Assessing the Hazard from Aging dams in the U.S.A.

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Abstract

Climate change, inadequate maintenance, and aging beyond the design life increase the probability of dam failure. 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, transportation, water supply, and environmental services. The existing dam hazard classifications in the United States do not formally characterize "hazard hotspots" considering these impacts. Given that there are over 90,000 dams with different states of disrepair, maintenance, and budgetary constraints, a better way to rank their potential hazard and allocate resources for risk mitigation is needed. We present an approach that is scalable over many regions for rapidly assessing the magnitude and exposure of a dam failure for a preliminary ranking of the priority areas of concern. The estimation of the consequences of a dam failure including financial losses, affected critical infrastructure, and population is addressed using publicly available dam break and consequence tools and national infrastructure datasets. Dams can be ranked using seven criteria following the Analytical Hierarchical Process. The application of the framework is demonstrated with dams in the Cumberland River Basin. The main barrier to applying this approach at a national scale is the estimation of the inundation area upon dam failure, and we outline a strategy to implement it. The importance of increasing the resilience of dams is becoming more critical given the increasing interest in hydropower as a renewable energy source in the face of climate change.

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Key Points:

- Aging dams, inadequate maintenance, and climate change are increasing the risk of dam failure in the United States.
- Existing dam hazard classifications do not identify "hazard hotspots" considering financial and social losses.
- We present an approach for rapidly assessing the exposure of dam failure for a preliminary ranking of the priority hazard areas.

Abstract

Climate change, inadequate maintenance, and aging beyond the design life increase the probability of dam failure. 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, transportation, water supply, and environmental services. The existing dam hazard classifications in the United States do not formally characterize "hazard hotspots" considering these impacts. Given that there are over 90,000 dams with different states of disrepair, maintenance, and budgetary constraints, a better way to rank their potential hazard and allocate resources for risk mitigation is needed. We present an approach that is scalable over many regions for rapidly assessing the magnitude and exposure of a dam failure for a preliminary ranking of the priority areas of concern. The estimation of the consequences of a dam failure including financial losses, affected critical infrastructure, and population is addressed using publicly available dam break and consequence tools and national infrastructure datasets. Dams can be ranked using seven criteria following the Analytical Hierarchical Process. The application of the framework is demonstrated with dams in the Cumberland River Basin. The main barrier to applying this approach at a national scale is the estimation of the inundation area upon dam failure, and we outline a strategy to implement it. The importance of increasing the resilience of dams is becoming more critical given the increasing interest in hydropower as a renewable energy source in the face of climate change.

Plain Language Summary

Failing dams can cause extraordinary flooding. Water and wastewater treatment plants, electricity generation facilities, bridges, highways, population centers and other dams often lie below a dam. A catastrophic failure of services and loss of life could occur from the subsequent flood. The large number of poorly maintained, aging dams may spell disaster for many communities and regions if overtopped in an extreme rainfall event. Such events are now more frequent. How should we prioritize dams that need immediate attention and fix or remove them? This paper presents an approach and its example application to achieve this given limited budgets, before a major catastrophe occurs.

1 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, buffering drought risks, and also providing a renewable source of energy. However, age, poor maintenance, and climate change compromise their safety.

A dam fails by overtopping when inflows exceed its storage and discharge capacity. Therefore, the risk of overtopping increases as extreme precipitation events increase in magnitude and frequency (Hossain et al., 2012; Mallakpour et al., 2019). Aging is also a risk factor. As a dam ages and fills up with sediment, its storage capacity is reduced, decreasing its performance (Halperin, 2019) and making it more prone to overtopping. Lack of maintenance and changes in structural fragility that occur with age and extreme environmental conditions can compound the risk of dam failure.

In the United States there are over 90,000 dams with an average age of 57 years in the National Inventory of Dams (NID) (USACE, 2019). Figure 1 shows dams categorized as high hazard across the country, classified by age above or below 60 years, with on overlay of county population. The risks and challenges posed by aging dams in the country are widely acknowledged (ASCE, 2017; Ho et al., 2017; Imbrogno, 2014). On average, there have been 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 for dams less than 15 meters tall (McCann, 2018). The Associated Press released a report in 2019, which identified more than 1,680 dams in the U.S. as being in poor or in unsatisfactory condition (Lieb et al., 2019) . One of the dams deemed unsatisfactory, the Edenville Dam in Michigan, overtopped in May 2020 causing the cascading failure of a downstream dam and the dislocation of thousands of people. There are currently no publicly available analyses of the estimated financial and other risks that would be posed by the failure of these dams in light of their susceptibility to failure accounting for how the climate has changed relative to the data available when these dams were designed 50 to a 100 years ago. Perhaps as a consequence, the number of dam overtopping incidents far exceed structural failure in the United States (ASDO, 2019; Imbrogno, 2014). About 1/3 of dam failures occur by overtopping (Costa, 1985), often 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 and storage loss due to sediment, their design may not guarantee safety anymore (Chen & Hossain, 2019). It was estimated that even without considering reduced storage capacity due to sedimentation, the probability of hydrologic failure will increase for most dams in California by 2100 (Mallakpour et al., 2019). 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 et al., 2017), increasing the risk of overtopping. Currently there is no comprehensive research on understanding this risk, or of its financial implications for industry, communities or government across the United States. 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. 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).

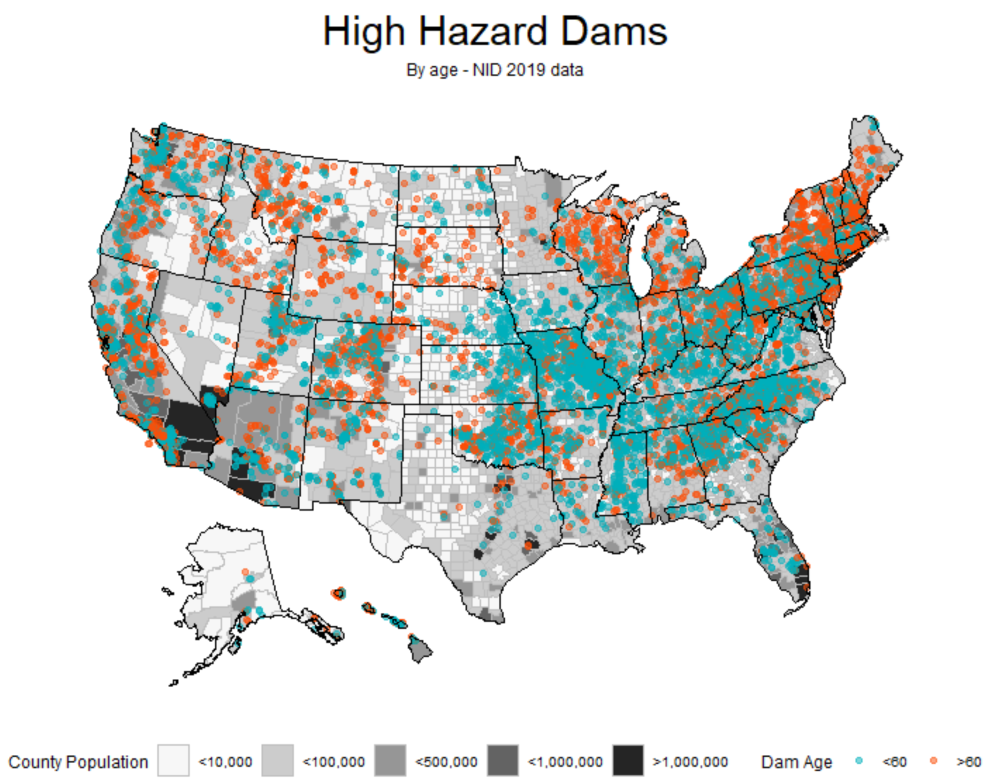

Figure 1. High Hazard dams in the United States by age. Data obtained from the National Inventory of Dams (USACE, 2019). The dataset from Texas is incomplete. High hazard refers to potential loss of life. Significant hazard (economic loss) dams are not shown as their inclusion overwhelms the figure. There are over 25,000 dams classified as high or significant hazard.

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 responsibility over the regulations, inspection, permitting, and enforcement of the non-federally owned dams located within its boundarie. There is highly variable staffing, assessment, and overall 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. In 2019 the Association of State Dam Safety Officials estimated that it would cost US$65.89 billion to rehabilitate all non-federal dams, and $4.78 billion for federally owned dams (ASDO, 2019). However, the U.S. Army Corps of Engineers in 2017 estimated that $25 billion are needed just to address deficiencies in the 716 dams they operate (ASCE, 2017; USACE & BR, 2019). 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 had a grant pool of $10 million for all dams classified as high hazard potential in the U.S. (FEMA, 2019). The Water Infrastructure Improvements for the Nation Act (WIIN) provides funds for dam rehabilitation for non federally-owned, high-hazard dams. In 2020 the WIIN funds were 40 million (Baron, 2020). There are other sources of small dam rehabilitiation grants (Baron, 2020). This is in stark contrast to estimate of $80 million for the repair of one of Oregon's dams alone (McClain, 2019).

The post-failure costs to repair the spillways of the Oroville dam, which failed in February 2017, have exceeded $1.2 billion (Fimrite, 2020). Nearly 200,000 people had to be evacuated. The flow over the spillway was only 5% of the design flow, and while this came after an unusual wet period, spillway maintenance and not climate change was the critical factor associated with the failure during overtopping. At 770 feet high, this is the tallest dam in the USA, and the City of Oroville has sued the owner, the State of California for negligence in maintaining the dam. Issues with the spillway were documented as early as 2005.

Given budgetary and personnel constraints, a method to prioritize allocation of funds for risk mitigation by dam removal or repair, that accounts for the likelihood and consequence of dam failures is required to ensure improvements in dam safety where it is most needed. The likelihood of dam failures is not mapped but dam hazard classifications based on possible loss of life or property damage. Variations among federal agencies and states have led to the lack of a consistent national assessment of dam hazards (ASDSO, 2020; FEMA, 2012, 2013a), even though Federal funds are invariably required to address the associated disaster. Despite initial refusals, President Trump covered the cost of Oroville spillway repairs, and a Presidential Disaster Declaration followed the Edenville and Sanford dam failures in Michigan. The NID includes hazard classifications for dams, but state and federal agencies report on 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 potential high hazard dams in the U.S. propelled by changes in land use and development downstream of the dams. Currently there are 15,627 dams in this category as per the NID (USACE, 2019). However, it is unclear to us what the criteria are to change a dam hazard classification, that is, whether the assessments to change a dam hazard classification comprehensively examine the current state of the dams (siltation, concrete, foundations, and unique environmental conditions), or of downstream ecosystems, population and critical infrastructure exposed, and if updates related to the increasing intensity and persistence of precipitation under climate change are included.

The financial impacts of dam failure can be quite significant. These are amplified by the potential cascading failure of other critical infrastructure, and the associated direct and indirect economic impacts. In October 2015, South Carolina 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, SC, 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).

Insurance mechanisms exist 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 & 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 be much greater than the 1 in 100-year flood area in the NFIP (National Research Council, 2012) but FIRMS, although available throughout the U.S., do not consider dam failure. Communities therefore cannot make informed decisions to prevent or mitigate the consequences of dam failures, nor can insurers and financial institutions, if there is no visibility to potential catastrophic flood risks or their aggregate effects (National Research Council, 2012). 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 90,000 dams in 3000 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, and a 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 mitigation, 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.

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 & Higgins, 2008), and summarized in a decision matrix. Due to the subjectivity associated to the choice of criteria weights, a sensitivity analysis is required. The weighted sum method (WSM) is a simple and often used MCDA technique in many fields (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 (approximated as 63% of the direct costs), and indexes accounting for other social and environmental impacts, including variables such as heritage impact, river channel morphology, biological habitat and others. They assign "accident levels" in four categories based on defined intervals of the criteria. 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 mixed method techniques (i.e. 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). This was the ranking technique chosen in the framework presented here, and is described in detail in the methods section.

We offer a framework to create a national dam hazard map to complement FIRMS to help identify "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, toxic and hazardous material storage facilities, 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. We use the Decision Support System for Infrastructure Security Lite (DSS-WISE™Lite) to estimate the inundated area because of its computational efficiency and simple input data. U.S. Infrastructure valuation databases and damage-depth curves available in FEMA's Hazard-US (HAZUS) software were used to estimate the direct financial losses. 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 provide a preliminary comparative analysis and ranking of the financial consequences of dam failures, highlighting critical infrastructure to prioritize the allocation of resources in state dam programs and insurance premiums. We use 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. The test case is in the Cumberland River Basin. This basin has multiple interconnected dams that serve different purposes including electricity generation, recreation, water supply, and flood control.

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, 1990). Figure 2 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 (shown in the yellow rectangle in Figure 2). All of these dams are classified as High hazard in the NID.

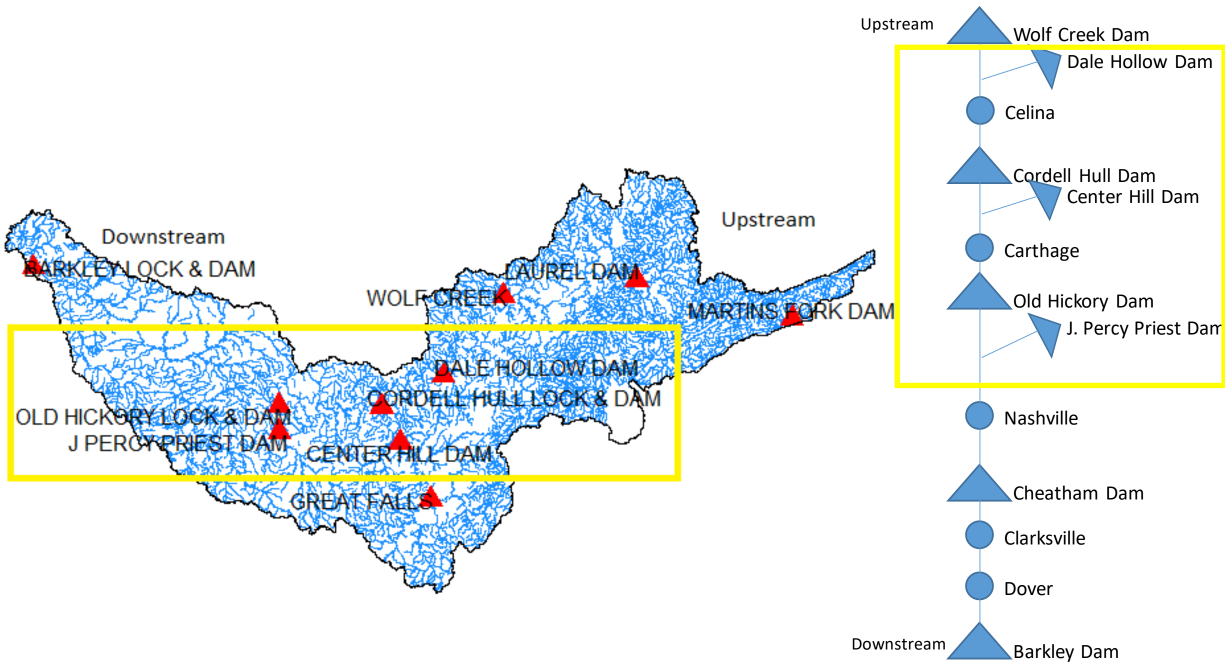

Figure 2. High hazard dams operated by USACE in the Cumberland River Basin. Dams in the test case are highlighted in the yellow rectangle.

2 Materials and Methods

Different approaches have been developed to estimate the exposure and expected losses of dam failures (R. Albano et al., 2014; Bowles et al., 1998; DHS, 2011; FEMA, 2016; Fread, 1989; Golder Associates, 2017; Zhang & Tan, 2014) and floods (Scawthorn et al., 2006; 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 (C., 2008; Fread, 1989; Froehlich, 2016; 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 & Halgren, 2011), and 3) estimating the expected losses in the inundated area using depth-loss curves, building inventories, GIS methods, and other data (R. Albano et al., 2014, 2018; Raffaele Albano et al., 2017; Charles et al., 2006; FEMA, 2013b; Meyer et al., 2013; Quinn et al., 2019; Wing et al., 2018). Figure 3 shows our proposed approach for dam hazard classification. The prediction of the outflow hydrograph and inundation area are carried out with a dam break inundation program called DSS-WISE™Lite. The estimation of expected losses is divided into seven criteria that are used to rank dam hazard using AHP. In this section, we provide a description and justification of the selected data and methods used in the framework.

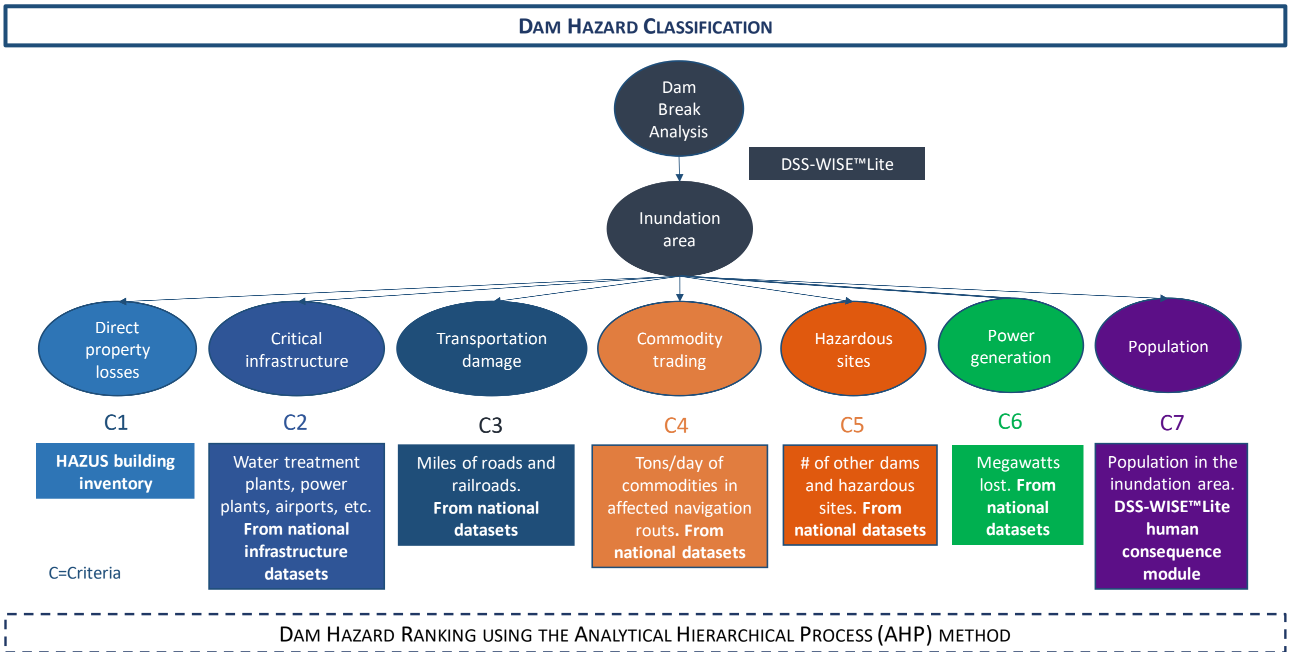

Figure 3. Framework for dam hazard classification

2.1 Estimation of the inundation area

There are many software products available to facilitate the estimation of the outflow hydrograph and the inundated area of a dam failure (R. 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, but is more challenging to implement (Salt, 2019). Here, DSS-WISE™Lite is used to estimate the dam inundation areas and losses because it allows the analysis of multiple dams where limited information is available. DSS-WISE™Lite supports simplified dam-break flood simulations combining 2D numerical flood modeling with GIS-based tools (https://dsswiseweb.ncche.olemiss.edu, accessed March 2019). It was developed by the National Center for Computational Hydroscience and Engineering at the University of Mississippi on behalf of USACE (Altinakar & 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.

We consider the scenario of dam failure by overtopping, which is the most common mode of failure. Such an event could occur during flood conditions, and can dramatically affect how the inundation area is defined. 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 estimate 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. 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 results presented are based on the S1 scneario. 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). All the modeling parameters and resulting inundation areas are available as supplementary information in a repository (Concha Larrauri, 2020).

Modeling the failure of dams in tandem or in series and breaching in cascade is desirable to capture the full risk of breaching, since many dam systems are in fact organized sequentially, 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 this is not available in 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 Significant and High hazard 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.

2.2 Estimating the losses of a dam failure

Costs associated with dam failures are not simple to measure given the varied consequences that different segments of society may experience. Some costs appear immediately and locally while others are felt months or years later in places far away from a dam, impacting not only fixed assets but also other income streams (Ellingwood et al., 1993). In general, costs are considered as direct, indirect, and intangible (e.g. cultural heritage loss, societal effects). The issue with comprehensively estimating the costs of dam failures in a regional or country scale is often the lack of data. Here, we use databases available nationally and consider direct costs, potential interruption of services provided by critical infrastructure such as wastewater treatment plants and power plants (without assigning a dollar value), potential transportation interruptions, health hazards associated to releases of toxic materials, and population directly exposed. This is the first step to improve the current dam hazard classification and many dam failure- related costs are not yet quantified in the framework. We plan to develop the necessary national databases and improve the loss quantification as a follow up of this work.

Considering the data available, 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.

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). Replacement costs for these infrastructures 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. Drinking water plants and water distribution stations were excluded from the analysis because a national database of their locations and capacity does not exist publicly (these are primarily available at the state level), however the framework can easily be adapted to include this information.
C3-Route miles of major roads and railways.
C4-Tons/day of commodities in affected navigation routes – obtained from national datasets.
C5- Number of Significant and High hazard 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.
C7-Total affected population in the inundation area.

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.. 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. 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, using the GBS and depth-damage curves. 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). There are numerous categories for each building occupancy class (i.e. there can be 10 or more depth-damage curves for a residential building). We simplified the damage functions to have a single depth-damage curve per building occupancy type (i.e. one depth-damage curve for residential buildings, one for power plants, one for commercial buildings, and so on), taking the mean of the percent damage by depth in each class. We appreciate that HAZUS estimates of property damage are a generalized tool and are not expected to accurately represent actual damages, nor is their uncertainty quantified. Here, we use them as a benchmark, recognizing that they may include at least some spatial discrimination of asset valuation, and are hence useful for ranking potential loss across a portfolio of dams.

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. Therefore, for our example, the loss estimation analyses were executed in the open-source software R, extracting the GBS datasets from HAZUS and using the depth-damage functions from the R package called Hazus (Goteti, 2015). The other infrastructure and utilities datasets used in the estimation of criteria C2 to C7 were obtained from different sources as shapefiles (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 respectively. This is similar to the approach of Wobus et al., (2019) for estimating flood damages. 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 & 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 (2019 dollars). We acknowledge that the cost approximation per storage volume is highly uncertain, but this gives indication of the relative order of magnitude of the costs for replacing the dams to allow comparisons.

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. There are no depth-damage curves suitable for these criteria, for example, the damage functions in Hazus for roads and railways are in the form of return flood-damage and in the case of dam failure, this approach would not apply. 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. C7 is obtained from the human consequence module included in DSS-WISE™Lite. For simplicity, this reflects the total estimated population within the inundation area, but the analysis in DSS-WISE™Lite includes day time and night time population, age, and others, in case more granularity is desired.

2.3 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 has equal weight and there is no quantitative measure of the hazard. For example, the hazard classification of all the test case 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. Taken verbatim from FEMA, (2013a)

Criteria	Hazard potential classification		
	Low	Significant	High
Direct loss of life [1]	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 [2]	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 [3]	Private agricultural lands, equipment and isolated buildings	Major public and private facilities	Extensive public and private facilities
Environmental Losses [4]	Minimal incremental damage	Major mitigation required	Extensive mitigation cost 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 downstream impacts. These followed the principles of the weighted sum method 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 used to design the dam capacity but not for 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 & 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:

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

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 & 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, which acts as a sensitivity analysis and shows how rank reversals may occur depending on the weights. 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.

3 Data

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

4 Results

4.1 Hazard rankings

Taking the median ranks of each dam's scores obtained with the permutations (i.e. the sensitivity analysis), the hazard order from highest to lowest is: 1) J Percy Priest; 2) Center Hill; 3) Cordell Hull; 4) Old Hickory; 5) Dale Hollow. This is the same result as when giving equal weights to the criteria. It is important to note that in the NID all of these dams are classified as High hazard but the ranking obtained gives more visibility to the different consequences of the failure of each dam. 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, mainly reflecting changes in the weight of C1 in some of the permutations (refer to Figure 4). This highlights that rankings are always subjective and depend on how the criteria are weighted. 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. Here, the purpose is direct public sector investment so that there is an efficient use of funds to mitigate the hazard.

The largest direct financial losses for infrastructure replacement (C1) 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 criterion 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.

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 railway miles. Connectivity of roadways can in many ways be as much of a significant factor as roadway or rail mileage. That is, intersections affected can produce a greater impact on travel but this was not considered in the analysis. 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.

With regard 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 affecting the water supply, 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, which also accounts for damages to other power plants within the inundation area. 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.

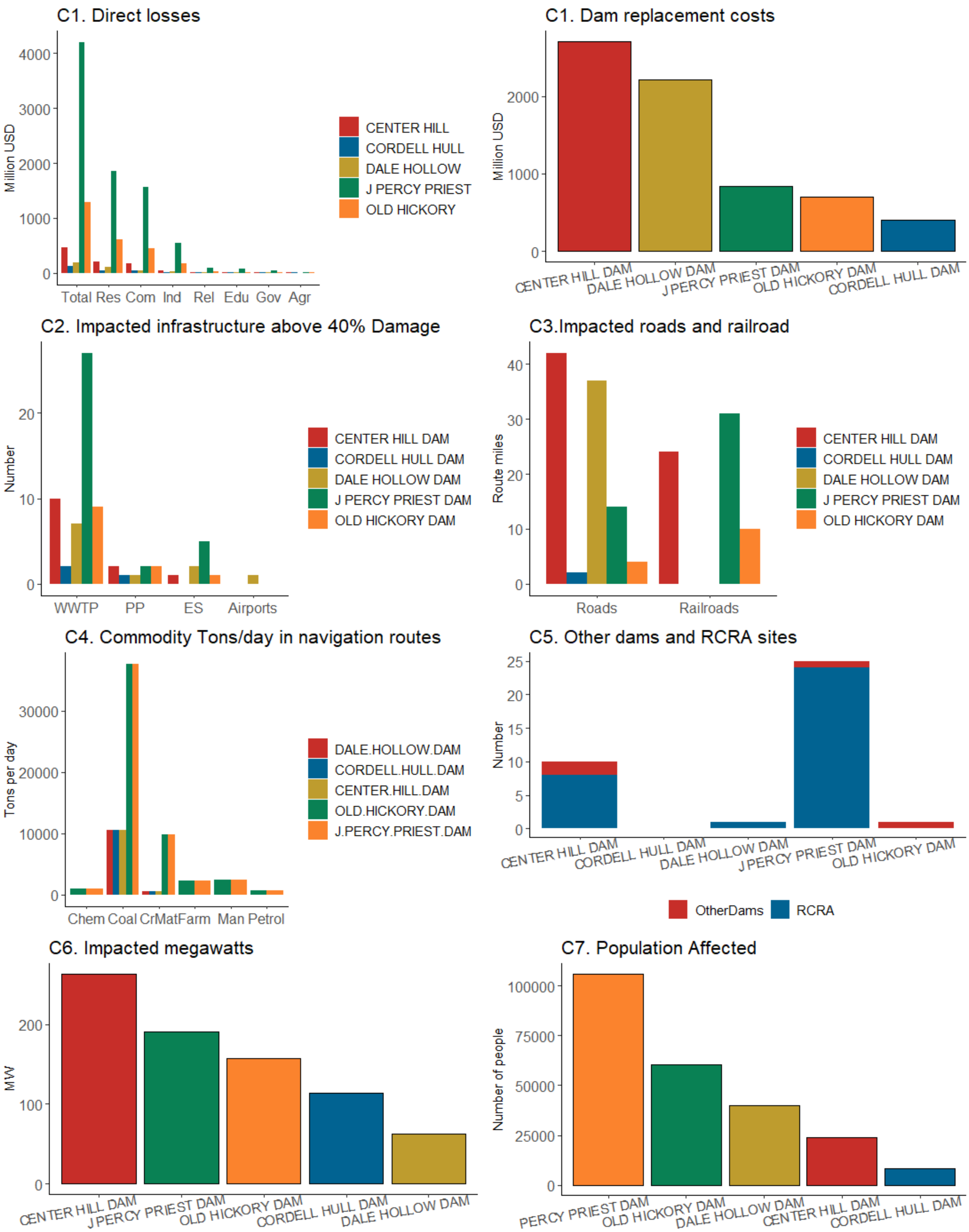

Figure 4. Criteria results across dams

4.2 Analysis of losses using flood insurance rate maps (FIRMS) and the failure of Percy Priest in Nashville

It is useful to explore the differences in damages and insurance needs included in the 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 because the flood insurance rate maps obtained for Kentucky did not include flood depth for most of the areas. Therefore, 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 (refer to Figure 5). It is evident from the results in Tables 2 and 3 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. The damage of this critical infrastructure has cascading effects to other sectors, e.g. industrial, commercial, etc. and can result in high impact to the local economy. The quantification of these losses was out of the scope of this paper, requiring the development of models to assess how damages in one sector will propagate through production and trade to other sectors.

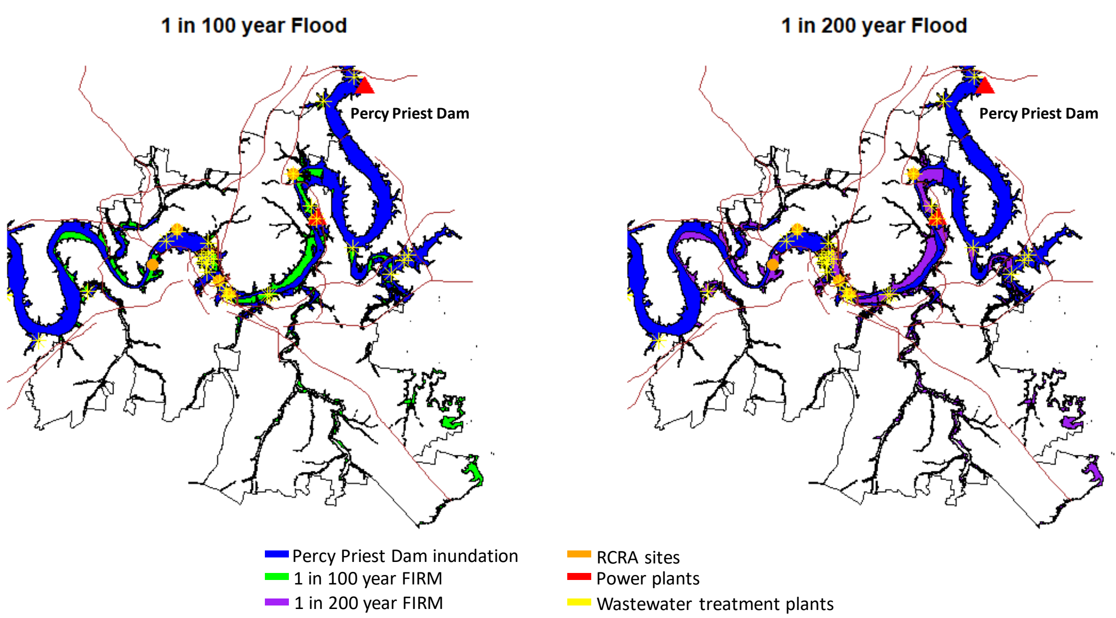

Figure 5 Inundation in Nashville due to the failure of Percy Priest Dam compared to FIRM maps

Table 2. Infrastructure affected in Nashville in different inundation scenarios. MWs= Megawatts, WWTPs= wastewater treatment plants, ES=electric substations

Inundation Extent	MWs	WWTPs	Roads (mi)	Major roads (mi)	ES	Railroad (mi)	RCRA sites	Tons/day in Navigation route
FIRM 1%	0	16	5.9	2.3	6	6	1	0
FIRM 2%	0	28	10.1	4.3	12	14	4	0
FIRM 1% and Percy Priest Dam	33.8	52	17.0	7.8	14	20	6	53,987
FIRM 2% and Percy Priest Dam	33.8	54	18.4	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
37,674.6	724.5	1,020.1	9,864.4	2,466.0	2,236.8	0.4

5 Summary and Discussion

This paper represents a first step to understand the current state of dam hazard classifications in the United States, using an integration of readily available methods, tools, and data available, specifically for financial loss estimation. 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 such as those reflected in the criteria used. 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. This may be quite time consuming considering that there are approximately 90,000 dams in the U.S.

A suggested approach for a national hazard mapping is to start by identifying basins with a high concentration of High and Significant hazard dams as per the NID classification, and prioritize dams past their design age that are owned by the state or privately (these usually represent lower financial and technical resources). In some states where dam inundation areas have already been estimated, the application of the framework may be straight forward. For example, California required dam owners to submit dam break inundation analyses in 2017, so with that information the hazard ranking can be obtained within the state boundaries. However, to have a national hazard map that is comparable across states the dam break parameters for the inundation simulation have to be standardized, for instance, replicating the ones used in this paper.

From a portfolio perspective, particularly for correlated risks that result from extreme weather events or prolonged wet spells within a region, risk scoring methods such as AHP 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. The framework does not yet include the risks of a portfolio of dams, since we believe that the configuration of the dams (i.e. in parallel or in series) and the joint and conditional probabilities of failure need to be included to have visibility to the risk. The objective here was just to address the hazard variable of the risk equation but the assessment of the probability of dam failure is an important separate step that we are pursuing as a compound risk characterization framework.

An approach to 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, is still needed. An important barrier to estimate this type of loss 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. With the data, the indirect economic 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 (Botzen et al., 2019; Martinich & Crimmins, 2019; Nordhaus, 2019; Stern, 2013). 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.

A national cost-benefit analysis of the dams across the U.S. needs to be done, acknowledging that many dams across the county are no longer providing the services that they were built for (Hansen et al., 2020). This would give visibility to the dams that most urgently need to be repaired or removed. This cost benefit analysis would consider the current conditions of a dam (e.g. with the data produced by the Associated Press in 2019;Lieb et al., 2019), the likelihood of failure, the quantification of losses in case of failure considering cascading effects, and an analysis of the current benefits/services the dam provides. A conceptual framework of how this would be implemented is presented in Figure 6. For this purpose, beyond the presentation here, we are working on improving indirect loss quantification considering cascading effects, and on developing a method to rapidly estimate the likelihood of failure conditional on climate, sedimentation, and structural fragility to perform risk assessments (a diagram of the estimation of the likelihood of failure is presented in Figure 7). With this, we aim to inform a national strategy of dam management that minimizes social and economic risks.

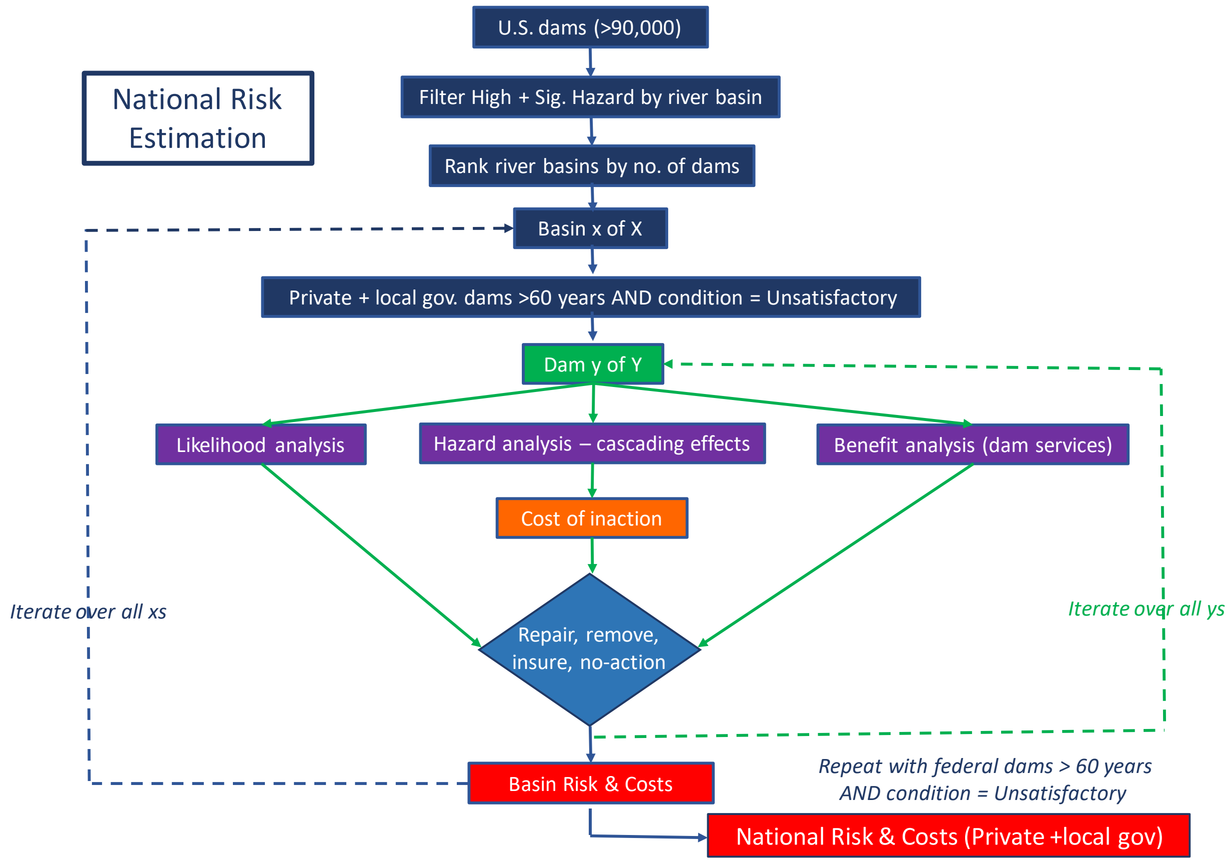

Figure 6. Conceptual framework for the estimation of dam risks and costs in the United States.

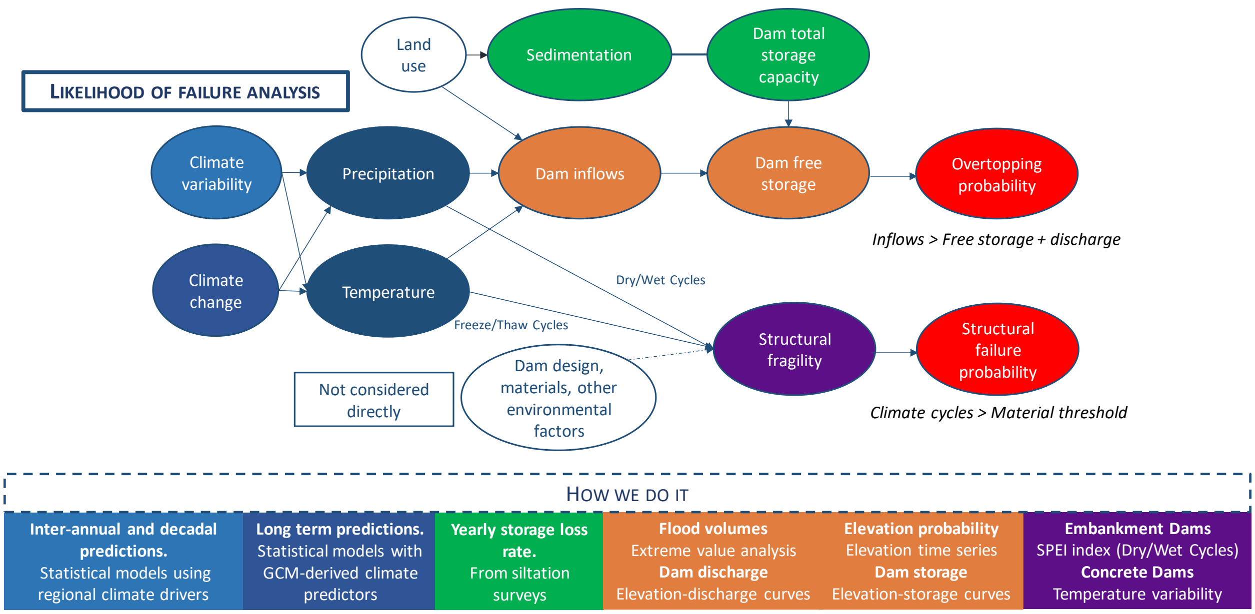

Figure 7. Conceptual framework for the likelihood of dam failure

Appendix

Datasets used in the analysis

- Dams data for Tennessee and Kentucky were obtained from the latest version in the NID (USACE, 2019).
- General 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).
- 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-geoplatform.opendata.arcgis.com/datasets/electric-substations
- Data from 2017 on navigation routes and transported commodities was 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-/xxxs-vvs4
- Airport data retieved from the U.S. Department of Transportation, Federal Aviation Administration-Aeronautical Information Services. 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, U.S Census retrieved from: https://www.census.gov/programs-surveys/cfs.html

Acknowledgments, Samples, and Data

We would like to thank U.S. Army Corps of Engineers Great Lakes and Ohio River Division and the Nashville District for their openness to share their data.
References of the datasets used for this research are included in the Appendix of this paper.

The inundation areas and other data resulting from the dam break simulations are available for download in Concha Larrauri, (2020) [Creative Commons Attribution 4.0 International].

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