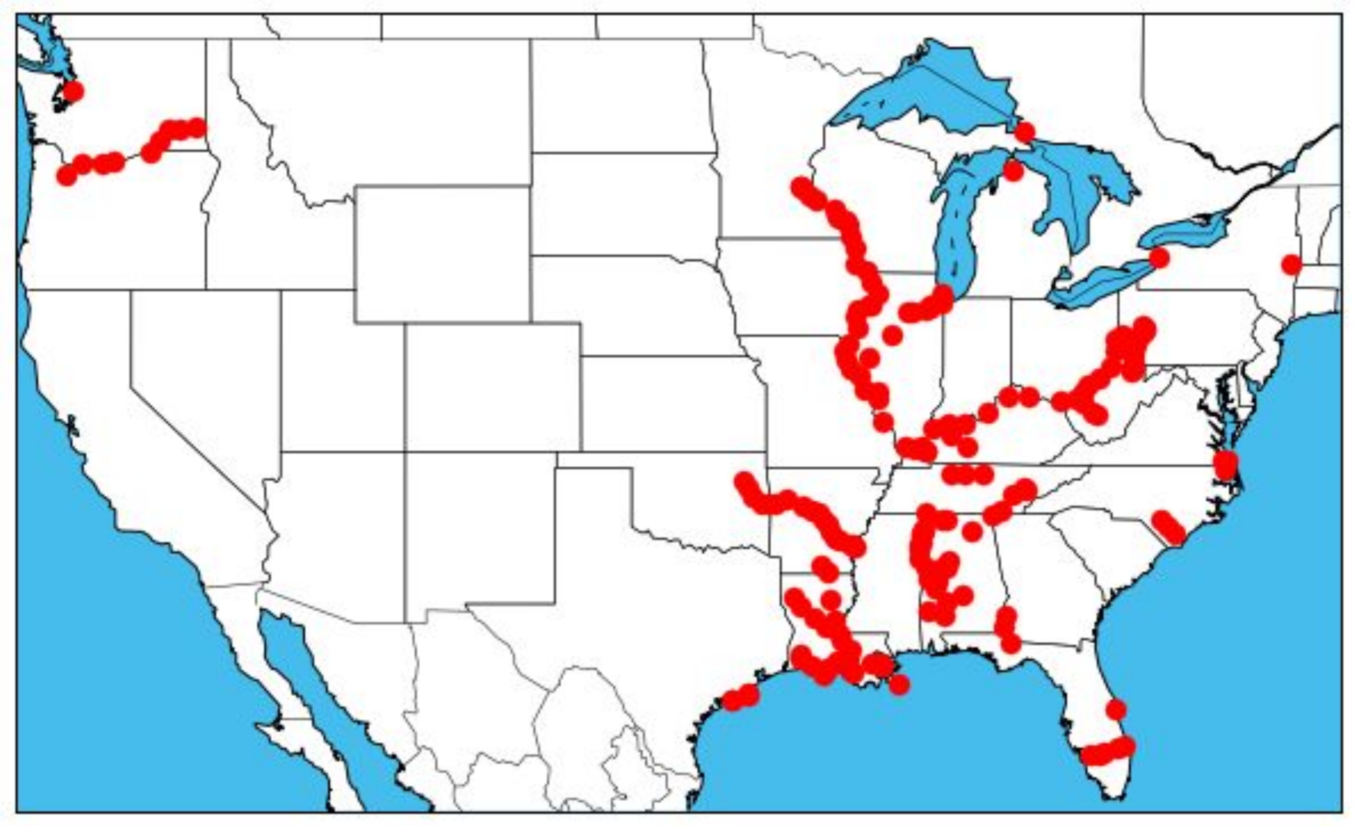
Predicting Vessel Delays at Army Corps of Engineers Locks

A Machine Learning Classification Study

Cargo vessel traffic on US waterways and through US Army Corps of Engineers-managed locks plays an important role in the transport of foreign and domestic goods into and out of the United States.

Lock and Dam 1, Minneapolis. Photo by Patrick Loch.
http://www.mvp.usace.army.mil/Media/Images/igphoto/2001935893/



Locations of 196 locks owned or managed by the US Army Corps of Engineers and monitored with the Lock Performance Monitoring System (LPMS).

Goal: to determine what factors predict extended vessel delays at locks.

US Army Corps of Engineers

IWR: Institute of Water Resources

NDC: Navigation and Civil Works Decision Support Center

LPMS: Lock Performance Management System

Maintain Data for:

- Waterborne commerce
- Vessel Characteristics
- Navigation locks data
- Commodity and Transport data

US Army Corps of Engineers

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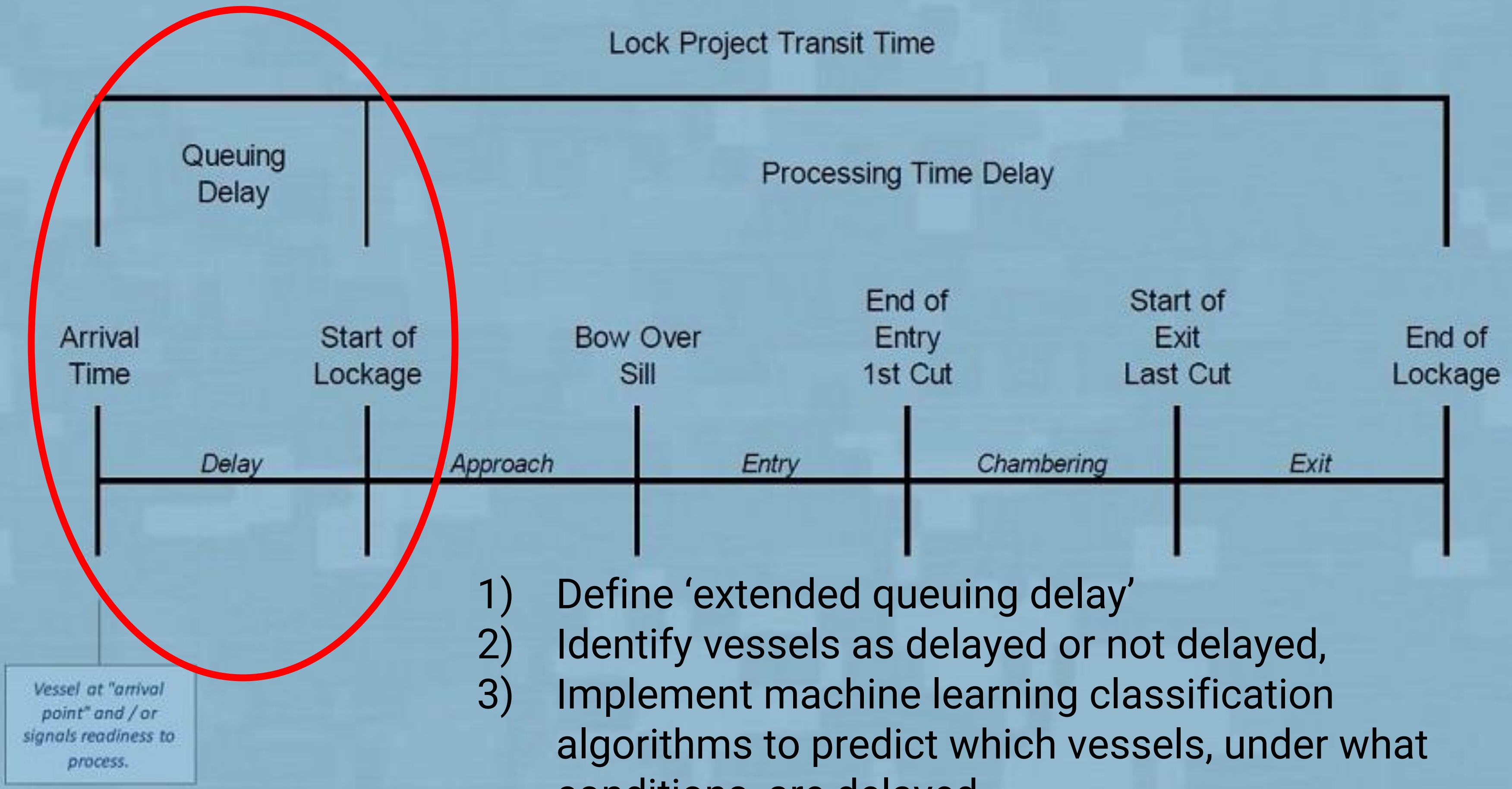
LPMS Analysis Request:

- Deeper analysis of the national network of waterway locks
- Explore relationships relevant to budgeting, maintenance, scheduling.
- Identify factors causing delays at locks.



1) Define ‘extended queuing delay’
2) Identify vessels as delayed or not delayed,
3) Implement machine learning classification algorithms to predict which vessels, under what conditions, are delayed.

LPMS Data Details

Vessel Traffic Table:

- Limit to 5 years
- Random subsample
- Vessel, River, Lock IDs
- Vessel Function Types
- Lockage Types
- Time marks during lockage
- Calculated: Delay Time

Stall Stoppage Table:

- Limit to 5 years
- Vessel, River, Lock IDs
- Begin/End Stop Dates
- Scheduled Stop or not?
- Reason Code for Stops
- Calculated: Duration of Stop

LPMS Data & NOAA Weather Data

Daily Summaries at 7 nearby weather stations:

- Min/Max Temp
- Precipitation
- Wind speeds
- Presence/Absence of 19 extreme weather types.

Define Extreme Delay

15% of vessels are delayed awaiting lockage

Define 'delay' on a lock-by-lock basis:

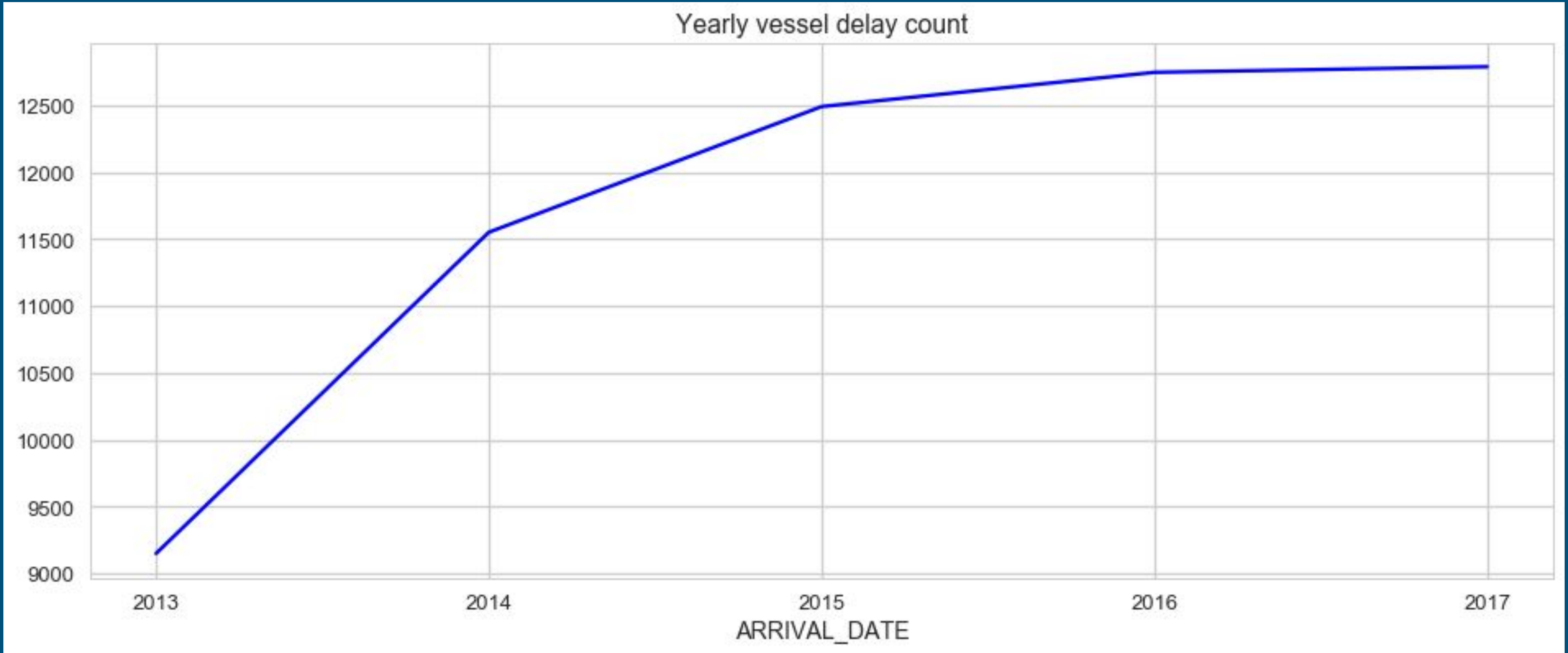
- True delay: duration greater than 75th percentile/lock.
- False delay: delay-time less than 75th percentile/lock.
- Extreme delay ranges from minutes to 29 hours.

Unplanned Stall Stoppage Metric

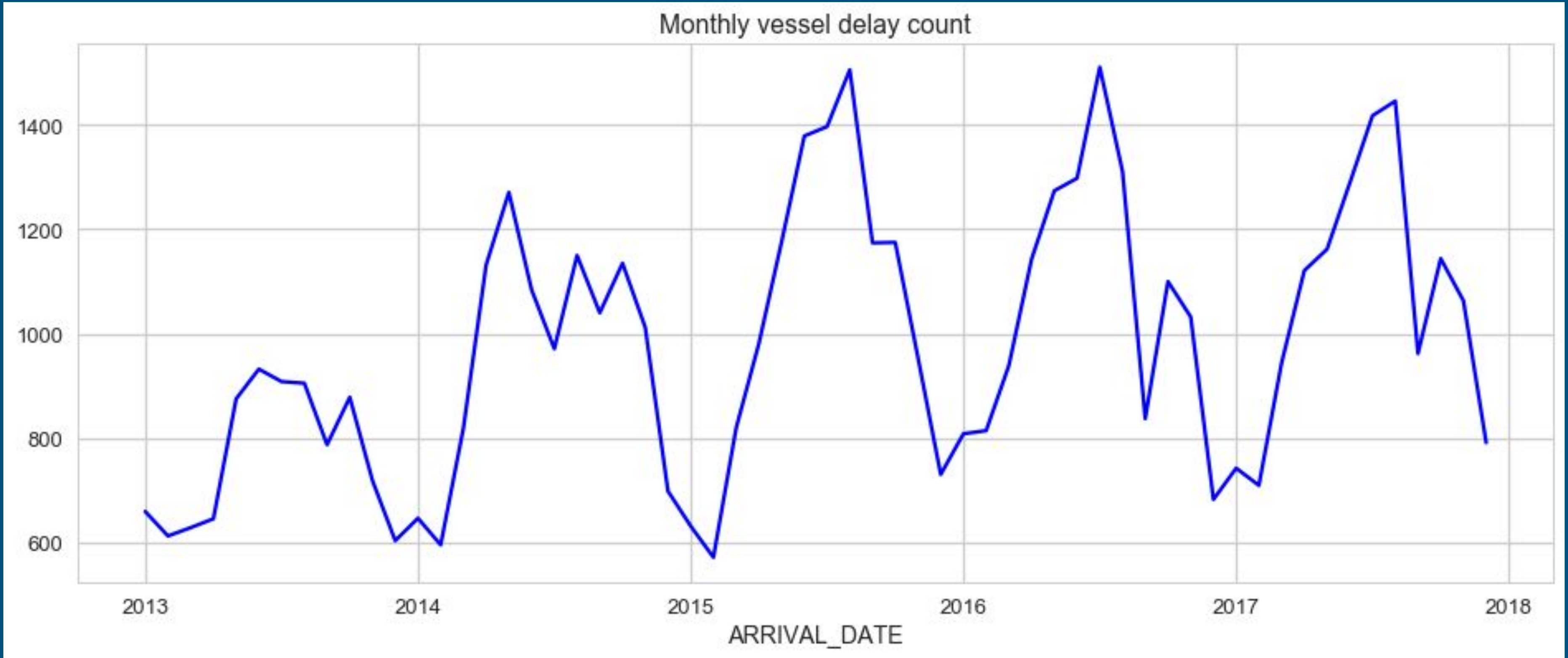
Average duration of unplanned stops: 24 hours

Stall Stoppage Data:

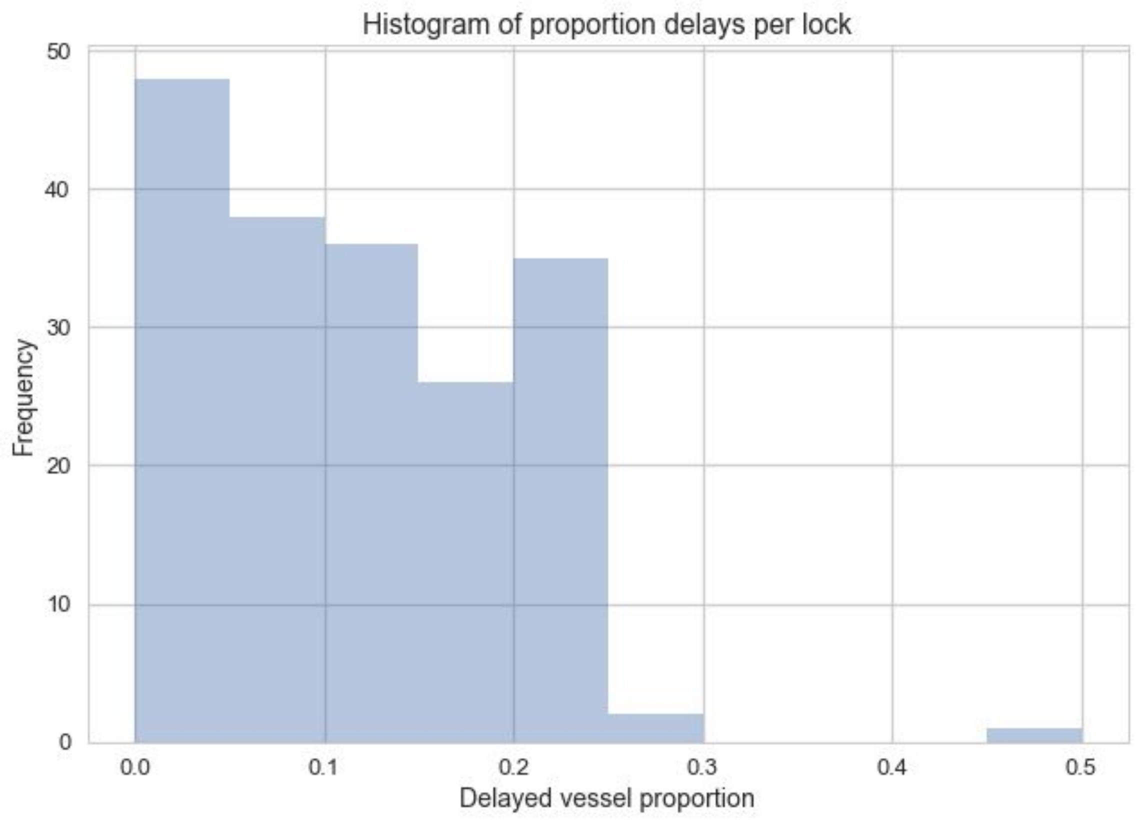
- Removed vessel records where there was a ‘Scheduled’ stop on a day.
- Included maximum duration of unplanned stops at a lock/day.
- Longest unplanned stoppage in 5-year study was 3 months long.



Overall extreme-delay counts are increasing



Extreme-delay counts have a seasonal pattern with fewer delays, and perhaps less vessel traffic during the colder seasons.



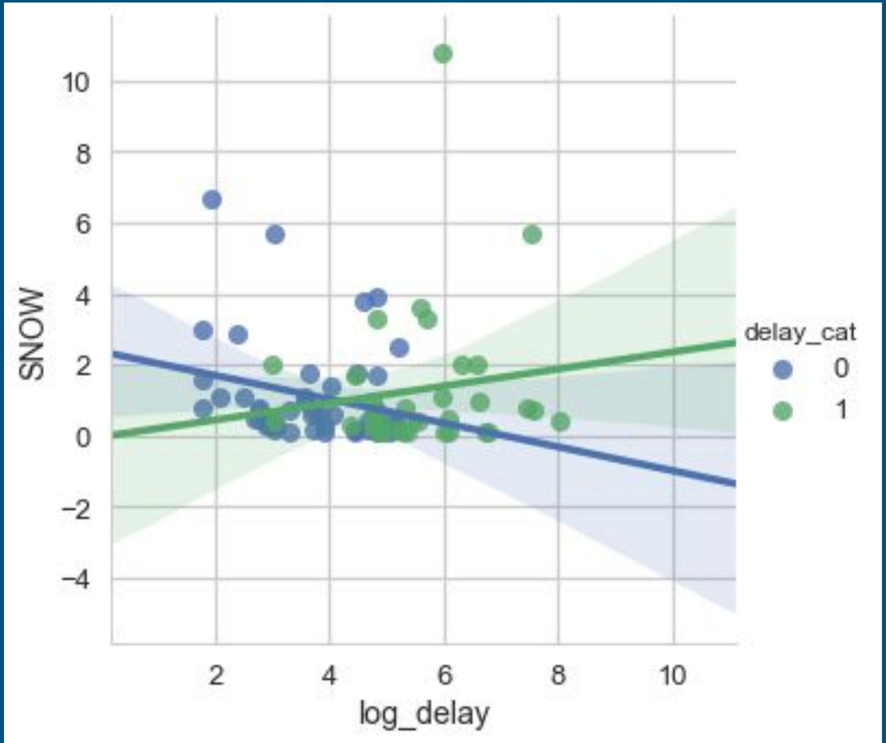
The distribution of delay proportions for locks.

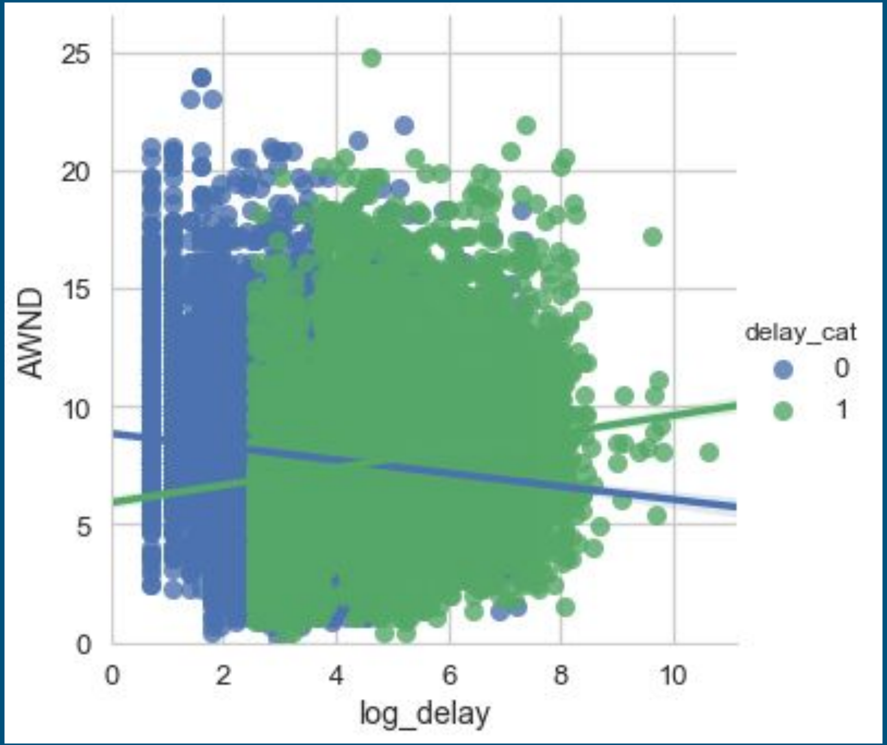
- Determined the artificial cut-off for 'low' and 'high' proportions of delays
- Dropped all locks with delay proportions less than 0.15 from the pool of locks for machine learning.
- Selected 'focal locks' from locks with high vessel traffic & proportion delayed.

Locations of 10 focal locks located in 5 states: Texas (3 locks), Indiana (1), Illinois (1), Louisiana (4 locks — two pairs of locks), and Washington (1).

Focal Lock Data:

- One vessel per day per lock.
- Kept delayed vessels in data.
- 8435 non-delays
- 7103 delays





Snowfall depth and average wind speed may have linear relationships by delay-type, but differences are not meaningfully different between the groups.

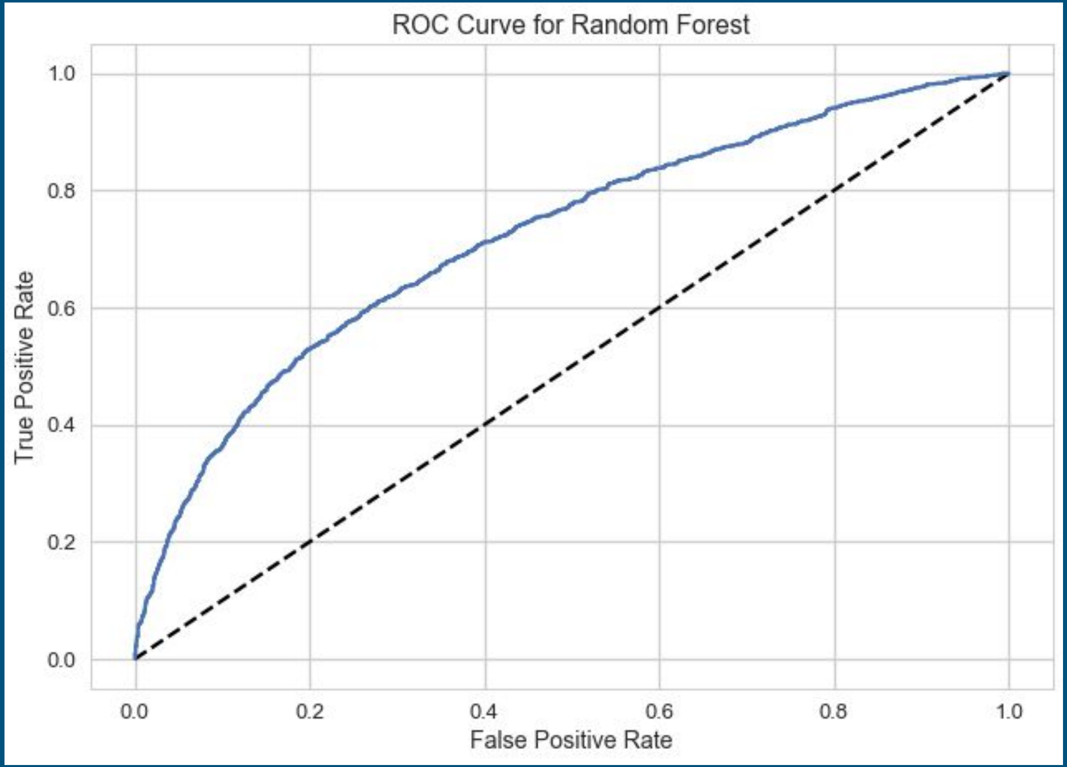
Classifying vessels: extreme delays

- Machine Learning Approach: supervised learning classification problem.
- Binary target variable (y): ‘delay’ as defined in EDA steps.
- Feature groups:
  - Lock or vessel related
  - Weather metrics
  - Date & Time derived features
- Matrix of predictive features:
  - 44 features
  - 11 continuous variables
  - 33 binary, including dummy variables for categorical variables.

Model Selection

Compare: Logistic Regression and Random Forest Classifier

- Model 10 focal locks
- Scaled & standardized continuous variables
- Explore models after Recursive Feature Elimination
- Examine feature importances
- Model individual locks separately
- Compare models with ROC-AUC scores



Random Forest Classifier with Grid Search Cross Validation, Full Focal Lock Dataframe, ROC-AUC = 0.729

Important Features for Predicting Delays

Feature Name	Importance
Average Wind Speed	0.1202
Temperature Minimum	0.1151
Temperature Maximum	0.1120
Fastest 5-second wind speed	0.1011
Fastest 2-minute wind speed	0.0898
Temperature Average	0.0628
Precipitation	0.0508
Night	0.0262

Recommendations

USACE:

1. Weather and Time variables most influential.
2. Revist management plans, update procedures.
3. Advise vessel operators based on forecast & known heavy traffic days.
4. Provide delay-time estimates.

Stakeholders:

1. Incorporate weather and vessel traffic during route planning.
2. Use per-lock definition of extreme delay to estimate queuing delays under different conditions.

Caveats & Future Directions

Future Use:

- LPMS data are rich in additional variables: e.g., barge number, flotilla metrics, chamber types.
- Other target variables: e.g., predict scheduled/unscheduled stalls, maintenance.
- Linear Regression to predict lockage duration.

Deployment Possibilities:

- Real-time delay tool for managers and stakeholders.
- Adjust model over time based on economic/climatological factors.
- Include sensor metri (e.g., precision/recall) to detect change below certain level, retrain model.
- Tool would reduce travel time & expense for stakeholders.