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Modeling Commodity Flow as a Statistical Function of Lock Unavailability and Usage

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An Undergraduate Honors College Thesis

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Abstract

The inland waterway system in the United States allows for the transportation of commodities, and interruptions to the system can have remarkable economic consequences. This research estimates statistical models of commodity flow as a function of lock usage and lock unavailability to discover relationships between system disruption and economic penalties. Findings specifically complement a portfolio of research conducted by the Maritime Transportation Research & Education Center (MarTREC) for the United States Army Corps of Engineers (USACE) to aid in decision making and resource planning for lock maintenance.

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Introduction

The General Survey Act of 1824 made navigation the earliest civil works mission of the United States Army Corps of Engineers (USACE) by authorizing and funding USACE to improve safety on the Mississippi and Ohio rivers (“Improving Transportation,” n.d.). To this day, USACE seeks to provide efficient, environmentally sustainable, reliable, and safe channels, harbors, and waterways in the United States (“Navigation,” n.d.). They work to operate and maintain this system of 239 locks on 25,000 miles of waterways which directly serve and support commerce in 41 states and more than 500,000 jobs (“2017 Infrastructure Report Card,” 2018).

Each year, approximately 600 million tons of commodities are transported along the inland waterway system, making up 14% of all domestic freight. The commodities delivered via waterway in 2015 were worth $229 billion. The U.S. agriculture industry and energy sectors are especially reliant on inland waterway transport which is the most fuel-efficient mode of ground transportation. Sixty percent of grain exports, 22% of domestic petroleum and 20% of coal are transported along inland waterways (“2017 Infrastructure Report Card,” 2018).

USACE is responsible for making maintenance decisions concerning waterway infrastructure, with the intention of minimizing delays caused by scheduled and unscheduled lock and dam closures. To maintain the current level of delays on the inland waterway system, USACE estimates an investment need of $4.9 billion over the next 20 years (“2017 Infrastructure Report Card,” 2018). For this reason, the American Society of Civil Engineers reported, “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” (“Failure to Act,” n.d.). Without adequate maintenance, vessel delays will increase, causing the economic attractiveness of inland waterway transport, as seen by shippers, to decline, and force shippers to seek more expensive but more reliable modes of transportation. This cost increase will be transferred to the end customer, potentially making U.S. shippers less competitive globally and impacting the nation's economy negatively.

Lock use, performance, and characteristics data are collected by USACE and published by the Navigation Data Center each year. The data include variables describing lock and dam use, commodity type, and tonnage transported ("Lock Use, Performance, and Characteristics," 2016). These data can be organized and analyzed to estimate the economic impact of inland waterway system delays or unavailability via its relationship to tonnage transported or commodity flow. This thesis describes modeling commodity flow as a statistical function of lock unavailability and usage, motivated by the goal to help USACE make better operations and maintenance decisions.

Background

To successfully maneuver boats, ships, and barges across the country, the inland waterway system utilizes locks and dams to facilitate smooth transportation along varying water levels. As displayed in Figure 1, a vessel first enters a lock chamber. Once the vessel is completely within the lock chamber, the rear gate closes. Then, a valve is opened to adjust the water level underneath the vessel as well as the water level of the following lock. Once a balance is reached, the gate separating the two locks will open and allow the vessel to travel into the subsequent lock. This process continues until the vessel reaches the end of the lock and dam system where it can continue traveling at the new water level (Lyng, Field, Lander, Cooper, & Carlson, 2008).

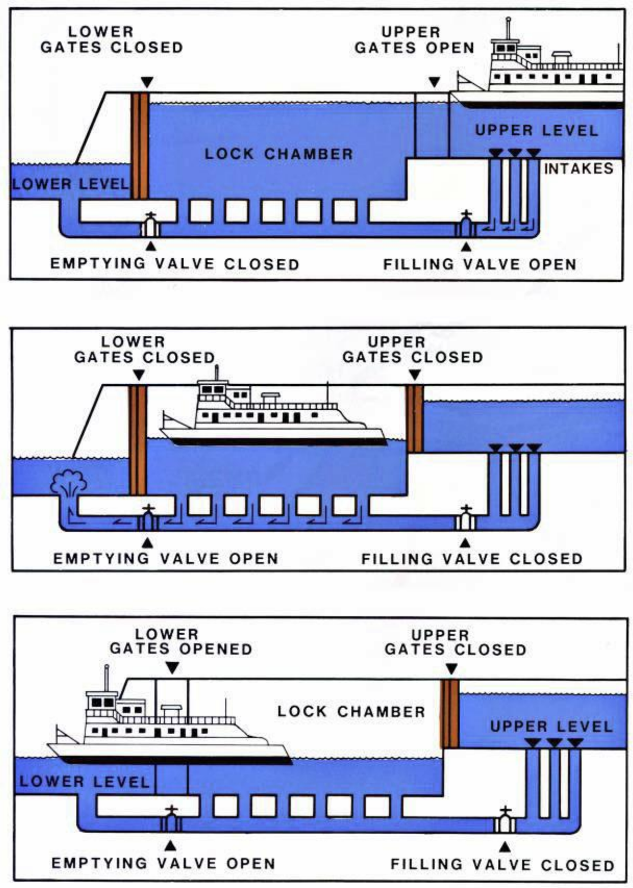

Figure 1 – Locks and dams facilitate transportation along varying water levels (Lyng, Field, Lander, Cooper, & Carlson, 2008).

Data

We estimated statistical models based on the lock use, performance, and characteristics data from 1993 to 2015 concerning 42 total locks located on the Arkansas (15 locks), Illinois (7 locks), and Ohio (20 locks) waterways which appear in Figure 2 ("Lock Use, Performance, and Characteristics," 2016).

Figure 2 – The inland waterways studied include the Arkansas, Illinois, and Ohio waterways (“Navigable Inland Waterways,” 2009).

The datasets were made up of 28 variables (See Appendix). Of those, we included 12 in our initial regression analysis. After considering vessels, flotillas, and lockages are physically related, we chose to include the variables related to vessels and disregard the variables concerning flotillas and lockages as vessels make up a fleet and more than one fleet (flotillas) make up a lockage.

Our analysis also included one newly created variable, Total Commodity Flow. As commodities travel on the inland waterway system, they are characterized by one of seven commodity types (See Appendix). Total Commodity Flow results from the summation of the seven different commodity types. Previous research analyzed tonnage of each commodity type rather than total tonnage as we did here (Chimka, 2016; Chimka, Fernandez De Luis, & McGee, 2018).

When working with the data, we noticed many blank cells which fell under Scheduled Unavailabilities (SU) and Unscheduled Unavailabilities (UU). To handle this, we assumed if SU was blank and UU was not blank for the corresponding lock, SU equaled zero. Similarly, if UU was blank and SU was not blank for the corresponding lock, UU equaled zero. However, if both SU and UU were blank for the same lock, they both remained blank.

Overview of Models

We classified the variables detailing delays as unavailability variables which include Scheduled Unavailabilities (SU), Scheduled Unavailable Time (SUT), Unscheduled Unavailabilities (UU), and Unscheduled Unavailable Time (UUT). The remaining variables are considered usage variables: Average Delay, Average Processing Time, Barges Empty, Barges Loaded, Commercial Vessels, Non-Commercial Vessels, Percent Vessels Delayed, and Recreational Vessels. Usage variables were thought of as controls and included in every initial model. Unavailability variables were treated separately from one another because they are interdependent and relatively important to this study as we hypothesized the unavailability variables would show a statistical correlation to the response variable, Total Commodity Flow.

For each of the three waterways (Arkansas, Illinois, and Ohio), we began by estimating four main effects multiple linear regression models. Each of the four models included a different unavailability variable and evaluated Total Commodity Flow versus unavailability and usage variables.

The resulting R-squared values are shown in Table 1. The R-squared values indicate there is a strong linear relationship between the observations of total commodity flow and expectations for total commodity flow based on the regression models. Since models across waterway are based on different sample sizes we include adjusted R-squared values in Table 2, and to indicate how well these models may predict new observations of the response we include predicted R-squared values in Table 3.

Table 1 – R-squared values associated with initial main effects models

R-squared	Scheduled Unavailabilities	Scheduled Unavailable Time	Unscheduled Unavailabilities	Unscheduled Unavailable Time
Arkansas	0.8392	0.8394	0.8392	0.8392
Ohio	0.9799	0.9782	0.9805	0.9799
Illinois	0.9943	0.9946	0.9947	0.9942

Table 2 – Adjusted R-squared values associated with initial main effects models

Adjusted R-squared	Scheduled Unavailabilities	Scheduled Unavailable Time	Unscheduled Unavailabilities	Unscheduled Unavailable Time
Arkansas	0.8334	0.8336	0.8333	0.8334
Ohio	0.9795	0.9775	0.9801	0.9795
Illinois	0.9940	0.9943	0.9944	0.9939

Table 3 – Predicted R-squared values associated with initial main effects models

Predicted R-squared	Scheduled Unavailabilities	Scheduled Unavailable Time	Unscheduled Unavailabilities	Unscheduled Unavailable Time
Arkansas	0.8169	0.8171	0.8166	0.8161
Ohio	0.9790	0.9764	0.9795	0.9789
Illinois	0.9928	0.9934	0.9932	0.9921

Interdependence

While we separated unavailability variables due to their interdependence or multicollinearity, we were also proactive about identifying interdependence among usage variables by considering each variable's Variance Inflation Factor (VIF) which quantifies to what extent an independent variable is a linear function of other independent variables. A VIF of one (1) indicates correlation between the predictor variable and remaining variables does not exist. However, a VIF greater than four (4) may indicate interdependence ("Detecting Multicollinearity Using Variance Inflation Factors," n.d.). The variables with a VIF greater than four, to be addressed, are shown in Table 4.

Table 4 – The table reflects variables with VIF values greater than 4 from each regression analysis.

	Scheduled Unavailabilities	**Scheduled Unavailable Time**	**Unscheduled Unavailabilities**	**Unscheduled Unavailable Time**
Arkansas	Barges Loaded	Barges Loaded	Barges Loaded	Barges Loaded
Ohio	Barges Empty Barges Loaded Comm. Vessels	Barges Empty Barges Loaded Comm. Vessels	Barges Empty Barges Loaded Comm. Vessels	Barges Empty Barges Loaded Comm. Vessels
Illinois	Barges Empty Barges Loaded	Barges Empty Barges Loaded	Barges Empty Barges Loaded	Barges Empty Barges Loaded

To address interdependence, we excluded the variable with the highest VIF for each waterway as shown in Table 5. For each waterway, the variable with the highest VIF was consistent across all four models: Scheduled Unavailabilities, Scheduled Unavailable Time, Unscheduled Unavailabilities, and Unscheduled Unavailable Time. We then performed a multiple linear regression analysis for the four models of the three waterways again, and they all resulted with every remaining variable having a VIF less than four.

Table 5 – For each waterway, one variable was excluded to reduce variance of the regression coefficients.

Waterway	**Exclusion**
Arkansas	Barges Loaded
Ohio	Barges Empty
Illinois	Barges Empty

Table 6 shows each waterway and its corresponding predictors for further modeling. The table does not include the unavailability variables (SU, SUT, UU, UUT), but each model will include one unavailability variable as a predictor and be the only difference among the four models concerning a waterway. For example, an Arkansas waterway model is a function of Average Delay, Average Processing Time, Barges Empty, Commercial Vessels, Non-Commercial Vessels, Percent Vessels Delayed, and Recreational Vessels along with Scheduled

Unavailabilities, Scheduled Unavailable Time, Unscheduled Unavailabilities, or Unscheduled Unavailable Time.

Table 6 – After addressing VIF, regression analysis continued for each waterway using the corresponding predictors listed.

	Arkansas	**Ohio**	**Illinois**
Average Delay	x	x	x
Average Processing Time	x	x	x
Barges Empty	x		
Barges Loaded		x	x
Commercial Vessels	x	x	x
Non-Commercial Vessels	x	x	x
Percent Vessels Delayed	x	x	x
Recreational Vessels	x	x	x

Interaction

Looking at the twelve (12) main effects models, all with VIF values less than 4, we identified the insignificant variables for each model. In the regression analysis, our null hypothesis assumes each variable is insignificant and therefore unrelated to the response variable (Total Commodity Flow), controlling for other variables in the model. However, if the variable's p-value is less than 0.05, we reject the null hypothesis and conclude the variable is statistically significant. Conversely, a p-value greater than 0.05 indicates failure to reject the null hypothesis, and the variable is insignificant. The resulting insignificant variables are shown in Table 7.

Table 7 – Each model contained multiple insignificant variables.

	Scheduled Unavailabilities	Scheduled Unavailable Time	Unscheduled Unavailabilities	Unscheduled Unavailable Time
Arkansas	* Non-Commercial Vessels * Scheduled Unavailabilities	* Non-Commercial Vessels * Scheduled Unavailable Time	* Non-Commercial Vessels * Unscheduled Unavailabilities	* Non-Commercial Vessels * Unscheduled Unavailable Time
Ohio	* Commercial Vessels * Non-Commercial Vessels * Scheduled Unavailabilities	* Commercial Vessels * Non-Commercial Vessels * Scheduled Unavailable Time	* Commercial Vessels * Non-Commercial Vessels	* Commercial Vessels * Non-Commercial Vessels * Unscheduled Unavailable Time
Illinois	* Average Delay * Non-Commercial Vessels * Percent Vessels Delayed * Scheduled Unavailabilities	* Average Delay * Non-Commercial Vessels * Percent Vessels Delayed	* Average Delay * Non-Commercial Vessels * Percent Vessels Delayed	* Average Delay * Non-Commercial Vessels * Percent Vessels Delayed * Unscheduled Unavailable Time

After identifying the insignificant main effects in each of the twelve models above, we estimated full second order models, and highlighted interactions involving insignificant main effects. If a variable proved insignificant in the main effects model and did not participate in significant interaction in the full second order model, the variable was deleted from the main effects. Table 8 is an iteration of Table **7** showing the deleted main effects in bold text. The three shaded cells within Table 8 are the only models with one variable which proved insignificant in the main effects model but participated in significant interaction in the full second order model.

Table 8 – Bolded variables proved insignificant in both the main effects model and full second order model.

	Scheduled Unavailabilities	Scheduled Unavailable Time	Unscheduled Unavailabilities	Unscheduled Unavailable Time
Arkansas	* Non-Commercial Vessels * Scheduled Unavailabilities	* Non-Commercial Vessels *** Scheduled Unavailable Time**	* Non-Commercial Vessels * Unscheduled Unavailabilities	* Non-Commercial Vessels * Unscheduled Unavailable Time
Ohio	* Commercial Vessels *** Non-Commercial Vessels** * Scheduled Unavailabilities	* Commercial Vessels * Non-Commercial Vessels * Scheduled Unavailable Time	* Commercial Vessels * Non-Commercial Vessels	* Commercial Vessels *** Non-Commercial Vessels** *** Unscheduled Unavailable Time**
Illinois	* Average Delay *** Non-Commercial Vessels** *** Percent Vessels Delayed** *** Scheduled Unavailabilities**	* Average Delay *** Non-Commercial Vessels** * Percent Vessels Delayed	* Average Delay * Non-Commercial Vessels *** Percent Vessels Delayed**	* Average Delay * Non-Commercial Vessels * Percent Vessels Delayed *** Unscheduled Unavailable Time**

As displayed in Table 8, Average Delay participated in significant interaction in the full second order model for Illinois' SU model. Because we are justified in dropping the most variables using the Illinois SU model, we chose to move forward by directing our focus to the model.

Within the Illinois SU model, Average Delay, Non-Commercial Vessels, Percent Vessels Delayed, and Scheduled Unavailabilities proved insignificant in the main effects model. In the following full second order model, Average Delay significantly interacted with Barges Loaded and Commercial Vessels while Non-Commercial Vessels, Percent Vessels Delayed, and Scheduled Unavailabilities did not participate in any significant interaction, confirming the variables' insignificance and eligibility to be excluded from the Illinois SU model. We reevaluated the Illinois SU main effects model, including only Average Delay, Average Processing Time, Barges Loaded, Commercial Vessels, and Recreational Vessels. The result proved Average Delay to, again, be insignificant. Following our process, we ran a full second order model which revealed significant interaction between Average Delay and Barges Loaded. This result caused us to further analyze the effect Barges Loaded has on Average Delay. We classified the Barges Loaded data as one of two groups: low level of Barges Loaded and high level of Barges Loaded. Using K-means clustering, the cutoff point between low level and high level was calculated to be 15,400. Therefore, all data points with Barges Loaded less than 15,400 were classified as low level of Barges Loaded and all data points with Barges Loaded greater than or equal to 15,400 were classified as high level of Barges Loaded. Using this information, we can refit two main effects models for Illinois SU: one using the low Barges Loaded dataset and one using the high Barges Loaded dataset.

Illinois and Scheduled Unavailabilities

A new main effects model was estimated with Illinois' remaining SU variables (Average Delay, Average Processing Time, Barges Loaded, Commercial Vessels, and Recreational Vessels), using only low level of Barges Loaded data points, a sample size of 129. The resulting model contained one insignificant variable, Average Delay. Continuing with another full second order model, all Average Delay interactions proved insignificant. Omitting Average Delay and creating another main effects model resulted in a model with only significant variables. This indicates the stopping point, as there are no more insignificant variables to address. The normal probability plot of the residuals confirmed our assumption of normally distributed data (Shapiro-Wilk W test for normal data p-value = 0.301).

Using the same process, we analyzed high level of Barges Loaded which included 32 observations. The resulting main effects model showed Average Delay and Commercial Vessels to be insignificant. Estimating a full second order model indicated the model is significant, but the p-value for every independent variable indicated insignificance. This inconsistency seems likely caused by interdependence. Returning to the main effects model, Commercial Vessels has the greatest VIF value at 3.10. We decided to omit Commercial Vessels and estimate another main effects model. The model showed Average Delay as the only insignificant variable. The following full second order model, again, indicated the model contained significance, but the p-value for every interaction indicated insignificance. Returning to the main effects model to omit the variable with the now highest VIF, we omitted Average Delay with a VIF of 1.32. The following main effects model, now only a function of Average Processing Time, Barges Loaded, and Recreational Vessels, showed only significant variables, indicating our stopping point. The normal probability plot of the results confirmed our assumption of normally distributed data (Shapiro-Wilk W test for normal data p-value = 0.558).

As shown in Table 9, the resulting coefficients for both the low barges loaded main effects model and the high barges loaded main effects model coincide in direction for Average Processing Time, Barges Loaded, and Recreational Vessels. Average Processing Time and Recreational Vessels have an inverse relationship with Total Commodity Flow, indicating an increased Average Processing Time and an increased number of Recreational Vessels will slow commodity flow through a lock. Commercial Vessels, in the low Barges Loaded model, also has a negatively correlated relationship with Total Commodity Flow. Barges Loaded has a direct relationship with Total Commodity Flow, indicating the more Barges Loaded passing through a lock, the more Total Commodity Flow passing through the lock. By studying the magnitude of each variable’s coefficient, we can understand which variables have the greatest impact on Total Commodity Flow. In the low Barges Loaded model, Average Processing Time has the greatest influence with a factor of 107,096, signifying decreasing Average Processing Time should be the top priority when trying to increase Total Commodity Flow.

Table 9 – Displayed are the coefficients in the final models of commodity flow.

Term	Barges loaded < 15400	Barges loaded > 15400
Constant	2,037,876	5,112,708
Average Processing Time	-107,096	-22,042.31
Barges Loaded	1671.3	1375.3
Commercial Vessels	-546	
Recreational Vessels	-315.4	-278.7

Finally, it is interesting to note how our results differ from those in Table 10, for the full range of barges loaded, returned by automatic procedures in Minitab statistical software (backward, forward and stepwise).

Table 10 – Displayed are the coefficients in the model returned by automatic procedures in Minitab.

Term	Full range of barges loaded
Constant	2,150,520
Average Processing Time	-42,400
Barges Empty	-279.4
Barges Loaded	1674.7
Percent Vessels Delayed	-7527
Recreational Vessels	-343.4
Scheduled Unavailabilities	-4736

Conclusions and Future Work

Our resulting equations allow us to better understand the relationships between variables and Total Commodity Flow and identify the key players which USACE should pay close attention to when aiming to increase commodity flow with limited maintenance funding. Our methods and procedures can be used to identify important factors concerning commodity flow on specific waterways.

Further research concerning this topic should refer to Table 8 and follow the same procedure as described above for each of the eleven other models. By eliminating insignificant variables and clustering when needed, more relationships between variables and Total Commodity Flow will be revealed. Researchers should investigate the similarities across unavailability variables for each waterway, to understand which variables commonly influence the waterway of study, regardless of unavailability variable.

Automatic procedures like stepwise regression produce different results compared to our methods that address interaction and can create subsets of the data (see Tables 9 and 10). It would be interesting to investigate these differences and better understand tradeoffs between the two modeling philosophies. Also, there are alternatives to addressing interdependence by deleting variables (e.g., partial least squares regression).

While this research studied the Arkansas, Ohio, and Illinois waterways, future work should expand into other waterways, potentially by focusing on the waterways needing most maintenance attention according to USACE. Continuing this work will only lead to more insights into the inland waterway transportation system, hopefully aiding the USACE in maintenance decision making.

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Appendix

Definitions of Provided Variables

Average Delay (Hours)	The average delay time, expressed in hours, for vessels which passed through a lock chamber
Average Processing Time (Hours)	The average time, expressed in hours, to completely process all vessels through a chamber
Barges Empty (#)	The total number of barges with no commodities which have passed through a lock chamber
Barges Loaded (#)	The total number of barges containing commodities passing through a lock chamber
Commercial Flotillas (#)	The total number of commercial flotillas (tows with barges or self-propelled vessels carrying commodity) passing through a lock chamber
Commercial Vessels (#)	The total number of commercial vessels (includes tows, cargo carrying vessels, commercial fishing boats, lightboats – tows without barges, ferries) passing through a lock chamber
Commercial Lockages (#)	The total number of lockages involving commercial vessels [A lockage is a transfer of a vessel(s) through a chamber in a single direction.] For flotillas entering a smaller lock, where a chamber is too narrow to fit the vessel and its barges through, the flotilla is separated in to several trips through the lock, with each carrying a portion of the total barges; each of these trips is called a cut.
Non-Commercial Vessels (#)	The total number of non-commercial vessels (including U.S. government vessels) passing through a lock chamber
Non-Commercial Flotillas (#)	The total number of non-commercial flotillas passing through a lock chamber
Non-Commercial Lockages (#)	The total number of lockages involving non-commercial vessels [A lockage is a transfer of a vessel(s) through a chamber in a single direction.]
Percent Vessels Delayed (%)	The percentage of all vessels experiencing a delay between the arrival point and start of lockage
Recreational Lockages (#)	The total number of lockages involving recreational vessels [A lockage is a transfer of a vessel(s) through a chamber in a single direction.]
Recreational Vessels (#)	The total number of recreational vessels passing through a lock chamber
Total Lockages (#)	The total number of lockages for all vessels (commercial, recreational and "other") passing through a lock chamber
Total Vessels (#)	The total number of vessels of all types (commercial, recreational and "other") passing through a lock chamber

Scheduled Unavailabilities (#)	The number of unavailabilities that are scheduled in advance [Generally, these appear in Notices to Navigation Interests published by USACE districts.]
Scheduled Unavailable Time (Hours)	The amount of scheduled unavailability time, expressed in hours, at a lock
Unscheduled Unavailabilities (#)	The number of unavailabilities that are not scheduled in advance
Unscheduled Unavailable Time (Hours)	The amount of unscheduled unavailability time, expressed in hours, at a lock
Unavailabilities (#)	The sum of scheduled and unscheduled unavailabilities
Unavailable Time (Hours)	The sum of scheduled and unscheduled unavailable time
10 (tonnage)	The commodity type associated with all coal, lignite, and coal coke commodities
20 (tonnage)	The commodity type associated with all petroleum and petroleum products
30 (tonnage)	The commodity type associated with all chemicals and related products
40 (tonnage)	The commodity type associated with all crude materials, inedible, except fuels
50 (tonnage)	The commodity type associated with all primary manufactured goods
60 (tonnage)	The commodity type associated with all food and farm products
70 (tonnage)	The commodity type associated with all manufactured equipment & machinery

(“Definition of Terms,” n.d.; “Navigation-Locks Definitions,” n.d.)