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Economic Impacts of Lock Usage and Unavailability
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1. **Project Description**

Freight statistics should provide an objective baseline for transportation policy decisions, and national economic benefits of maritime transport necessitate improving inland waterways infrastructure. Proposed work included consolidating and learning from Lock Use, Performance, and Characteristics data collected by the US Army Corps of Engineers (USACE) and published by the Navigation Data Center. The objective is to estimate statistical models of annual tons locked by commodity group and lock, as a function of lock usage and unavailability (1993-2013), to discover knowledge of relationships between system disruption and economic consequences (commodity flow).

In 2010 cargo transported on the inland waterway system included more than half of all crude petroleum, and more than one third of all coal and other fuel oils, affecting efficiency of economic sectors that rely on energy. Inland waterways traffic is expected to increase 11% by 2020, from 2012.

> The greatest threats to the performance of the inland waterway system are the scheduled and unscheduled delays caused by insufficient funding for operation and maintenance needs of locks governing the traffic flow on the nation's inland system (American Society of Civil Engineers 2012, p. 6).

Lock Use, Performance, and Characteristics relate to economic impacts of US inland waterways usage and unavailability through annual tons locked by commodity at each of 193 different locks, over 54 waterways from Alabama to Willamette, Oregon. The data are current (updated February 2014), reliable and accurate (published by the Navigation Data Center), and ought to be mined for knowledge of relationships between system disruption and economic consequences. Analysis of existing data collected by USACE would seem like an efficiently gained and valuable addition to the national conversation about future financing for the inland waterways system.

The objective is to estimate annual tons locked by commodity group and lock, as a function of lock usage and unavailability (1993-2013). Usage data include average delay and processing time, barges empty and loaded, flotillas and vessels, lockages, and percent vessels delayed. Unavailability data include scheduled and unscheduled lock unavailabilities, and unavailable times. Estimation would require consolidation and statistical models of Lock Use, Performance, and Characteristics published by the USACE Navigation Data Center. Results would include effects of lock usage and unavailability on tons locked by commodity group (coal, petroleum, chemicals, crude materials, primary manufactured goods, food, and manufactured equipment).

In related literature Wilson, *et al.* (2011) quantified grain shipment delay costs on the Mississippi River. Fan and Wilson (2012) analyzed congestion for container imports with respect to ocean shipping and inland transportation networks. More recently Zhang, *et al.* (2015) analyzed Upper Mississippi River delay and lockage times to show the importance of modeling them separately.

2. **Methodological Approach**

Data for analysis were 1993 – 2013 Lock Use, Performance, and Characteristics; made publicly available online by the Navigation Data Center (February 2014), in the following form. Each of 193 locks had its own (3) commodity, delay and usage files. Therefore to create one master sheet we consolidated 193 (3) = 579 original files. The master sheet has 4053 rows which represent 193 locks by 21 years (1993-2013), 25 columns which represent variables (four delays, seven commodities, 14 usage). Multiplying columns by rows gives us 101,325 cells – or pieces of information – from which to learn.

Economic impact or performance is measured by annual commodity flow through an individual lock. Commodities are categorized and labeled with codes. The ones utilized here appear in Table 1. Independent variables used to control for lock usage – and lend greater credibility to significant significant and unscheduled delays – are the following.

- Average Delay and Processing Time
- Barges Empty and Loaded
- Non / Commercial Vessels, Flotillas, Lockages
- Non-vessel Lockages
- Percent vessels Delayed
- Recreational Vessels and Lockages

Independent variables of primary interest relate to scheduled and unscheduled unavailability.

- Scheduled Unavailabilities
- Scheduled Unavailable Time
- Unscheduled Unavailabilities
- Unscheduled Unavailable Time

Table 1. **Commodities**

Code	Label
10	Coal
20	Petroleum and Petroleum Products
30	Chemicals and Related Products
40	Crude materials except Fuels
50	Primary Manufactured Goods
60	Food and Farm Products
70	Manufacturing Equipment and Machinery

There was only one important problem related to missing data. Lockages are missing for 1993 – 1999. To solve this problem we created two separate paths and analyzed them separately.

1. Exclude Lockages, and include 1993 – 1999.
2. Exclude 1993 – 1999, and include Lockages.

Based on visual inspection of empirical distributions we assumed missing data related to scheduled unavailability should actually be zeros, and missing data related to unscheduled unavailability are truly missing (should remain blank). Finally on the topic of missing data we deleted the following commodities: Waste Material (80), and Unknown or Not Elsewhere Classified (90).

Three out of 54 waterways have 33 percent of the locks, so we focused this study on Mississippi, Ohio and Arkansas by creating 42 datasets for analysis (see Table 2): Commodity codes 10, 20, 30… 70; waterways Mississippi, Ohio and Arkansas; Paths 1 and 2 with respect to missing data, lockages and 1993 – 1999.

Table 2. Forty-two Datasets for Analysis

Commodities	Path 1	Path 2
Mississippi	10 – 70	10 – 70
Ohio	10 – 70	10 – 70
Arkansas	10 – 70	10 – 70

So results would be relatively easy to interpret we used (multiple) linear regression and systematically searched for models which are practically appropriate and efficient. Our definition of practically appropriate is the following. Constant error variance and lack of fit may be tested in case of repeat observations. Correlation coefficients were used with normal probability plots to test distribution assumptions. To be considered efficient a model included no insignificant variables. However we did not automatically delete insignificant variables – nor did we use stepwise regression – because we do not want to ignore the possibility of interaction.

For example assume $y = x_1 + x_2$ where x_1 is significant but x_2 is not in general. It is possible x_2 has a negative effect on y if $x_1 < z$, and x_2 has a positive effect of y if $x_1 > z$. In this case one should refit separate models $y = x_1 + x_2$ if $x_1 < z$, and $y = x_1 + x_2$ if $x_1 > z$. Therefore the following is our alternative to automatic deletion and stepwise regression.

1. Fit main effects model.
2. If insignificant main effects, explore interaction through the full second order model.
3. Delete insignificant main effects that do not participate in significant interaction terms, and refit main effects model.

4. If insignificant main effects do participate in significant interaction terms, take advantage by creating subsets.
5. Fit new main effects models of subsets (without previously deleted variables).

If multiple insignificant main effects do participate in significant interaction terms, create subsets based on the insignificant main effect that participates in the greatest number of significant interaction terms. To create subsets use a 2-means clustering algorithm to assign observations of the chosen main effect. If multiple insignificant main effects participate in the same number of interaction terms, create subsets that are most alike with respect to sample size.

3. **Results / Findings**

Twenty-two out of the 42 datasets resulted in at least one useful subset where we could employ our alternative to stepwise regression to find a linear model which is efficient and practically appropriate according to our definitions of those characteristics. Table 3 includes R^2 values associated with useful subsets, described by Commodity code 10, 20, 30… 70; waterway (MS, OH, Arkansas); and missing data path (1, 2). Values followed by asterisks are the greatest R^2 values among multiple useful subsets, within the same dataset.

Table 3. *R^2* Values Associated with Useful Subsets

Com	MS path 1	MS path 2	OH path 1	OH path 2	Ark path 1	Ark path 2
10	0.2261		0.6322	0.5620	0.5064	
20		0.3234	0.6528	0.8701*	0.4330	
30	0.6828	0.6587				
40	0.5481			0.8254	0.8730	
50		0.6594*			0.6362	0.6739
60		0.9235*	0.7982		0.8946	0.7367
70		0.2811		0.5763		

Also worth noting is how the 22 values in Table 3 can be distributed with respect to *strength* of regression if we adopt the following rules of thumb (Devore 2004). More than half of the 22 R^2 values indicate strong correlation (see Table 4).

- $R^2 < 0.25$ indicates weak correlation between expected values and observations used to fit the model.
- $R^2 > 0.64$ indicates strong correlation between expected values and observations used to fit the model.

Table 4. Distribution of R^2 Values

R^2	Count
Weak (0, 0.25)	1
Moderate (0.25, 0.64)	9
Strong (0.64, 1)	12

In order to draw conclusions based on the 22 models we look across them for consistent effects (+/-) with respect to unavailability. This (lack of) consistency is communicated in Table 5.

Table 5. Unavailability and Consistency

Consistency	Unscheduled	Scheduled
Unavailabilities	No (inconsistent signs)	Yes (consistently negative)
Unavailable Time	Yes (consistently negative)	No (inconsistent signs)

Effects of Scheduled Unavailable Time and Unscheduled Unavailabilities are inconsistent where they appear across the 22 models, with respect to sign (+/-), so we relegate those variables to control status and focus on the other two. Scheduled Unavailabilities and Unscheduled Unavailable Time are consistent where they appear across the 22 models, so we present those effects in some detail next, first with respect to Scheduled Unavailability.

- Based on a useful subset of Arkansas path 1, one Scheduled Unavailability is associated with decreasing 3714 tons of Food, controlling for Barges Empty and Loaded, Commercial Flotillas and Unscheduled Unavailabilities.
- Based on a useful subset of Ohio path 2, one Scheduled Unavailability is associated with decreasing 3970 tons of Crude Materials, controlling for Average Processing Time, Barges Empty and Loaded, Commercial Flotillas and Vessels.

The following tonnage decreases are associated with one Unscheduled Unavailable Hour based on various subsets of waterway path, controlling for other (significant) variables.

- 442 tons of Primary Manufactured Goods
- 482 tons of Chemicals
- 959 tons of Petroleum
- 933 tons of Food

4. **Impacts / Benefits of Implementation**

Soon we will extend this project to Climate Impacts on Lock Use and Performance. The objective of that work will be to integrate resilience planning and climate change preparedness for water-resource infrastructure. Statistical models of Climate Impacts on Lock Use and Performance should help DOT and USACE integrate Climate Change Adaptation with Lock Operations and Marine Services by quantifying fixed route infrastructure vulnerability.

5. **Recommendations and Conclusions**

In future work we want to consider uncertainty – not just point estimates – of consistent effects for better maintenance decisions. They should also address the boundaries of useful subsets and consider to what extent it may be appropriate to extrapolate. One way of doing this is fitting our final models outside of their useful subsets and analyzing goodness.

We have not proactively addressed multicollinearity, because it did not present a major obstacle to learning from data. However we know some of our variables are physically related, and interdependence might have decreased the available number of useful subsets. Further multicollinearity may be responsible for inconsistent results with respect to Scheduled Unavailable Time and Unscheduled Unavailabilities.

Future work may benefit from reorganizing locks according to district and division, operationally as opposed to naturally or physically as we have done here, and convergence toward useful subsets may be moved more quickly by using transformations *(e.g., natural logarithm of tons)*. Finally we want to compare and contrast our results to those of stepwise regression.

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