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Suggested citation format:

Wu, S., M. Mallory, T. Serra, and T. Hubbs. 2025. "Impeded Grain Barges: Midwest Regional Grain Price Dynamics under Mississippi River System Water Level Fluctuations." Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, Chicago, Illinois, April 14-15, 2025.
[http://www.farmdoc.illinois.edu/nccc134/paperarchive]

IMPEDED GRAIN BARGES: MIDWEST REGIONAL GRAIN PRICE DYNAMICSUNDER MISSISSIPPI RIVER SYSTEM WATER LEVEL FLUCTUATIONS

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Paper prepared for the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, 2025.

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Abstract: *This study investigates the relationship between the water levels in inland waterway systems and the corn Gulf spread, defined as the difference between local corn prices and the Gulf export price. Barge transportation, the primary mode for transporting corn to the Gulf export market, becomes unreliable during unusually high or low water levels, disrupting market dynamics. Using a spatial Durbin model (SDM) we analyze both the indirect and spillover effects of water levels on the Gulf spreads. The results indicate an inverse U-shaped relationship between the regional spread and both own-region water levels and neighboring water levels which drive significant spread changes, particularly during extreme water conditions. The optimal water level for minimizing the Gulf spread is estimated at about 21 feet, with a 10-foot deviation widening the spread by 4.55 cents per bushel and a 20-foot deviation increasing it by 18.17 cents. Our findings provide direct insights into how fluctuations in water levels shape local grain markets.*

Key Words: grain barge transportation, Mississippi river floods and droughts, spatial Durbin model, price analysis

Introduction

Grain barges traveling through the Mississippi River system play a key role in the United States' world-leading grain export industry. Concentrated in the Midwest, corn production drives substantial demand for transporting grain from the production sites to New Orleans, the largest US grain export hub[5]. The Mississippi waterway system flows southward through major corn fields, ultimately merging into the Gulf of Mexico. This serves as a natural channel for barge movements that connect Midwest supply with the demand of the Gulf export market in New Orleans. Barge transportation accounted for 53% of the US corn exported in 2020 (Henderson et al., 2023), due to its cost-efficiency and effectiveness.

According to the Law of One Price (von Cramon-Taubadel & Goodwin, 2021), the price difference between two locations reflects the transaction costs, with transportation costs being a major component. Consequently, disruptions in grain barge traffic due to unfavorable water levels can affect the dynamics between the export and local prices. These unfavorable conditions arise when water levels are either too low to support barge navigation, or too high making barge movements risky.

The direct effect of water levels on the Gulf spread has not been studied by previous research. Some studies focus on the impact of water levels on barge rates, while others evaluate the effects of barge rates on spreads. Li (2013b) demonstrates that barge rates increase nonlinearly and rapidly when water levels drop to critical lows, estimating that a one-foot decrease below a certain benchmark leads to a 1.51% rise in barge rates using regression analysis.

[5] Agribusiness Consulting, 2019, USDA Agricultural Marketing Service, https://www.ams.usda.gov/sites/default/files/media/ImportanceofInlandWaterwaystoUSAgricultureFullReport.pdf

Chen & Cheng (2024) further explore this by employing the SDM to assess the impact of river lock closures on barge rates. Chen et al. (2024) take a different approach by using a Gradient Boosting Decision Tree machine learning method, revealing an inverse U-shaped relationship between barge rates and water levels. Yu et al. (2007) use cointegration analysis to show that shocks in barge rates affect the export-local price dynamics over the long run. Similarly, Li (2013a) finds that a 1 cent per bushel increase in barge rates between St. Louis and New Orleans results in a 0.34 cent decrease in the average corn spot price in the Midwest relative to the Gulf.

Some other studies focus on flooding. Fahie (2019) reports that the 2019 flooding on the Mississippi River caused the St. Louis Harbor to be closed for 38 consecutive days and 6.3 million tons of grains to be unshipped. Amorim et al. (2023) suggest that the navigability of the Mississippi River has diminished and become fragmented in recent years, primarily in response to high water levels rather than low ones.

The literature has also assessed how a particular drought impacts local grain prices. This literature has modeled the impacts of low water levels as a one-time treatment, comparing the results of the treatment against non-treatment periods. McNew (1996) focuses on the 1993 drought's impacts on price transmission between New Orleans and St Louis or Memphis. Through regression analysis and a dummy variable representing the 1993 drought, McNew (1996) finds that price transmission was halved during this period. Flores and Janzen (2023) employ a difference-in-difference model to measure the impact of the 2022 drought on local soybean spot-gulf price difference. Specifically, they analyze changes in the October local price spread between the 2015-2021 period and 2022, considering elevators' proximity to the river and controlling for production changes. Their results suggest that the 2022 drought impacted the local spread, with the effect declining with the distance to the river and with proximity to soybean processing facilities.

The existing research has shed light on the complex relationship between barge rates and water levels, as well as between barge rates and the Gulf spread. However, there is limited understanding of how water level fluctuations specifically impact the Gulf spread. While barge rates are influenced by water levels, they are also affected by factors such as supply and demand dynamics and fuels costs. Hence, the two-step link between water levels and the Gulf spread is not a direct reflection of water levels. This article aims to bridge this gap by controlling for other intervening variables. By accounting for these variables this article seeks to provide a clearer understanding of the implicit pathways through which water levels impact the Gulf spread.

This paper measures the effects of fluctuations in the Mississippi River system's water levels on grain prices. We focus on the difference in corn prices between the export hub and local elevators, known as the Gulf spread. Unusually high and low water levels will have price impacts that spill over the geography through the grain transportation network. We disentangle water level price effects into direct and indirect, with the latter resulting from spillover effects across elevators in different regions. We use the Spatial Durbin Model (SDM) (LeSage, 2014) as our baseline model to assess the global spillover effects on regional Gulf spreads.

This study contributes to the literature on Mississippi River grain barge transportation and grain prices in three ways. First, we investigate the direct impact of water level fluctuations on the regional Gulf spread and depict the relationship across the full spectrum of water levels.

Our results reveal an inverse U-shaped dynamic relationship and identify the optimal water level for barge movement. Second, we utilize the SDM to disentangle the direct effects of water levels on regional Gulf spreads from the spillover effects across regions. The direct effect of water levels reveals a statistically significant impact on the Gulf spread. The spread widens when water levels are either too low or too high. Spatial spillover effects are more pronounced than the direct effects, amplifying the pattern and making the total impact significantly larger than the direct effect alone. Third, our study enhances the understanding of risks facing the grain market in the context of climate change. Climate change has increased the frequency of extreme events, such as floods and droughts, causing water levels to significantly deviate from their optimal range (Stott, 2016). We find the optimal water level for barge operation is 20.62 feet, and a 10-foot deviation expands the Gulf spread by 4.55 cents per bushel, while a 20-foot deviation widens it by 18.17 cents.

Background Information

The U.S. is one of the world's leading corn exporters, with production concentrated in the Midwestern states, an area known as the Corn Belt (Appendix A). According to the USDA[6], 16.59% of U.S. corn production in 2022 was directed to the export market, with the remaining majority used domestically for ethanol production or animal feed. The Mississippi River serves as a major channel for transporting significant quantities of bulk grains to export hubs in New Orleans via barges (Henderson et al., 2023).

In 1930, the U.S. Congress authorized a 9-foot channel navigation project on the Upper Mississippi River system, including the Mississippi River and the Illinois River, to facilitate barge movements (Appendix B). This initiative involved constructing a series of locks and dams, managed by the U.S. Army Corps of Engineers (USACE). The project divided the river into sections at different elevations, regulating water flow with dams. Behind each dam, the riverbed was dredged to create a navigation channel deep enough for barges to pass through. To enable barges to navigate the different elevations created by the dams, locks were constructed alongside them, serving as lifts for barges. The Lock and Dam 27 in St. Louis is the last facility on the Upper Mississippi River system. South of St. Louis, the waterway is usually deep and wide enough for barges to move freely due to convergence of several tributaries.

The Upper Mississippi River locks are managed by three districts of the USACE: the St. Paul district,[7] which oversees locks 1 to 10; the Rock Island district,[8] which manages locks 11 to lock 22 and the Illinois River locks; and the St. Louis district[9] which is responsible for locks 23 to 27. During the wintertime, districts may close their locks due to freezing conditions. The St. Paul district usually ends the navigation season by the end of November and resumes in late March. The Rock Island district generally closes the river from the beginning of December to early March. The St. Louis district rarely announces lock closures due to winter freezes.

Figure 1 shows the monthly average of downbound grain barge movements in tons from

[6] WASDE Feb 2024: https://downloads.usda.library.cornell.edu/usda-esmis/files/3t945q76s/6108x0329/gx41p613n/wasde0224.pdf
[7] https://www.mvp.usace.army.mil/
[8] https://www.mvr.usace.army.mil/Missions/Navigation/
[9] https://www.mvs.usace.army.mil/

lock 15 to lock 27[10]. These are consistent with river closures. At lock 15, there is no grain barge tonnage recorded in January and February and tonnage is infrequent in December and March. A similar pattern is observed in lock 25, though with slightly more tonnage. Since lock 25 is located near the south end of the Upper Mississippi River (Appendix B), winter freezes can shut down significant amount of barge operations throughout most of the region, weakening the linkages between the water levels and the Gulf spread.

Despite the effort of regulating the water levels for favorable barge navigation, extreme water levels can still cause troubles as documented by previous research. The effects of the 2012 and 2022 droughts are documented by Li (2013b) and Flores & Janzen (2024) and Steinbach & Zhuang (2023), respectively, while Fahie (2019) studies the 2019 flood. When water levels decrease, shrinking the Mississippi River system channels, barge traffic is restricted. Barges must reduce their loading capacity to reduce draft and avoid running aground (Appendix C). A low water level also limits towboats' working size, further reducing the barge transportation capacity. On the other hand, extreme high water levels also disrupt barge transportation, as floods create unsafe navigation channels, forcing locks and dams to close. It is thus relevant to study how water levels impact the Gulf spread.

Data and Descriptive Analysis

We access daily corn spot bids from GeoGrain through Bloomberg for the period from 04/02/2012 to 11/30/2022. This dataset includes grain corn bids (in dollars/bushel) for grain elevators, ethanol plants, and feed mills, along with the geographical coordinates. We aggregate corn ethanol plants and feed mills into a single category to represent local corn markets. We exclude elevators with more than 15% missing values during the sample period from the dataset. We source daily corn export bids (in dollars/bushel) from the Louisiana and Texas Export Bids report published by the USDA, which provides corn bids from export elevators at Gulf Coast ports in Louisiana.

We collect water level data (in foot) from 25 stations of the Mississippi River system from the USACE[11] and USGS (United States Geological Survey)[12] websites (Appendix C). These include 21 stations on the Mississippi River, 3 on the Illinois River, and 1 on the Ohio River. Water levels are measured using three different vertical datums—MSL1912[13], NGVD29[14], and NAVD88[15] —adjusted by zero gages specific to each location to accurately reflect the true water level. The water level data covers the same timespan as corn prices data. We analyze the relationship between water level changes and the Gulf spread via barge transportation, excluding data from December to March each year to eliminate the impact of river freezes on barge traffic. Winter months are assessed separately in the robustness check section.

[10] Lock numbers increase from north to south, with lock 15 being farther north than lock 27.
[11] https://rivergages.mvr.usace.army.mil/WaterControl/new/layout.cfm
[12] https://dashboard.waterdata.usgs.gov/app/nwd/en/?region=lower48&aoi=default
[13] Mean Sea Level 1912
[14] National Geodetic Vertical Datum of 1929. MSL1912 = NGVD29 + 0.51 feet https://www.cityofdubuque.org/DocumentCenter/View/30733/Port-of-Dubuque-Master-Plan-and-Stormwater-Management-Table_FINAL?bidId=
[15] National American Vertical Datum of 1988. MSL1912 = NAVD + 0.68 feet

We impute missing values in the daily dataset using the previous observation. Then we aggregate to a weekly frequency by averaging daily values from each calendar week. This reduces data staleness and facilitates econometric model estimation. Sytsma and Wilson (2021) find a strong preference for transporting grain by barge over rail for elevators within 50 miles to the waterway, with this preference declining to zero at 175 miles. To ensure a strong connection between the water and the price, we focus on grain elevators within a 50-mile radius of each river station. We match each grain elevator with the nearest river station.

We collect state-level weekly prices for ethanol and distiller's dried grain with soluble (DDGS) from the USDA National Weekly Grain Co-product Report. We calculate the market value of ethanol and DDGS produced from one bushel of corn using state-level prices. This value (in dollars/bushel), referred to as the processing value, is uniformly assigned to all processing facilities within a state. We match each elevator with the nearest processing facility within a 50 mile-radius based on Euclidean distance. This ensures that local markets are located at a similar distance as the shipping point.

We approach the transportation cost from the elevator to the nearest processing facility by multiplying the diesel price (in dollars/gallon) by the distance. This metric measures accessibility to the local processor market, given that trucks handle over 80% of domestic corn transportation (Henderson et al., 2023). We calculate transportation costs from the elevator to the river by multiplying the diesel price by the distance between each water station and the elevator. We retrieve the weekly diesel price in the Midwest from the US Energy Information Administration (EIA).

Because water level is only available by water station, we calculate the mean elevator price by averaging prices across all matched elevators for each station. Although the water stations may not be the exact locations where elevators load their barges, they provide an approximation to the relevant water levels for each elevator. Figure 2 shows the locations of grain elevators (green dots), processors (red dots), water level stations (blue triangles), and the waterways (blue), under the 50-mile distance band. Our sample elevators and processing facilities are mainly located in Illinois, Iowa, Minnesota and Wisconsin.

Figure 3 presents the historical variations in water levels at the St. Louis[16] station and downbound corn barge movements through lock 27 (St. Louis) on the Mississippi River from 2012 to 2022. The plot reveals similar seasonal patterns in water levels and barge activities, typically rising in the first half of the year and declining starting around June and July. The major exception happened in 2019 when the lock of St. Louis shut down for over a month due to flooding (Fahie 2019). The figure also shows exceptionally low water levels in 2012 and 2022, with levels dropping to or below 0 from September to November. Although water levels during the 2012 and 2022 droughts were similar, barge rates differed significantly between the two periods. Figure 4 demonstrates that barge rates in 2012 were consistent with those in other years. However, during the 2022 drought, barge rates spiked significantly, likely driven in part by the sharp increase in energy prices that began in early 2022.

[16] St Louis is situated at the confluence of the Missouri and Illinois rivers with the Mississippi River. Thus, the water level and downbound barge movement here reflect the conditions of the Mississippi River system.

The drought years 2012 and 2022 had the lowest water level in October, while the flood year of 2019 had the highest water level in June. Using the remaining sample years benchmarks, figure 5 shows heatmaps of county-level average Gulf spread differences, expressed in cents per bushel, between the October and June in each drought and flood year and the corresponding month in benchmark years. As discussed, Gulf spreads represent the difference between local prices and the Gulf price. In line with the Law of One Price, spreads tend to be negative, reflecting transportation costs. If transportation is impeded by unfavorable water level, then the spread is going to be more negative (wider). In October 2012, spread changes were less pronounced than in October 2022. In 2012, except for some counties south to St. Louis, where spreads decreased significantly (about 100 cents lower), most counties saw an increase in spreads, around 10-20 cents. Meanwhile, in October 2022, most counties experienced a substantial spread decrease of over 100 cents. For reference, the average October water level in St. Louis during benchmark years was 9.22 ft, which dropped by about 10 ft to similar levels both in 2012 (-0.94 ft) and 2022 (-1.53 ft). In June 2019, due to the closure of lock 27, counties closer to the river experienced an expansion in spreads of about 20-30 cents, while more distant areas were less affected. The mean June water level in 2019 was 41.26 ft compared to 22.65 ft in benchmark years. These plots reveal that studying single drought or flood year provides limited insight into how extreme events affect barge transportation and, subsequently, grain prices, due to idiosyncratic differences across years. This highlights the importance of controlling for intervening variables such as energy prices that may influence outcomes and help isolate the impact of water levels on transportation and pricing.

Method and Empirical Approach

Our objective is to understand the spatial dynamics of Gulf spreads across different elevator clusters and their relationship with Mississippi river system water levels using our panel data. We rely on spatial regression models instead of traditional panel data methods because they are better suited for analyzing spatially correlated data. These models explicitly account for spatial dependencies among observations, allowing us to capture the direct influence of water levels at one location and their indirect effects through neighboring locations through spatial spillovers. This helps understanding how shocks propagate geographically. Additionally, by allowing for serial correlation, these models provide more accurate estimates of the parameters, reducing the bias that may arise from ignoring spatial correlation.

There are three main types of spatial models, the spatial autoregressive model (SAR), the spatial error model (SEM), and the spatial Durbin model (SDM). SAR models measure how the dependent variable in one location is affected by the value of the dependent variable in neighboring locations. The SEM accounts for spatially correlated unobserved factors that may affect the dependent variable. The SDM allows for spatial interactions between both spatially lagged dependent and independent variables, and the dependent variable in the model. Choosing among these models requires implementation of model selection tests that we describe in the empirical implementation section.

We use the Moran's I test (Bivand & Wong, 2018) to examine the presence of spatial autocorrelation across the clustered Gulf spreads, which is essential to determine if a spatial model is needed. The test statistic is calculated as:

$$I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(B_i-\bar{B})(B_j-\bar{B})}{\sum_{i=1}^{N}(B_i-\bar{B})^2}, \quad (1)$$

where N is the number of cross-sectional units (clusters), B_i (B_j) denotes the Gulf spread of water station i (j), w_{ij} is the spatial weight representing the geographical relationship between water station i and j, specified as the K-nearest weight matrix (K = 5), which assigns a same weight to the 5 closest neighborhoods. $\bar{B}$ is the Gulf spread mean across all water stations. The expected value of Moran's I is calculated as $E(I) = \frac{-1}{N-1}$. The variance $Var(I)$ is determined under the randomization assumption. Standard normal deviates $Z(I) = \frac{I-E(I)}{\sqrt{Var(I)}}$ are computed based on the estimated means and variances, with $Z(I)$ allowing to test the null hypothesis that there is no spatial autocorrelation (Bivand & Wong, 2018). If I is significantly lower (higher) than $E(I)$, there exists a statistically significant negative (positive) spatial autocorrelation, otherwise there is no spatial autocorrelation. We calculate Moran's I test for each week and for the entire sample to assess spatial correlation at both time frequencies (Beenstock & Felsenstein, 2019).

After confirming the presence of spatial correlation and the need for a spatial model, we refer to LeSage (2014) for guidance on the appropriate spatial model specification. LeSage (2014) argues that researchers in the presence of global spillover effects one should utilize the SDM model. The key difference between local and global spillover effects is that local spillovers are confined to a specific group of entities, while global spillovers extend beyond neighbors to affect more distant areas. The U.S. corn markets exemplify this global setting, as no local corn market operates in isolation from the broader network. Thus, we model the Gulf spread using the SDM model, and apply it to the panel data:

$$Y = \rho WY + \Psi\alpha + \Phi\mu + X\beta_1 + WX\beta_2 + \varepsilon,$$

$$\varepsilon \sim N(0, \sigma^2\Omega), \quad (2)$$

where Y is a $NT \times 1$ matrix of regional Gulf spreads sorted first by region (i) and then by time (t), where N is the total number of regions and T the total number of weeks. W is defined as $W = w \otimes I_T$, with I_T being a $T \times T$ identity matrix, $\otimes$ denoting the Kronecker product and w ($N \times N$) capturing the spatial relationships between different regions. WY is the spatial lag matrix, which is measured as the linear combination of Y values from neighboring water stations. We expect the parameter representing spatial correlation ρ to be positive, as an increase in Gulf spreads in one area may lead to increases in adjacent areas, indicating a tendency for spreads to propagate positively across the geographic space. $\Psi = I_N \otimes \iota_T$ is a region fixed effects matrix capturing time-invariant characteristics that are unique to each region, where ι_T is a vector of order T containing ones. $\Phi = \Psi \otimes \xi$ is the interactive fixed effect incorporating region and crop year. Let $\xi = \xi_w \otimes \iota_N$ be a crop year fixed effects matrix that controls for changes in the supply of corn across years, where $\xi_w = \iota_a \otimes \iota_w$ is a $T \times 1$ matrix, where w is the number of weeks in a crop year and a is the number of crop years in the sample, with $T = a \times w$ and ι_N is a vector of order N containing ones. The crop year fixed effect is defined by dividing the sample period into crop years. Each crop year runs from November of the previous calendar year to October of the current calendar year. This division assumes that the harvest is nearly complete by November, representing the start of the new crop for each cycle. The region fixed effects control for time-invariant differences in each region, such as the distance to the Gulf. The interactive fixed effect controls for the characteristics unique to each crop year and region, such as regional production, demand, and storage.

We calculate the regional Gulf spreads by subtracting the export bids from the elevator spot bids and averaging on the regional level. The Gulf spread tends to be narrower prior to the harvest season, as corn supply and stocks usually reach their lowest levels, compared to wider spreads in the months after harvest. To account for seasonality in the Gulf spread, we de-seasonalize the spreads by subtracting the monthly mean from each monthly observation.

X is a $NT \times K$ matrix of K exogenous characteristics for each region, including the lagged processing value reflecting domestic demand and transportation costs to processors, which reflect the impact of accessibility to local demand sources. X also includes transportation costs to the river and water levels, which jointly reflect transportation costs to the export market. Considering that export and local demand are the two primary destinations for elevators to sell their grains, in the absence of arbitrage opportunities, elevators should be indifferent between the two markets.

By incorporating variables that reflect alternative corn markets to the Gulf, we control for major weekly spread variations that are not attributable to water. We expect that increases in transportation costs from the elevator to the local processor will depress local prices, thus reducing the local Gulf spread. Transportation costs to the river are part of the costs of the overall costs of shipping corn from elevators to the Gulf. An increase in transportation costs to the river is likely to have a negative impact on the local Gulf spread, independent of water levels. Conversely, an increase in the local processing value may signal higher local demand and prices, leading to an increase in the Gulf spread. Based on literature insights, we hypothesize that the relationship between water levels and the Gulf spread follows an inverse U-shape, where deviations from optimal water levels for barge transportation reduce (widen) the Gulf spread. To capture this non-linear relationship, we include a quadratic term for water level. $WX_{i,t}$ is a linear combination of the values of $X_{i,t}$ from neighboring regions which captures the influence of local markets and water levels in neighboring areas on the own Gulf basis.

The panel consists of T = 389 time periods and N = 25 cross sectional units. We estimate the SDM model using Monte Carlo Markov Chain (MCMC) methods. To evaluate the SDM model against the SAR and the SEM models, we follow the approach outlined by Koley (2023 & 2024). Specifically, we conduct the Rao's score (RS) tests to determine if the SDM degenerates into a spatial autoregressive model (SAR, $\beta_2 = 0$), spatial error model (SEM, $\rho = 0$), or even a simple OLS model ($\beta_2 = 0$ and $\rho = 0$). First, a joint test of $\beta_2 = 0$ and $\rho = 0$ assesses whether the true model specification significantly deviates from a simple OLS model. Then, separate tests on $\beta_2 = 0$ and $\rho = 0$ are performed to ensure that each spatial parameter is significant unconditional on the other one's presence. If all three tests reject the null hypothesis, the SDM specification is a good fit.

The SDM model estimates cannot be interpreted as simple partial derivatives of the dependent variable with respect to the explanatory variables due to the complex spatial dependencies involved. A change in one region affects all other regions through spatial spillovers. Hence, we use summary measures of direct, indirect and total impacts. We calculate the partial derivative matrix for the SDM following Golgher & Voss (2015). The average direct effect captures the impact of a unit change in a regional right-hand side variable on the Gulf spread in the same region, averaged across the *N* regions and *T* periods, reflecting the contemporaneous response at the same location. The average indirect effects represent the impact of a unit change in the regressor at neighboring locations on the Gulf spread in a particular region, averaged across *N* regions and *T* periods, capturing the spillover effects from changes in exogenous variables at nearby regions. The sum of the direct and indirect effects results in the average total effects, which measure the comprehensive response of the dependent variable to a unit change of the regressor.

Results

First, we apply the Moran's I test to the weekly regional Gulf spreads to test for the presence of spatial autocorrelation. Figure 9 presents the kernel density plot of the weekly Moran's *I* in blue and its corresponding expected value E(*I*) in red. Test results for 378 out of 389 weeks are positive and statistically significant at the 5% level, suggesting a prevailing positive spatial autocorrelation among regional Gulf spreads on a weekly level. Table 1 shows the Moran's I test result for the regional spread over the 389 weeks. The significance of the test statistic proves the existence of positive spatial autocorrelation over the whole sample.

Next, we test the robustness of the SDM specification. Table 2 summarizes the results of both the joint and the individual tests. First, the joint test suggests that either β_2 or ρ, or both should be nonzero. Hence, at least one spatial term should be included, making the OLS model inappropriate. The RS test and the adjusted RS test for β_2 and ρ indicate that both terms should be included in the model, confirming that the SDM model is the appropriate choice.

Table 3 presents the results of the SDM estimation of the regional Gulf spread, decomposed into average direct, indirect, and total effects. For context, recall that the Gulf spread is generally negative. The coefficients for water level and squared water level show how changes in water levels affect the average spread between regional elevator prices and the Gulf export price. The estimated ρ of 0.7 suggests a robust spatial relationships among the Gulf spreads in each region. The total effects of water level confirm an inverse U-shape, reflecting a nonlinear relationship with a positive linear and a negative quadratic term. This inverse U-shape suggests that the optimal water level that minimizes the Gulf spread is 20.62 ft. A 10-foot deviation from this optimal level widens the Gulf spread by 4.55 cents per bushel, while a 20-foot variation widens the spread by 18.17 cents per bushel. The recent droughts in 2022-23, which resulted in water level decreases of around 20 ft in just 11 weeks[17], highlight the potentially significant impact of extreme droughts, which can increase the Gulf spread by up to 18.17 cents per bushel.

[17] Source: https://theconversation.com/record-low-water-levels-on-the-mississippi-river-in-2022-show-how-climate-change-is-altering-large-rivers-193920

We decompose the total effects of water levels into direct and indirect effects. The direct effects measure the average impact of region-specific water levels on the Gulf spread. These suggest that a 10-foot deviation from the vertex would widen the Gulf spread by 0.81 cents, and a 20-foot deviation would increase the impact to 3.21 cents. The indirect effects of water levels are larger than the direct effects and imply that a 10-foot (20-foot) deviation from the vertex expands the Gulf spread by 3.74 (14.96) cents. These results highlight that, when the water level becomes more unfavorable for barges, the primary impact on the Gulf spread comes from the spillover effects from neighboring regions. This occurs because droughts or floods affect elevators located farther north, which must transport grain through multiple river segments to reach the Gulf, thus amplifying the impact on the Gulf spread.

The coefficient for the corn processing value reflects how the Gulf spread reacts to the prices of corn processing outputs (ethanol and DDGS). A higher processing value may increase regional elevator prices, potentially redirecting more grain to domestic use, and weakening the connection between Gulf and elevator prices through transportation. Results suggest that a one-dollar increase in the processing value is associated with a 4.36-cent per bushel reduction in the Gulf spread. While the direct and indirect effects are positive, they are statistically insignificant at the 5% level, indicating that the Gulf spread is more influenced by the overall processing value rather than its regional variations.

Higher transportation costs to processors reduce elevators' access to the local processing market, potentially lowering elevator prices and widening the Gulf spread. The Gulf spread is estimated to widen by 0.19 cents per bushel for every dollar per mile increase in transportation costs from the elevator to the nearest processing facility within a 50-mile radius. The indirect effect is not significant, which suggests that each elevator's spread is only affected by its own transportation cost to the processor. The total effect is 0.21 cents per bushel, reflecting the overall impact of transportation costs.

Similarly, higher transportation costs to the river reduce accessibility to the export market and should expand the Gulf spread. While the direct effect is unexpectedly positive and significant, the indirect effect is negative and significant, resulting in a negative and significant total effect, with every dollar per mile increase widening the spread by 0.0047 cents. It is worthy to note that the impacts of the two transportation costs differ significantly in magnitude. Despite both costs being influenced by the same diesel price and similar distances (<=50 miles), truck costs to the river have a much smaller effect on the Gulf spread than the truck costs to the processor.

Robustness Checks

In this section we check the robustness of our results during winter, when segments of the river may freeze, impeding transportation, and for elevators located at different distances from the river.

Winter Season

Our analysis excludes the winter season from December to March, based on the hypothesis that water levels during this period matter less due to freeze-related lock closures. However, since not every lock closes during winter and closure periods vary by lock, the linkage between water and the spread may still be relevant. Table 4 shows the SDM estimation results using data from December to March. The parameter ρ is 0.49, reflecting a much weaker spatial relationships among the Gulf spreads during winter. Consistently, the indirect effects of water levels are similar in magnitude to the direct effects during winter, whereas in non-winter months the indirect effects are much larger than the direct ones. These findings suggest that northern elevators, which must transport grain through multiple river segments to reach the Gulf, cannot ship during freezes. Hence, their neighbors' water levels no longer affect their spreads. As a result, local markets become the primary demand source for these elevators, resulting in positive and statistically significant direct, indirect and total effects of processing values.

Alternative distance bands

Elevators farther from the river may also be affected by water levels. To examine how the distance from the river influences prices, we estimate our model for elevators located in the 50-100-mile and 100-150-mile distance bands, while keeping their maximum distance to the closest processor to 50 miles. Tables 4 and 5 present the estimation results. First, we observe that the spatial correlation coefficient ρ decreases as elevators farther from the river, indicating that their prices are less spatially correlated. This suggests that barges build stronger regional price correlations than trucks or rails. Second, the impact of water levels diminishes as distance increases. In the 100-150-mile range, the indirect and total effects of water become insignificant, suggesting that local price variations are more strongly driven by processing demand. Finally, while the indirect effect of transportation costs to processor is insignificant at the 50-mile distance, it becomes significant at the 50-100 and 100-150 ranges, suggesting a stronger connection between the local prices and processors as the distance from the river increases.

Conclusion

Grain barge activities on the Mississippi River are relevant to agricultural economists and grain handlers as they are the primary means of transporting grain from production areas to the export market in New Orleans. Barge transportation becomes less reliable during extremely low and high water levels, creating a nonlinear relationship between water levels and the Gulf spread, defined as the difference between local prices and the Gulf export price. This paper studies, for the first-time, the impact of water levels on the Gulf spreads and disentangles the direct effect and spillover effect using a spatial Durbin model.

Our results suggest that the impact of water levels on the Gulf spreads has an inverse U-shape, which is substantially strengthened by spillover effects. We estimate that the optimal water level is 21 feet, with a 10-foot deviation from this level widening the spread by 4.55 cents per bushel, while a 20-foot deviation results in a 18.17-cent widening. The latter more accurately reflects recent extreme weather events. The influence of water on the spread decreases with the distance to the river, becoming insignificant for elevators placed beyond 100 miles from the river, with local price variations being essentially related to the domestic demand. The effects of water may be compensated by a strong internal demand, with a one-dollar increase in the processing value being associated with a 4.36-cent per bushel reduction in the Gulf spread.

The findings of this study carry implications in the context of climate change, which is expected to increase the frequency and severity of extreme weather events, including droughts and floods. By better understanding the relationship between the water levels and the Gulf spread, we provide a clearer picture on how the changing climate may impact the grain market from a transportation perspective.

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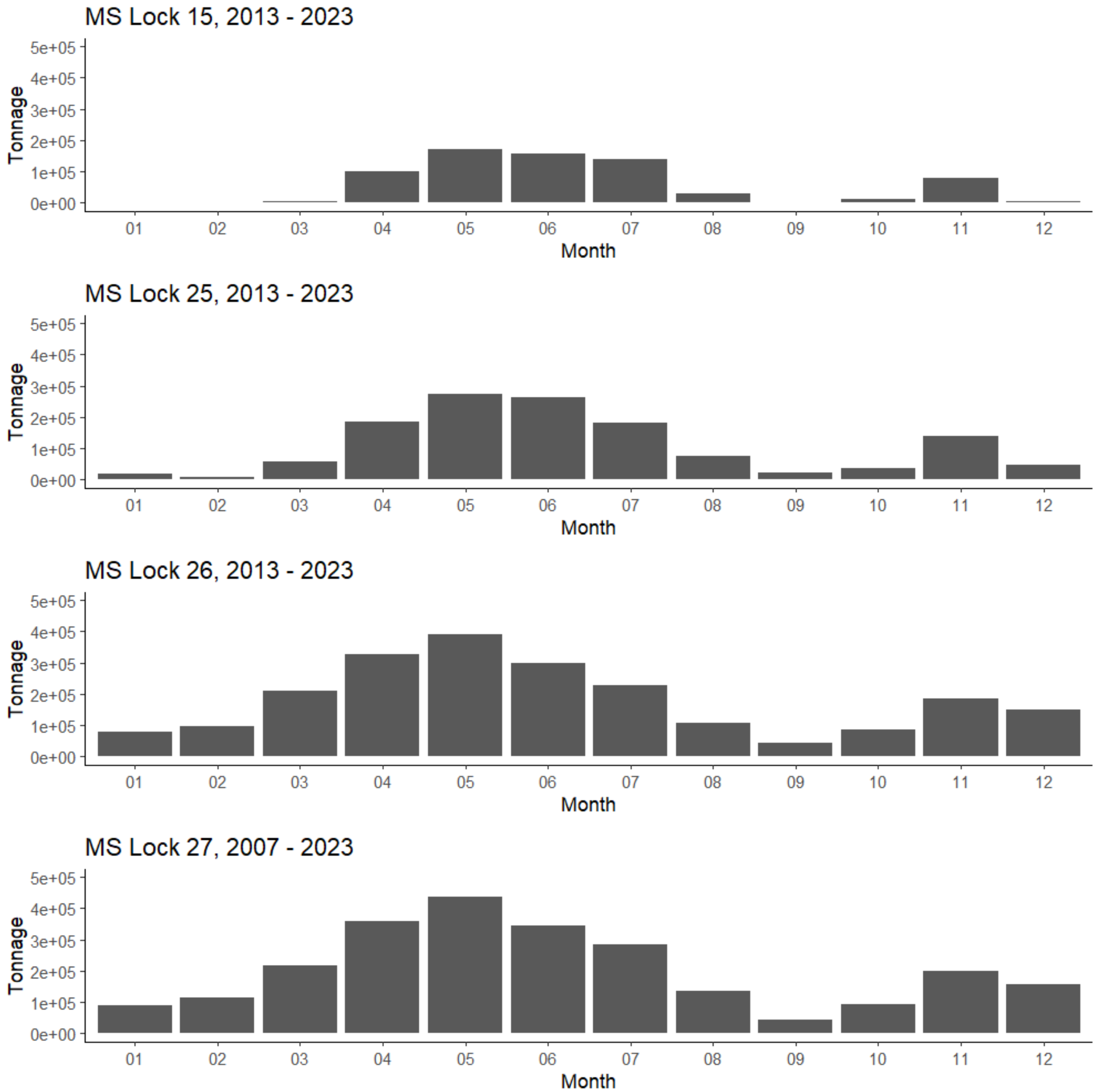
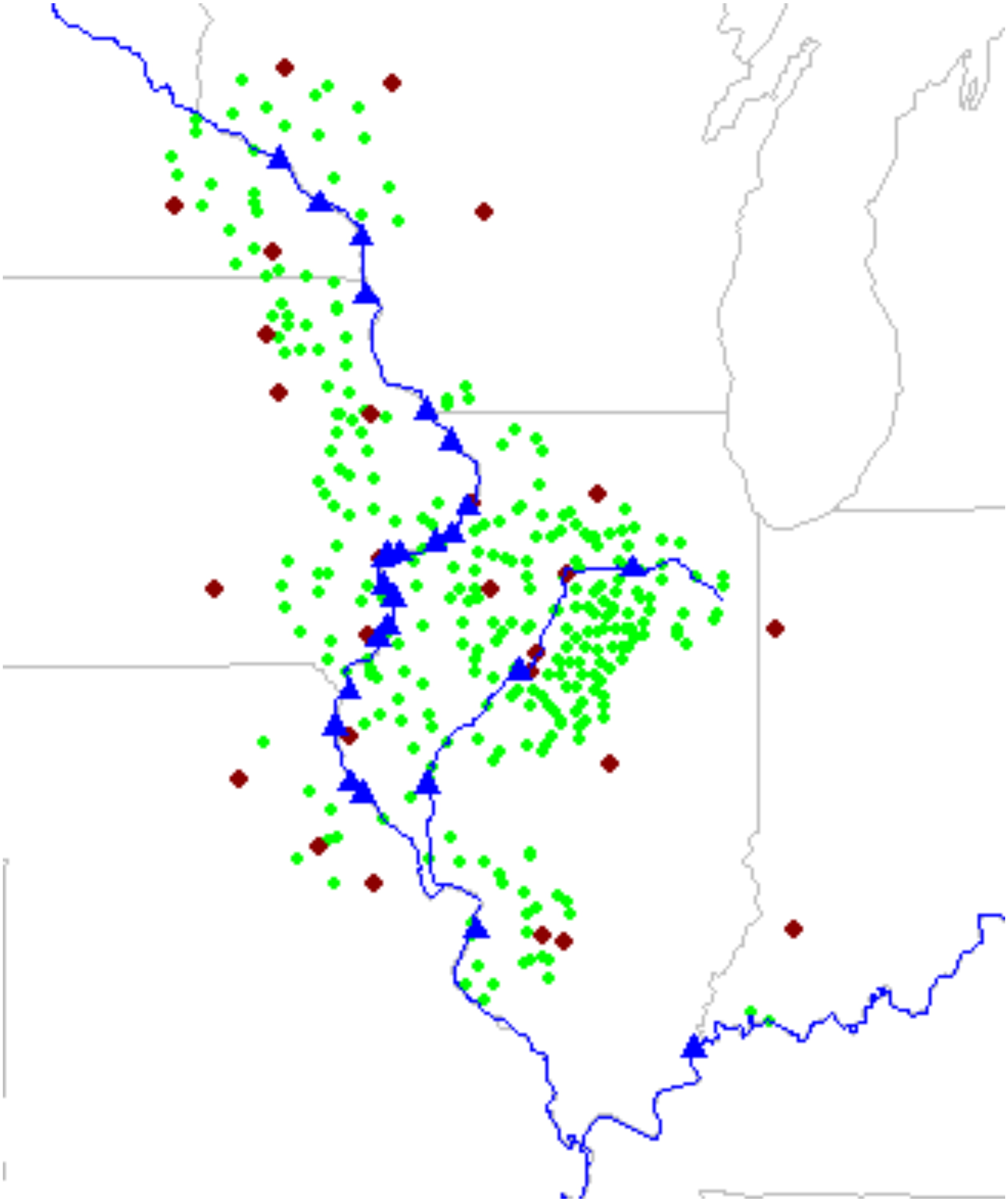
Figures

Figure 1. Downbound grain barge movements by month



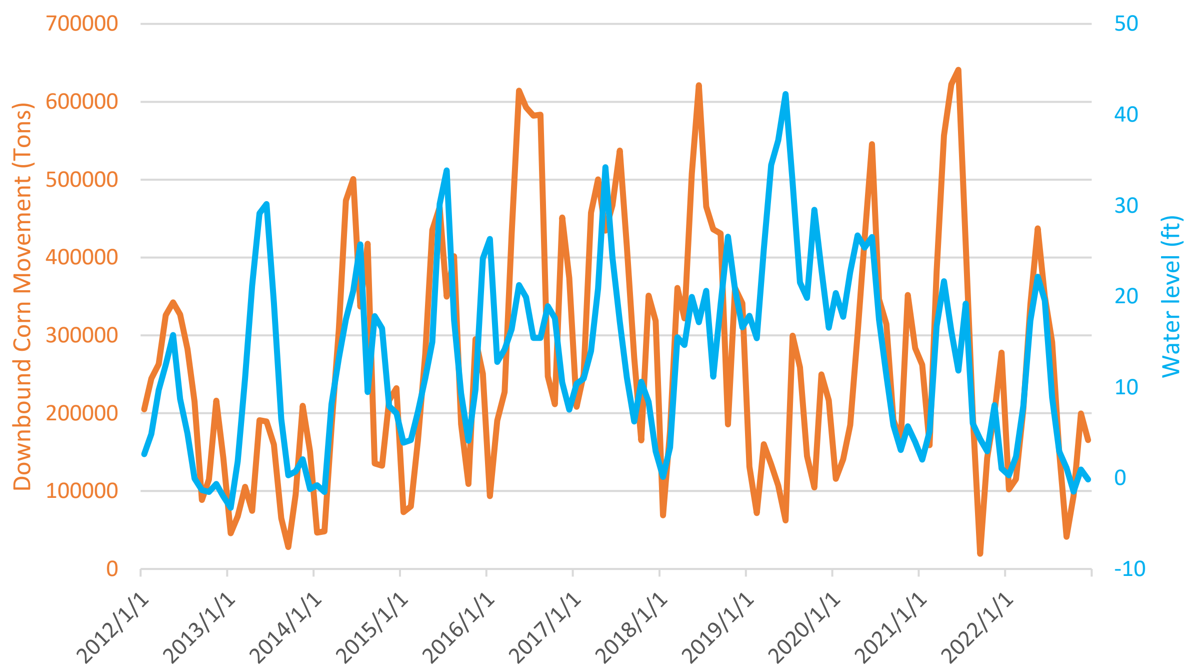
Note: This figure displays the average monthly tonnage moved between Lock 15 and Lock 27 over different time periods for each lock. Lock numbers increase from north to south, with Lock 15 located farther north than Lock 27. Data covers 2013 to 2023 for Locks 15, 25, and 26, and 2007 to 2023 for Lock 27. The data is sourced from the USDA Downbound Barge Grain Movements report (https://agtransport.usda.gov/Barge/Downbound-Barge-Grain-Movements-Tons-/n4pw-9ygw/about_data).

Figure 2. Map of price, water level locations, and rivers



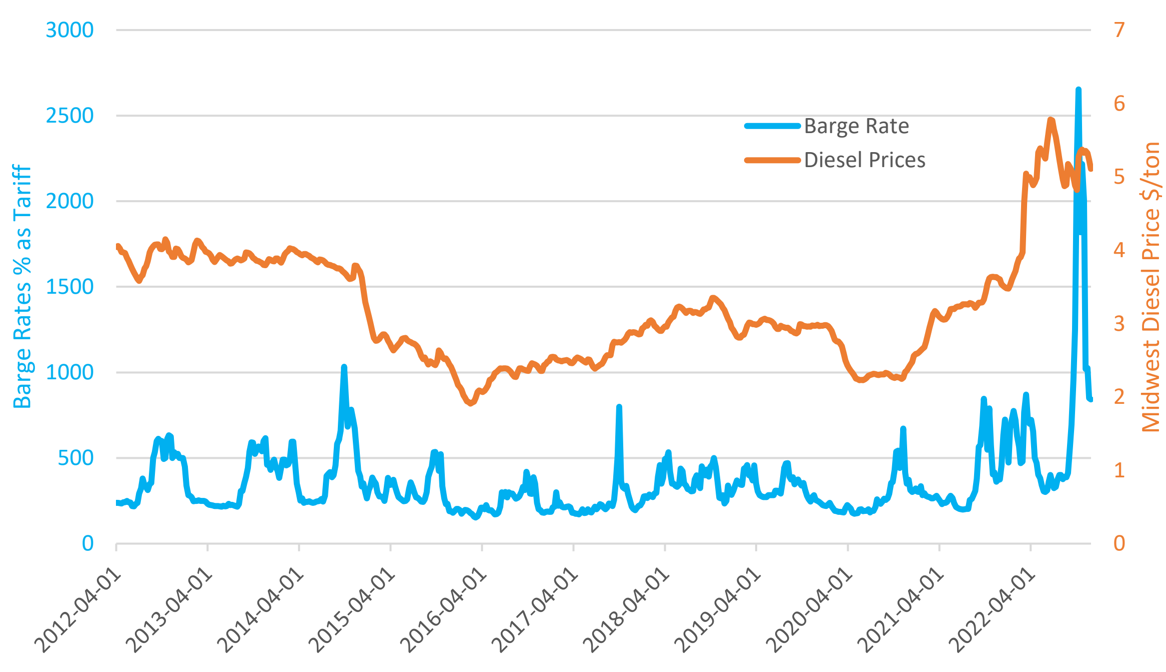
Note: This figure plots the locations of grain elevators (green dots), processors (dark red dots), water level stations (in blue triangles), and the Mississippi River, Illinois River, and Ohio River (blue lines)

Figure 3. Monthly water levels and downbound corn movement trends in St. Louis, 2012 - 2022



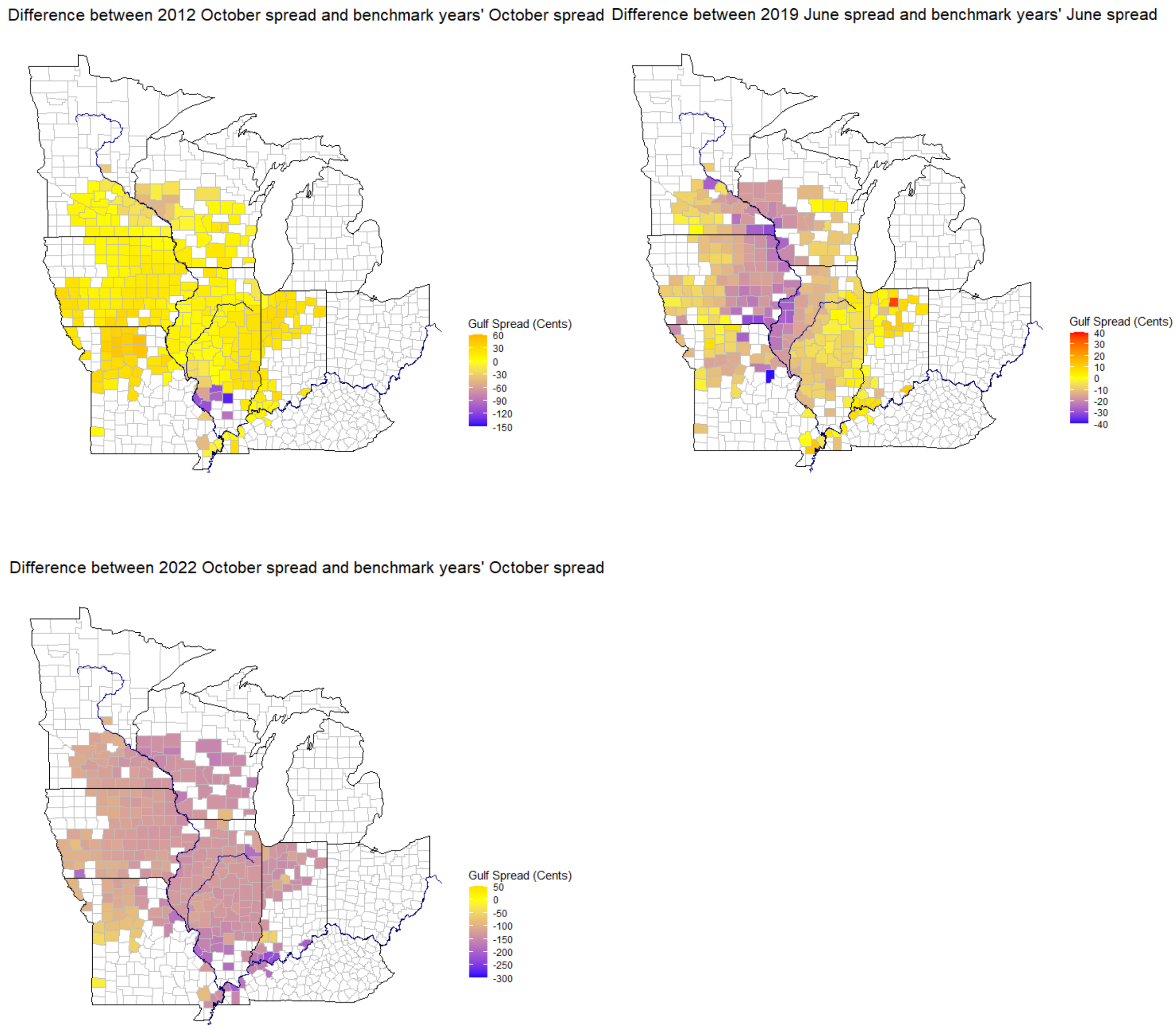
Note: This figure plots the average monthly water levels and corn downbound corn movement over time for the Mississippi River System at St. Louis, for the years 2012 to 2022. The barge activity and water levels share a similar seasonality, except for the summer of 2019, characterized by a flood that shut down the river for over a month.

Figure 4. Historical barge rates in St. Louis and Midwest diesel prices, 2012 - 2022



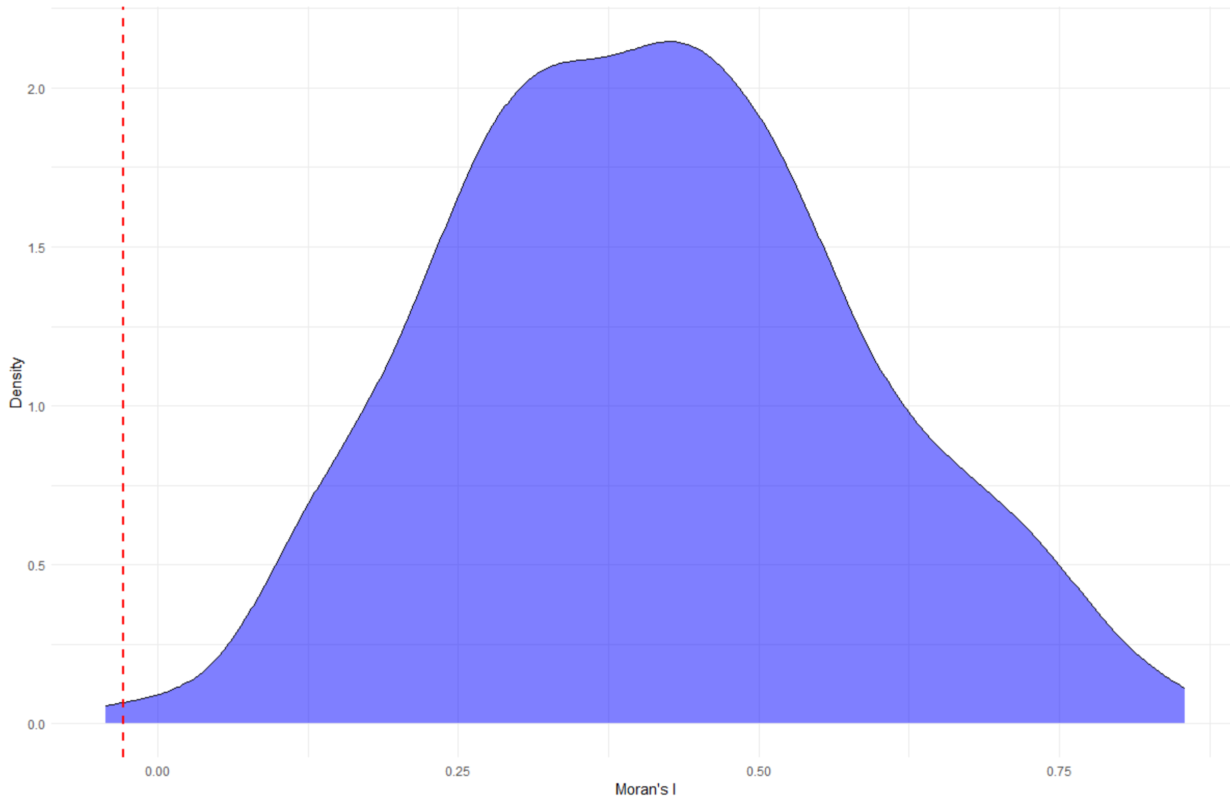
Note: The orange curve represents weekly historical barge rates in St. Louis, expressed in percentage of the base tariff rate (measured in the left axis) representing a local benchmark rate and expressed in dollars per ton. The blue curve shows weekly historical Midwest diesel prices (measured in the right axis).

Figure 5. The Gulf spread difference (in cents) between 2012 (2019) [2022] October (June) [October] and benchmark years' October (June) [October]



Note: The three plots describe how the Gulf spread changed in each county during the most severe month of the drought (flood) years (2012, 2019, 2022), compared to the same month of the benchmark years (2013 to 2018 and 2020 to 2021). Yellow denotes no change. If the color leans toward red (blue), it means the change is more positive (negative).

Figure 6. Kernel density plot of weekly Moran's I



Note: This dot plot shows the distribution of weekly Moran's I values. The red dashed line indicates E(I). There are 378 Moran's I more positive than E(I) at 5% significance level.

Tables

Table 1. Moran's I test result on averaged Gulf spread over the sample period

I	p-value	E(I)	$Var(I)$
0.305	3.432E-05	-0.029	0.007

Note: The test examines the spatial autocorrelation among the regional Gulf spreads over the 389 weeks. I is the test value, p-value is the significance level, $E(I)$ is I's expected value and $Var(I)$ is the I's variance calculated under randomization assumption.

Table 2. Spatial Durbin Model Parameter Tests

	Statistics	p-values
Joint test: $\beta_2 = 0, \rho = 0$	55.53	1.02E-10
RS test for WX: $\beta_2 = 0$	55.09	3.11E-11
Adj. test for WX: $\beta_2 = 0, \rho \neq 0$	55.74	5.97E-11
RS test for WY: $\rho = 0$	12.72	3.62E-04
Adj. Test for WY: $\rho = 0, \beta_2 \neq 0$	14.07	1.76E-04

Note: The table presents five parameter tests for the SDM model $Y = \rho WY + \Psi + \Phi + X\beta_1 + WX\beta_2 + \varepsilon$. The model is estimated using Markov Chain Monte Carlo (MCMC) methods. The joint test examines whether the true model deviates from the OLS model. The RS tests are the Rao's score tests to determine if the parameters significantly differ from zero. The Adj tests are adjusted Rao's score tests that examine the significance of the parameters given the other parameters are significant.

Table 3.Estimation result of SDM

	Direct effect	Indirect effect	Total effect	Estimate
Water level	4.20E-03***	1.45E-02***	1.87E-02***	
Water level^2	-8.00E-05***	-3.74E-04***	-4.54E-04***	
Processing value	2.25E-02*	2.10E-02	4.36E-02***	
Truck costs to processor	-1.92E-03***	-1.99E-04	-2.12E-03**	
Truck costs to river	2.00E-04***	-2.48E-04***	-4.80E-05**	
ρ				0.70***

Note: This table presents the estimation result of SDM for the Gulf spread $Y = \rho WY + \Psi\alpha + \Phi\mu + X\beta_1 + WX\beta_2 + \varepsilon$. The model is estimated using Markov Chain Monte Carlo (MCMC) methods. *(**)[***] denote 10%(5%)[1%] significance levels.

Table 4. Estimation result of SDM in winter

	Direct effect	Indirect effect	Total effect	Estimate
Water level	7.06E-03***	8.95E-03***	1.60E-02***	
Water level^2	-1.73E-04***	-3.04E-04***	-4.78E-04***	
Processing value	-8.02E-02***	8.96E-02***	9.40E-03***	
Truck costs to processor	-1.42E-03***	-3.44E-04	-1.76E-03**	
Truck costs to river	2.17E-04***	-2.73E-04***	-5.60E-05***	
ρ				0.49***

Note: This table presents the estimation result of SDM for the winter (December to March) Gulf spread $Y = \rho WY + \Psi\alpha + \Phi\mu + X\beta_1 + WX\beta_2 + \varepsilon$. The model is estimated using Markov Chain Monte Carlo (MCMC) methods. *(**)[***] denote 10%(5%)[1%] significance levels.

Table 5. Estimation result of SDM for 50 – 100 miles

	Direct effect	Indirect effect	Total effect	Estimate
Water level	4.30E-03***	7.59E-03**	1.19E-02***	
Water level^2	-1.03E-04***	-2.80E-04**	-3.83E-04***	
Processing value	9.39E-02***	-5.16E-02***	4.23E-03***	
Truck costs to processor	-2.40E-03***	-6.76E-03***	-9.16E-03***	
Truck costs to river	1.05E-04***	-3.40E-04	-4.10E-05***	
ρ				0.66***

Note: This table presents the estimation result of SDM for elevators that are in the 50-100 mile distance band, while their distance to processors are still 50 miles. Gulf spread $Y = \rho WY + \Psi\alpha + \Phi\mu + X\beta_1 + WX\beta_2 + \varepsilon$. The model is estimated using Markov Chain Monte Carlo (MCMC) methods. *(**)[***] denote 10%(5%)[1%] significance levels.

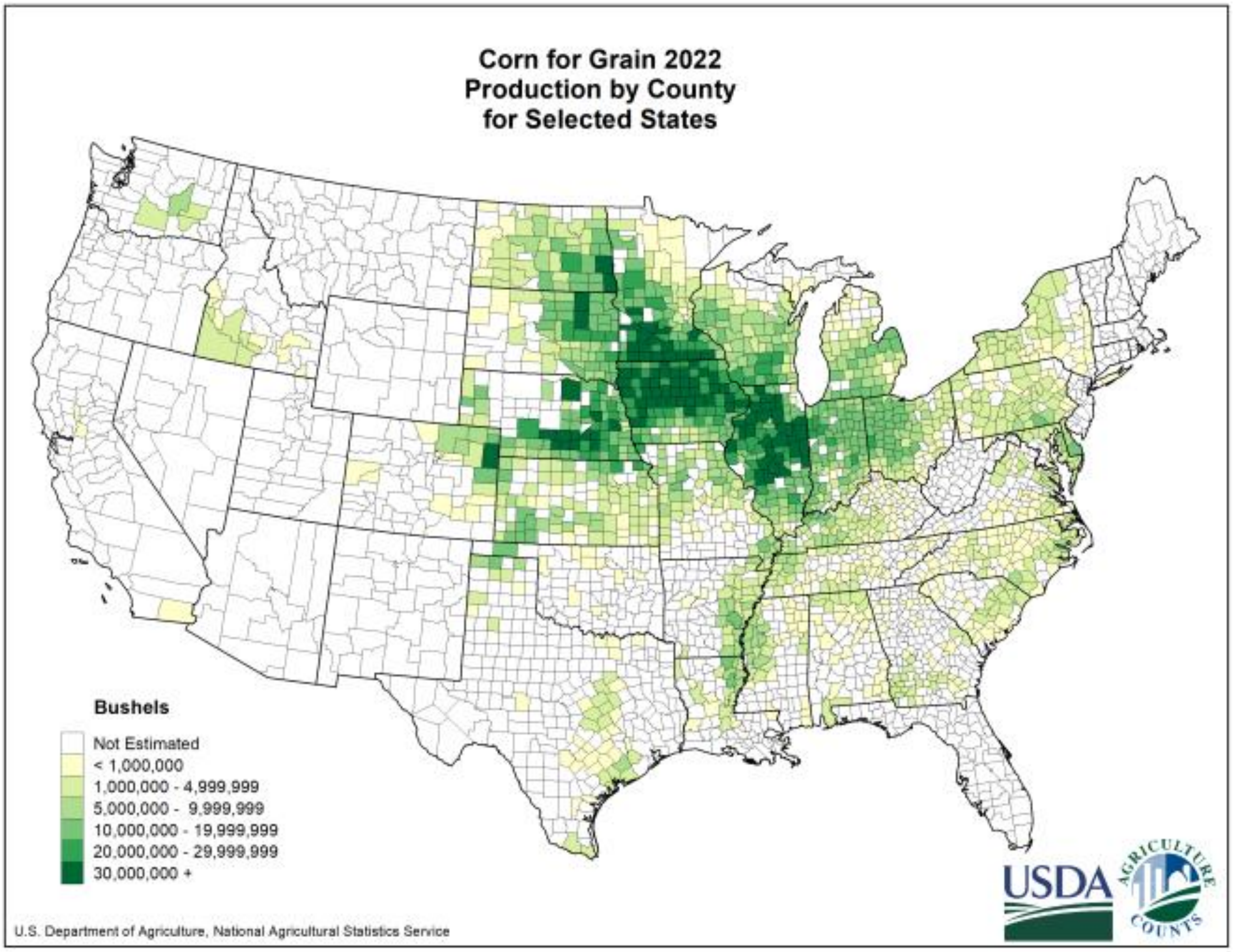
Table 6. Estimation result of SDM for 100 – 150 miles

	Direct effect	Indirect effect	Total effect	Estimate
Water level	1.23E-02***	-2.50E-03	9.80E-03	
Water level^2	-2.98E-04***	-2.20E-05	-3.20E-04	
Processing value	8.14E-02***	-4.22E-02**	3.92E-02***	
Truck costs to processor	-2.77E-02***	-7.37E-02***	-1.01E-01***	
Truck costs to river	1.15E-04**	2.36E-03***	2.48E-03***	
ρ				0.57***

Note: This table presents the estimation result of SDM for elevators that are in the 100-150 mile distance band, while their distance to processors are still 50 miles. Gulf spread $Y = \rho WY + \Psi\alpha + \Phi\mu + X\beta_1 + WX\beta_2 + \varepsilon$. The model is estimated using Markov Chain Monte Carlo (MCMC) methods. *(**)[***] denote 10%(5%)[1%] significance levels.

Appendix A

Figure A. Corn production map, 2022



Note: Source: USDA

Appendix B

Figure B. Upper Mississippi River Locks system.

Note: This figure shows the locks and dams of the Mississippi River and the Illinois River from the Upper Mississippi River system, retrieved from:
https://upload.wikimedia.org/wikipedia/commons/0/09/Upper_Mississippi_Lock_and_dams.jpeg

Appendix C

Table C. Information of water gages and summary statistics of water level

River	Gage	Longitude	Latitude	WL Mean (ft)	WL Min (ft)	WL Max (ft)	WL St.Dev.	WL Skew.
Illinois	Marseilles	-88.7171	41.3270	12.99	10.72	21.84	1.64	2.09
	Kingston Mines	-89.7773	40.5534	9.38	2.15	24.68	4.53	0.56
	Valley City	-90.6431	39.7032	8.07	1.92	25.23	4.39	0.88
Ohio	Old Shawneetown	-88.1397	37.7255	27.27	15.38	50.43	8.11	0.69
Mississippi	Wabasha	-92.0369	44.3872	7.78	6.88	15.15	1.13	3.23
	Winona	-91.6375	44.0556	6.46	5.36	17.01	1.54	3.38
	La Crosse	-91.2589	43.8017	8.47	4.65	32.50	7.50	2.70
	Lansing	-91.2131	43.3603	8.54	5.89	17.21	1.19	3.75
	Dubuque	-90.6528	42.4993	9.59	7.16	21.74	2.20	2.12
	Lock 12	-90.4211	42.2728	7.69	3.95	19.32	2.65	1.21
	Camanche	-90.2511	41.7814	10.74	3.79	20.40	1.90	1.69
	Lock 14	-90.4031	41.5744	5.60	4.15	13.52	1.52	2.10
	Lock 15	-90.5662	41.5170	7.51	3.57	19.14	2.83	1.30
	Fairport	-90.8936	41.4378	11.00	9.89	19.71	1.39	4.04
	Lock 16	-91.0128	41.4255	6.41	2.81	19.17	2.99	1.68
	Muscatine	-91.0552	41.3909	8.60	5.62	20.48	2.70	1.89
	Lock 17	-91.0556	41.1914	7.53	2.55	20.52	3.53	1.05
	Keithsburg	-90.9594	41.1061	8.78	5.32	18.83	2.63	1.15
	Lock 18	-91.0225	40.8814	4.73	0.78	16.09	3.04	1.17
	Burlington	-91.0917	40.7981	10.58	7.43	20.30	2.57	1.25
	Lock 19	-91.3742	40.3975	6.08	2.31	19.81	3.45	1.56
	Lock 20	-91.5146	40.1439	6.74	2.41	20.24	3.49	1.36
	Hannibal	-91.3544	39.7119	12.22	10.01	23.73	2.30	2.59
	Lock 22	-91.2489	39.6362	8.01	3.89	22.93	3.70	1.55
	St. Louis	-90.1798	38.6123	9.38	-4.09	40.03	9.15	0.78

Note: This table shows the locations of each water level gage and the mean, minimum, maximum, standard deviation and skewness of water level recorded at each gage, 2012 – 2022, excluding December, January, February, and March