic losses is also needed to inform the economic loss model.*

- *Transportation routes*. Information of transportation routes at the national scale is available. However, we would like to create databases of the major trading routes, trading traffic, and estimate the value of goods transported per day. This database would also inform the economic loss model.

- *Building inventories and their updated replacement costs*. Currently HAZUS database is the best nationwide although as mentioned earlier, it relies on many assumptions and can have outdated information. However, attempting to develop a new database would be a major undertaking.

Financial and Economic Data

- Market impacts from the extended loss of dam services.
- Impacts across sectors due to flood damage and loss of critical services and infrastructure.
- Impacts on jobs (losses and job creation in new sectors)

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