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Climate Financing for Marine Transport: Analyzing the Impact of Climate Adaptation Investments in Inland Waterways

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FINAL RESEARCH REPORT PREPARD BY:

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1 Project Summary

The U.S. inland waterways play a vital role in the domestic economy, but extreme weather events (e.g., floods and droughts) perennially threaten to disrupt their operations. Exacerbating these concerns, climate change is expected to increase the frequency and severity of these disruptions in the future. However, despite these known risks, researchers have devoted little attention to evaluating the financial implications of climate change on inland waterway supply chains. Moreover, traditional financial valuation methods do not facilitate an accurate quantification of long-term risks associated with investments in climate resilient infrastructure, which leads to a systemic under-investment in resilience and adaptation.

Here, we develop a state-of-the-art, data-driven approach to evaluate climate financing strategies for inland waterways based on future costs of inland waterway supply chain disruptions due to climate change. The approach combines recent developments in financial analysis, climate modeling, simulation, statistical inference, and economic modeling. With this methodology in place, we can then evaluate cases where investments in resilient, waterborne infrastructure can offer cost-effective means of mitigating projected impacts of climate change. Our project paves the way for researchers being able to quantify the return on investment from climate adaptation strategies based on economic impacts of climate change on inland waterway supply chains and can help policymakers better allocate funding for mitigating future supply chain disruptions.

The report is outlined as follows. Section 2 discusses the motivation for our research and delineates the specific goals for this project. Section 3 presents an overview of a novel financial framework that is better suited for quantifying costs and benefits of investments in climate-resilient infrastructure and discusses how this framework relates to current financial practices, with a particular focus on inland waterway developments. Section 4 details how we project future climate scenarios and waterway conditions. Section 5 discusses the economic modeling framework we use to measure holistic impacts of disruptions. Section 6 describes follow-ups to this project (i.e., Phase 2). Section 7 gives our concluding remarks.

2 Introduction

2.1 Background

The U.S. inland waterways are a collection of navigable channels, ports, and locks and dams that are crucial for maintaining the success of the domestic economy (MacKenzie et al., 2012; Whitman et al., 2019; Johnson et al., 2022). Every year, more than 2.3 billion tons of commodities are transported along the inland waterways, and these shipments have exemplary safety records and low costs compared to other modes of transport (Schweighofer, 2014; Philip and Johnson, 2018). Most importantly though, ports along the inland waterways serve as hubs connecting vast, multimodal network of barge, rail, and highway transports (MacKenzie et al., 2012; Oztanriseven and Nachtmann, 2020).

Extreme weather events, notably floods and droughts, perennially threaten to disrupt operations along the inland waterways (Pregnolato et al., 2017). Major disruptions can have severe consequences for supply-chains and economies of impacted areas (Folga et al., 2009; Magalhães et al., 2020; Oliveira et al., 2020). For example, in 2019, sections of the Upper Mississippi River (UMR) were closed for more than a month due to major flooding, which resulted in approximately \$1.2 billion of grain not being shipped (Fahie, 2019; Johnson et al., 2022). To exacerbate concerns, climate change is expected to increase the frequency and severity of these weather-induced disruptions in the future (Camp et al., 2013).

Despite these risks, researchers have devoted little attention to evaluating the economic implications of extreme weather disruptions along the inland waterways (Folga et al., 2009; MacKenzie et al., 2012; Oztanriseven and Nachtmann, 2017; Darayi et al., 2019; Oliveira et al., 2020). Moreover, to the best of our knowledge, no study has quantified impacts of flood- and drought-related disruptions under future climate scenarios. This shortcoming is in large part due to the fact that current financial frameworks do not facilitate an accurate assessment of the long-term risks associated with investments in climate resilient infrastructure (David Espinoza et al., 2022). In other words, not only is there uncertainty in natural hazards when projecting impacts of future climate scenarios (e.g., floods and droughts), but there is also much uncertainty regarding how climate-resilient waterborne infrastructure could be funded and implemented to help mitigate impacts of these disruptions (e.g., flood-resilient ports). Without reasonable approaches for measuring costs and benefits associated such projects, it is impossible to accurately portray risks of disruptions due to climate change. This knowledge gap has resulted in a lack of investor sentiment, especially in the private sector, to fund such opportunities (David Espinoza et al., 2022). Our goal is to develop a data-driven framework that addresses these gaps and in turn helps facilitate investments in resilient infrastructure by enabling researchers and policy-makers to better quantify the risks and returns of such projects.

2.2 Project Goals

Here, we propose a novel approach to evaluate climate financing strategies for inland waterways based on future costs of inland waterway supply chain disruptions due to climate change. The approach integrates the decoupled net present value (DNPV) financial framework with climate modeling, agent-based simulation, Bayesian statistical models, and interdependent economic models. Using this methodology, we can evaluate cases where investments in resilient, water-borne infrastructure can offer cost-effective means of mitigating projected impacts of climate change. Although we demonstrate our methodology for disruptions due to droughts and floods along the Upper Mississippi River, our framework can be easily extended to other regions and sections of the inland waterways as well as other transportation modes and infrastructure sectors.

A holistic view of our approach can be found in Figure 1. Items highlighted in blue are the focus of this phase of the project (Phase 1). Here, we first run global climate projections drawn from various Representative Concentration Pathway (RCP) scenarios (Item 1). These global projections serve as inputs to down-scaled weather projections for predicting high and low water conditions along the Upper Mississippi River (Item 2). Additionally, we establish use-cases for applying the novel, DNPV financial framework to better evaluate investments in climate-resilient infrastructure along the inland waterways (Item 4).

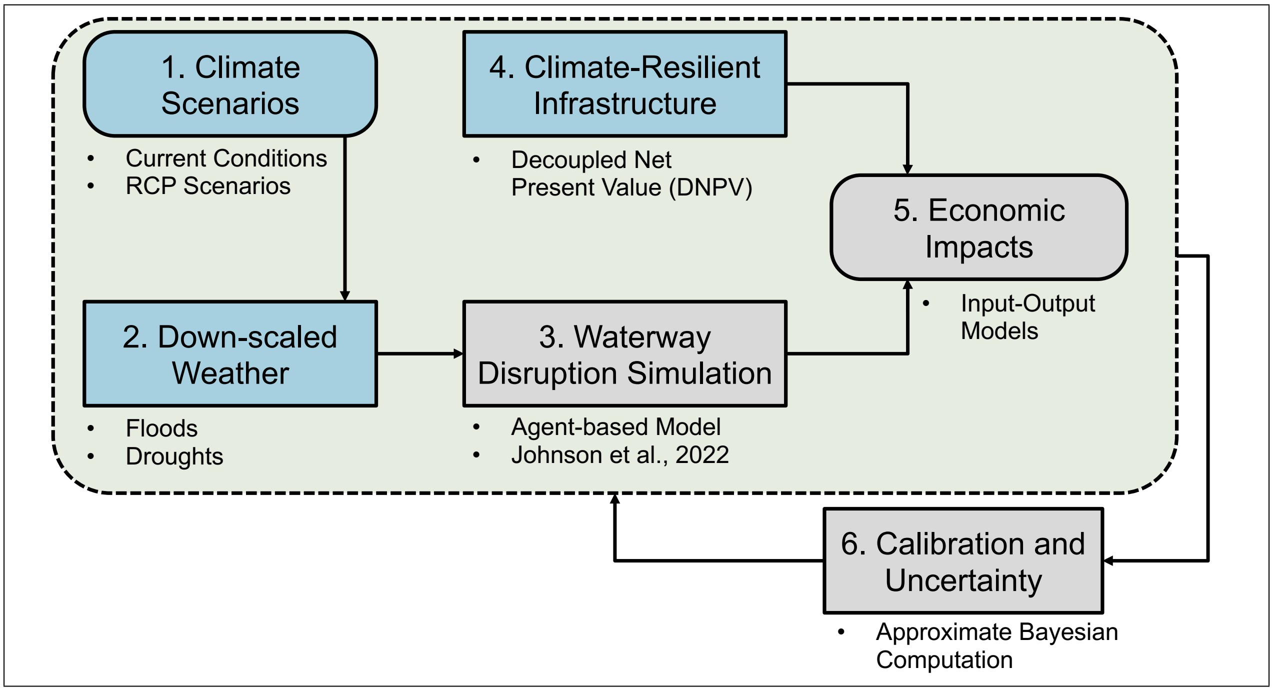

Figure 1: Evaluating Investments in Climate-Resilient Waterborne Infrastructure

In future work (i.e., Phase 2), these items will be integrated with supply chain disruption simulations (Item 3) and Input-Output economic models (Item 5) to help estimate impacts on dependent industry sectors and surrounding region. Moreover, we will use a cutting-edge statistical approach called approximate Bayesian computation (ABC) to calibrate our approaches and quantify uncertainty of model parameters (Item 6). Combining these items with the DNPV financial framework, we can in turn estimate expected costs and benefits of the different investments in climate-resilient, waterborne infrastructure under various climate scenarios and waterway disruptions.

3 DNPV Financial Framework

3.1 Background

With the increasing number and severity of climate-related events, there is a critical need to explore investment opportunities in climate-resilient infrastructure (Item 4, Figure 1). However, there are several challenges involved with projecting costs and benefits associated these types of investments. In particular, current financial practices do not allow for the costs of climate risks to be separated from other risks (e.g., market risks), of which the former can be mitigated by investments in the infrastructure itself (D. Espinoza et al., 2020). Related, because climate-resilient infrastructure developments typically have a long investment horizons, their funding is highly sensitive to discount rate assumptions (i.e., the rate of return that is applied to the present value calculation) (Nordhaus, 2014). These rates are often arbitrarily set or determined (David Espinoza et al., 2022). In the following paragraphs, we discuss these shortcomings and show how DNPV remedies them.

Standard infrastructure project valuations are categorized into basic revenues (i.e., tolls, fuel and motor taxes, etc.) and expenditures (i.e., operation expenditures, maintenance, etc.) taken on by the project. These values are subject to a discount rate, which shows how the project's valuation changes over long time horizons. These discounting rates are used to capture the risk a project takes over it's lifespan.

Typical discounting and valuation practices fail to quantify how cash flows of infrastructure are affected by climate, which has led to various debates in the field about proper discounting practices. Prevalent climate economists have introduced ideas that include matching discount rates to market or treasury rates (e.g., 20-year US Treasury inflation protected securities rate) (Stern, 2007). Others assume that costs to future generations need to be factored in the rates (i.e., inter-generational equity) (Nordhaus, 2014). The issue with these ideas is that the arbitrary selection of a discounting practice in an attempt to account for all types of risks and factors has made the standard net present value (NPV) framework untenable for infrastructure investment planning over long investment horizons.

For example, Table 1 shows a traditional cash flow statement for a hypothetical yet realistic investment scenario involving the development of a solar wind farm (David Espinoza et al., 2022). Here, the risk-adjusted interest rate (i.e., the interest rate that attempts to factor in all feasible risks of the project) is determined by investors to be 10%. In this scenario, the initial $130M investment is never recouped (i.e., the NPV of the project is negative), so the project is not funded.

Table 1: Cash flow example (NPV)

	Year 0	Year 1	Year 2	...	Year 19	Year 20
Cash Flow ($M)	(130)	14.50	14.50	...	14.50	14.50

NPV = -$65.5M, assuming risk-adjusted discount rate of $r = 10\%$

Table 2 presents the DPNV alternative. The DNPV framework introduces the concept of ”risk as a cost”, where risks are more transparently incorporated directly in cash-flows. In turn, discount rates are more informed and often lower because assumed risks are already accounted for in the cash-flows themselves.

Table 2: Cash flow example (DNPV)

	Year 0	Year 1	Year 2	...	Year 19	Year 20
Cash Flow ($M)	(130)	14.50	14.50	...	14.50	14.50
Cost of Risk ($M)						
Market Risks		(2.42)	(2.42)	...	(2.42)	(2.42)
Climate Risks		(1.67)	(1.67)	...	(1.67)	(1.67)
Risk-Adj Cash Flow ($M)	(130)	10.41	10.41	...	10.41	10.41

NPV = $48.4M, using a risk-free discount rate of $r = 1.52\%$ based on current 20-year treasury inflation-protected securities (TIPS) rate (May 22, 2023)

In this example, market risks (e.g., price fluctuations) and climate risks (e.g., damage from extreme weather) are modeled as distinct processes. Given that these risks are now explicitly defined as costs, a “risk-free” rate can be used to discount returns instead of a risk-adjusted rate (David Espinoza et al., 2022). The risk-free rate is more straightforward to estimate (e.g., 20-year US Treasury inflation protected securities rate), and project valuations are less sensitive to changes in these assumptions (i.e., changes in risk-free rates are historically small) (Stern, 2007). As seen in Table 2, even though the projected cash-flows of the solar wind farm project are reduced compared to Table 1 because the former includes more types of costs, the overall valuation of the project is more favorable because known risks are better accounted for and not simply lumped together in an arbitrarily high rate that is compounded over many years (David Espinoza et al., 2022).

Despite its advantages, there are additional challenges with the DNPV framework. In particular, modeling risks as distinct processes is more time-consuming and a more rigorous procedure than the quick NPV calculations, which is why the latter is currently favored by industries (David Espinoza et al., 2022). Additionally, data necessary to ground assumptions in DNPV calculations are not always easily available. This notion is especially true regarding the inland waterways; financial data are not readily available for many infrastructure projects (e.g., improvements to locks and dams). When data are available, they often don't contain enough detail to accurately model involved risks. Similarly, documentation regarding methods and assumptions of projected cash flows are often missing or not publicly provided. In the following section, we discuss these points in more detail and recommend a path forward for our project.

3.2 Inland Waterway Project Funding

Although historical financial data involving inland waterway infrastructure developments are hard to come by, the USACE provides post-annualized cost reports (PACR) on various waterway, lock and dam, and port revitalization projects which contain cash-flows for each of these individual locations. An example of a PACR provided by the USACE is shown in Figure 2 for the Olmsted Lock and Dam system in the Ohio River and Great Lakes Division (Hancock, 2012).

As seen, the example PACR report shows a discount rate of 7% for the project. However, the report does not describe how the this rate is calculated and/or its underlying assumptions.

Cost/Benefit Analysis – 7.0% Discount Rate

Annualized Benefits	
Transportation Benefits	$823,272,341
Fuel Tax Revenues	$19,976,006
Less WOPC Normal O&M	$7,664,548
Less LD 52 Repairs	$12,291,092
Less LD 53 Repairs	$11,860,808
Incremental Annual Benefits	$875,064,795
Annualized Costs	
Construction	$211,450,732
Interest During Construction	$19,093,734
Normal O&M	$3,832,274
Main Chamber Maintenance	$277,669
Aux Chamber Maintenance	$314,605
Dam Maintenance	$60,200
Incremental Annual Costs	$235,029,214
Net Annual Project Benefits	$640,035,580
BENEFIT - COST RATIO	**3.7**

Figure 2: Cost Benefit Analysis from Post Annualized Cost Report on Olmsted River

Furthermore, the costs and benefits realized by the port are shown at a fairly high level (i.e., there is no distinction between cost of climate-related risks, marketing risks, or operational risks). Other reports, such as feasibility reports provided on similar waterway systems, provide cost benefit analyses with little to no discussion on rates underlying assumptions, and have costs with minimal discussion (Dixon, 1991). As such, it is difficult to establish baseline assumptions for calculating potential costs and savings from investments in climate-resilient developments within the DPNV framework.

To help alleviate this lack of data, we will use Monte Carlo analyses to simulate reasonable estimates for relevant cash-flow items (Phase 2). In turn, we will leverage a technique called approximate Bayesian computation (ABC) to calibrate these simulations (Item 6, Figure 1). ABC will allow us calibrate the simulated DNPV outcomes with observed data from other parts of the framework (Toni et al., 2009). In other words, we can take parts of the framework where we have more data (e.g., climate projections and economic impacts) and use this information to rarefy the simulated DPNV items and quantify uncertainty thereof. ABC has proven to be effective for calibrating complex models even when validation data are sparse, and our team has had prior success in applying this technique to similar analyses (Cisewski, 2014; Thiele et al., 2014; Johnson et al., 2022).

4 Climate Scenarios

Item 1 in our modeling framework, shown in Figure 1, is concerned with developing future climate-driven hazard scenarios that will impact the operation and performance of inland waterway navigation. These scenarios will be used to assess the cost of future disasters in the economic and financial valuation models. While our ultimate goal is to examine multiple hazards scenarios, we first begin by investigating flood risk by considering multiple future climate projections and evaluating the corresponding flood risk under each scenario in various sections of the Upper Mississippi River Navigation System.

4.1 Background

As climate change continues to cause more intense precipitation events, and urbanization causing extreme land-use changes, the need for flood risk modeling becomes increasingly important (Hettiarachchi et al., 2018). Flood risk modeling plays a critical role in understanding and mitigating the potential impacts of floods, which pose a significant threat to infrastructure. In particular, port infrastructure is often located in low-lying coastal regions and is susceptible to various types of flooding, including storm surge, high tides, and heavy rainfall (Ribeiro et al., 2023). Extensive disruptions of this kind of infrastructure can have devastating impacts on the economic well-being of the region, and it is important to assess its flood risk under different uncertain future scenarios. The analysis will be run on a case study of the Upper Mississippi River (Figure 3), which runs from Lake Itasca, Minnesota, to Cairo, Illinois, as it intersects with the Ohio River.

Figure 3: Map of the Upper Mississippi River (Source: steamboats.org)

4.2 Methodology

In order to analyze river flood probability, we need to gather past and future flow data. The first step is to obtain modeled river discharge data from a Global Climate Model. We chose CMIP6 as our source. CMIP6 represents the latest global climate model data that is currently accessible. This data is highly reliable and forms the fundamental basis for the Assessment Reports of the Intergovernmental Panel on Climate Change (Climate Data Canada, 2023).

The parameters we chose to configure our model were the following:

- The variable name was 'rivo', which is the river outflow discharge.
- The experiment IDs were 'historical', to obtain flows from 1850 to 2014, and 'SSP126', 'SSP245', 'SSP370' and 'SSP585' to obtain flows from 2015 to 2100 under different climate scenarios. These scenarios (Intergovernmental Panel on Climate Change, 2023) were chosen based on the fact that they cover a wide range of future possible scenarios, and they are the most commonly used in climate scenario analyses:
  - SSP126: low GHG emissions and CO2 emissions cut to net zero around 2075.
  - SSP245: intermediate GHG emissions and CO2 emissions around current levels until 2050, then falling but not reaching net zero by 2100.
  - SSP370: high GHG emissions and CO2 emissions double by 2100.
  - SSP585: very high GHG emissions and CO2 emissions double by 2050.
- The timescale is daily.
- The geographic scale is 50km.
- The variant label that was used was r1i1p1f2, and the selected model was CNRM-CM6-1 from the National Center for Meteorological Research, Météo-France and CNRS laboratory.

The second step is to obtain observed discharge data from river gages to compare them to the model historical discharge data. Eleven Upper Mississippi River gages were selected from USGS (Figure 4), based on how far back in time the data is available. The common timespan between them was 1964-2014. These gages were then clustered according to the river segment they belong to, and their locations are shown in Table 3:

Table 3: Gages and their Locations

Cluster	Gage	Latitude	Longitude
Itasca Cluster	USGS 5211000	47°13'56" N	93°31'48" W
	USGS 5227500	46°32'26" N	93°42'26" W
	USGS 5267000	45°49'34" N	94°21'18" W
	USGS 5288500	45°07'43.81" N	93°17'56.56" W
Minnesota Cluster	USGS 5331000	44°56'40.0" N	93°05'17.2" W
	USGS 5344500	44°44'45" N	92°48'00" W
	USGS 5378500	44°03'20" N	91°38'15" W
Wisconsin Cluster	USGS 5420500	41°46'50" N	90°15'07" W
Missouri Cluster	USGS 7010000	38°37'44.4" N	90°10'47.2" W
	USGS 7020500	37°54'02.7" N	89°49'48.8" W
	USGS 7022000	37°13'12.9" N	89°27'47.4" W

4.2.1 Bias Correction

Bias correction (Figure 5) is used to adjust climate model outputs to better align them with observed climate data. This process is necessary because climate models often exhibit systematic biases that can affect their reliability in reproducing historical climate conditions and projecting future climate scenarios (Copernicus Climate Change Service - Global Impacts, n.d.). Bias correction is used to improve accuracy, and ensure consistency with historical observations.

Figure 6 shows the difference between the annual peak flows from 1964 to 2014 of the CMIP6 Model and the USGS gages for the Missouri cluster. While it seems both datasets follow the same pattern, it is apparent that the modeled dataset overestimates the discharge.

There have been several proposed bias correction methods. We use the Quantile Mapping Bias Correction (Gudmundsson et al., 2012). The computational process is mathematically

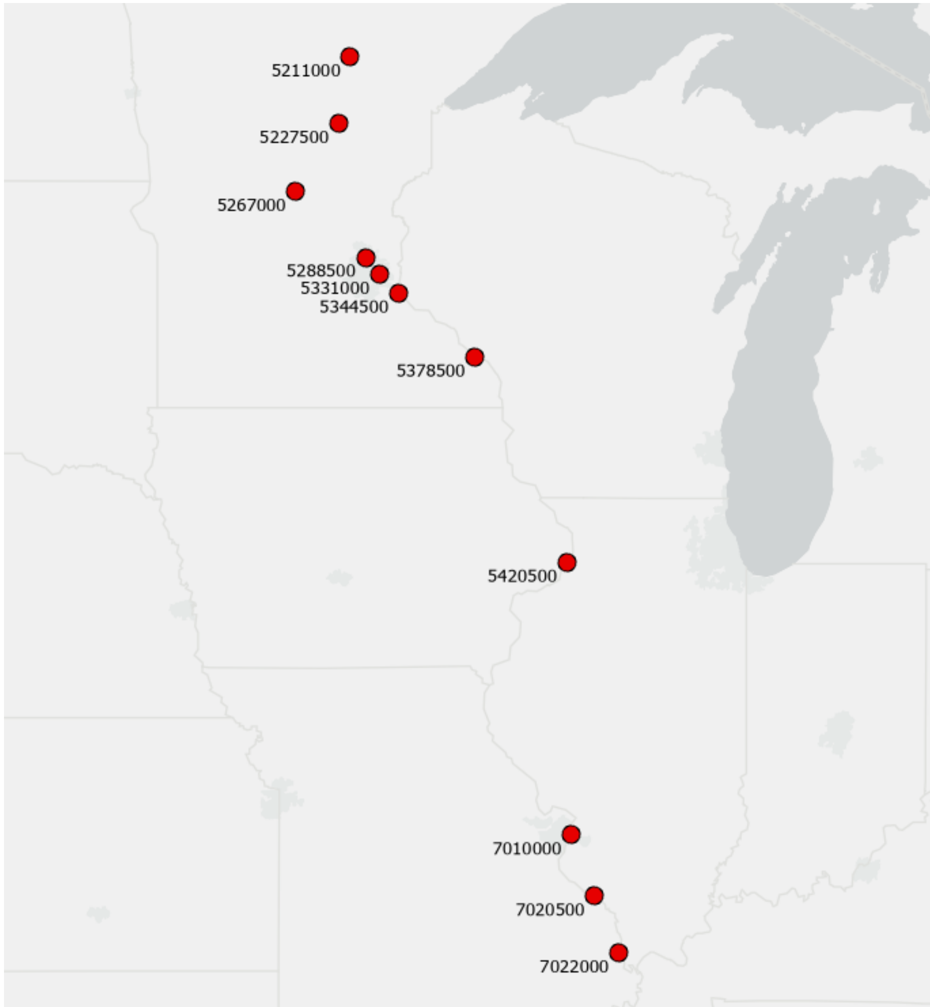

Figure 4: Gage Map

expressed in Equation 1.

$$X_{future,adjusted} = F^{-1}_{observed}(F_{modeled}(X_{future})) \tag{1}$$

In Equation 1, $F_{modeled}$ is the eCDF of the model data and $F^{-1}_{observed}$ is the inverse eCDF of the observed data. Corresponding corrections for the Missouri cluster can be seen on Figure 7. Figures 8 and 9 show the corrected annual peak flows of the Missouri cluster for the historical values, as well as each scenario values, respectively.

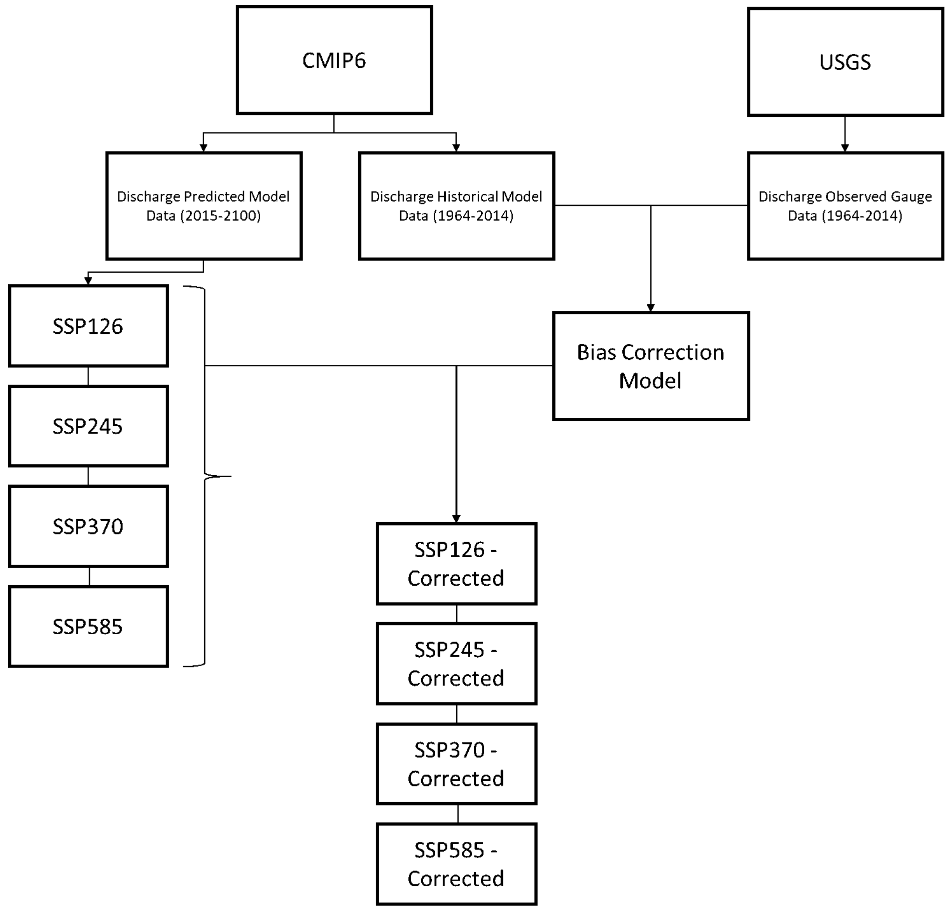

Figure 5: Bias Correction Methodology

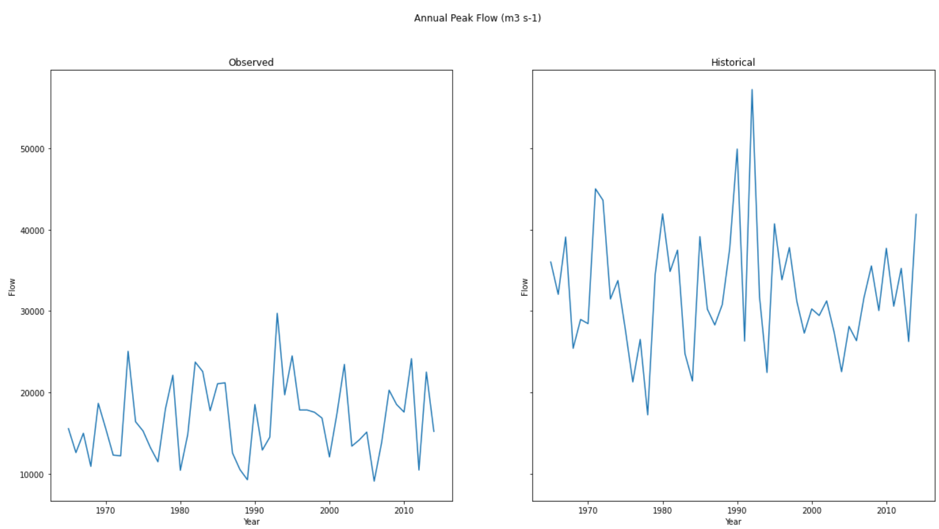

Figure 6: Difference Between USGS Observed Annual Peak Flows and CMIP6 Historical Annual Peak Flows

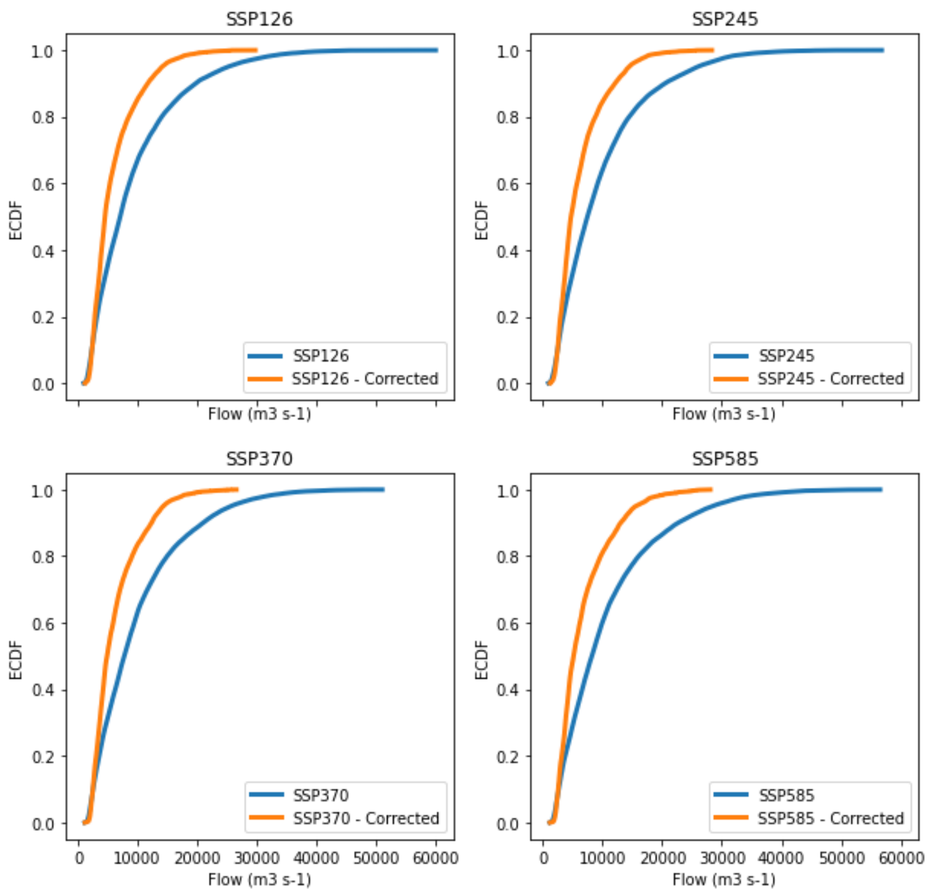

Figure 7: Corrected Scenario Flows

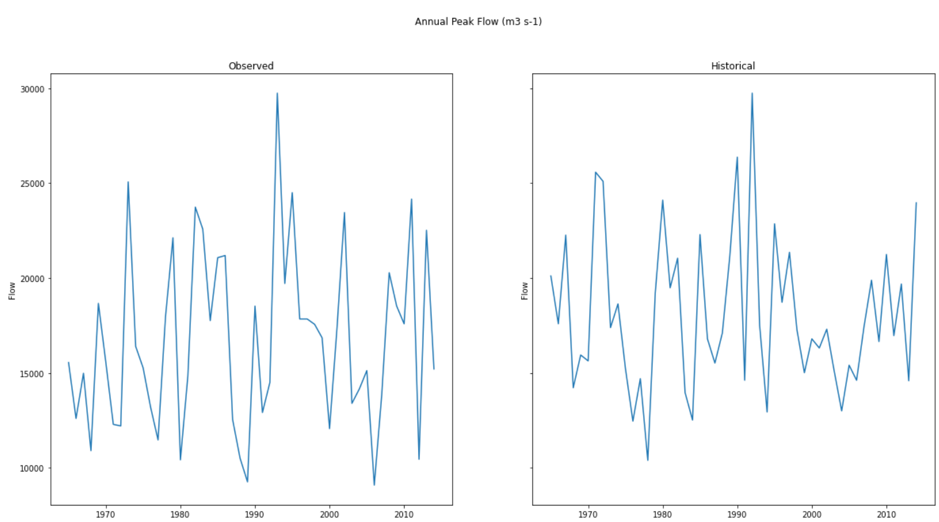

Figure 8: Corrected Historical Annual Peak Flows

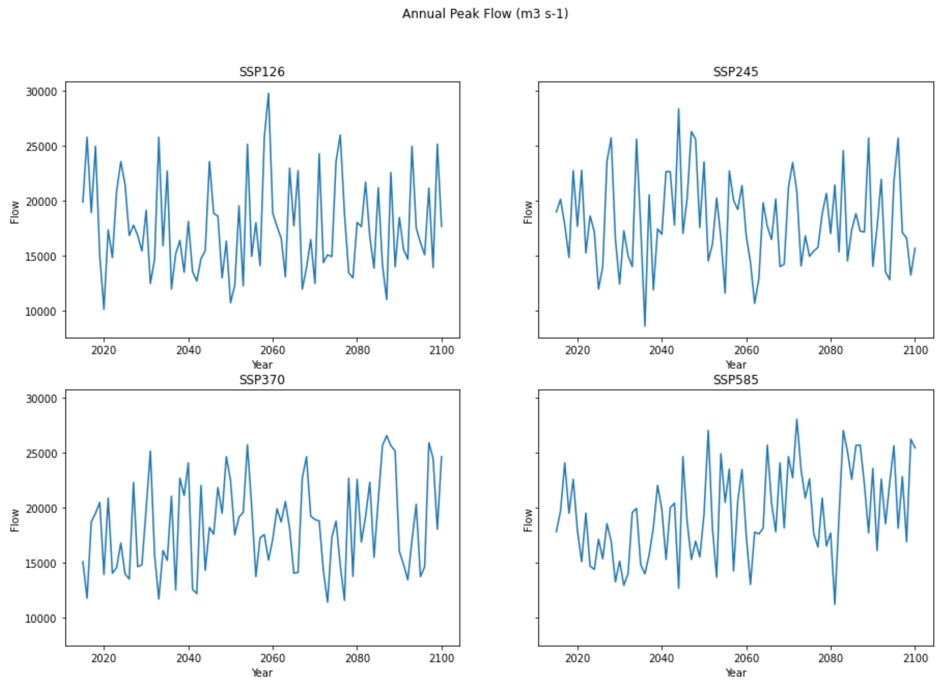

Figure 9: Corrected Scenario Annual Peak Flows

4.2.2 Future Peak Design Flow Determination

The overall process of determining the future peak design flow consists of multiple steps (Figure 10). First, the best fit distribution of the annual peak flows is determined. Then, a return level is determined for each return period. Finally, the future design flows are calculated using the Delta Change Factor Method (Aryal et al., 2022).

We chose a set of 10 candidate distributions that often appear in the literature of flood hazard frequency analysis. The distributions are: Beta, Gamma, Gumbel, Normal, Log-Normal, Weibull, Generalized Pareto, Generalized Extreme Value, Generalized Logistic, and Pearson Type III. Best-fit analysis based on the Kolmogorov–Smirnov (K-S) test was performed to narrow down the available options. At a confidence level of 95%, the null hypothesis is rejected in favor of the alternative if the p-value is less than 0.05. Then, Q-Q plots are plotted for each distribution that was not rejected. A Q-Q plot is a scatter plot where the x-axis represents the quantiles from the reference distribution, and the y-axis represents the quantiles from the observed data. Each point on the plot represents a pair of corresponding

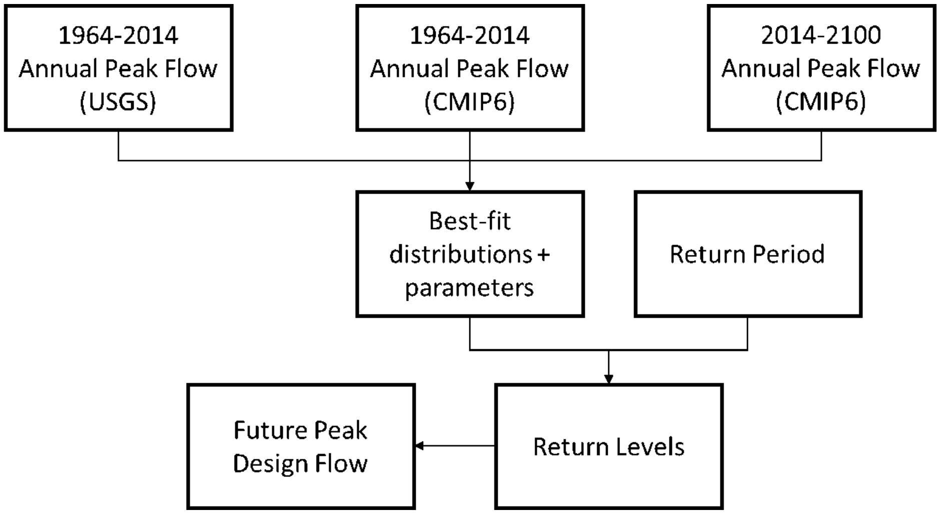

Figure 10: Future Peak Design Flow Determination Methodology

quantiles. If the data follows the reference distribution, the points should roughly fall on a straight line, which suggests a good fit between the reference distribution and the observed data. An example Q-Q plot is shown on Figure 11. Based on these tests, the Gumbel distribution is chosen as the best-fit distribution (Figure 12).

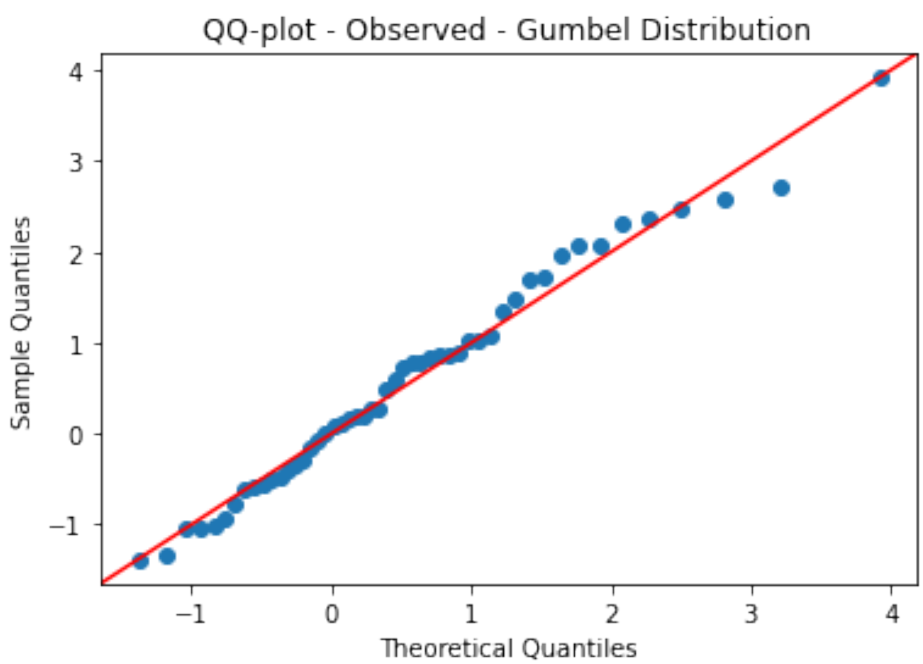

Figure 11: Q-Q plot of the Observed Data Using a Gumbel Distribution

Gumbel Distribution is fit to each scenario to obtain their corresponding distribution

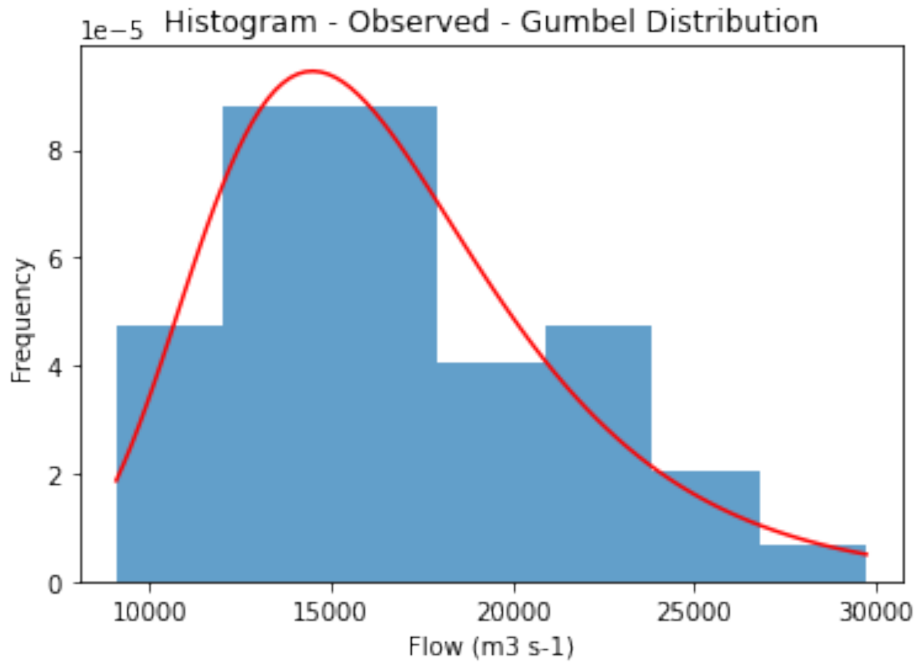

Figure 12: Histogram of the Observed Data fit to a Gumbel Distribution

parameters. Then, the inverse survival function is plotted for each scenario. The survival function is the probability that a variable takes a value greater than x (Engineering Statistics Handbook, 2023). The inverse survival returns the value x, which is the return level, that corresponds to a probability of $\frac{1}{\text{return period}}$. An example survival function is shown on Figure 13. The return levels are calculated for each scenario for the return periods of 2, 5, 10, 25, 50, 100 and 500 years.

From the return levels, the future peak design flow is calculated using the change factor methodology (VishnuPriya and Agilan, 2022). In this approach, the Delta Change Factor (DCF) is calculated for each future scenario for each return period, as shown in Equation 2. The DCF factor is the model ratio of future flow to present/past flow. It shows the direction of change realtive to the baseline. A DCF value less than one means the flow has decreased, whereas a value more than one means the flow has increased. Using the DCF, changes predicted by the climate model can be applied to observed data to obtain the projections.

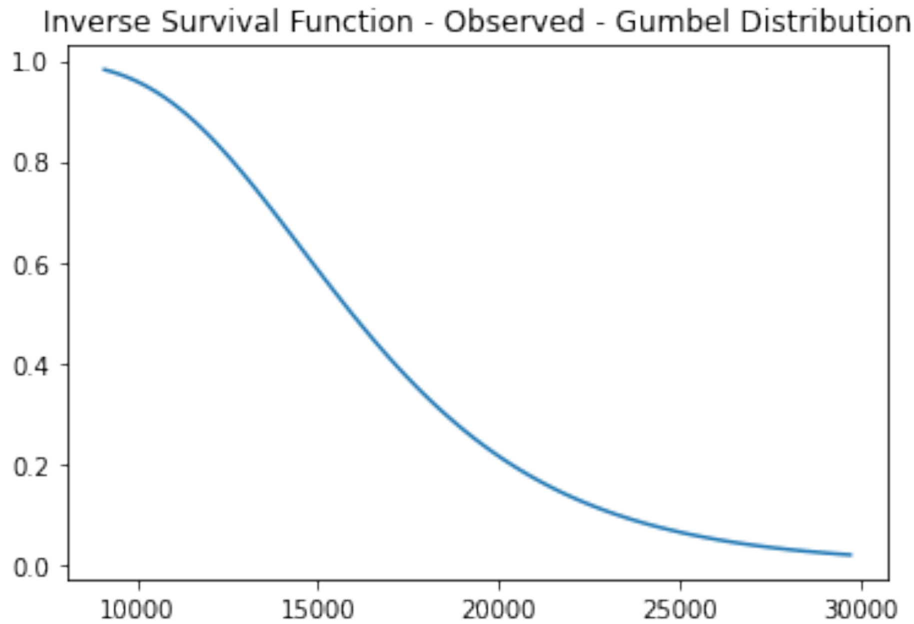

Figure 13: Inverse Survival Function of the Observed Data Using a Gumbel Distribution

$$DCF = \Delta Q = \frac{Q_{future,model}}{Q_{historical,model}} \tag{2}$$

For a more conservative analysis, the maximum DCF value for each return period under consideration is selected. The future peak design flow is then determined using Equation 3:

$$Q_{future} = DCF \times Q_{observed} \tag{3}$$

Tables 4, 5, 6 and 7 show the DCF values for the Missouri, Wisconsin, Minnesota and Itasca clusters, respectively. For the Missouri cluster, the maximum DCF values for 100-year and 500-year flood are 1.081427 and 1.081292, respectively. These values correspond to design flows of 35021.25 and 41802.49 m3 s-1. For the Wisconsin cluster, the maximum DCF values for 100-year and 500-year flood are 0.987055434 and 1.001031807, respectively. These values correspond to design flows of 9478.61437 and 11664.55316.49 m3 s-1. For the Minnesota cluster, the maximum DCF values for 100-year and 500-year flood are 0.883511379 and 0.883050906, respectively. These values correspond to design flows of 11791.61675 and

15603.23576 m3 s-1. For the Itasca cluster, the maximum DCF values for 100-year and 500-year flood are 1.049166783 and 1.060665614, respectively. These values correspond to design flows of 2498.832002 and 3112.671737 m3 s-1.

Table 4: DCF values for the Missouri cluster

	2-year	**5-year**	**10-year**	**25-year**	**50-year**	**100-year**	**500-year**
SSP126	0.966474	0.982131	0.989763	0.99738	1.001969	1.005852	1.012955
SSP245	1.002792	1.021177	1.030137	1.039081	1.04447	1.049029	1.057371
SSP370	1.014248	1.02394	1.028664	1.033379	1.03622	1.038624	1.043021
SSP585	1.082179	1.081879	1.081734	1.081589	1.081501	1.081427	1.081292

Table 5: DCF values for the Wisconsin cluster

	2-year	**5-year**	**10-year**	**25-year**	**50-year**	**100-year**	**500-year**
SSP126	0.899331	0.936469	0.953442	0.969709	0.9792	0.987055	1.001032
SSP245	0.898148	0.899496	0.900111	0.900703	0.901048	0.901332	0.90184
SSP370	0.883892	0.890483	0.893496	0.896385	0.89807	0.899464	0.901945
SSP585	0.939164	0.933153	0.930405	0.927772	0.926236	0.924964	0.922703

Table 6: DCF values for the Minnesota cluster

	2-year	**5-year**	**10-year**	**25-year**	**50-year**	**100-year**	**500-year**
SSP126	0.947028	0.899613	0.891636	0.886486	0.884175	0.882541	0.880111
SSP245	0.836169	0.848059	0.850059	0.851351	0.851929	0.852339	0.852949
SSP370	0.842757	0.832164	0.830382	0.829231	0.828714	0.828349	0.827807
SSP585	0.895729	0.886745	0.885235	0.884259	0.883821	0.883511	0.883051

Table 7: DCF values for the Itasca cluster

	2-year	**5-year**	**10-year**	**25-year**	**50-year**	**100-year**	**500-year**
SSP126	0.96387	0.963024	0.962672	0.962351	0.962168	0.962023	0.961774
SSP245	0.964295	1.003177	1.019424	1.034203	1.042484	1.049167	1.060666
SSP370	0.919712	0.942014	0.951329	0.959806	0.964554	0.968388	0.974983
SSP585	0.962541	0.949886	0.944593	0.939784	0.937087	0.934914	0.931171

The climate and flood risk analyses shown in this section will help determine the hazard scenarios of the modeling framework and evaluate projected costs of inland water disruption under different climate resilience strategies.

5 Economic Modeling

5.1 Background

The climate models and DNPV framework discussed in the previous tasks will eventually be linked to input-output (I-O) economic models (Item 5, Figure 1). I-O models are a long-standing approach for describing and quantifying the interdependent nature of sectors of an economy (Leontief, 1936; Santos and Haimes, 2004). The I-O models will allow us to estimate the cascading impacts across multiple industry sectors and regional changes in productivity resulting from disruptions due to extreme weather events along the inland waterways. In turn, we can see what industries and areas are most vulnerable to impacts and various climate scenarios (Haimes et al., 2005). Similarly, we will be able to quantify indirect benefits of savings from mitigated impacts by developing climate-resilient infrastructure.

For our approach, the key decision-making process underlying these economic models is that when a disruption occurs, freight scheduled to ship through an inland waterway port might be rerouted. In the case of a localized disruption (i.e., one port is closed), shipments could theoretically be redirected through another nearby port if circumstances permit (MacKenzie et al., 2012). However, if the disruption is more widespread and an entire section of a river is closed, which is often the case with disruptions due to extreme weather events, alternative waterway routes are generally limited (Folga et al., 2009). As such, impacted businesses can reroute shipments via other modes of transport, namely truck or rail, or decide to leave their product on a barge or at port for the duration of the disruption (MacKenzie et al., 2012; Oztanriseven and Nachtmann, 2017). These rerouting decisions are case-specific with regards to the costs, preferences, and constraints of each business making them and will be later modeled in Phase 2 of this project via an agent-based simulation (Item 3, Figure 1). Even though businesses may not consider the downstream impacts of their rerouting decisions, if they leave products at port, interdependent industries will experience delays in production (MacKenzie et al., 2012; Oztanriseven and Nachtmann, 2017).

In particular, we will utilize the multiregional inoperablility input-output model (MRIIM), a risk-based extension to the traditional I-O model, to quantify how these shipping delays propagate through the a region's economy (Crowther and Haimes, 2009; Whitman et al., 2019; Magalhães et al., 2020). Several studies have also utilized the MRIIM framework to quantify regional economic impacts resulting disruptions along the inland waterways (MacKenzie et al., 2012; Pant et al., 2015; Thekdi and Santos, 2016; Oztanriseven and Nachtmann, 2017; Darayi et al., 2019; Whitman et al., 2019), including work done by PI Baroud to quantify economic impacts of inland waterway disruptions and measure infrastructure resilience (Baroud et al., 2015). The technical definition of the MRIIM is specified by Equation 4 (Santos and Haimes, 2004; Crowther and Haimes, 2009):

$$\begin{pmatrix} \tilde{\mathbf{q}}^1 \\ \tilde{\mathbf{q}}^2 \\ \vdots \\ \tilde{\mathbf{q}}^p \end{pmatrix} = \mathbf{T}^* \begin{pmatrix} \mathbf{A}^{*1} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{A}^{*2} & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{A}^{*p} \end{pmatrix} \begin{pmatrix} \tilde{\mathbf{q}}^1 \\ \tilde{\mathbf{q}}^2 \\ \vdots \\ \tilde{\mathbf{q}}^p \end{pmatrix} + \mathbf{T}^* \begin{pmatrix} \tilde{\mathbf{c}}^{*1} \\ \tilde{\mathbf{c}}^{*2} \\ \vdots \\ \tilde{\mathbf{c}}^{*p} \end{pmatrix} \tag{4}$$

where

$\tilde{\mathbf{q}}^r$ = an inoperability vector of length n consisting of the difference between normal production levels and disrupted production levels, expressed as a percentage of normal production levels, of the n^{th} industry sector in region r of p total regions;

$\mathbf{T}^* = [\text{diag}(\tilde{\mathbf{x}}^1, \tilde{\mathbf{x}}^2, \dots, \tilde{\mathbf{x}}^p)]^{-1}\mathbf{T}[\text{diag}(\tilde{\mathbf{x}}^1, \tilde{\mathbf{x}}^2, \dots, \tilde{\mathbf{x}}^p)]$;

$\tilde{\mathbf{x}}^r$ = a vector of length n consisting of industry sector production in region r;

$$\mathbf{T} = \begin{pmatrix} \mathbf{T}^{11} & \mathbf{T}^{12} & \dots & \mathbf{T}^{1p} \\ \mathbf{T}^{21} & \mathbf{T}^{22} & \dots & \mathbf{T}^{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{T}^{p1} & \mathbf{T}^{p2} & \dots & \mathbf{T}^{pp} \end{pmatrix};$$

$\mathbf{T}^{rs}$ = an $n \times n$ trade interdependency matrix consisting of the proportion of a commodity consumed in region s that is produced in region r;

$\mathbf{A}^{r}$ = an $n \times n$ industry interdependency matrix of region r composed of elements a_{ij}^{r};

$\mathbf{A}^{*r}$ = the inoperability matrix for region r, $[\text{diag}(\tilde{\mathbf{x}}^{r})]^{-1}\mathbf{A}^{r}[\text{diag}(\tilde{\mathbf{x}}^{r})]$;

$$a_{ij}^{r} = \begin{cases} l_i^r a_{ij} & , l_i^r < 1 \\ a_{ij} & , l_i^r \geq 1 \end{cases};$$

a_{ij} = the input of industry sector i to j, expressed as a proportion of the total production inputs to industry sector j;

l_i^r = the location quotient, $\frac{x_i^r/x^r}{x_i/x}$;

x_i^r = industry sector i's production in region r;

x^r = total economic production in region r;

x_i = industry sector i's production across the nation;

x = total national economic production;

$\tilde{\mathbf{c}}^{*r}$ = a demand-side perturbation vector of length n consisting of the difference between normal demand and disrupted demand, expressed as a percentage of normal production levels, of the n^{th} industry sector in region r of p total regions

For the MRIIM we use in our approach, there are 71 North American Industry Classification System (NAICS) industry sectors (i.e., $n = 71$). Additionally, the twelve states (Louisiana, Mississippi, Arkansas, Tennessee, Kentucky, Missouri, Illinois, Indiana, Ohio, Iowa, Minnesota, and Michigan) that have significant amounts of inbound/outbound shipments through the UMR comprise the regions of interest (i.e., $p = 12$, and r represents a given state). Company shipments that do not reach their destination in a timely manner are modeled as perturbations in demand (Horowitz and Planting, 2009; MacKenzie et al., 2012). In other words, if companies in state r decide to keep their products at port, the value of these products, expressed as a proportion of that state-sector's normal shipments, forms the corresponding entry in $\tilde{\mathbf{c}}^{*r}$. Given $\tilde{\mathbf{c}}^{*r}$ for all twelve states, we then solve for $\vec{\mathbf{q}}$ (vector of length $n \times p$) in Equation 4 to estimate the disruptions to each industry sector in each state. All assumptions and data contained within Equation 4 need to be updated with the latest economic data to help ensure accurate projections of impacts from disruptions.

5.2 Data

We have recently updated the MRIIM with new baseline commodity flow and GDP projections (i.e., economic characteristics without a disruption present). These data will allow us to establish baselines that help reveal what industries and areas are most vulnerable to waterway disruptions from future climate events. Additionally, insights stemming from these baselines will help us ensure that are simulation(s) outcomes are intuitive.

Figure 14 shows the total economic production by region (x^r) and industry sector production (x^i) for the top 5 leading industries produced by the MRIIM. These are based on the most data from the Bureau of Economic Analysis (BEA). As expected, the data reveal a high amount of regional economic production in Illinois, and a high amount of industry production from wholesale trade and general and local government.

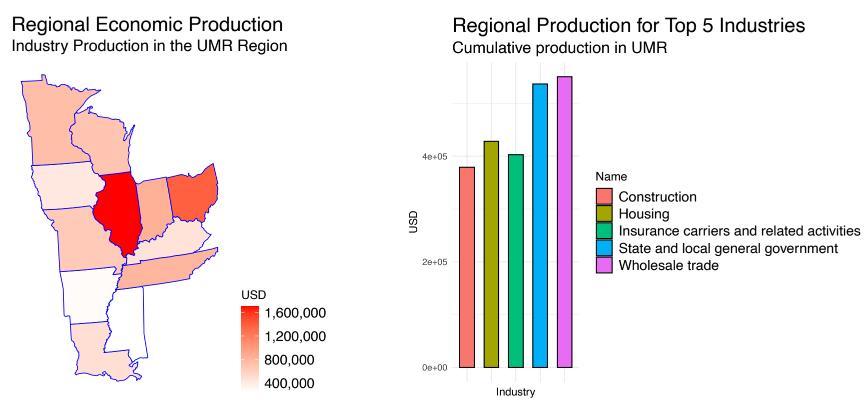

Figure 14: Regional Economic Production by State and by Industry Respectively

For economic analysis of the inland waterway network in particular, the United States Army Corps of Engineers (USACE) Waterborne Commerce Statistics Center (WCSC) provides varying data sources for domestic commodities shipped, tonnages of shipping, and inbound and outbound traffic. The most recent data includes records from 2021, which are used in the following figures.

Figure 15 shows tons of inbound and outbound shipments from the 12 states included in our economic model (i.e., those that are most affected by disruptions along the UMR). These figures reveal high amounts of inbound and outbound waterborne commerce traffic in Louisiana, and high amounts of outbound commerce traffic out of Minnesota and Ohio.

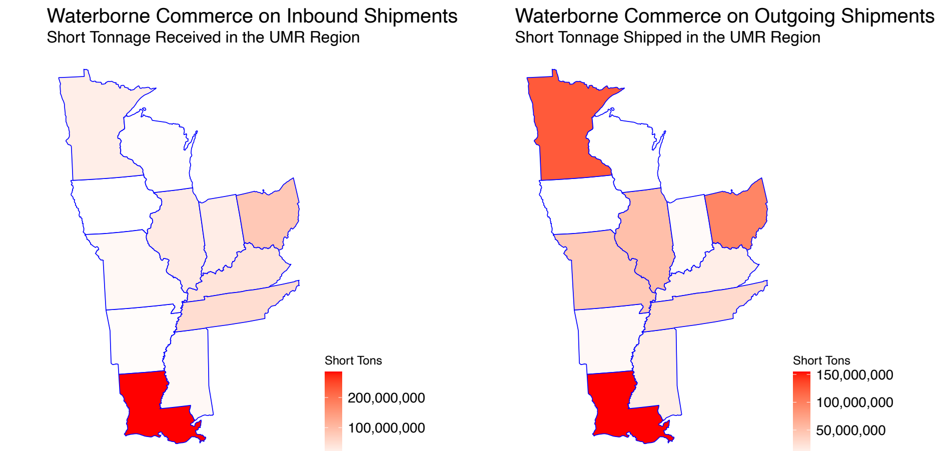

Figure 15: Domestic Inbound and Outgoing Tonnages for Waterborne Shipments by State in the UMR

Using the same data from the WCSC, the bar charts in Figure 16 show the leading commodity groups by tonnage on incoming and outbound shipments in the UMR region. Results show that a strong majority of commodities shipped in the UMR are Agricultural and Mineral products.

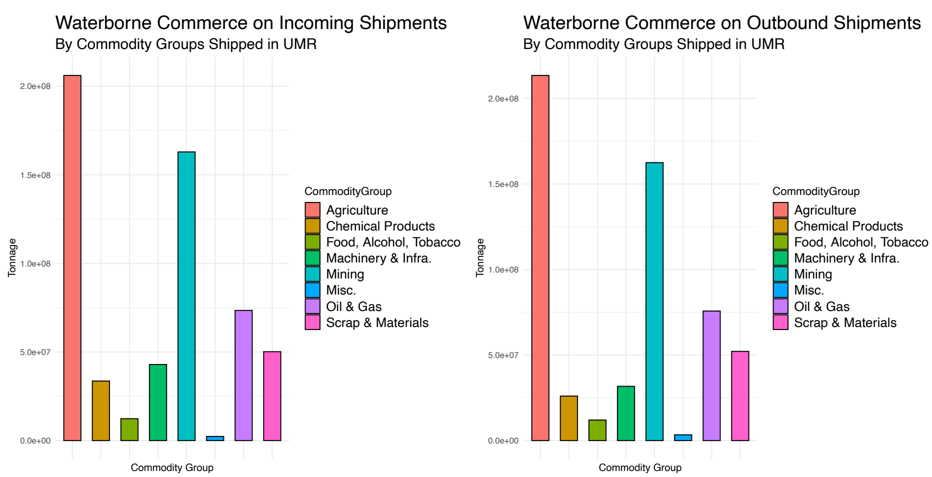

Figure 16: Domestic Inbound and Outgoing Tonnages by Commodity in the UMR

Figure 17 displays domestic inbound waterborne commerce shipments by tonnage, state, and commodity for 2021. Results show that high amounts of agricultural commodities are shipped to Louisiana, high amounts of mineral products are shipped to Ohio, Indiana and Kentucky, and high amounts of Scrap and Material based commodities are shipped to Tennessee.

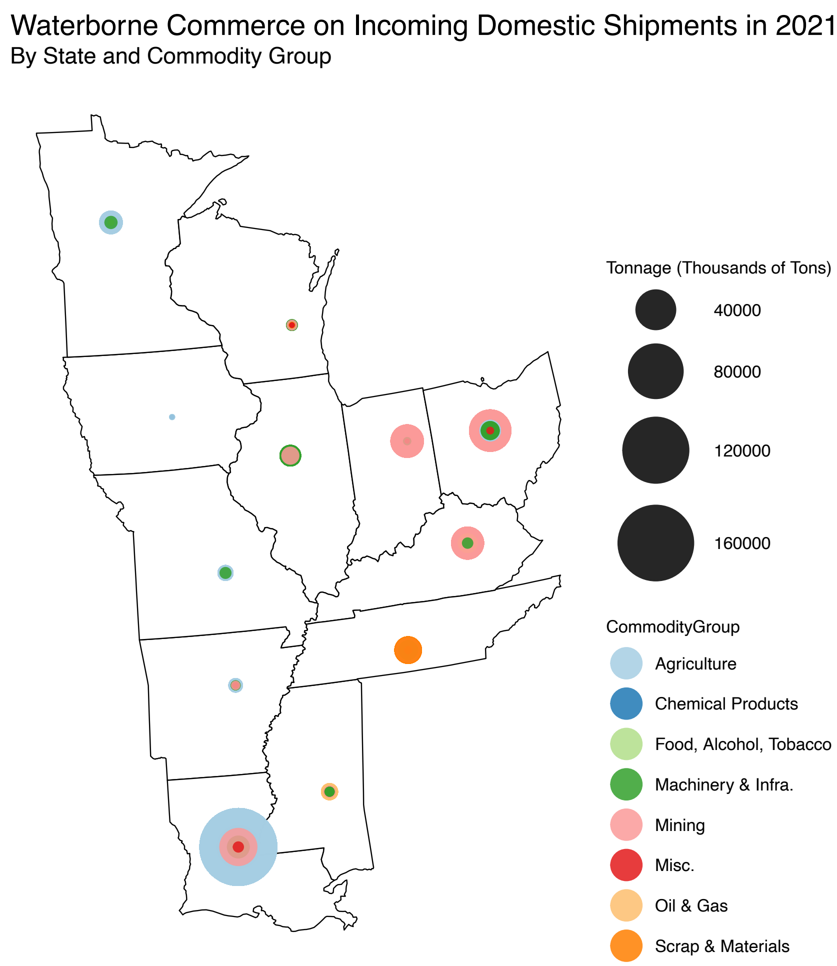

Figure 17: Domestic Incoming Waterborne Commerce Shipments by State, Commodity, and Tonnage Shipped

Related, Figure 18 depicts domestic outbound waterborne commerce shipments by tonnage, state, and commodity for 2021. Results show high amounts of Oil and Gas commodities being shipped out of Louisiana, Scrap and Material based commodities being shipped out of Minnesota, and Mining commodities being shipped out of Ohio.

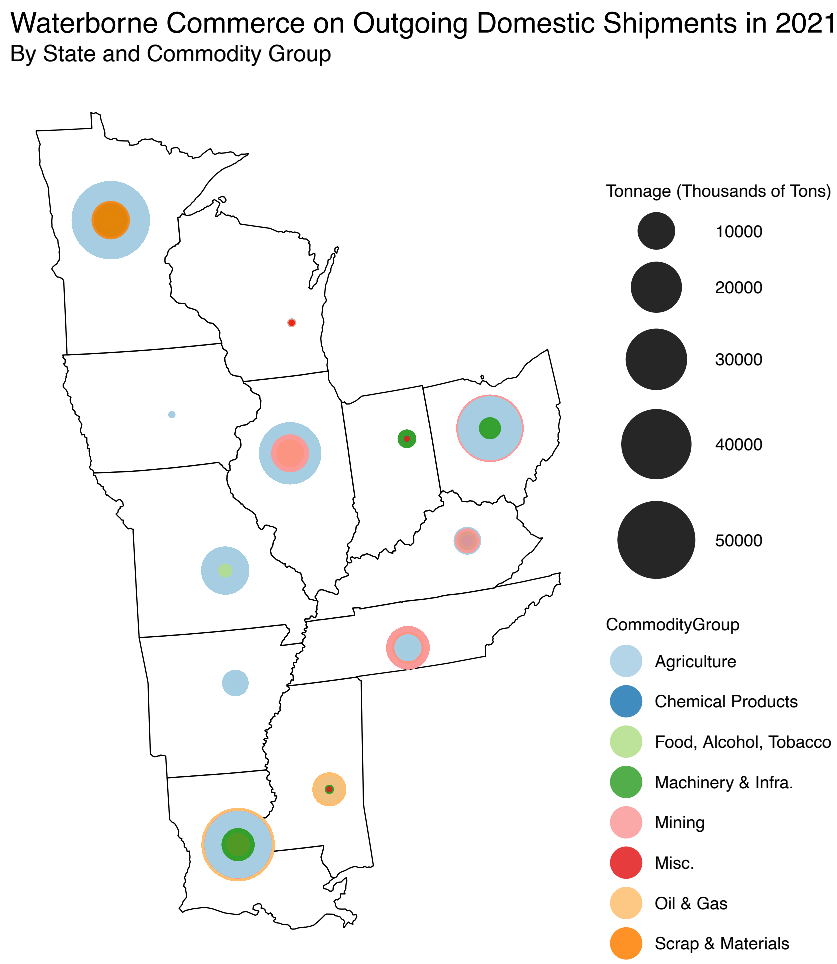

Figure 18: Domestic Outbound Waterborne Commerce Shipments by State, Commodity, and Tonnage Shipped

6 Future Work

Phase 1 of our integrated approach focused on developing the necessary inputs and assumptions regarding climate projections and the DNPV financial framework (i.e., items 1, 2, and 4 highlighted in blue in Figure 1). These are the items we have discussed in the report.

Phase 2 of this project will focus on assessing the losses and quantifying uncertainty of the various climate scenarios scenarios. As mentioned, the approaches developed in Phase 1 will be linked to a waterway disruption simulation that helps model decisions of industries to reroute shipments when facing disruptions along the inland waterways. This simulation will then be linked to the input-output (I-O) economic models, which we've already updated with current economic data, to help estimate impacts on dependent industry sectors and surrounding regions.

Moreover, as mentioned, we will use approximate Bayesian computation (ABC) to calibrate our approaches and quantify uncertainty of model parameters. This technique will be critical in addressing some of the data availability issues and uncertainty embedded in the DNPV financial framework. Because we will simulate DNPV cash-flow projections, as historical data are lacking, the ABC technique will help us narrow down with simulated outcomes are most reasonable and quantify key assumptions thereof. These estimates can in turn be included in the IO models, which will help us establish bounds of uncertainty on potential impacts and savings under the different climate scenarios.

Our immediate next step is to model the flood along the river for the calculated design flows (Figure 19). HEC-RAS will be used to model the river flow across sections of the river. The output floodplain from the analysis will be compared with the corresponding FEMA flood map. In turn, these river flows will serve as direct inputs to the waterway disruption simulations.

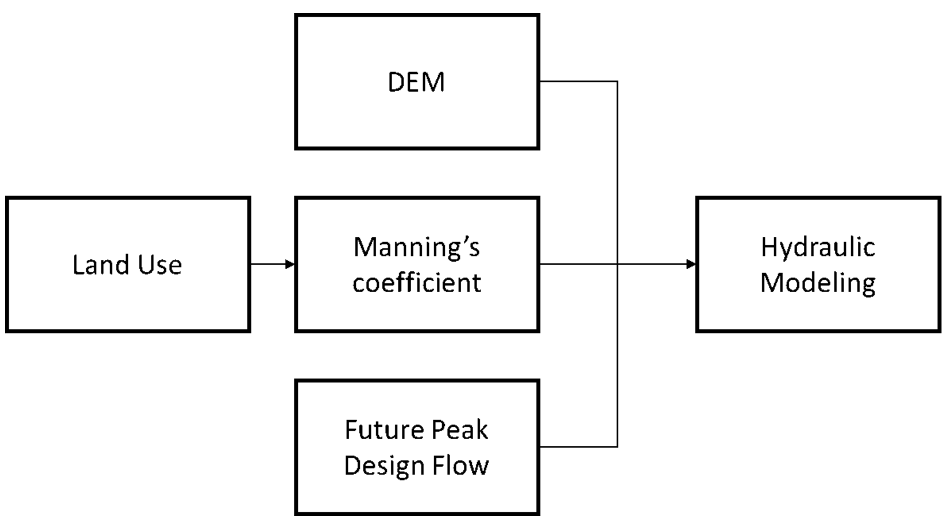

Figure 19: Hydraulic Modeling Methodology

7 Conclusion

The U.S. inland waterways are an important yet often overlooked part of the domestic economy. Extreme weather events, namely floods and droughts, perennially threaten to disrupt their operations, and these events are expected to increase in severity and frequency due to a changing climate. Despite these known risks, little work has been done to evaluate how investments in resilient, water-borne infrastructure can help mitigate impacts of these disruptions. This shortcoming is in large part due to the fact that current financial practices do not facilitate accurate and transparent assessments of long-term costs and savings from such infrastructure projects.

In this report, we have presented the initial steps necessary to develop a novel, integrated, and data-driven approach to evaluating investments in water-borne infrastructure. These steps have included translating climate scenario projections into inland waterway conditions, analyzing current shortcomings in financial frameworks, especially in the context of waterway infrastructure, and updating interdependent economic models with current data.

The outputs from these efforts will serve as inputs to waterway disruption simulations (Phase 2) to quantify expected costs and benefits of different investments in climate-resilient, waterborne infrastructure under the uncertainty of a changing climate. In doing so, we aim to facilitate investments in such infrastructure projects by providing researchers, policy-makers, and the investment community with more accurate and transparent estimates of corresponding risks and benefits.

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