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LETTER

The nonlinear impact of climate change on inland waterway transportation in the Upper Mississippi—Illinois River Region

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Abstract

The U.S. inland waterway system has played a critical role in promoting economic growth by efficiently transporting agricultural and manufacturing commodities along major riverine systems, such as the Mississippi River. However, the system faces escalating challenges due to the growing disruptions caused by climate change. For instance, the drought of the Mississippi River during the fall of 2022 resulted in an unprecedented increase in barge shipping rates. While the industry generally recognizes that climate change can significantly impact agricultural supply chains, it remains unclear how various environmental factors, including changes in water levels and temperature, affect inland waterway operations. This study aims to fill this research gap by conducting an empirical assessment of the impact of climate change-related factors on the operations of the inland waterway system in the Upper Mississippi—Illinois River Region. Unlike previous studies using conventional regression analysis, this study investigates the nonlinear relationship between changes in barge shipping rates and various environmental factors using the Gradient Boosting Decision Trees machine-learning method. Our analysis identifies the 29 ft gage height as a pivotal threshold influencing barge rates; rates tend to rise as the gage height decreases, and surpassing this threshold can also lead to increased shipping rates. This new approach enhances the model's predictive capacity, allowing for a better understanding of the nonlinear effects of climate change on barge rates and productivity. It also enables planners and operational agencies to better understand the uncertainty of environmental conditions on the variations in barge rates and productivity performance. These findings provide valuable insights for decision-makers to understand the threshold effect of environmental conditions on inland waterway operations and facilitate the creation of effective adaptive strategies to mitigate future risks and consequences of climate change-induced disruptions.

1. Introduction

The inland waterways system is vital for ensuring the efficient movement of U.S. agricultural goods from production areas to markets. In 2019, the U.S. inland waterways facilitated the transit of 514.9 million tons of waterborne cargo, accounting for approximately 14% of all intercity freight with a value of $134.1 billion. This makes the system the most cost-effective, safest, and environmentally friendly option with the lowest carbon footprint (Waterways Council 2023). Despite these advantages, the system has faced increased challenges from climate change due to its dependence on the availability and reliability of water resources.

For instance, drought can cause low water levels which may reduce the cargo-carrying capacity of vessels, increase transportation costs and affect the competitiveness of inland waterway transport (Vinke *et al* 2022). Jonkeren *et al* (2007) found that low water levels could reduce the load factors of vessels by up to 50% on some sections of the Rhine–Main–Danube corridor. In 2022, a severe drought significantly affected inland waterway transportation (IWT) in both the Rivne River in Europe and the Mississippi River in the U.S.

Another major threat is flooding, which can suspend of navigation due to high water levels, causing delays, damage to infrastructure and property, and safety risks for people living near waterways. For example, Hurricane Harvey in 2017 caused widespread flooding and suspended navigation on several inland waterways in Texas. Similarly, a stalled weather system in 2015 caused record-breaking rainfall and flooding in South Carolina, affecting many inland waterways.

Although understanding the effects of climate change on IWT is crucial, given its significance for various regions and sectors, especially agriculture, the impact of climate change on the system remains inadequately explored. Most existing studies (Folga *et al* 2009, Oztanriseven and Nachtmann 2017, 2020) have focused on waterways utilizing diverse methods and scenarios but failed to consider the complex nonlinear influences of climate variables, hydrological processes, and navigation conditions on the performance of IWT. For instance, it is unclear to what extent changes in water levels such as reductions caused by droughts or increases due to flooding, impact barge shipping rates[1]. Many existing studies rely on traditional statistical or simulation models that fail to capture the full range of uncertainties and dynamics inherent in the environment.

From an operational and planning practice perspective, it would be highly valuable to ascertain the environmental conditions under which substantial changes in barge shipping rates are likely to occur. This knowledge could help shippers optimize their shipping schedules, aiding barge transportation companies and lock and dam systems in preparing for potential disruptions. Ultimately, this proactive approach can mitigate the risk of losses and damage to agricultural commodity shipments, ensuring a more efficient and resilient transportation network.

This study aims to address these gaps by developing a novel evaluation framework using machine-learning methods to address the research question of the nonlinear impacts of climate change on the U.S. agricultural IWT system. The hypothesis is that climate change has significant nonlinear effects on the efficiency and reliability of the IWT system, impacting the transport of grain exports. Specifically, climate change is defined in this study as changes in temperature, precipitation patterns, and the frequency and severity of extreme weather events. The focus on the U.S. is motivated by its possession of one of the largest and most developed IWT networks globally, responsible for transporting approximately 60% of the country's grain exports. The study incorporates real-world historical data on barge shipping performance, weather information, water levels, and lock and dam operational data from various sources, including the National Oceanic and Atmospheric Administration (NOAA), the United States Geological Survey (USGS), the U.S. Army Corps Engineers and the United States Department of Agriculture (USDA). To analyze the data and generate predictions, the study utilizes the state-of-the-art machine-learning technique known as Gradient Boosting Decision Trees (GBDT). This technique offers several distinct advantages for data analytics, including exceptional predictive accuracy, the capability to reduce bias and variance, effectiveness in handling nonlinearity, missing data, and outliers, and the ability to conduct feature importance analysis, facilitating the interpretation of results (Ma *et al* 2017).

This study offers several key research highlights compared to previous work in this field. Firstly, it provides a comprehensive and systematic assessment of the impact of climate change on the agricultural IWT system with a focus on the key locks and dams system in the IMR-IR, considering multiple dimensions, such as water levels, discharge volume, different extreme weather events, and system disruptions[2]. Secondly, it employs machine-learning techniques to handle large and diverse datasets, capturing complex relationships between factors and barge shipping rates as well as productivity. Furthermore, the application also has the potential to provide probabilistic and scenario-based predictions, enabling more evidence-based planning and operational decision-making in the context of climate change. Thirdly, it captures the non-linear and dynamic nature of the system through path-dependent plots, revealing potential tipping points or thresholds that may lead to abrupt changes in barge shipping costs. Understanding these threshold effects of various environmental conditions may help develop specific strategies to make the IWT resilient to future climate change induced disruptions.

In sum, this study contributes to the literature on climate change adaptation and mitigation in the transport sector by providing new insights and evidence to understand the non-linear impact of climate change on IWT. It offers valuable information and guidance for policymakers, planners, operators, shippers,

[1] Barge shipping rates refer to the cost associated with transporting goods via barges on inland waterways. In this study, we use the weekly barge shipping rate data provided by the US Department of Agriculture. Given that majority of the discussion in this study is about inland waterway shipment in the Upper-Mississippi River and Illinois River down to the Port of New Orleans, the rate, which represents the percent of 1976 tariff benchmark index (1976 = 100%), is an index reflecting the shipping rate of one tons of agriculture commodities from a given lock to the Port of New Orleans.

[2] Discharge volumes denote the amount of water flowing through a river or waterway at a given time. Gage heights are measurements of water levels in rivers or streams, crucial for determining navigability and operational safety.

farmers, researchers, and other stakeholders involved in IWT, enabling them to understand current and future challenges and opportunities under different climate scenarios. Moreover, it helps identify potential adaptation strategies to enhance the resilience and sustainability of IWT in a changing climate.

The rest of the paper is organized as follows: section 2 provides a summary of relevant literature and identifies research gaps. Sections 3 and 4 introduce the data and methodology, respectively. Section 5 discusses the empirical results of the analysis, while section 6 concludes by outlining implications for planning and policy decision-making.

2. Literature review

Climate change's impacts on transportation systems can have significant economic, social, and environmental implications. This review focuses on the impacts of climate change on the transportation system's performance and operation, with a special emphasis on the impacts on the US agricultural inland waterway system. The review is organized into four subsections, namely the impact of climate change on transportation system, the impact of climate change on barge transportation for agricultural commodities, the application of machine-learning, and research gaps.

2.1. Impact of climate change on transportation systems

Climate change poses significant challenges to transportation systems worldwide, impacting their performance and operation (Suarez *et al* 2005). Changing climate patterns, including the increased frequency and intensity of extreme weather events, have profound implications for transportation infrastructure, operations, and overall system resilience. Various studies, such as Chapman (2007), Koetse and Rietveld (2009), and Markolf *et al* (2019), have examined the effects of climate change on transportation systems, highlighting the need for adaptation strategies. For instance, Koetse and Rietveld (2009) identified several severe consequences of climate change that can disrupt transportation systems, such as rising sea levels, storms, flooding, increased precipitation, and low water levels affecting inland waterway transport. Markolf *et al* (2019) explored the pathways through which climate change and extreme weather events disrupt transportation systems, emphasizing the importance of recognizing indirect disruptions resulting from interconnections with other critical infrastructure. Similarly, Chapman (2007) suggested that modal shift is one possible solution to improve transportation systems' resilience to climate change. In sum, to improve the resilience of transportation systems to climate change, interconnection among critical infrastructures and multiple transport modes should be considered.

2.2. Impact of climate change on barge transportation for agricultural commodities

In the United States, the agricultural IWT system plays a crucial role in the movement of goods, including agricultural commodities. However, climate change impacts, such as changes in precipitation patterns, increased frequency of droughts, and rising water levels, pose significant threats to the performance and reliability of this transportation mode. The vulnerability of the U.S. agricultural inland waterway system necessitates a deeper understanding of the specific impacts of climate change on barge transportation for agricultural commodities.

Climate change significantly affects barge transportation for agricultural commodities by altering water levels, river flow patterns, and navigation conditions. These changes directly impact the feasibility and efficiency of barge operations (Millerd 2011, Jonkeren *et al* 2014). The negative influences of these specific conditions on the safety of barge operations can increase substantially if environmental thresholds are exceeded. For instance, increased precipitation can lead to higher river levels, causing navigational challenges and potential disruptions of barge operations (Posey 2012). Conversely, drought events can reduce water levels, limiting the navigable depth and capacity for barge transportation (Koetse and Rietveld 2009).

Studies have demonstrated that climate change-induced disruptions to barge transportation can have severe economic consequences for the agricultural sector. For instance, Chen and Cheng (2024) evaluated the regional economic impact of inland waterway system failures due to various disruptions. Their study showed that a 30 day disruption of Lock 25 could generate $3 billion in losses to the U.S. GDP due to disruptive impacts on the US agricultural supply chain. The inability to transport commodities efficiently can lead to increased costs, reduced market access, and supply chain disruptions. Johnson *et al* (2023) evaluated the economic impacts of various flood disruptions along the Upper Mississippi River using a combined methods of agent-based modeling, economic interdependence and Bayesian modeling. Their study found that Illinois, Louisiana, Minnesota, and Missouri could suffer the most from flooding disruptions in the inland waterway system. The agricultural industry's dependence on barge transportation necessitates a comprehensive understanding of climate change impacts to develop effective adaptation and mitigation strategies.

In terms of environmental effects on barge operations, Jonkeren *et al* (2011) used a GIS-based strategic freight network model to show that lower water levels in the Rhine River can reduce inland waterway transport volumes by 2.3% to 5.4%. Koetse and Rietveld (2009) concluded from many empirical studies that changes in temperature and precipitation can impact on river levels and, consequently, the inland shipping industry by significantly increasing transport costs. However, it should be noted that these estimations were based on selected scenarios of lower water level conditions, and it remains unclear to what extent the impact varies with changes in conditions.

2.3. The application of machine-learning

Recent studies have begun to utilize machine-learning approaches to investigate the relationship between climate change and transportation system performance (Rolnick *et al* 2022). These models can simulate the effects of changing climate conditions on various performance indicators, such as travel time, infrastructure deterioration, and system reliability. By incorporating climate projections and historical data, machine-learning techniques provide insights into potential future scenarios and help identify critical areas for adaptation and investment.

For instance, Piryonesi and El-Diraby (2021) examined influential factors affecting the condition of asphalt road, such as temperature, precipitation, freeze conditions, and traffic, using machine-learning methods. Their study developed an interactive online decision-support tool to predict future road conditions under different environmental circumstances. Chikaraishi *et al* (2020) assessed the effectiveness and interpretability of machine learning models in predicting traffic states during transportation disruptions. They found that random forest and XGBoost models outperformed others in prediction accuracy. Similarly, Chen *et al* (2021) evaluated the predictability of machine learning methods in understanding the influences of climate change factors on aviation and high-speed rail system's on-time performance. Their study also demonstrated that predictability varies among different types of machine-learning models.

The application of machine learning methods has significantly improved researchers' understanding and forecasts for IWT. For example, Yueling *et al* (2019) assessed the efficacy of artificial neural networks (ANNs) in forecasting water levels up to 10 d ahead at critical gauges in the Rhine River Basin, Germany. Zhang *et al* (2022) introduced a machine learning approach utilizing big data analytics to assess the risk of ship grounding. Additionally, other researchers have employed various machine learning techniques such as ANNs, convolutional neural networks, support vector machines, and Bayesian networks, to model waterway network vulnerability, analyze accidents, and forecast traffic flow in IWT (Wu *et al* 2014, Wang and Yang 2018, Muthukumaran *et al* 2022).

The emergence of machine-learning approaches facilitates the simulation of complex disruption scenarios, the prediction on future events and effects, and the examination on non-linear effects between climate change and transportation systems.

2.4. Research gaps

While significant progress has been made in understanding the impacts of climate change on transportation systems, several research gaps persist. Firstly, although a few studies have attempted to evaluate the economic impact of IWT in the face of climate change and disruptive scenarios, most studies were based on selective or deterministic environmental scenarios. There is a lack of understanding regarding how sensitive barge shipping rates are to variations in environmental conditions, such as temperature, water levels, and discharge volumes. Without specific information on the vulnerabilities and risks of IWT to climate change, the implications for stakeholders, including shippers, barge transportation companies and lock and dam operators, are quite limited.

Furthermore, existing studies have examined the impacts of climate change on transportation infrastructure and operations with a focus on a single performance metric, such as transportation costs, or system frequency. However, there remains a crucial gap in assessing the effects across the agricultural supply chain with a focus on both rate variations and productivity changes. The former reflects the interactions between supply and demand of transportation services, while the latter reflects the efficiency of transportation system operations. Understanding these interactions can enable the formulation of comprehensive adaptation strategies to effectively respond to future disruptive events.

In addition, the application of machine-learning techniques in studying the impacts of climate change on transportation systems is still relatively new and evolving. While emerging efforts are addressing this gap (e.g. Lei *et al* 2022, Rolnick *et al* 2022), the application of the methods to study the impact of climate change on IWT is still in its infancy.

Figure 1. The geographic focus of the inland waterway system in the assessment.
Source: Chen and Cheng (2024)

3. Data

3.1. Region of investigation and data collection

To address the existing research gaps and refine our understanding while boosting predictive capabilities, we focused on examining the impacts of climate change on the performance of the IWT system. Our focal point lies within the Upper Mississippi River—Illinois River (UMR-IR) region, encompassing seven major locks and dams illustrated in figure 1. These specific locks and dams—MISS 15, MISS 25, MISS 26, MISS 27, ILL 8, OHIO 52, and ARK 1—were selected based on two criteria. First, these infrastructure points are critical components of the UMR-IR navigation system but face challenges stemming from aging structures and severe shifts in environmental conditions. Second, our choice was influenced by data availability, as the USDA provides comprehensive data on barge volume and weekly rate monitoring solely for these seven locks.

Studying this region is essential due to its role in transporting a significant portion of the nation's agricultural commodities, particularly grain exports. The UMR-IR waterways are heavily utilized and are vital to the national and global food supply chains. Additionally, the region's susceptibility to climate change-induced fluctuations, such as droughts and floods, makes it imperative to understand how these environmental changes impact navigation and operational efficiency. Insights gained from this study can help develop adaptive strategies to ensure the resilience and reliability of the waterway system, thereby safeguarding economic and operational viability.

The dataset used in this study has previously been employed to assess the regional economic consequences of disruptions in the inland waterway system, as demonstrated by Chen and Cheng (2024). A notable limitation of the earlier study is its reliance on conventional spatial econometric models that assume a linear statistical relationship to estimate the impacts of environmental factors on barge rate variations. This approach is inherently limited, as it does not account for the complexity and nonlinearity of environmental influences.

In this study, we leverage the same dataset to further investigate the nonlinear implications of climate change on the functionality of selected locks and dams in the UMR-IR region. By quantifying the functional relationships between environmental metrics and barge operation/shipping rates, we aim to improve the methodology through the application of nonlinear machine-learning techniques. This approach enhances our understanding of the intricate relationships between barge performance and environmental conditions, providing a more realistic and comprehensive perspective. Such an understanding is critical for planning and policy development, as it allows for the creation of more targeted and effective strategies to address the multifaceted impacts of environmental changes on barge transportation.

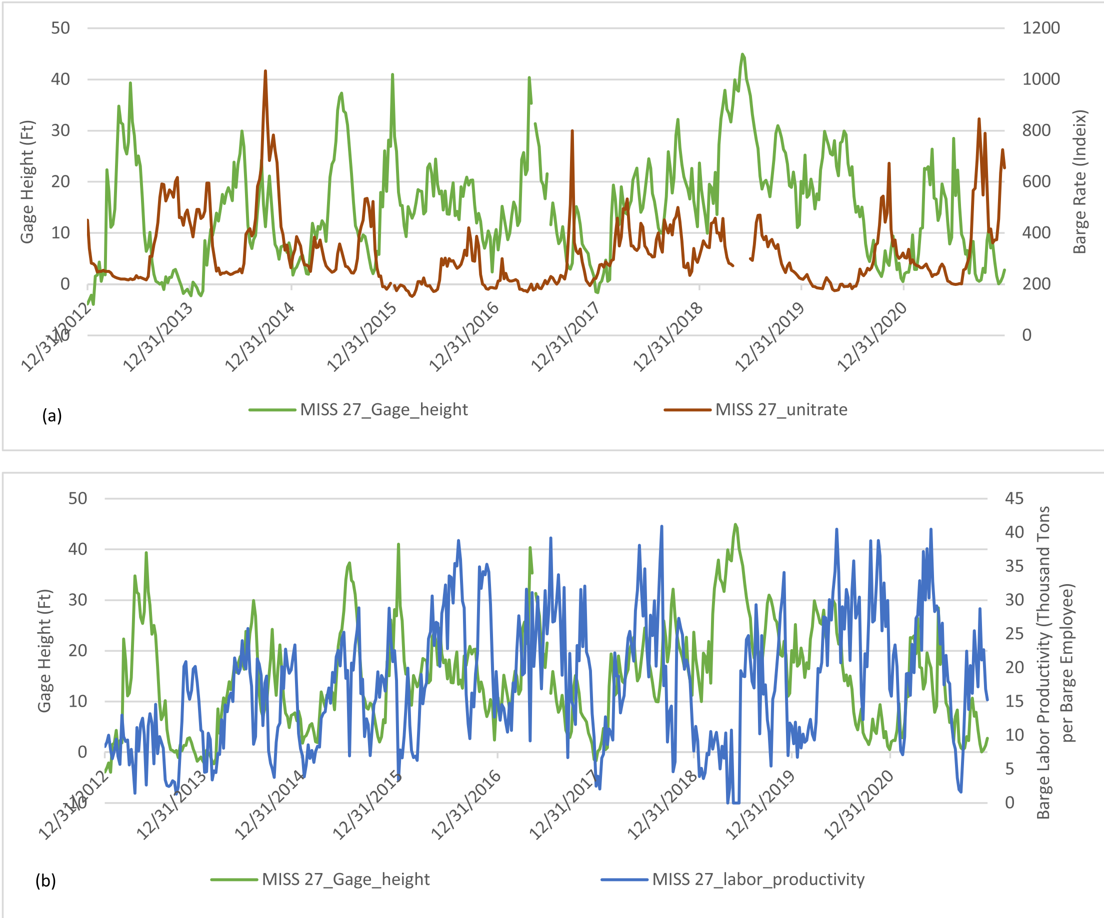

Figure 2. Historical Trend of Gage Height and Barge Rate and Performance at Lock 27.

Data collection for this study involved gathering weekly barge transportation data spanning from 2013 to 2021 at the seven locks and dams. The data was obtained from the Grain Transportation Report datasets, made available by the Agricultural Marketing Services of the USDA. The collected dataset comprises information on the weekly total barge grain movement, measured in 1000 tons, passing through each lock and dam. In addition, the dataset includes the weekly barge freight rate, which represents the average shipping cost per ton from the nearby areas of each lock and dam to New Orleans. We measure barge service performance using labor productivity, which indicates the number of agricultural commodities transported per barge employee. This metric is adopted because it is a standard and widely recognized measure of transportation system performance (Meyer and Gomez-Ibanez 1980, Chen *et al* 2016, Vu and Hartley 2022).

Figure 2 illustrates the fluctuations in gage height alongside changes in barge rate and productivity, utilizing lock 27 as an illustrative example. In figure 2(a), a negative correlation is evident between gage heights and alterations in barge rates. This indicates that lower gage heights correspond to relatively higher barge shipping rates. Notably, during specific weeks—9/29/2014, 10/2/2017, and 10/18/2021—the barge rates surged to unprecedented levels concurrently with lower gage heights. These low gage heights correspond with high barge shipping rates, suggesting the negative impacts of drought, which cause water levels to drop, forcing ships to reduce their loading capacity and thereby increasing shipping rates.

Figure 2(b) illustrates the relationship between gage height fluctuations and barge labor productivity over the period from January 2013 to December 2020. The green line represents the gage height at MISS 27, while the blue line depicts the barge labor productivity measured in thousand tons per barge employee. Unlike figure 2(a), which focus on barge rates, this figure highlights a discernible pattern where changes in gage height appear to correspond with variations in barge labor productivity. Specifically, periods of increased gage height generally coincide with higher productivity levels, whereas lower gage heights tend to align with reduced productivity. This correlation suggests that riverine conditions, as indicated by gage height, have a notable impact on the efficiency of barge operations. High water levels likely facilitate better

navigation and loading conditions, thereby enhancing productivity, while low water levels may impede these operations, reducing overall efficiency.

3.2. Factors influencing barge rate and productivity

To investigate the factors influencing barge rate and productivity, our study considered several elements based on data availability and existing literature. Specifically, Scheepers *et al* (2018), Gass (2014), Yu *et al* (2016) and Chen and Cheng (2024) suggest that factors such as gage heights, temperature, precipitation, and types of disruptions significantly affect barge operations. These disruptions include both scheduled and unscheduled events at locks. Therefore, our study incorporated weather-related variables (temperature and precipitation), water levels (gage height and discharge), and various disruptive events at locks to comprehensively analyze their impact on barge rate and productivity.

Daily weather data, encompassing temperature and precipitation, were sourced from the Daily Temperature and Precipitation Reports provided by the National Centers for Environmental Information within the NOAA. Furthermore, daily water level data, specifically gage height and discharge, were collected from the USGS National Water Dashboard. Gage height refers to the water height in the stream relative to a reference point, while discharge quantifies the volume of water passing through a specific point in the stream within a given time period. Both variables were incorporated to assess the extent to which changes in waterway conditions could influence barge performance.

To ensure compatibility with other key investigative variables, such as barge rates, we adopted weekly median metrics for river discharge volume, gage height, and precipitation, along with the weekly mean temperature data. This approach allows for a consistent time frame for analysis and comparison, enhancing the robustness of our model's performance.

Additionally, we collected comprehensive data on lock and dam disruptions from the Navigation System Status website, managed by the Army Corps of Engineers (USACE). This dataset includes detailed information on the start and end times of stoppages, reasons for disruptions, and their types (scheduled or unscheduled). By calculating the duration between the start and end times of each interruption, we were able to analyze the impact of these disruptions on barge operations.

The statistical analysis reveals that 97% of disruption events lasted no more than one day, with only 1.52% lasting more than seven days, 0.72% lasting more than 30 d, and 0.58% exceeding 60 d. Notably, no disruption events extended beyond 180 d. Hence, we classified events lasting more than seven days as severe disruptions. Additionally, the disruption events were categorized into eight types, including drought, flood, fog, snow and ice, other weather-related factors, system failure, system maintenance, and water level changes. These classifications were transformed into different dummy variables for analysis.

Furthermore, we calculated the duration of each disruption type on a weekly basis, as well as the duration of both scheduled and unscheduled disruptions. To provide a comprehensive overview, Appendix 1 summarizes the descriptive statistics of all the variables utilized for analyzing barge performance and environmental conditions.

4. Methodology

Different from conventional statistical analysis using panel regression models, the GBDT method was adopted to examine the non-linear association between climate change-related factors and barge system performance. GBDT is a powerful machine learning technique that has gained popularity in various domains due to its ability to model complex relationships and handle non-linear patterns in data (Wu *et al* 2019, Tao *et al* 2020). It combines the strengths of decision trees and boosting algorithms to create an ensemble of weak learners, gradually improving their predictive performance (Tao *et al* 2020).

In the context of evaluating the non-linear impact of inland waterway system failure on a panel dataset, the GBDT method offers several advantages (Ma *et al* 2017). Firstly, it can effectively capture non-linear relationships between predictor variables (Elith *et al* 2008) (such as the changes in barge shipping rates) and the response variable (various economic and environmental factors). This is crucial as the impact of different variables on IWT performance may not follow a simple linear trend. For instance, the performance of IWT may not be affected until the water level or river discharge volume exceeds certain safety levels. According to the National Weather Service, the Army Corps requires that year-round target water levels are between 11.5 and 12.2 feet for a safe navigation of barge system in Mississippi River near the city of Louisiana[3]. Hence, the GBDT method excels in capturing complex interactions and non-linear patterns, enabling a more accurate representation of the underlying dynamics.

[3] The specification discussion is obtained from https://water.weather.gov/ahps2/hydrograph.php?gage=lusm7&wfo=lsx (accessed in September 2023).

Secondly, the GBDT method is suited for panel datasets, which consist of observations over multiple time periods for a set of entities (e.g. regions, cities, or industries). Panel datasets often exhibit within-entity correlations and individual heterogeneity, and the GBDT algorithm can account for such characteristics to capture the temporal dynamics and heterogeneity of the data, as well as handle missing values and high-dimensional features. GBDT can also perform feature selection by ranking the features by importance or by using a group testing procedure, which helps us better identify the relatively important factors affecting the performance of the outcome variable (Friedman 2001).

Furthermore, the GBDT method can handle missing data and automatically handle variable selection, making it robust and efficient for analyzing large and complex datasets (Tao *et al* 2020). This is particularly important when dealing with real-world data, where missing values and redundant variables are common challenges.

By employing the GBDT method on a panel dataset, we can gain insights into the nonlinear impact of climate change on IWT performance variation. The ability of GBDT to capture complex relationships and accommodate panel dataset characteristics makes it a valuable tool for uncovering the nuanced effects of system failure and informing decision-making processes related to inland waterway infrastructure management and policy interventions. The model specifications were introduced in Appendix 2.

The performance of the IWT was described using two variables, including the weekly barge shipping rate (UnitRate) and barge labor productivity. Other variables, such as the year trend (yeartrend), the dummy variable representing the periods of trade tension between China and the US (tradewar) and the duration of lock/dam disruptions (tdistruption) were treated as control variables. In total, two sets of GBDT models were developed to investigate the nonlinear relationships between changes of the waterway environment and variations in barge rate and productivity, respectively.

5. Results

To prevent overfitting resulting from increasing model complexity, we utilized a five-fold cross validation method and reported the root mean square error (RMSE) and the number of iterations for the best performing model under cross-validation (CV), as shown in figure 3. Our analysis demonstrates that the mean squared error (MSE) decreases and stabilizes as the number of iterations increases across all five models. The green line indicates the MSE for the testing dataset under CV, while the black line shows the MSE for the training dataset. The vertical blue dashed line marks the iteration point where the model achieves its optimal performance.

To determine and quantify the contribution or impact of different variables in the GBDT model, we generated relative importance diagrams for two groups of analyses using the gbm package in R. As shown in figure 4, it becomes evident that several key factors exert significant influence over variations in barge rates. These primary factors include gage height, discharge volume, temperature, year trend, and the duration of lock and dam system disruptions. In particular, the gage height variable presents over 25% of relative influence on the model's predictability, suggesting the pivotal role of water level as the crucial environmental factor affecting barge rates.

Figure 5 presents a similar pattern, examining the relative influences of factors in predicting barge labor productivity, although with a slightly different ranking of the aforementioned variables. For instance, discharge volume, gage height, and temperature emerge as the top three variables with the highest relative influences.

Figure 6 presents partial path dependent plots highlighting the influential variables' impact on barge rate changes and productivity[4]. Specifically, figure 6(a) shows the relationship between gage height and barge shipping rates. When the median gage height of the Mississippi River ranges from 12 to 25 feet, the barge shipping rate stabilizes around 330 units. However, if the gage height drops below approximately 12 feet, the shipping rate is expected to increase by 120 units, representing a 36% increase, reaching approximately 450 units. Conversely, as the gage height rises to around 30 feet, the rate decreases to its lowest level at around 100 units, indicating a 70% reduction. Further increases in gage height lead to a rebound in the shipping rate to approximately 300 units. These results emphasize the complex, nonlinear relationship between gage height and barge rates, with critical thresholds that significantly influence outcomes.

[4] Partial dependence plots are used to demonstrate the marginal effect of predictor variables. They were generated as part of the post-processing analysis using the pdp package in R. These plots are not direct outputs of the model itself but are derived through a secondary process. After training the GBDT model, we utilized the partial function from the pdp package to compute the marginal effect of selected features on the predicted outcome. This function calculates the average prediction over the marginal distribution of the feature of interest, while all other features are held constant. The resulting PDPs illustrate how changes in a particular feature influence the predicted outcome, providing a visual representation of feature impact that enhances interpretability.

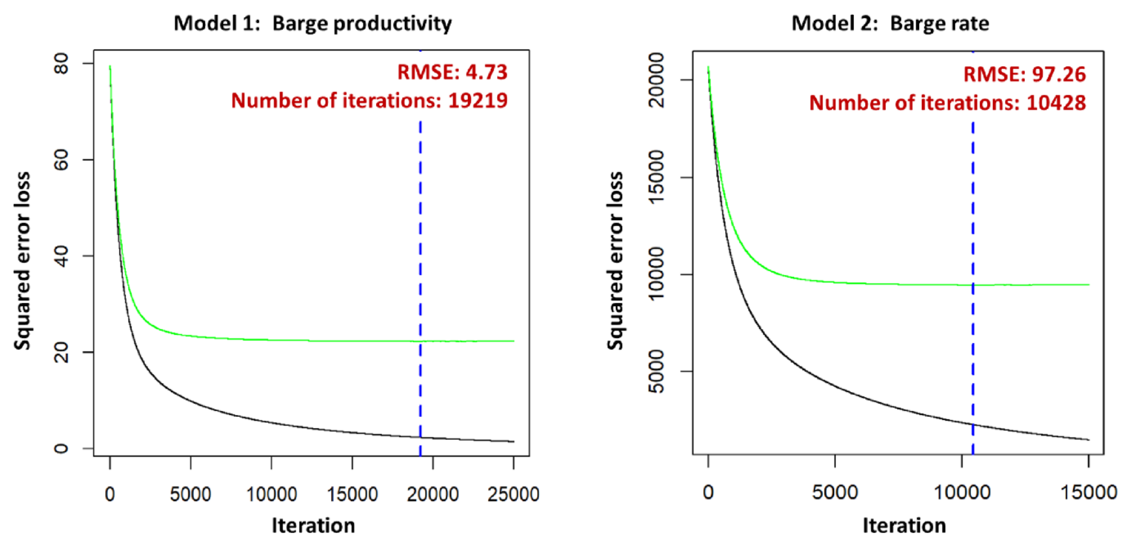

Figure 3. Model performance with RMSE and number of iterations with best performance under CV.

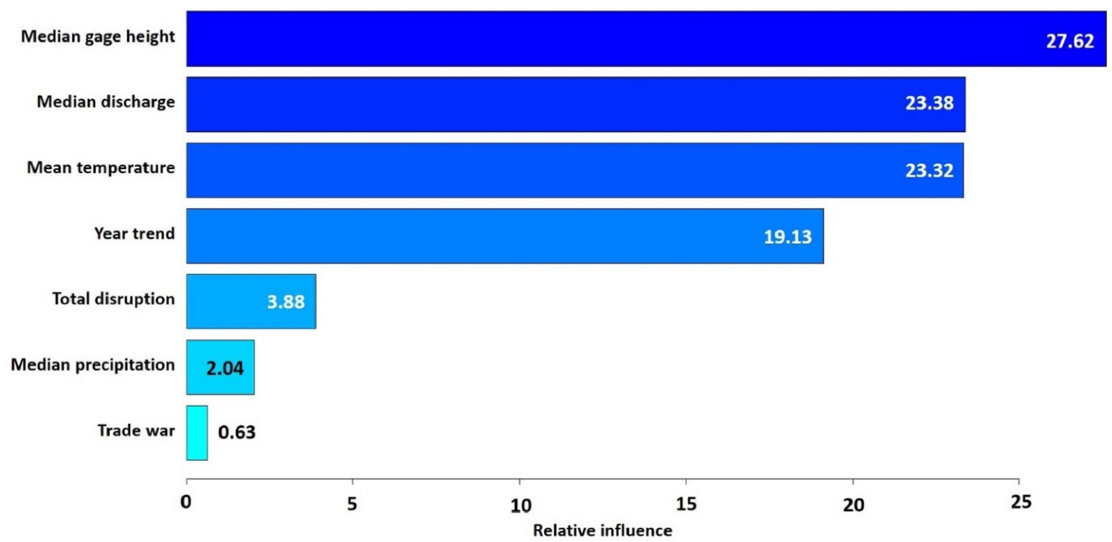

Figure 4. Relative influence of independent variables on barge rate change.

The diagram further highlights the presence of a nonlinear relationship between gage height and productivity. Specifically, when the median gage height is below 12 feet, there is a notable upward trend in productivity with increasing gage height. However, as the gage height continues to rise, reaching around 40 feet, productivity experiences a significant decline, dropping from 14 to just 2. Beyond this point, any further increase in gage height appears to have no discernible impact on the variation in barge productivity, as it remains consistently low. This nonlinear pattern underscores the complex and nonlinear relationship between gage height and productivity, with clear inflection points where the effect of gage height on productivity undergoes distinct changes.

Figure 6(b) reveals a negative association between median river discharge volume and barge shipping rates. When the weekly median river discharge volume exceeds 200 000 cubic feet per second, the barge rate remains below 300 units. However, when the volume falls below 200 000 cubic feet per second, the rate experiences an exponential increase by 50%, surpassing 450 units. This result indicates that lower discharge volumes, often associated with drought conditions, have severe implications for barge rate changes.

In terms of its impact on barge productivity, figure 6(b) unveils a noteworthy positive correlation between the median riverine discharge volume and productivity. As the volume remains below 600 000 cubic feet per second, there is a substantial increase in productivity. Interestingly, as the volume continues to rise beyond the 600 000 cubic feet per second threshold, productivity maintains a relatively high level. This

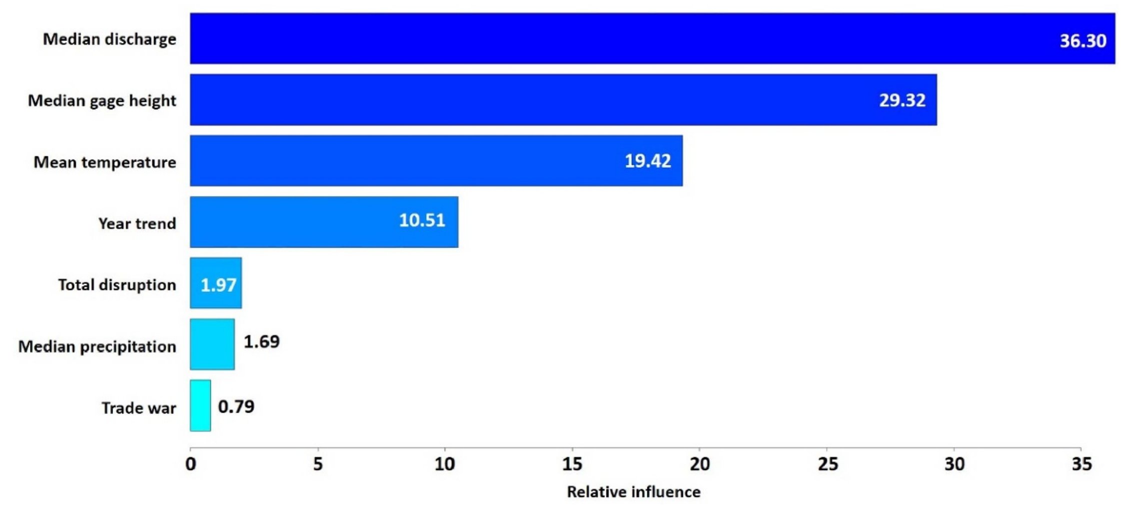

Figure 5. Relative influence of independent variables on barge productivity change.

outcome not only underscores the existence of a nonlinear relationship between the median riverine discharge volume, the barge shipping rate, and productivity but also emphasizes that the median river discharge volume exerts a different influence on the barge shipping rate and productivity.

Figure 6(c) depicts the relationship between mean temperature and barge rate changes. Generally, when the temperature is below 62 degrees Fahrenheit, the barge rate increases as the temperature rises. However, once the temperature surpasses 62 degrees, the rate significantly declines. In addition, figure 6(c) also presents the relationship between mean temperature and productivity. Generally, this pattern reflects the sensitivity of barge operations to temperature variations, with higher temperatures potentially reducing barge efficiency and increasing costs.

Regarding the influence of precipitation, figure 6(d) demonstrates that changes in precipitation levels influence barge rate and productivity, particularly when the median weekly precipitation volume falls below 0.5 inches. Lower precipitation typically denotes dry weather or limited rainfall, leading to notable fluctuations in barge rates. When the weekly precipitation volume exceeds 0.5 inches, the barge rates stabilize, indicating that moderate to high precipitation level may provide more consistent conditions for barge operation.

This phenomenon can be attributed to several factors. Firstly, moderate precipitation over the period likely contributes to maintaining optimal water levels, facilitating smoother and more predictable barge navigation. Additionally, higher precipitation reduces the variability in water conditions, thereby minimizing disruptions and operational uncertainties. However, it is also important to consider potential limitations and noise in the data. The model's capacity to capture these patterns accurately might be influenced by the quality and resolution of the precipitation data. Furthermore, the observed stabilization might reflect a broader trend within the dataset, indicating that barge operations benefit from more stable environmental conditions provided by consistent rainfall. Overall, these insights underscore the importance of considering environmental factors in transportation planning and policymaking, highlighting the nuanced ways in which different levels of precipitation can impact inland waterway operations.

International trade policies can significantly affect barge shipping rates. The impact of a trade war on these rates can vary depending on several factors, including the countries involved, specific trade policies implemented, and the duration and intensity of the trade war. In the case of the United States and China, an escalating trade dispute unfolded starting in June 2018. China, in response to US tariffs, announced its own tariffs on $50 billion worth of U.S. goods on June 16 (Chengying *et al* 2022). The targeted industries included agriculture, automobiles, and energy. Subsequently, on June 29, as a countermeasure to increased tariffs on Chinese goods, China further intensified the trade war by imposing tariffs on a wide range of U.S. products, such as soybeans, pork, and automobiles.

To examine the extent to which the barge shipping rate was influenced before and after the U.S.-China trade war, a dummy variable was created. Figure 6(e) illustrates the relationship between barge rate and productivity variations pre- and post-trade war. The trade war was found to have a negative impact on the barge shipping rate, and a positive impact on productivity. On average, the shipping rates were 7 units lower after the initiation of the trade war and the productivity was about 0.7 units higher after the initiation of the trade war. The observed decrease in barge shipping rates can be attributed to multiple factors. Firstly, it is

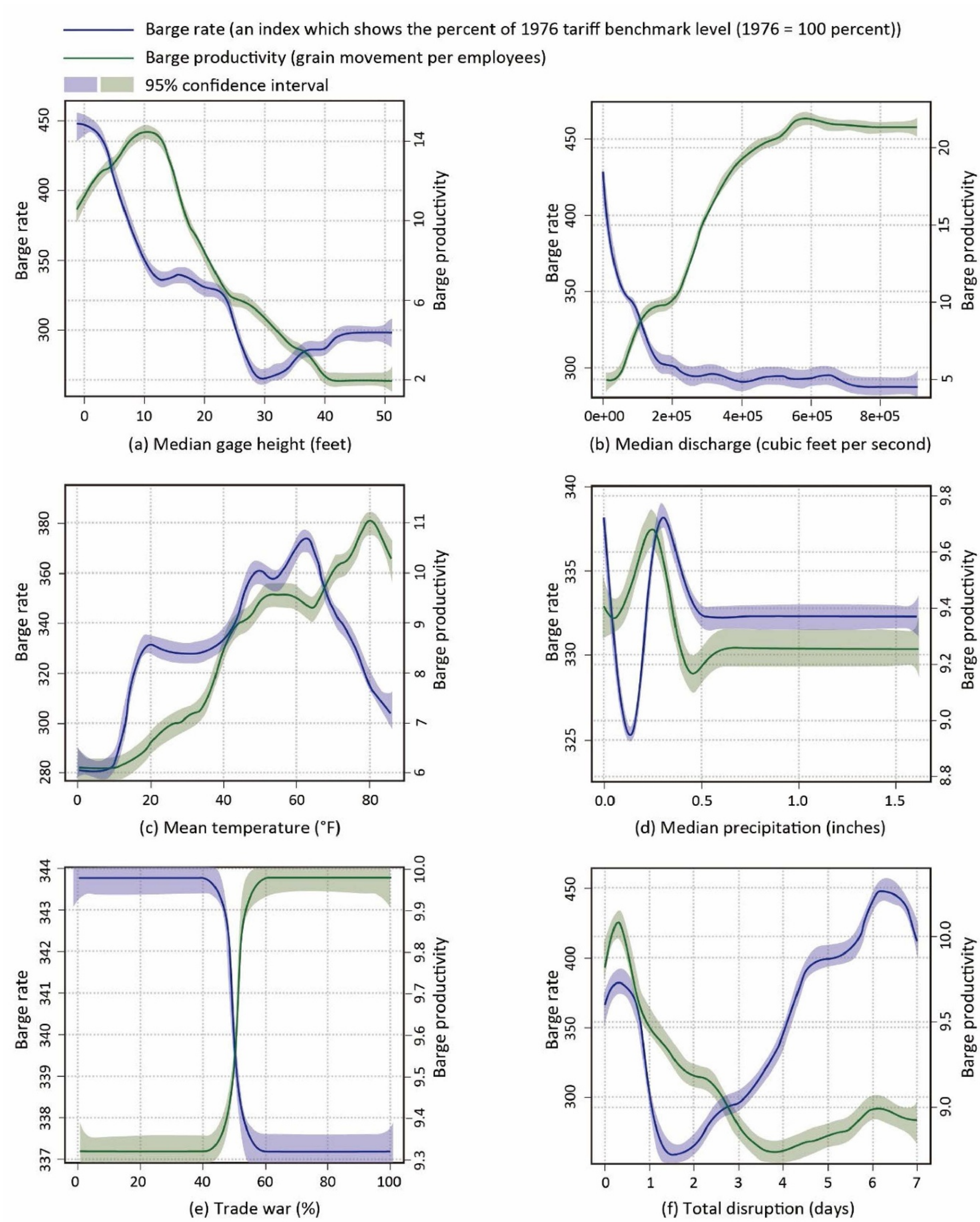

Figure 6. Non-linear relationships between inland barge shipping rate, productivity and various factors.

possible that the reduction in rates is a consequence of the diminished demand for agricultural commodities resulting from the influence of the trade war. Secondly, trade wars have the potential to disrupt established supply chains and trade relationships. As major agricultural importers, countries like China may seek alternative trading partners or adjust their import/export strategies, leading to shifts in the transportation patterns of specific commodities. Consequently, these shifts can affect the demand for certain goods and subsequently impact barge shipping rates. Thirdly, the decrease in rates could also be attributed to the economic uncertainty and market volatility generated by the trade war.

Figure 6(f) illustrates the relationship between the duration of lock and dam system disruptions and corresponding changes in barge shipping rates and productivity. The productivity reveals a decreasing trend as the disruption duration increases, reaching its lowest point at 8.7 when the disruption period spans approximately 3.5 d. An intriguing observation is that the shipping rate exhibits a declining pattern as the disruption duration increases, reaching its lowest point at 322 when the disruption period spans

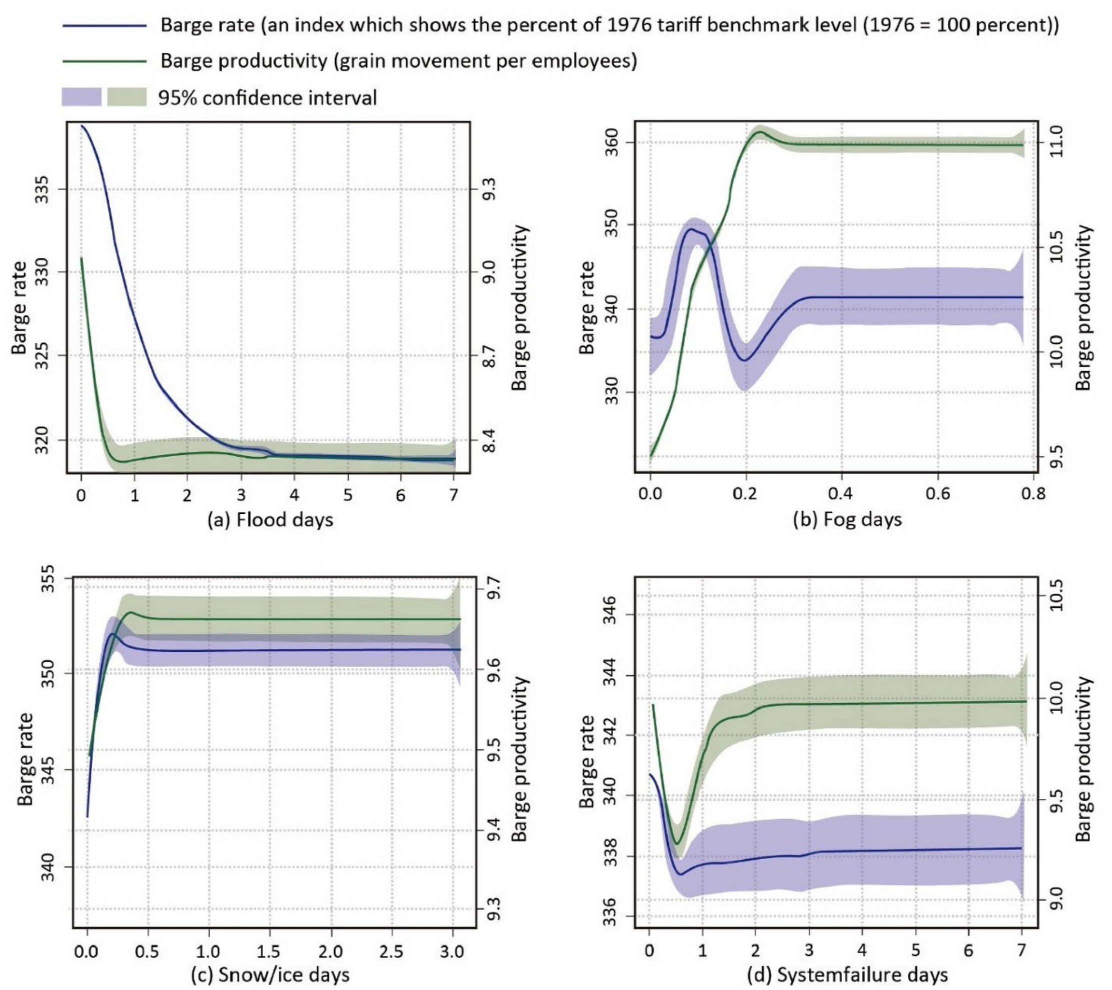

Figure 7. Non-linear relationships between inland barge shipping rate, productivity and various extreme weather and disruptive conditions.

approximately 1.5 d. However, as the duration of disruptions extends further, the shipping rate displays a continuous increase.

This trend can be attributed to several factors. In the initial phase of a short disruption, the barge shipping rate may decrease due to concerns surrounding a potential decrease in service supply. The temporary disruption raises apprehensions among shippers, leading to a cautious approach and a reduction in shipping rates. However, as the disruption duration prolongs, the mounting concerns of potential barge service disruptions among shippers may trigger a panic buying behavior. This phenomenon arises from the fear of further disruptions and a desire to secure transportation services, driving an increase in shipping rates.

Therefore, the observed pattern of decreasing rates followed by an eventual increase can be understood because of the interplay between short-term concerns about service availability and a relative long-term apprehension regarding prolonged disruptions. These dynamics influence the decision-making of shippers, ultimately shaping the fluctuation in barge shipping rates during different durations of lock and dam system disruptions.

To understand how barge shipping rate may vary due to different types of disruptions caused by different events, we also generated the path dependent plots based on four major types of events: flooding, fog, snow and ice, and system failure. As illustrated in figure 7(a), as the duration of lock and dam closure increases, both the barge shipping rate and productivity are likely to experience a substantial decrease especially in the first two days of closure. As the period of disruption further extends, the magnitude of shipping rates reduction and productivity reduction tend to be decreased as well, until it stabilizes.

Regarding fog-related disruptions, figure 7(b) shows that overall, the influence of fog has a relatively mild effect on fluctuations in barge shipping rates and productivity. Nevertheless, there may be instances of notable fluctuations during the initial disruption, typically occurring over a half-day period. Similarly, the impact of lock and dam disruptions caused by snow and ice is also observed to be relatively minor, as

indicated in figure 7(c). This could be attributed to the proactive measures taken by various industries and businesses during the winter season to adapt to potential disruptions. These measures include adjustments to shipping schedules and the implementation of winter maintenance practices.

While the earlier discussion of the results focused on deterministic estimates, figures 6 and 7 also incorporate confidence intervals, which provide valuable insights into the uncertainty of these estimates. These intervals delineate the range within which the true values are likely to fall, thus highlighting the reliability and precision of the model's predictions. For instance, the wider confidence intervals observed at extreme values of precipitation, trade war effects, fog delays, and system failure-related delays suggest a higher degree of uncertainty. This indicates that predictions in these ranges should be interpreted with caution.

Furthermore, the presentation of results with narrower confidence interval reflects the inherent variability in the data and the model's precision of predictivity given the different inputs. The use of these figures ensures a balance between precision and readability, acknowledging the model's accuracy without overstating the exactness of the results. This level of precision is particularly important in practical applications, as overly precise estimates might convey a false sense of certainty.

6. Conclusions

This study focused on estimating the nonlinear impact of climate change on the U.S. agricultural IWT system using the innovative approach of GBDT machine-learning method. By examining the relationship between barge shipping rates, productivity, and various environmental factors, we aimed to fill the research gap regarding the effects of climate change on inland waterway operations.

Our findings provide valuable insights into the nonlinear associations between environmental conditions and variations in barge rates and productivity. The GBDT analysis revealed that factors such as water levels, temperature, and disruptions to lock and dam systems have significant impacts on barge shipping rates. We observed threshold effects, where small changes in environmental conditions resulted in minimal rate fluctuations, while larger changes caused substantial rate changes. Moreover, such threshold effect varies across various inland waterway operational indicators (e.g. barge shipping rates and productivity). This reveals that different and specific strategies may be required to cope with different weather variations to achieve different transportation operational goals.

To gain a deeper insight into the interplay among barge shipping rates, productivity changes, and different disruption types, figure 6 elucidates critical thresholds that delineate distinct relationships between barge performance indicators and environmental condition factors. Our analysis identifies the 29 ft gage height as a pivotal threshold influencing barge rate changes; rates tend to rise as the gage height decreases. However, surpassing this threshold can also lead to increased shipping rates. Conversely, a decrease in gage height from 41 ft to 11 ft is associated with heightened barge operational productivity, likely due to improved navigation system safety during flooding events. However, when the gage height falls below 11 ft, productivity experiences a further reduction. From a shipper or barge operational standpoint, these threshold levels offer valuable guidance for adjusting shipping arrangements under diverse environmental conditions.

For instance, when the gage height is below 11 ft, the analysis suggests a high disruptive impact on the barge operation supply chain, characterized by both increased rates and decreased productivity. Hence, shippers may consider alternative shipping options, such as changing the mode of transportation if the goal is to deliver the goods to the destination on time. Of course, the reality of the decision-making can be more complicated given the consideration of costs.

Examining the interaction between temperature and barge performance in figure 8 reveals that when the temperature exceeds 80 degrees, barge productivity is likely to decrease, accompanied by a reduction in barge rates. This suggests that high temperatures could negatively affect barge operations, possibly due to increased maintenance requirements or reduced efficiency of barge crews working in hotter conditions. Additionally, elevated temperatures can exacerbate water level reductions due to increased evaporation, further complicating navigation and potentially leading to higher operational costs.

The findings highlight the varying rates and extents of barge productivity responses under different weather or system conditions. Generally, barge rate changes appear more sensitive to disturbances of various types, as their lower threshold for initial change is less than that of productivity.

These insights are particularly relevant for future risk management of IWT given the understanding of the interplay between climate change conditions and the system performance. For example, expected higher temperatures due to climate change may affect barge rates and productivity by increasing the frequency of low water levels, necessitating more frequent load adjustments and increasing maintenance costs. Similarly, changes in precipitation patterns, resulting in either more intense droughts or floods, could further impact barge operations by either limiting navigability or causing damage to infrastructure.

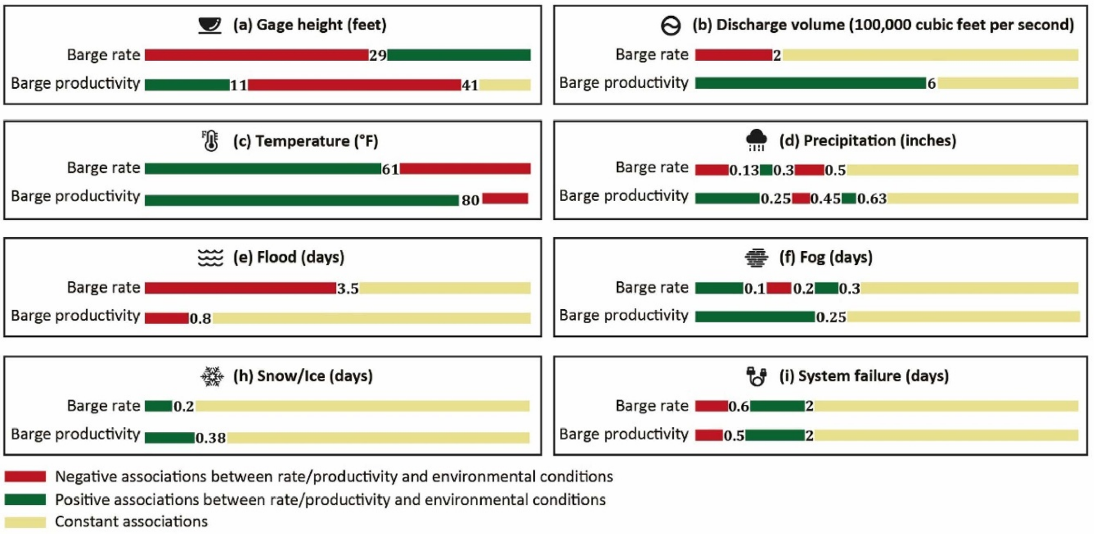

Figure 8. Climate change risk on barge performance.

The analysis also reveals that the relationship between environmental conditions and barge performance, as measured by barge rates and productivity, is inherently nonlinear. This finding contrasts with earlier work by Chen and Cheng (2024), which assumed a linear relationship. Our study demonstrates that ignoring the nonlinear nature of these interactions can potentially lead to misleading outcomes, particularly when estimating the macroeconomic impact of IWT disruptions caused by water level changes. This underscores the practical relevance and necessity of applying nonlinear models to accurately capture the complexities of environmental influences on barge transportation.

Understanding the threshold effects of environmental conditions on inland waterway operations is crucial for decision-makers. This knowledge can aid in the development of adaptive strategies to mitigate future risks and consequences arising from climate change-induced disruptions. Policymakers may also benefit from these findings to develop more effective policies for future infrastructure investments that enhance the resilience of the US inland waterway system.

Despite the robust findings, there are limitations to this analysis. Firstly, the analysis focused on the selected locks and dams in the UMR-IR region, and the findings may not be directly applicable to other regions. Secondly, the reliance on median and mean values for aggregation might overlook short-term fluctuations that could be relevant in specific contexts. Thirdly, there may be other variables not considered in our analysis that could influence barge rates.

In terms of the methodology, while the use of GBDT allows for the capture of nonlinear relationships and interactions among variables that simpler models might overlook, it is essential to recognize the potential disadvantages of using such sophisticated models, including the risk of overfitting and the challenges associated with model interpretability. In addition, GBDT models can be susceptible to biases if the training data is not representative of the broader context.

To mitigate the risk of overfitting, it is important to employ techniques such as cross-validation, regularization, and pruning within the model-building process. Furthermore, ensuring a robust and representative dataset is crucial for enhancing the generalizability of the model's findings. Issues related to data quality, such as aggregation and noise, can affect the accuracy and reliability of the results. Addressing these data quality issues through preprocessing and validation steps is essential for improving model performance.

Conversely, one may also note that simpler methods, while potentially less capable of capturing nonlinearities, can offer more straightforward interpretations and may be useful for identifying broad trends. These methods can serve as complementary tools to complex models, providing a baseline for comparison and validation of findings.

Future research should consider expanding the scope of the study to encompass a wider range of regions and factors. Incorporating additional variables, such as economic indicators or infrastructure conditions, could provide a more comprehensive understanding of the complex dynamics within the IWT system. Additionally, conducting scenario-based analyses to assess the potential impacts of future climate change scenarios on barge rates would further enhance our understanding and enable more informed

decision-making. Such efforts would contribute to a more holistic view of the system and its vulnerabilities, ultimately supporting more resilient infrastructure planning and policy development.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI:https://agtransport.usda.gov/stories/s/Barge-Dashboard/965a-yzgy/.

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