

ASSESSING THE HAZARD AND EXPOSURE OF DAMS IN THE U.S.

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Abstract

Dam failures can have significant social, financial, and environmental impacts. Financial losses can extend beyond infrastructure replacement costs, with cascading effects in multiple sectors such as electricity generation, transportation, and water supply. The existing dam hazard classifications in the U.S. do not give visibility to the “hazard hotspots” considering these losses, and given that there are approximately 85,000 dams with different states of disrepair, maintenance, and budgetary constraints, having a better way to rank them and therefore allocate resources is important.

We are developing a framework for rapidly assessing the probability and magnitude of the impacts of a dam failure. The 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. This interim report is on the estimation of the consequences of a dam failure including financial losses, affected critical infrastructure, and population. A framework is proposed to improve the current dam hazard classifications to gain visibility as to the types of risks that could emerge from a failure and to rank the dams as to the level of concern based on disruption and financial losses. The method uses publicly available dam break and consequence tools developed by the US Army Corps of Engineers (USACE) and the Federal Emergency Management Agency (FEMA), and national infrastructure datasets. Dams are ranked using seven criteria following the Analytical Hierarchical Process methodology. The criteria cover direct costs of infrastructure replacement, damage to critical infrastructure, potential damage to roads and railways, impacts to commodity transport, other dams and hazardous sites within the inundation area, shocks to electricity supply, and affected population.

While we want to develop a strategy for a scalable analysis at the national/portfolio level, we began with a detailed regional analysis to shed light on the kinds of financial impacts that may emerge as a concern, and for which public data is available such that the approach could be generalized. We introduce the dam break-financial consequence framework in a test case in the Cumberland River Basin. This basin has multiple interconnected dams that serve different purposes including electricity generation, recreation, water supply, and flood control. All the dams in the test case are currently classified as High, yet we see great variations in the potential consequences of their failure. Additionally, dam break analyses were pursued to compare the inundation that would result from the failure of a dam in Nashville, TN., to the FEMA 100 and 500 year flood plain maps

The next stage of the project will focus on assessing the probability of failure by overtopping, which is linked to clustering of extreme precipitation events, long term wet periods, reduction of dam capacity due to sedimentation, and inappropriate design for a changing climate. A discussion of how this would be applied for portfolio risk analysis is provided at the end of the paper.

Introduction

The potential failure of aging dams and levees, in combination with an increasing frequency of climate extremes pose risks to communities around the world. The financial risk associated with the failure of such infrastructure is largely unmapped. This is due in part to the complexity of the chain of events triggered by the failure of a major dam or levee (Egan, 2007), the lack of data (Meyer et al., 2013), and the difficulty of estimating the probability associated with a failure (Hariri-ardebili, 2018; Hariri-Ardebili, 2017; Stedinger et al., 1996).

In the United States there are over 85,000 dams with an average age of 57 years in the National Inventory of Dams (NID) (USACE, 2018). 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 (Ho et al., 2017). 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 are needed just to address deficiencies in the dams they operate (ASCE, 2017). The concerns over dam safety are real. Lakes are being drained in Texas to repair old dams (Ksat12news, 2019), 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 has a grant pool of \$10 million for all dams classified as high hazard potential in the U.S. (FEMA, 2019); the repair of one of Oregon's dams alone is estimated at \$80 million (McClain, 2019).

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 exist in the U.S. but variations among federal agencies and states make it difficult to develop a consistent national assessment of dam hazards (ASDWO, 2000; FEMA, 2013a). A summary of state dam hazard potential classifications is included in FEMA, (2012). Federal agencies conduct quantitative risk-based analysis to assign hazard ratings while for non-federally owned dams' hazard ratings may be based on qualitative judgment (Ho et al., 2017),. The NID includes hazard classifications for the dams, but each state and federal agency reports the classifications according to their own metrics. Even for states that conduct dam-breach scenarios, there is no consistency regarding which flood events should be modeled in the Emergency Action Plans (EAPs) (FEMA, 2013a). 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 (USACE, 2018). 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.

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, when other critical infrastructure can fail. In October 2015, South Carolina (SC) experienced an estimated 1 in 500 year storm event (Musser et al., 2016), and 36 small dams failed as a result of the storm (Murphy, 2016). 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 (Murphy, 2016).

Different approaches have been proposed to improve dam hazard classifications, most notably multi-criteria decision analysis (MCDA) techniques, since they can include variables expressed in different units (monetary, impacted population, damaged infrastructure, etc.); (Sun et al., 2014; Yang et al., 2011; and many others reviewed in Zamarrón-Mieza et al., 2017). 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 (Hajkowicz and Higgins, 2008), and summarized in a decision matrix. The weighted sum method (WSM) is a simple and often used MCDA technique (Drake et al., 2017; Stoycheva et al., 2018), where a score is calculated multiplying the performance criteria value by the criteria weight and all the weighted scores are added. Yang et al., (2011) used WSM to assess interventions to aging dams in China considering the direct economic losses (infrastructure damage using depth-damage functions), economic risk of public infrastructure (railways, telephones and electricity using a binary score for infrastructure within or outside from the inundated area without accounting for depth), population, social hotspots, and erosion as an environmental criterion. Sun et al., (2014) (and their follow up test case paper in Zhou et al., 2014) also propose a framework for dam risk ranking using MCDA techniques. The criteria considered are the potential loss of life, the direct economic loss and indirect economic loss (taken as 63% of the direct costs), and indexes accounting for other social and environmental impacts (both dimensionless), including variables such as heritage impact, river channel morphology, biological habitat and others. Then they assign “accident

levels” in four categories based on defined intervals of the criteria. Criteria weight assignment, and also dam failure probabilities in the case of Sun et al., (2014) rely on expert opinion and sensitivity analysis is needed to test for rank reversal. The analytic hierarchy process (AHP; Saaty, 1987) is the most popular MCDA technique in the academic literature for dam risk ranking (Zamarrón-Mieza et al., 2017), 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 (Sun et al., 2014).

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 (Farrow and Scott, 2013). FEMA’s guidance for flood risk analysis and mapping recommends the inclusion of dam flood risk information in flood risk maps as best practice (FEMA, 2016), 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. *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.* 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) and 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, some of a significant large dam was to fail, 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 also 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.*

We propose a framework to create a national dam hazard map to complement FIRMS and allow the identification of “hot spots” beyond the current dam hazard classifications using AHP as a ranking method. *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.* The framework uses publicly available dam break and consequence tools developed by the US Army Corps of Engineers (USACE) 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; a description of these tools is included in the methods section. The proposed framework is not a substitute for detailed dam break analysis and hazard at local scales but rather a preliminary ranking of the priority areas of concern beyond the current dam classification. The goal is to gain visibility as to the financial consequences of dam failures, highlighting critical infrastructure to prioritize the allocation of resources in state dam programs and insurance premiums.

While we want to develop a strategy for a scalable analysis at the national/portfolio level, we began with a detailed regional analysis to shed light on the kinds of financial impacts that may emerge as a concern, and for which public data is available such that the approach could be generalized. We introduce the dam break-financial consequence framework in a test case in the Cumberland River Basin. This basin has multiple interconnected dams that serve different purposes including electricity generation, recreation, water supply, and flood control.

Lastly, we discuss how clustered extreme events can lead to multiple dam failures within a region, including cascading dam failures, and indicate how this may translate into a fat tail risk for regionally invested insurance portfolios.

Methods and Data

Review of the approaches for dam hazard characterization

Different approaches have been developed to estimate the exposure and expected losses of dam failures (Albano et al., 2014; Bowles et al., 1998; DHS, 2011; FEMA, 2016; Fread, 1989; Golder Associates, 2017; Zhang and Tan, 2014) and floods (Scawthorn et al., 2006a; Schröter et al., 2014). Three primary tasks in the analysis of expected losses from a dam failure are 1) the prediction of the reservoir outflow hydrograph (Fread, 1989; Froehlich, 2016, 2008; Peter et al., 2018; Pierce et al., 2010), 2) routing the hydrograph downstream to determine the inundated area, flood depth, and flow velocity (Altinakar et al., 2017; Dewals et al., 2011; Reed and Halgren, 2011), and 3) estimate the expected losses in the inundated area using depth-loss curves, building inventories, GIS methods, and other data (Albano et al., 2018, 2017, 2014; FEMA, 2013b; Meyer et al., 2013; Quinn et al., 2019; Scawthorn et al., 2006b; Wing et al., 2018). In this section, we provide a description of these three steps and the selected methods for the proposed framework.

Outflow hydrograph and inundation area

There are many software products available to facilitate the estimation of the outflow hydrograph and the inundated area of a dam failure (Albano et al., 2018; FEMA, 2013a). 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 (Salt, 2019). 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 is a tool to compute simplified dam-break flood simulations combining 2D numerical flood modeling with GIS-based tools (<https://dsswiseweb.ncche.olemiss.edu>). It was developed by the National Center for Computational Hydroscience and Engineering at the University of Mississippi on behalf of USACE (Altinakar and McGrath, 2012). DSS-WISE™ Lite takes into account the levees in the USACE National Levee Database (NLD) and bridges in the flood analysis, and uses the United States Geological Survey (USGS) 1/3 arc-second National Elevation Dataset.

The framework considers the scenario of dam failure by overtopping, which occurs when the inflow exceeds the capacity of the dam, and it is the most common mode of failure. Such an event could occur during flood conditions. The starting pool elevation 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 failure were modeled: sudden and complete failure labeled as S1, and partial failure using parameters for breach formation from empirical equations (Froehlich, 2008) labeled as S2. The simulation conditions are consistent with the regulations to model inundation maps in California, considering sunny day failures at the maximum possible storage elevation (Barclays official California Code of Regulations, § 335.6. Modeling Requirements. 23 CA ADC).

Modeling the failure of dams in tandem or in series and breaching in cascade is desirable to capture the full risk of breaching, but this capability is not yet available in the web version of DSS-WISE™ Lite. Dewals et al., (2011) proposed a modeling approach of cascading dam failure using two-dimensional fully dynamic models and a simplified lumped model but it requires detailed inputs that may not be available from public datasets. DSS-WISE™ has been used to model individual breaches and cascading failures (Altinakar et al., 2017), but not the public online version DSS-WISE™ Lite. Therefore, cascading failures were not modeled in our framework but 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. 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.

Estimating the losses of a dam failure

We classified the consequences of a dam failure into seven criteria for the AHP analysis:

C1-Direct economic losses - Includes the depreciated replacement costs of residential, industrial, commercial, government, religious, and agricultural infrastructure, and the dam replacement cost. These are estimated with building inventory databases included in FEMA's Hazard-US (HAZUS) software, and an approximation of dam replacement costs as a function of storage (Petheram and McMahon, 2019). HAZUS is computationally and time intensive and an ArcGIS license is needed to use it, therefore the loss estimation analyses proposed in the framework were executed in the open-source software R, extracting datasets from HAZUS and using the depth-damage functions from the R package called Hazus (Goteti, 2015).

C2 –Critical infrastructure – This includes the number of utilities with damages greater than 40% including wastewater treatment plants (WWTP), power plants (PP), Airports (Air), and electric substations (ES). These were obtained from national infrastructure datasets (details included in the Appendix). Replacement costs for these infrastructure were not available nationwide, but the number of buildings with high percent damage can inform the prioritization of insurance providers, property owners, and government officials.

C3-Miles of major roads and railways – Obtained from national datasets. This estimation does not consider the inundation depth. The damage functions in Hazus for roads and railways are in the form of return flood-damage. In the case of dam failure, this approach would not apply.

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. This criterion reflects other types of hazards to the population (i.e. cascading dam failures, or release of toxic materials).

C6 -Affected power generation in megawatts – obtained from national datasets.

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

Estimation of direct losses- C1

The U.S. Department of Homeland Security (DHS) recommends HAZUS to estimate flood damages (DHS, 2011). HAZUS is a publicly available model developed by FEMA to estimate the financial consequences of floods at the census block level. It cannot model dam breaks but the depth-area grids of dam break simulations obtained in other programs such as DSS-WISE™ Lite and HEC-RAS can be inputs. HAZUS has an inventory of buildings (referred as general building stock or GBS) and critical infrastructure in each region, used to calculate potential damage based on depth-cost curves. The exact locations of the buildings in HAZUS' GBS are unknown and the software assumes that they are uniformly distributed to estimate damages at the census block level. However, HAZUS provides the option of using detailed local data for the analyses if available but this is not applicable in the proposed framework since the purpose is to use data that is available across the U.S. HAZUS estimates direct losses for infrastructure replacement (dollar exposure), which can be depreciated. The damage functions in HAZUS include buildings, essential facilities (hospitals emergency centers and schools), transportation systems (highways, railways, buses, ports, ferries, and airports), utility systems (potable water, wastewater, oil and gas, electric power, and communications), agricultural products, and vehicles. Depth-damage curves in HAZUS come from a variety of sources including FEMA, the Federal Insurance and Mitigation Administration, and the USACE Institute for Water Resources (IWR). Depth-damage curves have numerous categories for each building occupancy class (e.g. there can be 10 or more depth damage curves for a residential building) and they were simplified because nation-wide data on building characteristics at the individual level are not available. The mean of the percent damage by depth across occupancy classes was calculated to have a single depth-damage curve by building type (i.e. one depth-damage curve for residential buildings, one for power plants, one for commercial buildings, and so on.).

While HAZUS is useful for assessments at the asset level, it is computationally intensive and difficult to implement when several dams within a region are to be evaluated or when rapid assessments are needed (Gall, 2017), and an ArcGIS license is needed to use it. If the use of HAZUS is not possible, the DHS suggests GIS methods, and that is the approach taken here, with geospatial analysis done within the open source R software.

The GBS datasets and the depth-damage curves extracted from HAZUS were analyzed in R. Extracting data from HAZUS at the national level is not trivial, so all other datasets besides GBS of infrastructure and utilities were obtained from different sources as shapefiles covering the entire US (refer to the Appendix for details on the data sources). The infrastructure datasets were overlaid with inundation depths and extents obtained in DSS-WISE™ Lite to estimate the financial losses of the failure of selected dams. For the calculation of C1, the GBS database containing the depreciated exposure (in million USD) and the average

maximum flood depths were overlaid as both are available at the census block from HAZUS and from DSS-WISE™ Lite (the human consequence module) respectively. The losses in C1 are the multiplication of the percent damage and the building value included in the depreciated GBS dataset. The results are point estimates in million dollars aggregated by occupation type: residential, commercial, industrial, education, government, and religious.

Dam replacement costs included in C1 were approximated with the median cost of hydroelectric dams as a function of storage described in Petheram and McMahon, (2019). The cost of \$1,565 Australian dollars per ML (10^3 m^3) was converted to USD\$ 1,294 per acre-ft and multiplied by the maximum storage of the dams included in the NID. 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.

Although HAZUS includes databases of high potential loss facilities (dams, levees, nuclear power plants, and military installations), and hazardous materials facilities (hazardous material sites), these are not included in the software's reports of direct losses. The C2 to C6 losses capture some of the risks and potential losses related to those types of infrastructure.

For C2, the infrastructure percent damage estimations 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 (Ham et al., 2005). 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.

Classification

The USACE Dam Hazard Potential Classification System for Civil Works Projects has four criteria and three classifications shown in Table 1 (FEMA, 2013a). Each criterion in this case has equal weight and there is no quantitative measure of the hazard. For example, the hazard classification of all the test dams is High in the NID, but this classification does not have the granularity to differentiate and inform what is at risk, which complicates prioritizing across multiple dams.

Table 1 USACE Dam Hazard Potential Classification System. Taken verbatim from FEMA, (2013a)

Criteria	Hazard potential classification		
	Low	Significant	High
Direct loss of life	None expected (due to rural location with no permanent structures for human habitation)	Uncertain (rural location with few residences and only transient or industrial development)	Certain (one or more extensive residential, commercial or industrial development)
Lifeline losses ¹	No disruption of services – repairs are cosmetic or rapidly repairable damage	Disruption of essential facilities and access	Disruption of critical facilities and access
Property losses ²	Private agricultural lands, equipment and isolated buildings	Major public and private facilities	Extensive public and private facilities
Environmental Losses ³	Minimal incremental damage	Major mitigation required	Extensive mitigation cost Losses(5) or impossible to mitigate

¹ Based on inundation mapping of the area downstream. Analyses of loss of life potential should take into account the extent of development and associated population at risk, time of flood wave travel, and warning time.

² Indirect threats to life caused by the interruption of lifeline services due to project failure, or operation, i.e., direct loss of (or access to) critical medical facilities or loss of water or power supply, communications, power supply, etc.

³ Direct economic effect on the value of property damage to project facilities and downstream property. Also includes the indirect economic effect due to loss of project services, i.e., impact on navigation industry of the loss of a dam and navigation pool, or impact upon a community of the loss of water or power supply.

⁴ Environmental impact downstream caused by the incremental flood wave produced by the project failure, beyond which would normally be expected for the magnitude flood event under a without project conditions.

The States of California, Montana, and Washington developed methodologies to do risk-based dam *design* considering the downstream impacts. These followed the principles of the WSM (a total class weight or TCW in California, and consequence rating points for Washington), assigning criteria and weights. Some of the criteria included are dam height and capacity, the capital value of the dam, potential loss of life, and the potential for property damage (including residencies, transportation infrastructure, toxic sites, lifeline facilities, and commercial property). But even within these three states there were inconsistencies on the criteria, weights, and risk tolerances (FEMA, 2012). For example for Washington, loss of life accounts for 50% of the design weight while for California it is 33% of the total weight (FEMA, 2012), and 100 % for Montana. However, these methods are for the design capacity of the dam, not to do hazard rankings.

Our framework uses the MCDA method AHP for dam hazard ranking as proposed in other studies (Zamarrón-Mieza et al., 2017) with the seven afore mentioned criteria. All MCDA techniques require information of the relative or absolute importance of each criterion, and a challenge is how to process data that may be expressed in different units (Triantaphyllou and Baig, 2005). 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:

$$n.m = \frac{\min(x_j) - x_{ij}}{\min(x_j) - \max(x_j)} \quad \text{Eq.1}$$

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.

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 (Hyde et al., 2004; Maleki and Zahir, 2013). 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 (Hyde et al., 2004). In our case, we do not consider expert input as to what the weights should be, but rather we estimated the distribution of ranks for each dam using permutations of the weights across the seven criteria. We did this by sampling with replacement, seven numbers from a sequence of 0 to 1 in 0.05 intervals and keeping the ones adding to one (166, 131 weight vectors). Each weight vector was multiplied by the normalized matrix (n.m), and the summation of the matrix columns gave the final score to each dam. The scores were transformed to ranks and the process was repeated with all the weight permutations to obtain the rank distributions of the dams.

Data

Due to the extensive list of data sources, they were included in the Appendix.

Description of the study area: the Cumberland River Basin

The Cumberland River Basin (CRB) extends in parts of Kentucky and Tennessee. There are 352 dams within the basin and 107 of them are classified as high hazard. 55 dams are within the 1 in 500-year flood area included in DFIRM maps, and 20 of them are classified as high hazard. 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 (USACE/Nashville, 1990a). Figure 1 shows the order of the dams. The biggest urban center in the basin is the city of Nashville, downstream of J. Percy Priest Dam.

The criteria were estimated for five of the ten USACE operated dams: Center Hill, Cordell Hull, Old Hickory, Dale Hollow, and Percy Priest. Failure scenario 1 (sudden and complete failure; S1) was simulated for all the test dams, while scenario two (partial breach; S2) only for Percy Priest and Old Hickory Dam to compare inundation areas. The criteria and the ranking was done using the S1 results for all dams.

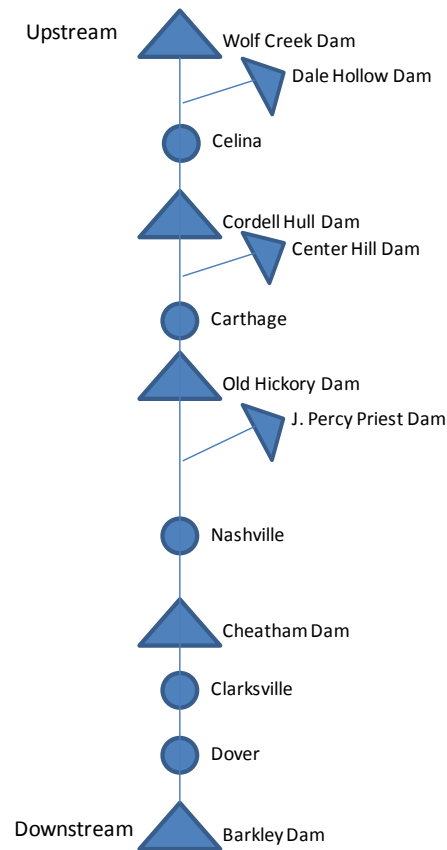


Figure 1 Diagram of USACE dams in the Cumberland River Basin. Image modified from (USACE/Nashville, 1990b)

Results

Figure 2 shows the ranking results using the weights permutations. Rankings are in descending order of hazard (i.e. rank 1 is the highest hazard). Taking the median ranks, the hazard order is J Percy Priest, Center Hill, Cordell Hull, Old Hickory, and Dale Hollow. Old Hickory Dam is the least sensitive to variations in criteria weights, whereas J Percy Priest and Dale Hollow show a larger spread of rankings dependent on the weights assigned. Ultimately, the final weighting scheme needs to consider the importance that the decision maker or experts give to the criteria. For example, government officials, insurance companies or investors can decide on giving different weights in their ranking assessments based on their different motivations.

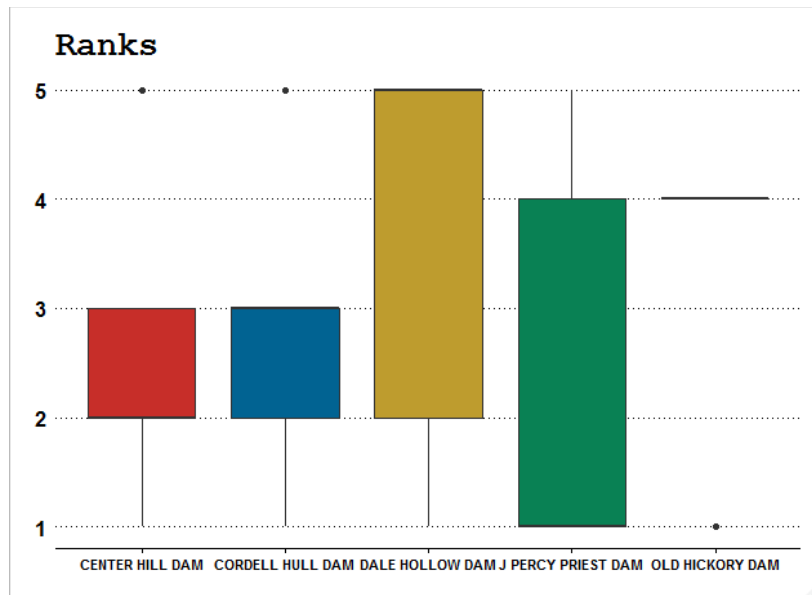


Figure 2 Hazard ranking across weights permutations. Ranking 1 corresponds to the highest hazard

Disaggregation of the criteria by dam

Here we discuss the results presented in Figure 3.

The largest direct financial losses for infrastructure replacement occur with the failure of Percy Priest dam because of its proximity to the city of Nashville; large commercial and residential losses would ensue. Compared with the failure of Percy Priest Dam, these losses are just a fraction in other dams such as Dale Hollow. However, Dale Hollow's replacement costs are estimated as more than double of those of Percy Priest Dam. We show both components of the C1 criteria separately to demonstrate that the type of direct losses are different for each dam. The replacement costs of the dams could exceed by far those calculated with the GBS in some dams like Center Hill and Dale Hollow. It is important to note that losses can accumulate in the time needed to repair the dam due to the interruption of its services and these are not included. So while this financial loss estimation allows ranking the infrastructure losses of the sectors included in the GBS, it leaves out other important risk elements. Some of these are included in the estimation of C2 to C6, but not as financial losses due to the lack of nationwide costs data.

For C2, WWTPs, which can be small plants within industrial facilities, would be the most affected, particularly with the failure of Percy Priest. PP in C2 include the hydroelectric plants of the failed dams; the failure of Percy Priest and Old Hickory dam could also impact additional PPs downstream. Moreover, the failure of both Percy Priest and Old Hickory dam could happen simultaneously given their spatial proximity and their similar exposure to extreme climate events.



Figure 3 Criteria results across dams

Potential interruptions to supply chains given damages in transportation routes are considered in C3 and C4. In C3, the failure of Center Hill and Dale Hollow would have greater impacts in highways and major roads, while Percy Priest's failure would affect more miles of railways. According to the CFS data for the Nashville-Davidson—Murfreesboro area, the total commodity value transported by truck or rail in 2012 was \$73,150 million, which is approximately \$200 million/day (the 2017 survey will be released in 2020). Therefore, railroad and highway damages in the area could produce large losses in commodity trade that may or may not be currently insured for such an event.

Impacts to navigation routes in C4 show that coal transport could be significantly affected, perhaps translating into further losses caused by power outages. The tonnage of commodities per year (data from 2017) was converted into tons per day to estimate the total loss considering certain duration of repair of the dam. Given the connectivity of the CRB dams, the navigation routes impaired are shared among them, but the failure of the southern dams (J. Percy Priest and Old Hickory), which are closer to Nashville could cause further interruption of navigation routes downstream. Ultimately, the Cumberland River joins the Ohio River, which is an important navigation route joining the Mississippi River.

In regards to additional dams within the inundated areas of the failed dams of the test case, all of them are classified as Low hazard, except for one in the inundation area of Center Hill that has a Significant hazard classification and corresponds to a tailings dam. The breach of a tailings dam and the ensuing water contamination could result in environmental and health impacts and significant financial losses for the dam owner. Also, the number of the potentially affected RCRA sites in Nashville pose an extra risk of water contamination, and given that this is a highly populated area, the health risks are higher.

All dams in the test case are used for electricity generation so their failure immediately translates into shocks to the electric supply estimated for C6. This is more significant at Center Hill Dam and Percy Priest.

In C7, the total population in the affected Census blocks shows that the failure of Percy Priest and Old Hickory dams would affect more people, especially in Nashville. These are people directly affected by inundation, excluding other effects product of the failure such as power losses. The population in the vicinity of Center Hill is relatively small, yet, its failure as seen previously, could cause other dams to fail, lead to closure of many roads, and cause power interruptions.

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. 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 2 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 3), 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.

Table 2 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 1 PCT	0	16	2.3	6	6	1	0
DFIRM 0.2 PCT	0	28	4.3	12	14	4	0
DFIRM 1 PCT and Percy Priest Dam	33.8	52	7.8	14	20	6	53,987
DFIRM 0.2 PCT and Percy Priest Dam	33.8	54	8.4	16	21	6	53,987

Table 3 Commodities (in ton/day) transported in the affected navigation routes in Nashville in case of failure of Percy Priest. Chem=Chemical materials, CrMat=Construction materials, Farm=agricultural products, Man=Manufactured goods

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

Future areas of study

Portfolio analysis

Very few studies in an extensive literature review of applications of MCDA to dam management focused on the analysis of interactions, dependencies, loops and feedbacks between criteria, factors and alternatives (Zamarrón-Mieza et al., 2017). From a portfolio perspective, particularly for correlated risks such as dam failures that result from extreme weather events or prolonged wet spells within a region, risk scoring methods may not be appropriate (Cox, 2009). Funding allocations in this case need to have a portfolio approach instead of looking at dams separately. The same applies when setting insurance premiums or analyzing investments. Cox, (2009) argues that optimizing the selection of risk- reduction opportunities as a subset or portfolio (be it as funding for dam maintenance or in investments) is more effective for risk

reduction per resources spent than scoring when correlated consequences are involved. The optimization has to consider the interdependencies of risk reduction activities.

Consider a portfolio of dams and/or other critical infrastructure elements whose failure could lead to a cascading failure of other systems with some probability. For assessing the risk profile across such a portfolio, one needs to consider the combinatorial probabilities for the joint failure of each set of assets at risk, and the subsequent impacts of such a failure. In the specific case of interest here, the river system can be considered as a convergent, dendritic (or tree like) network. As illustrated in the representation in Figure 1, several of these dams are located in “parallel” on this network, i.e., there are no other dams upstream of them (e.g. Dale Hollow Dam). Others, are located in series, i.e., one or more dams are upstream of a dam of interest (e.g. Cordell Hull and Old Hickory Dam). Dams that are in parallel, may or may not experience an overtopping event simultaneously, with a certain probability. For K such dams, the probability of 2 or more experiencing such an event can be derived based on regional precipitation and streamflow data, and used with the potential probability of failure on overtopping, to assess the joint probability distribution of failure of multiple such dams. A regional extreme precipitation event is of concern in this case, and these probabilities would be derived from the associated data. For dams in series, one needs the conditional probability of overtopping of the downstream dam, given that one or more of the upstream dams has failed (or not). This can also be derived from regional precipitation or streamflow records. Once these are estimated, one can examine all potential failure pathways in the portfolio, and score the probability and the potential loss associated with each pathway to derive a probability weighted measure of portfolio risk. Within the portfolio, one could identify the network links that contribute the highest expected loss along each of the metrics defined earlier. This procedure would then provide a mechanism for aggregated and disaggregated portfolio risk analysis that builds directly off the site level analysis presented earlier.

Conclusion

This paper was the first step to understand the current state of dam hazard classifications in the United States, and the methods, tools, and data available to improve it. The regional test case showing the application of the consequence estimation framework helps uncover risks not considered in existing dam hazard classifications or flood risk maps. Even though all dams in the test case are currently classified as High, with this framework the differences in the dam failure consequences became visible. Additionally, with the example of FIRMs in Nashville, we showed that the inundation product of a dam failure can be much larger and destructive than the current flood risk maps.

Still, expanding this methodology to the whole country to facilitate hot spot identification and portfolio analysis for different stakeholders requires the estimation of inundation areas, which can be quite time consuming considering that there are approximately 85,000 dams in the US. However, the example of

California, where dam owners were required to submit dam break inundation analyses in 2017, show that this could be possible, at least starting with selected states. For the next stage of this project we will use the dam failure inundation maps available in California to do the portfolio analysis described previously.

We would like to highlight that an important barrier to estimate dam failure losses at larger scales is the lack of regional/national datasets containing the necessary information. For example, it is desirable to calculate the direct losses associated to the interruption of services provided by the failed dam (i.e. irrigation, municipal and industrial water supply, power generation, flood damage reduction, etc.). The water provided to each service needs to be known to perform that assessment, but the NID does not include water allocations of a particular dam to the different users except for the installed electricity generation capacity in hydroelectric dams. Developing such databases would help improve the understanding of dam hazards across the nation.

Appendix

Data

- Dams data for Tennessee and Kentucky were obtained from the latest version in the NID (USACE, 2018).
- Operation Manuals for USACE dams in the Cumberland River Basin, USACE Digital Library <https://usace.contentdm.oclc.org/>.
- Building inventories and depreciated value by general occupation and single occupation were retrieved from HAZUS, selecting the counties along the Cumberland River (more information on how these databases were constructed can be found in HAZUS' manuals (<https://www.fema.gov/Hazus-mh-user-technical-manuals>)).
- Damage-depth curves used in HAZUS were retrieved with the R package HAZUS (Goteti, 2015).
- DFIRM Flood areas were obtained for Kentucky and Tennessee from the National Flood Hazard Layer available at FEMA Flood Map Center (<https://msc.fema.gov/portal/advanceSearch>)
- Tennessee shapefiles were downloaded from the University of Tennessee Knoxville <https://libguides.utk.edu/tngis/health>
- WWTP and RCRA Sites were retrieved from the USEPA Facility Registry Service Datasets: <https://www.epa.gov/frs>
- The shapefile of US Railroads was retrieved from: https://services.arcgis.com/P3ePLMYs2RVChkJx/arcgis/rest/services/USA_Railroads_1/FeatureServer
- The shapefile with US Major highways was retrieved from <https://www.arcgis.com/home/item.html?id=fc870766a3994111bce4a083413988e4>

- The electric power substations shapefile was retrieved from Homeland Infrastructure Foundation Level Data 2019, <https://hifld-geoplatfrom.opendata.arcgis.com/datasets/electric-substations>
- Data from 2017 on navigation routes and transported commodities were retrieved from the USACE, Waterway data: National Waterway Network <https://usace.contentdm.oclc.org/digital/collection/p16021coll2/id/1472%20/>
- Nashville Urban Services shapefile was retrieved from <https://data.nashville.gov/General-Government/Service-Districts-GIS/xxxxs-vvs4>
- Airport data, Federal Aviation Administration. This airport data is provided as a vector geospatial-enabled file format. Airport information is published every eight weeks by the U.S. Department of Transportation, Federal Aviation Administration-Aeronautical Information Services. Current Effective Date: 0901Z 15 Aug. 2019. to 0901Z 10 Oct. 2019. http://ais-faa.opendata.arcgis.com/datasets/e747ab91a11045e8b3f8a3efd093d3b5_0?geometry=-80.153%2C38.677%2C-73.44%2C40.163
- Commodity Flow Survey for the U.S., Preliminary results 2017 <https://www.census.gov/programs-surveys/cfs.html>

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