PIGGING PRODUCTS & SERVICES ASSOCIATION

VIRTUAL ILI – PREDICTING THE RESULTS OF AN IN-LINE INSPECTION

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PRESENTATION AUTHORS

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PRESENTATION OVERVIEW

- Virtual ILI
- Supervised Machine Learning
- Model Training & Performance
- Conclusions
- Questions

IMAGINE

ILI results with:

No changes in pressure or flow

IMAGINE

ILI results with:

No opening launchers or receivers

IMAGINE

ILI results with:
No spoilt product

IMAGINE

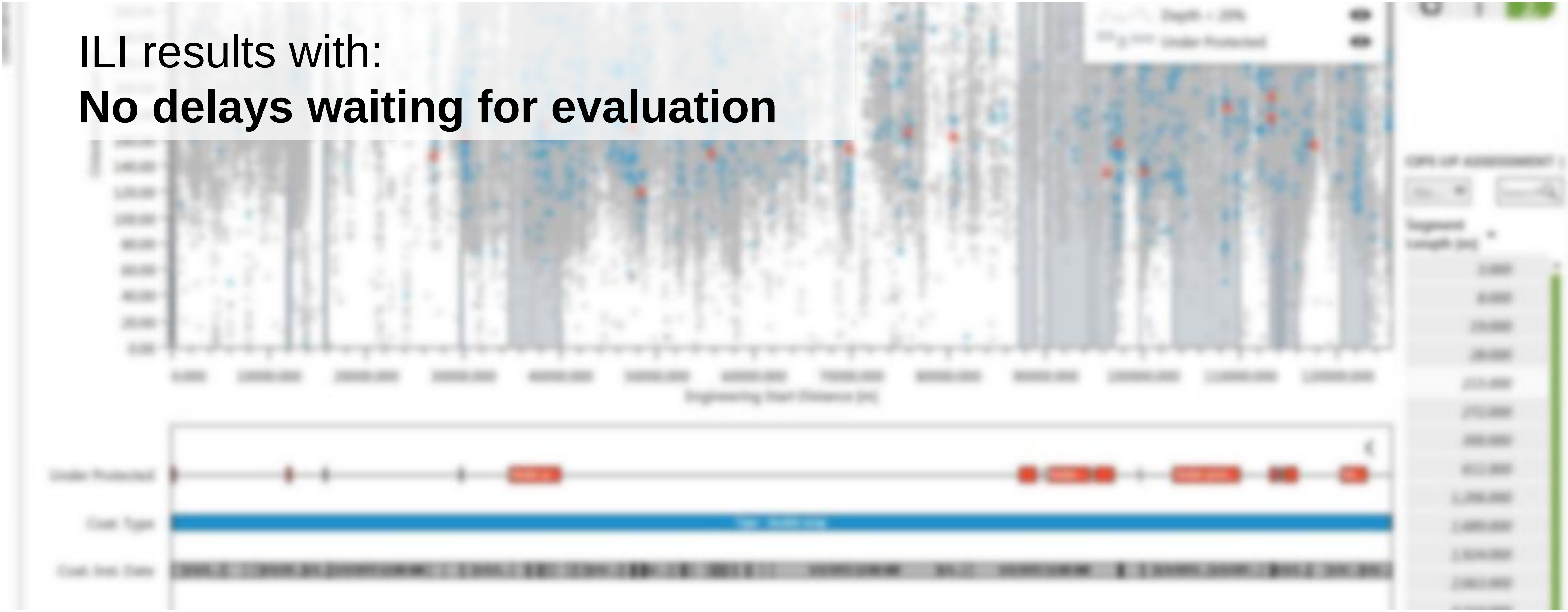
ILI results with:

No pig tracking

IMAGINE

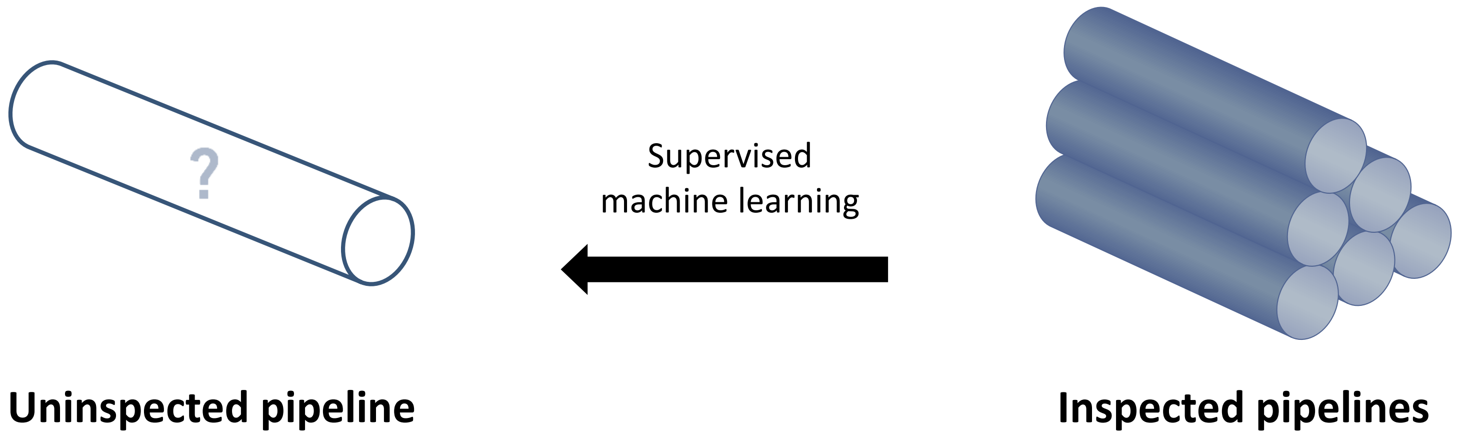
ILI results with:

No delays waiting for evaluation



VIRTUAL ILI

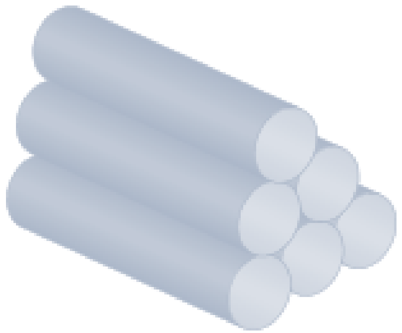
VIRTUAL ILI



Can we predict what we might expect to find in an uninspected pipeline using data and trends observed from inspected pipelines?

VIRTUAL ILI

Supervised machine learning using ILI results enriched with additional data to predict useful "condition metrics" for a pipeline



- **In-line inspection (ILI)**
  (metal loss, cracking, dents ...)
- **Design and construction**
  (construction year, coating type...)
- **Environment**
  (soil properties, land use, climate...)
- **Cathodic protection**
  (test post measurements)

VIRTUAL ILI

Pipeline condition class: *low* resolution

True Class

Predicted Class	L	M	H	VH
L	185	59	21	6
M	65	177	73	16
H	14	53	109	31
VH	4	14	26	62

Class	Anomaly density (mile^{-1})
Low	≤ 1
Moderate	(1, 10]
High	(10, 100]
Very high	> 100

VIRTUAL ILI

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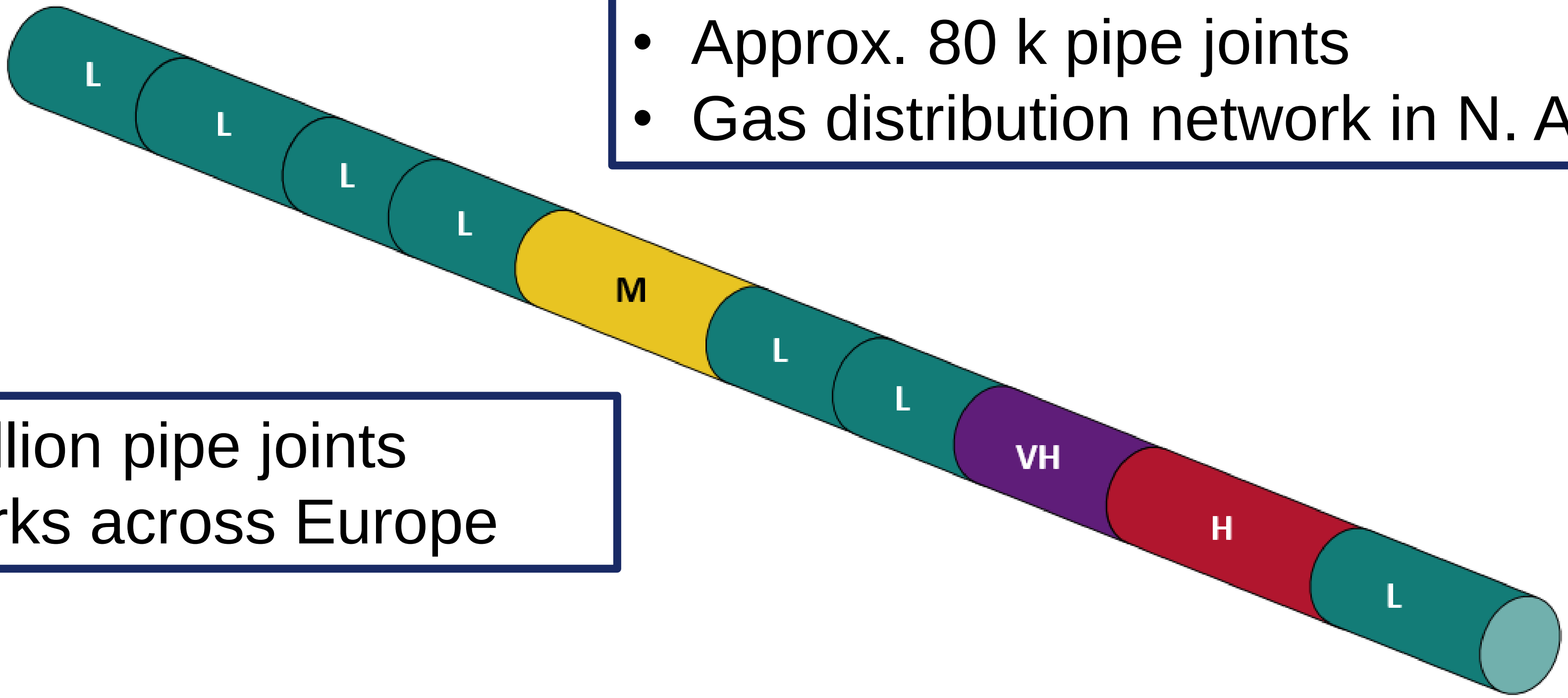
Pipe joint condition prediction: *high*-resolution model for external corrosion

- Approx. 80 k pipe joints
- Gas distribution network in N. America



- Approx. 3.5 million pipe joints
- Multiple networks across Europe

DATA PREPARATION

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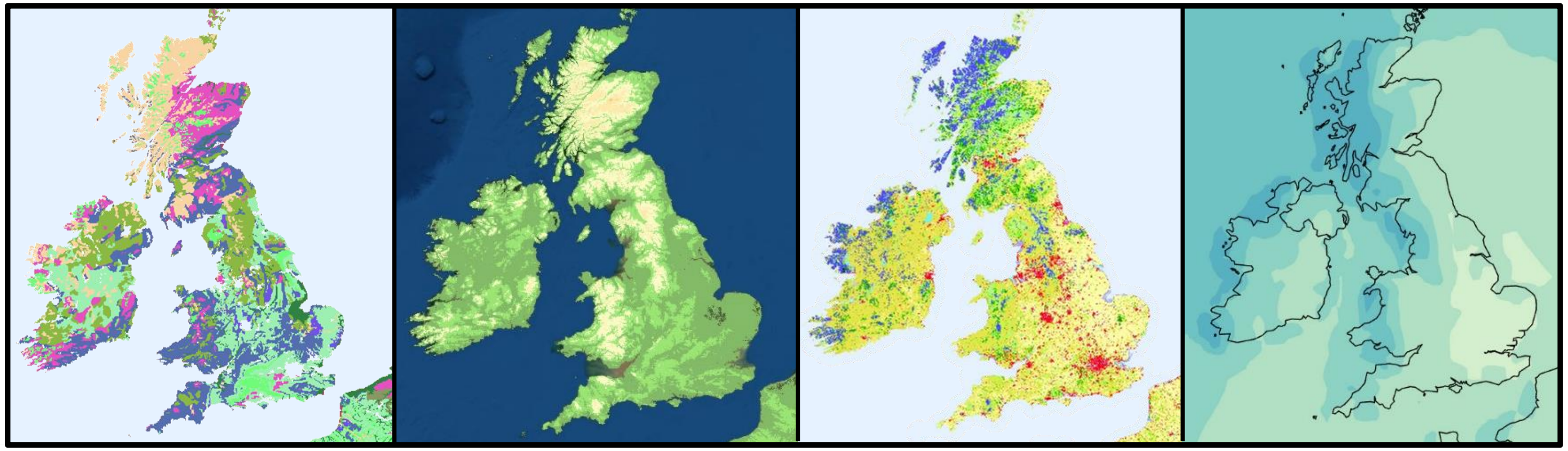
- ILI anomaly records
- Design and construction information
- Open-source geospatial datasets

Number of pipeline sections	755
Number of pipe joints	3,443,896
Inspection date range	2010–2020
Number of external corrosion anomalies	1,157,386

Soil Type **Elevation** **Land Use** **Precipitation**



SUPERVISED MACHINE LEARNING

- The science of getting computers to learn without being explicitly programmed

- The computer is trained using well-labeled data to generate predictive models

SUPERVISED MACHINE LEARNING

A function, *f*, is defined that maps a set of predictor variables, $\{x_i\}$, to a target variable, *y:*

$$y = f(x_1, x_2, \cdots, x_n)$$

Predictor variables

- Installation year
- Coating type (pipe body and field joint)
- Pipe grade
- CP potential
- Annual precipitation (rainfall and snowfall)
- Intersections (roads, railways, power lines)
- Terrain (elevation, slope, aspect)
- Soil properties (type, chemistry, drainage)

SUPERVISED MACHINE LEARNING

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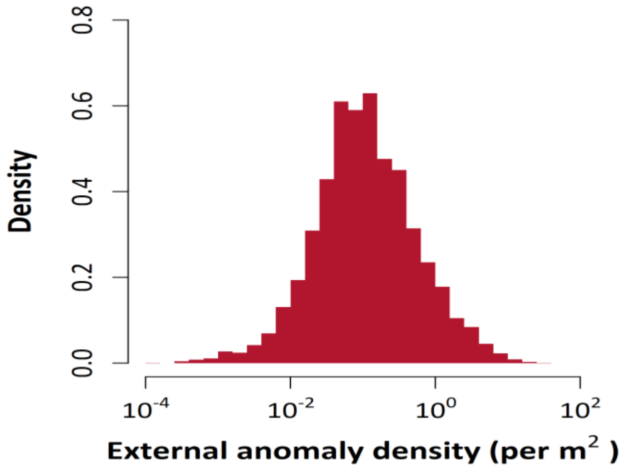
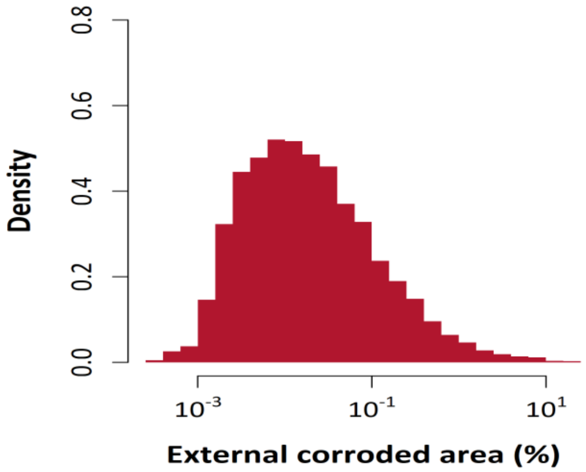
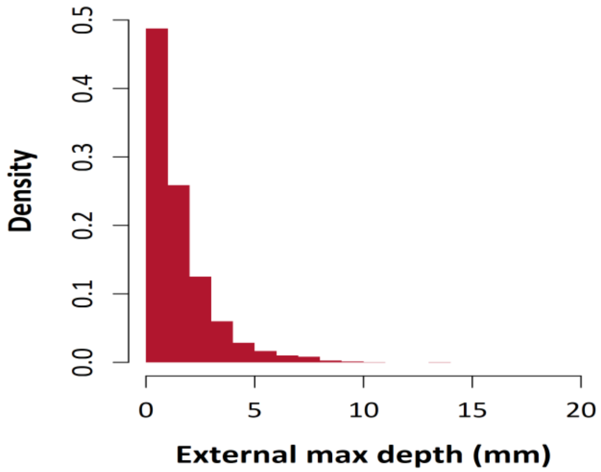
$$y = f(x_1, x_2, \cdots, x_n)$$

Target variable

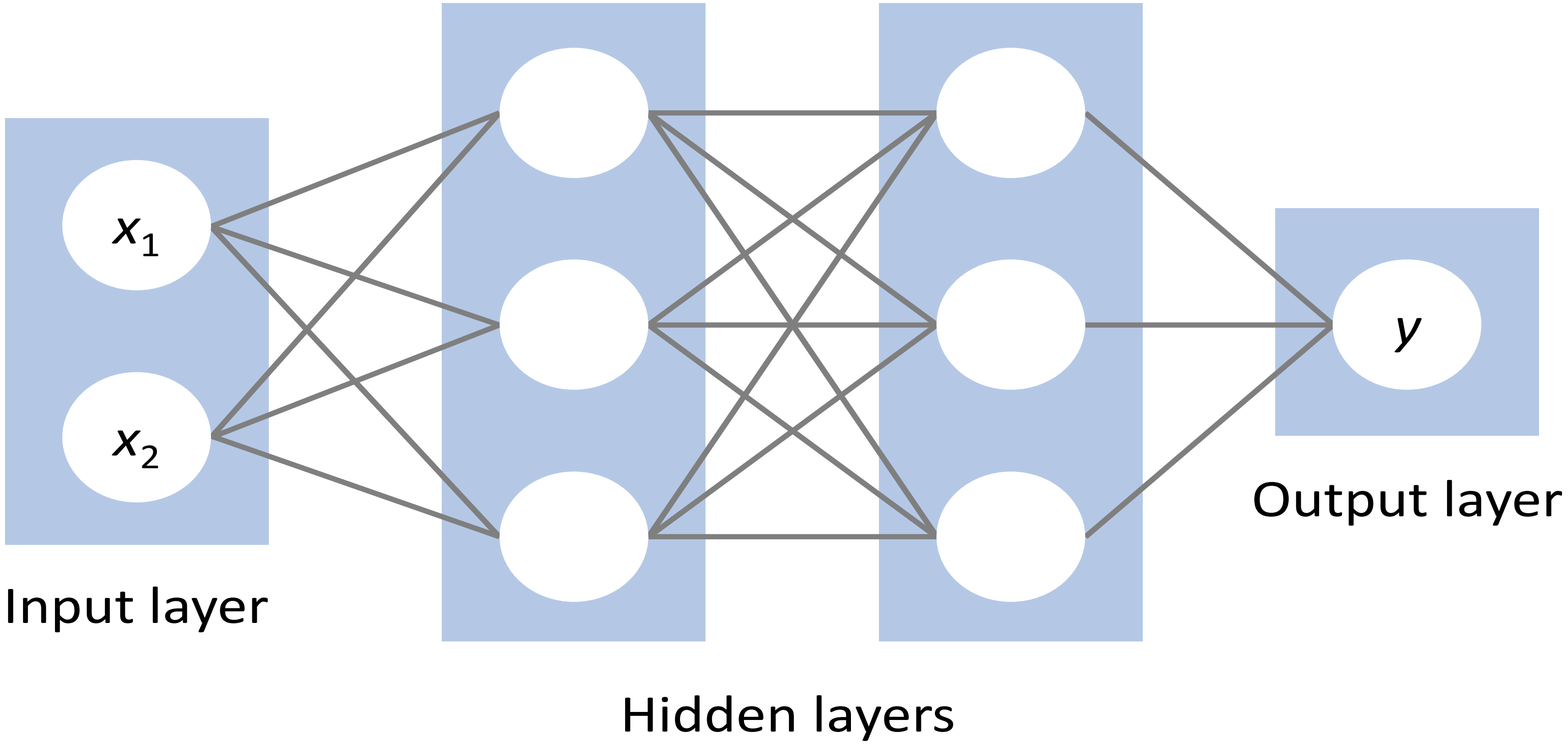




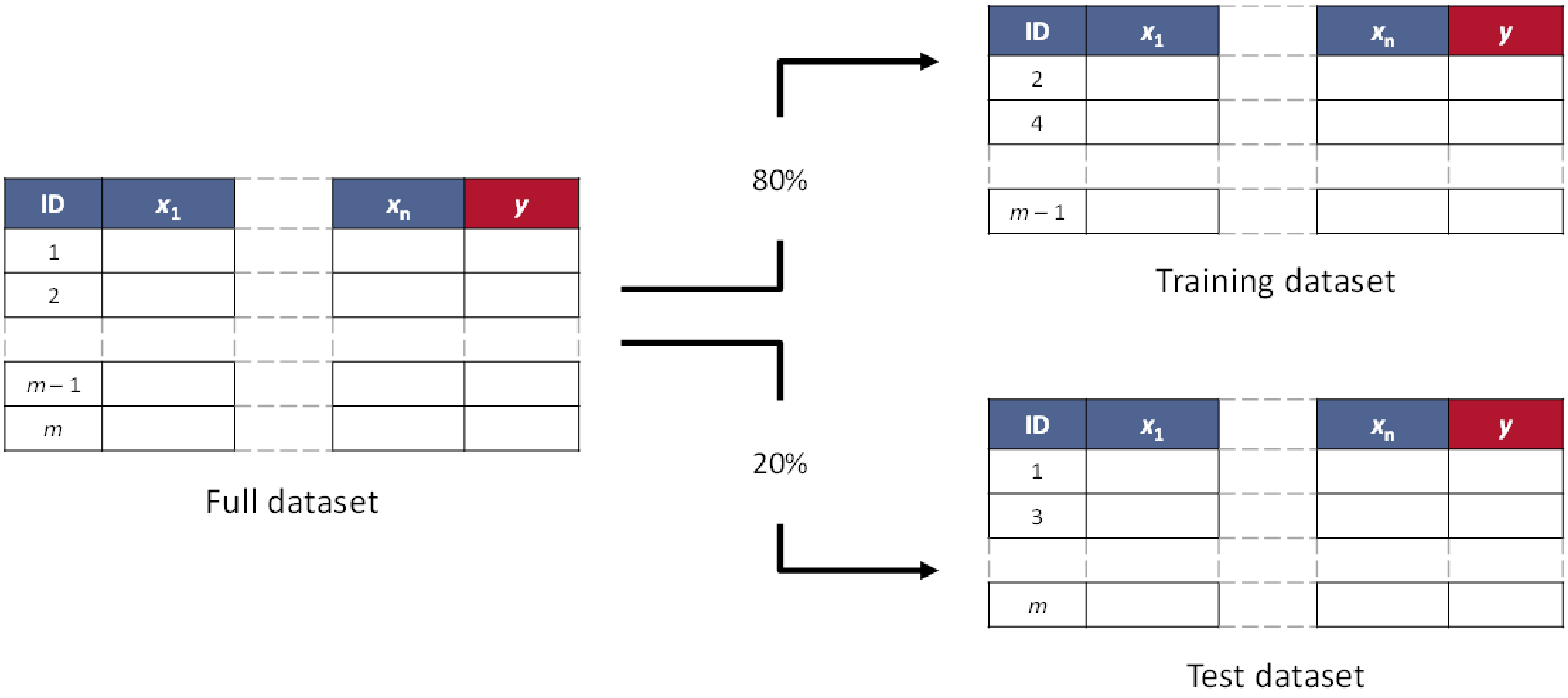


SUPERVISED MACHINE LEARNING

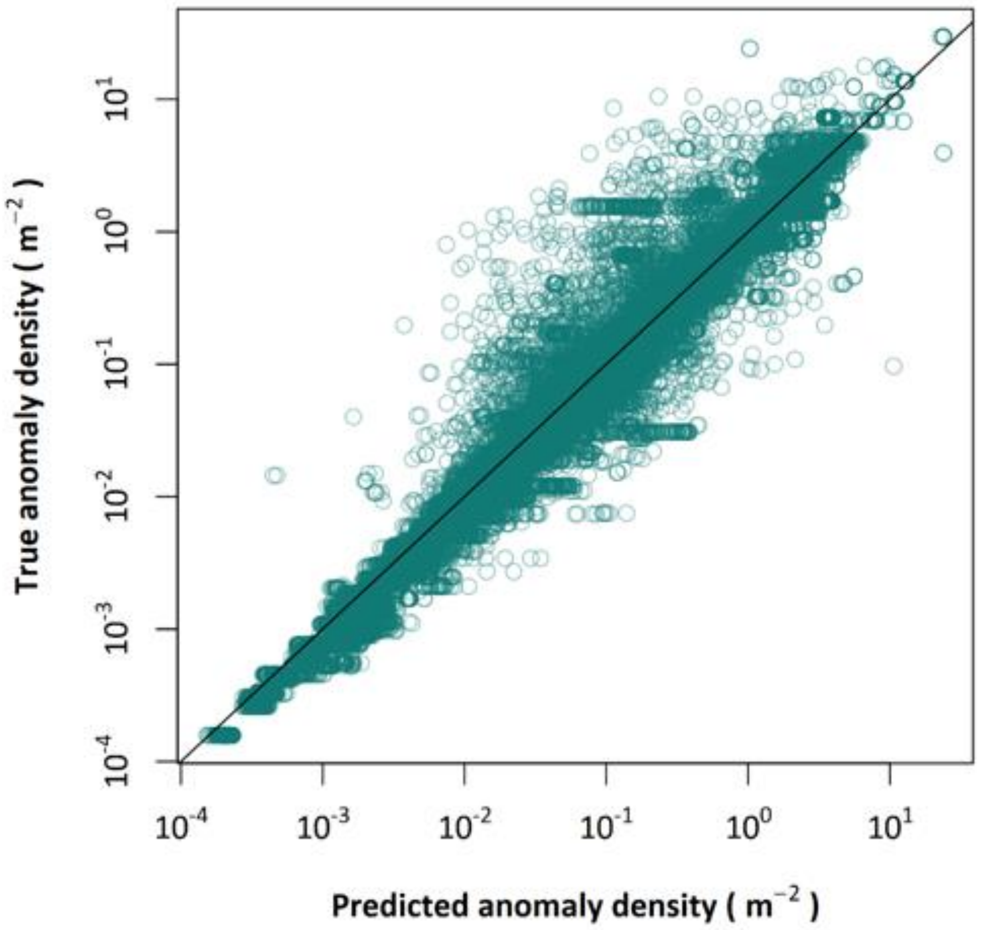
Each condition metric was predicted with its own deep neural network

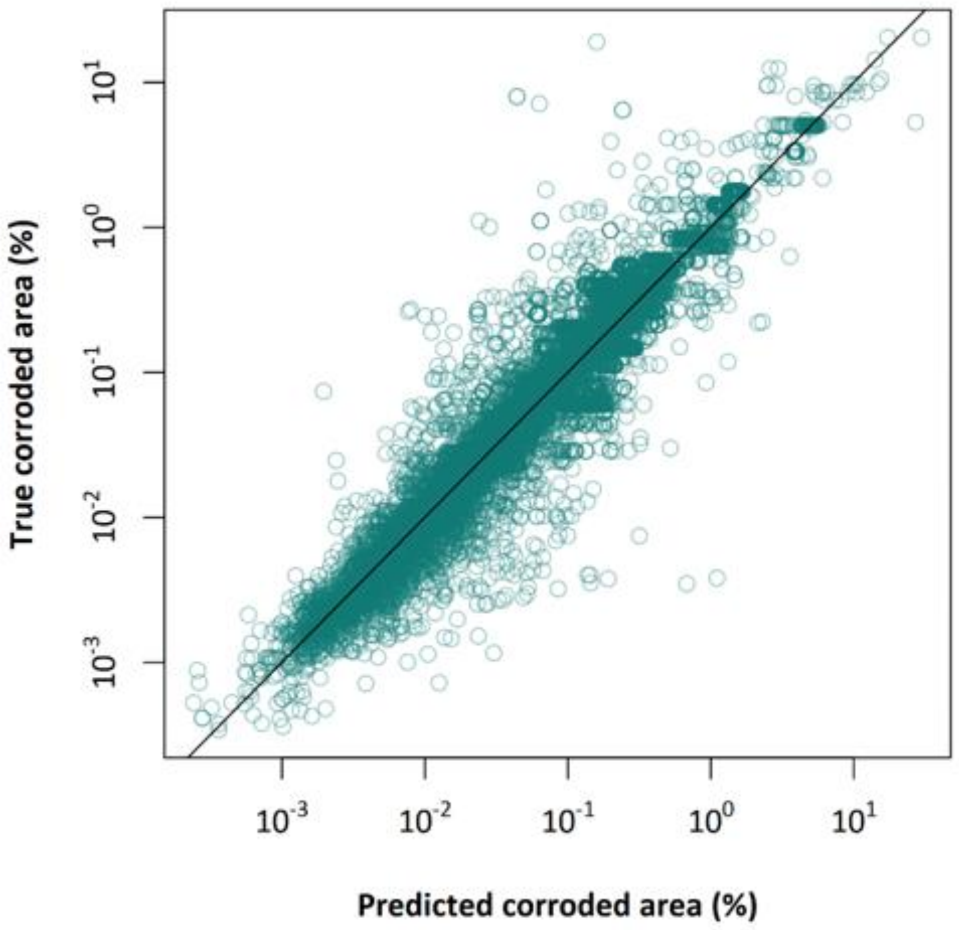


MODEL TRAINING

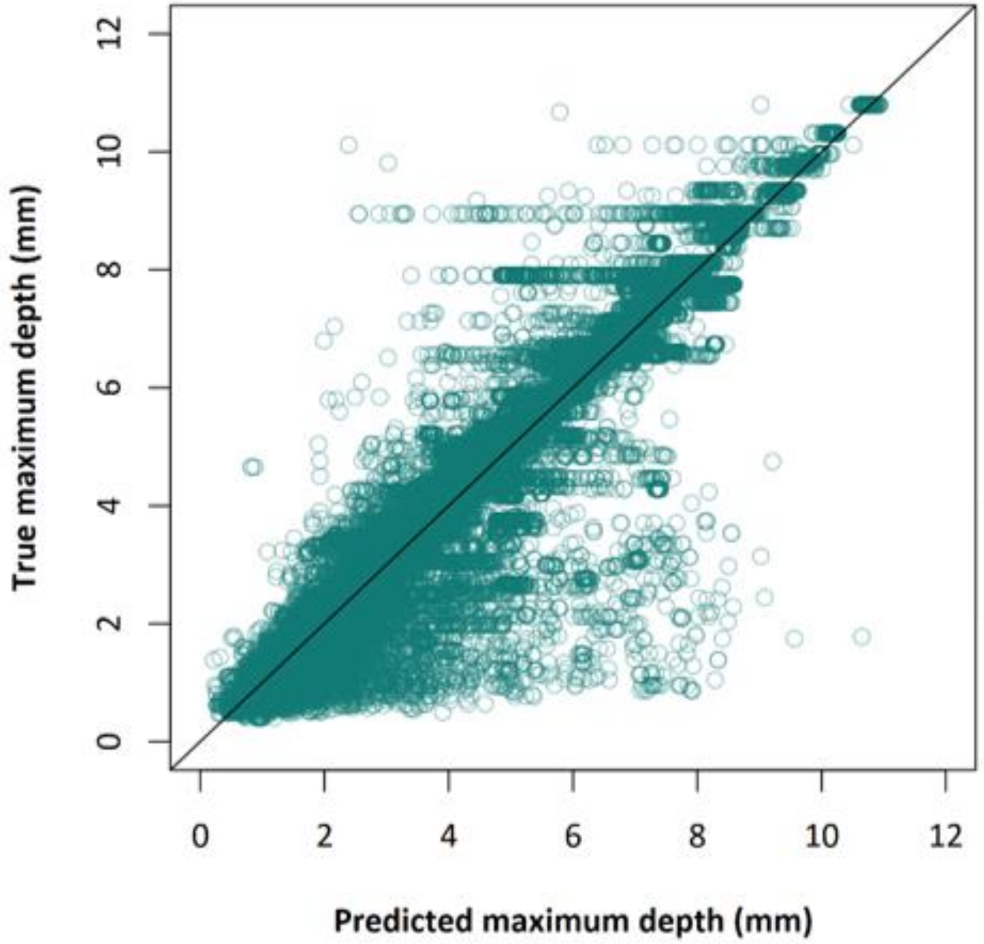


MODEL PERFORMANCE





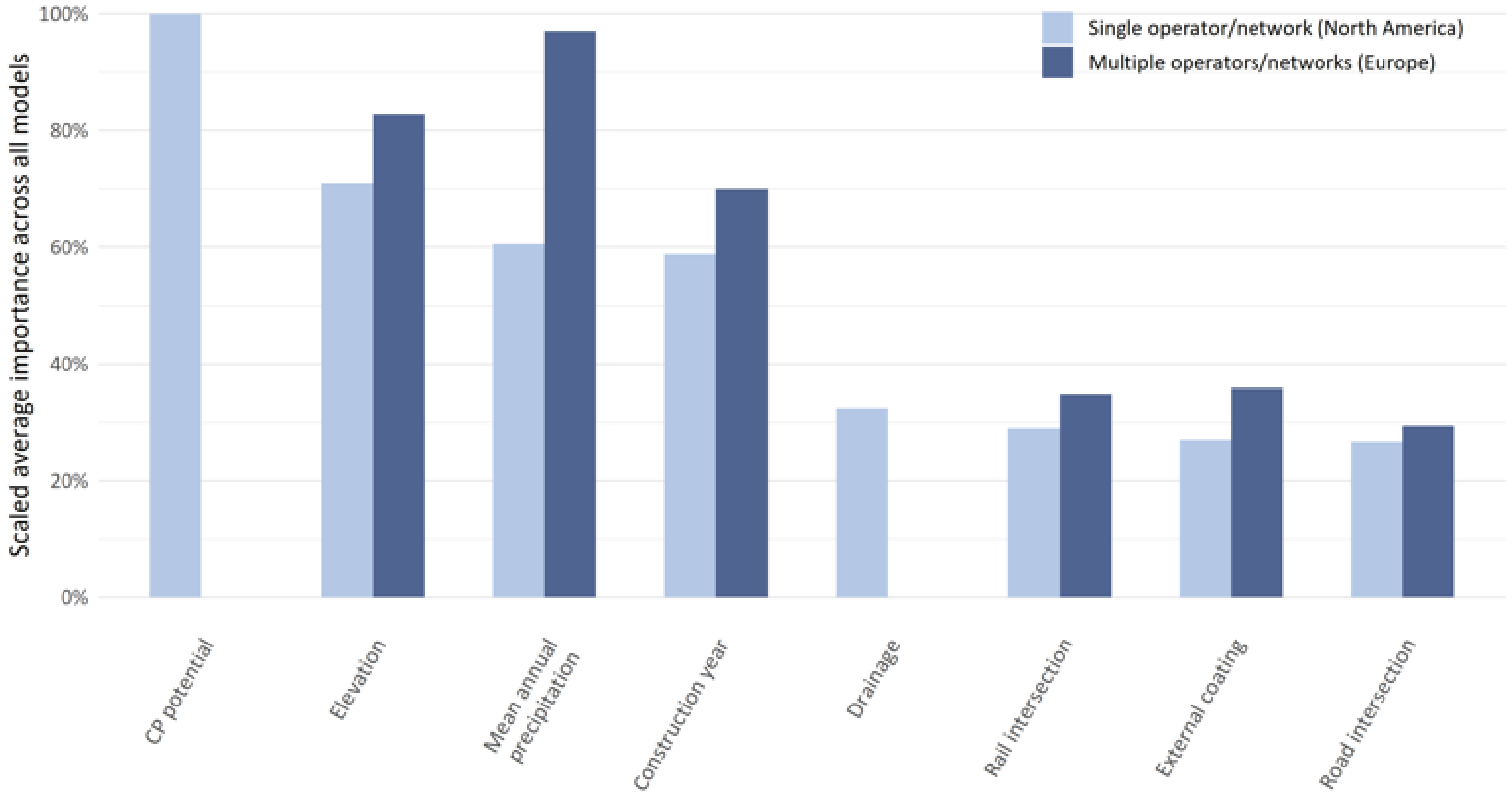
MODEL PERFORMANCE



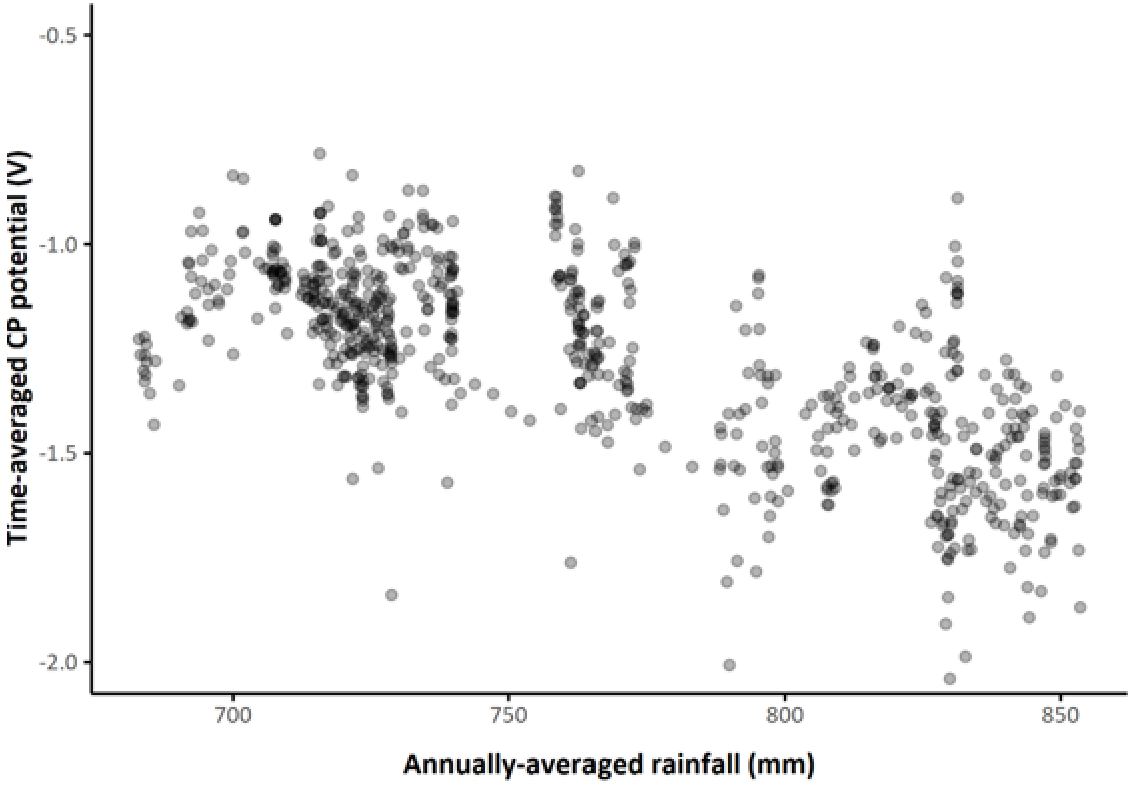
Condition metric	RMSE for test dataset
$\log_{10}$(anomaly density)	0.10
$\log_{10}$(corroded area)	0.12
Maximum depth	0.35 mm

COMPARISON TO PREVIOUS HIGH-RESOLUTION MODEL

Variable importance – the extent to which each predictor variable influences the prediction



COMPARISON TO PREVIOUS HIGH-RESOLUTION MODEL



Higher values of rainfall tend to correlate with more electronegative CP potentials in the models

CONCLUSIONS

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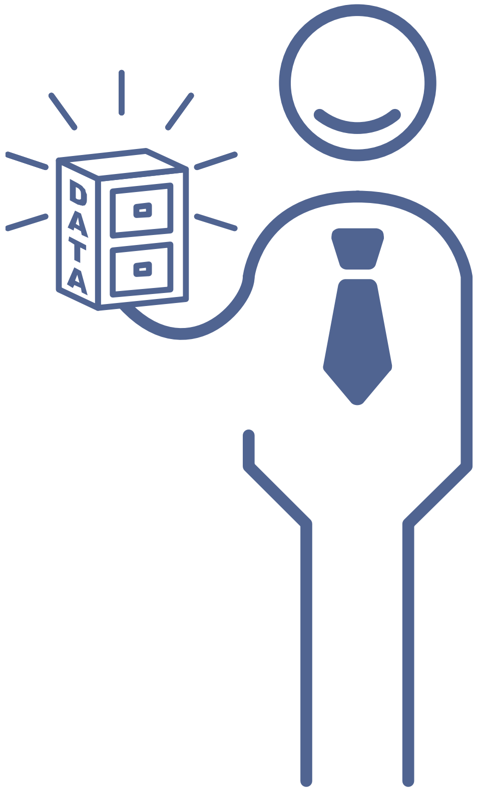
- Machine learning models applied to external corrosion condition metrics indicate a solid performance for Virtual ILI
- Low-resolution Virtual ILI reliably predicts condition at a pipeline level
- High-resolution Virtual ILI reliably predicts segment condition
- The approach is expected to be valuable for a variety of integrity management applications



SUMMARY

- There are a number of potential applications of Virtual ILI:
  - Condition prediction of uninspected / challenging-to-inspect pipelines:
    - e.g. gas gathering systems that must now be addressed due to recent changes in regulations
  - Screening predictions prior to pipeline inspection:
    - e.g. to maximize efficiency and cost in reacting to the findings of the actual inspection

- All of the benefits may only become clear as the data and prediction results are further explored

SUMMARY

Virtual ILI models must continuously improve as new datasets become available, and new predictor variables are collected:

- further data collection efforts are underway to increase the size and diversity of the training data sets…
- …these are expected to reduce outliers and improve overall performance

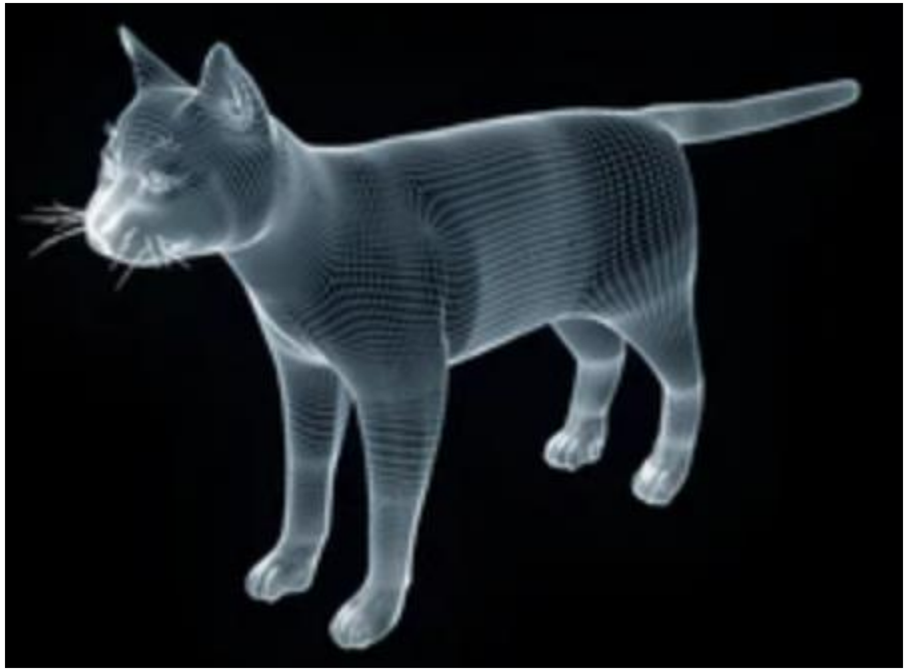
SUMMARY

Virtual ILI models must continuously improve as new datasets become available, and new predictor variables are collected; however…

- the challenges in terms of the extensive data engineering, robust data science, and domain knowledge needed to generate credible and useful results must not be underestimated

SUMMARY

But remember... as we get used to a virtual world...



…it's not the same as the real thing!

Questions?

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THANK YOU FOR LISTENING

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