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Climate and Spatial Impacts on Lock Unavailability
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Justin R Chimka
University of Arkansas
4207 Bell Engineering Center
Fayetteville, AR 72701
479-575-7392

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University of Arkansas
4190 Bell Engineering Center
Fayetteville, AR 72701
479-575-6021

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1. **Project Description**

“It is the policy of USACE to integrate climate change preparedness and resilience planning and actions in all activities for the purpose of enhancing the resilience of our built and natural water-resource infrastructure (USACE Climate Preparedness and Resilience Policy Statement 2014).” Moreover, “climate impacts will affect DOT's strategic goals of safety, state of good repair and environmental sustainability (US DOT Climate Adaptation Plan 2014).” DOT Modal Administrations specified by Ensuring Transportation Infrastructure and System Resilience include MARAD and the Saint Lawrence Seaway Development Corporation which works to integrate Climate Change Adaptation with Planning, Engineering and Maintenance, Lock Operations and Marine Services. The US Global Change Research Program National Climate Assessment (2014) defines Transportation Sector components that are increasingly vulnerable to Climate Change, including fixed node infrastructure (ports), fixed route infrastructure (locks, canals/channels), and vehicles (ships, barges). Inland waterways may experience greater floods due to changing land-use patterns and precipitation, drought can lower vessel drafts, and less ice on navigable waterways could increase seasonal windows for passage.

One goal of this project was to provide guidance related to Climate Change for MarTREC. Maritime Stakeholders have also expressed interest in temporal aspects of lock unavailability. We have considered them here along with spatial impacts on unavailability as well.

2. **Methodological Approach**

Our project approach was to extend the linear regression methods and philosophies of MarTREC 5004 – Economic Impacts of Lock Usage and Unavailability – to statistically model Climate and Spatiotemporal Impacts on Lock Use and Performance (Chimka 2016). Lock Use, Performance, and Characteristics were last updated by the Navigation Data Center in July 2015, to include Public Lock Commodity, Usage and Unavailability Reports through 2014. They include annual tons locked by commodity group and lock, usage data including average delay and processing time, barges empty and loaded, flotillas and vessels, and unavailability data. The effect of unavailability (scheduled and unscheduled maintenance) on tons locked has been the focus of MarTREC 5004. Extended focus would be the effect of Climate and Spatiotemporal variables on tons locked and unscheduled unavailability data. A new Key Lock Report provides monthly totals of barge traffic and commodity tonnages on the inland waterways. National Centers for Environmental Information link to Climate Data Online including temperature and precipitation Annual Climatological Summaries by ZIP code, and forward looking statements in Climate Change literature may be used to extrapolate from statistical models of Lock Use and Performance. It is anticipated that datasets established and lessons learned from MarTREC 5004 could serve as a valuable starting point for this new research.

3. **Results / Findings**

Table 1 represents 48 attempts to model unscheduled unavailability as a function of Climate variables, Spatiotemporal variables, or Both – for waterways Arkansas, Illinois, Mississippi and Ohio. Dependent variables are Unscheduled Unavailabilities (**UU**), the square root of Unscheduled Unavailabilities (**$UU^{1/2}$**), Unscheduled Unavailable Time (**UUT**), and the square root of Unscheduled Unavailable Time (**$UUT^{1/2}$**).

Table 1. **Forty-eight** (48) **attempts to model unscheduled unavailability**

	Climate	Spatiotemporal	Both
Arkansas	UU, $UU^{1/2}$ UUT, $UUT^{1/2}$	UU, $UU^{1/2}$ UUT, $UUT^{1/2}$	UU, $UU^{1/2}$ UUT, $UUT^{1/2}$
Illinois	UU, $UU^{1/2}$ UUT, $UUT^{1/2}$	UU, $UU^{1/2}$ UUT, $UUT^{1/2}$	UU, $UU^{1/2}$ UUT, $UUT^{1/2}$
Mississippi	UU, $UU^{1/2}$ UUT, $UUT^{1/2}$	UU, $UU^{1/2}$ UUT, $UUT^{1/2}$	UU, $UU^{1/2}$ UUT, $UUT^{1/2}$
Ohio	UU, $UU^{1/2}$ UUT, $UUT^{1/2}$	UU, $UU^{1/2}$ UUT, $UUT^{1/2}$	UU, $UU^{1/2}$ UUT, $UUT^{1/2}$

Climate variables are Average Temperature (**Temp**), Range of Temperature (**Range**), Snow (**Snow**), and Other Precipitation (**Other**). Spatiotemporal variables are – as defined by the dependent variable – UU, $UU^{1/2}$, UUT, or $UUT^{1/2}$ last year (**Lag**), upstream (**Up**), and downstream (**Down**). Every attempt to model unscheduled unavailability included its scheduled counterpart among regressors: Models of Unscheduled Unavailabilities (UU and $UU^{1/2}$) could be a function of Scheduled Unavailabilities (**SU**), and models of Unscheduled Unavailable Time (UUT and $UUT^{1/2}$) could be a function of Scheduled Unavailable Time (**SUT**).

In Tables 2 through 5 we have summarized regression models of unscheduled unavailability. Insignificant is code for an initial attempt at estimation which resulted in an insignificant main effects model ($p > 005$). Interaction is code for attempts at estimation that finally resulted in some regressors that could not be dropped due to significant interaction with other regressors. Interdependence is code for an initial attempt which resulted in a significant model with no significant main effects, the classic indication for independence or multicollinearity among independent variables. Remaining cells inside Tables 2 through 5 show significant independent variables in models that include only other significant variables. And in every case but one the significant variable has a positive coefficient; the regressor **Up** has a negative coefficient in an Illinois regression model of $UU^{1/2}$.

Table 2. **Arkansas regression models of unscheduled unavailability**

Arkansas	Climate	Spatiotemporal	Both
UU	Insignificant	Interaction	Interaction
$UU^{1/2}$	Insignificant	Interaction	Interaction
UUT	Interaction	**Lag**, **Up**, **Down**	Interaction
$UUT^{1/2}$	Interaction	Interaction	Interaction

Table 3. **Illinois regression models of unscheduled unavailability**

Illinois	Climate	Spatiotemporal	Both
UU	Insignificant	**Lag**, **Down**	**Lag, Down**
$UU^{1/2}$	Insignificant	**Lag**	**Lag**, (**Up**)
UUT	Insignificant	Insignificant	Insignificant
$UUT^{1/2}$	Insignificant	Insignificant	Insignificant

Table 4. **Mississippi regression models of unscheduled unavailability**

Mississippi	Climate	Spatiotemporal	Both
UU	**Temp**, **Range**, **Snow**, **Other**, **SU**	**Lag**, **Up**, **Down**, **SU**	Interaction
$UU^{1/2}$	**Temp**, **Range**, **Snow**, **Other**, **SU**	**Lag**, **Up**, **Down**	**Range**, **Lag**, **Up**, **Down**
UUT	Interdependence	**Lag**, **Up**, **Down**	**Lag, Up**
$UUT^{1/2}$	Interdependence	**Lag**, **Up**, **Down**	**Lag**, **Up**

Table 5. **Ohio regression models of unscheduled unavailability**

Ohio	Climate	Spatiotemporal	Both
UU	Interaction	**Lag, Up**, **Down**	**Lag**
$UU^{1/2}$	Interaction	Interaction	**Lag**, **Up**
UUT	Insignificant	Interaction	**Lag**
$UUT^{1/2}$	Insignificant	Interaction	**Lag**

We focus next on the significant Mississippi regression model of Unscheduled Unavailabilities (**UU**) where all Climate variables are significant (**Temp**, **Range**, **Snow**, **Other**) controlling for Scheduled Unavailabilities (**SU**, which is also significant). Sample size n = 696, and R^2 = 0.4093 which indicates moderate correlation between predictions and associated observations used to fit the model. In Table 6 are coefficient estimates associated with the independent variables. Here we can see how additional Unscheduled Unavailabilities may be expected to come with increasing temperatures, increasing variation in temperatures, and increasing precipitation both snow and other. It is also worth noting these results are controlling for Scheduled Unavailabilities which did not seem to mitigate the need for Unscheduled Unavailabilities. These results are replicated in the similar model of $UU^{1/2}$, and Range has the same effect on Mississippi controlling for Spatiotemporal variables.

Table 6. **Example**: **Unscheduled Unavailabilities versus Climate Variables**

Independent variable	Regression coefficient
Average Temperature (**Temp**)	1.404
Range of Temperature (**Range**)	0.872
Snow (**Snow**)	5.24
Other Precipitation (**Other**)	11.03
Scheduled Unavailabilities (**SU**)	1.143

Compared to Climate variables, much more variation in unavailability seems to be explained by Spatiotemporal variables. They were found to be significant in greater than half of all regression models where Spatiotemporal variables are available as regressors. Most notably, in every model where Spatiotemporal variables are significant the Temporal variable **Lag** is significant with a positive effect. In other words locks with a lot of unscheduled unavailability tend to stay that way, and vice versa. Also in nine (9) of the 17 models where **Lag** is significant the Spatial variable **Down** is significant with a positive coefficient; locks with a lot of unscheduled unavailability tend to have locks downstream from them with a lot of unscheduled unavailability.

Focusing our attention on the significant Mississippi regression model of Unscheduled Unavailabilities (UU) where all Spatiotemporal variables are significant (**Lag**, **Up**, **Down**) controlling for Scheduled Unavailabilities (**SU**, which is also significant): Sample size $n = 696$, and $R^2 = 0.7461$, so the model explains almost 75% of the variation in Unscheduled Unavailabilities. In Table7 are coefficient estimates associated with the independent variables. Here we can see how additional Unscheduled Unavailabilities may be expected to come with increasing Unscheduled Unavailabilities last year (**Lag**), upstream (**Up**) and downstream (**Down**). It is again worth noting these results are controlling for Scheduled Unavailabilities which did not seem to mitigate the need for Unscheduled Unavailabilities.

Table 7. **Example**: **Unscheduled Unavailabilities versus Spatiotemporal Variables**

Independent variable	Regression coefficient
UU last year (**Lag**)	0.697
UU upstream (**Up**)	0.1038
UU downstream (**Down**)	0.1468
Scheduled Unavailabilities (**SU**)	0.349

4. **Impacts / Benefits of Implementation**

We look forward to Learning from USACE Open Data for Locks in activities for MarTREC.

In August 2017 the US Army Corps of Engineers (USACE) began to enable unprecedented data access by publishing its USACE Open Data for Navigation online. Pages dedicated to dredging, waterborne commerce, ports and waterways are coming soon, but USACE Open Data for Locks has already brought together Lock Performance Monitoring Systems (LPMS) in an exciting way. In addition to creating new opportunities for leveraging old LPMS datasets USACE Open Data for Locks includes the following highlights.

- Corps Locks Queue Archive, historic queue data in the format displayed at the original Corps Locks website, and

- Public Lock Unavailability Detailed Report which describes stoppages not only in terms of downtime and whether or not it was planned, but also in terms of what caused the downtime.

5. **Recommendations and Conclusions**

Statistical models of Climate Impacts on Lock Use and Performance could help DOT and USACE integrate Climate Change Adaptation with Lock Operations and Marine Services by quantifying fixed route infrastructure vulnerability. As it is USACE policy to integrate Climate Change in activities for enhancing resilience our results may provide guidance related to Climate Change for MarTREC, its current contacts and stakeholders at DOT and USACE, researchers and educators. Lessons learned from this project will hopefully benefit and support ongoing Center activities such as MarTREC 5005 – Supporting Secure and Resilient Inland Waterways – and its dredge related projects which deal with environmental windows and weather patterns. Finally research into increasing seasonal windows for passage would be related to any future Center research into Panama Canal Expansion.

In conclusion we observed the following.

- Much variation in unavailability is explained by Spatiotemporal variables. They were found to be significant in greater than half of all regression models where Spatiotemporal variables are available as regressors: In every model where Spatiotemporal variables are significant the Temporal variable **Lag** is significant with a positive effect, and in most models where **Lag** is significant the Spatial variable **Down** is also significant with a positive coefficient. In other words the scale of unscheduled unavailability seems consistent in space (upstream and downstream) and time (year to year).
- Greater numbers of Unscheduled Unavailabilities were consistently observed with increasing temperatures, increasing variation in temperatures, and increasing precipitation both snow and other. These consistent results were observed controlling for either Scheduled

Unavailabilities or Spatiotemporal variables making them unlikely to have confounded our results related to climate.

- Finally and perhaps surprisingly when scheduled unavailability appears to be significant it comes with a positive coefficient. This suggests locks that experience a lot of unscheduled unavailability experience a lot of scheduled unavailability also. We did not observe in this study evidence that scheduled unavailability has any mitigating effect on unscheduled unavailability.

References

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