Innovative smartWhale* Ecological Modelling to Enhance NARW Ship Collision Regulatory Mechanisms

*A Canadian Space Agency (CSA) led initiative

WSP
Lead Consultant
Overall Project Managers and Integrators

DHI
Main Partner Consultant
Water Environment and Modelling Experts

CANADIAN WHALE INSTITUTE
NARW Expert
Whale Research and Conservation

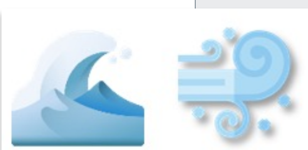
DALHOUSIE UNIVERSITY
Marine Risk Expert
Ship Trajectory Modelling

UQAR ISMER
Marine Biology Expert
Dynamic Habitat Modelling of *Calanus spp.*

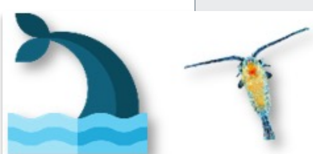
Presented by:

Josh van Berkel – DHI Water & Environment

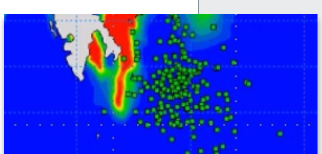
PROJECT OBJECTIVES



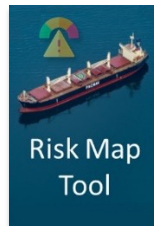
Set-up of **hydrodynamic (HD) model** to establish key hydrodynamic cues / oceanic habitat zones



Execution of **NARW dynamic habitat model (DHM)** to generate spatially and temporally explicit habitat suitability results



Execution of NARW movement simulations through use of **agent-based modelling (ABM)** coupled to HD and DHM models



Establishing a **NARW risk model** that dynamically predicts NARW risk using ABM results, applicable fishing zones and AIS data-based modelling of vessel traffic

Conversion of the model complex from hindcast to forecast mode, to forecast NARW and vessel movements and, ultimately, related NARW risk

Establishment of a **demonstrator NARW Spatial and Temporal Decision Support System (ST DSS)** in an operations platform to automate forecast modelling, access real time data feeds and provide user display, interfaces and tools.

PROJECT OBJECTIVES & TASKS

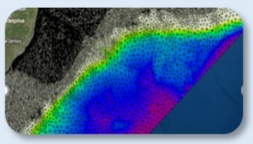
TASK 1 Project Management & Mobilisation

TASK 2

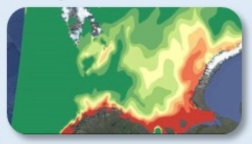
Data Collection & Management

TASK 3: Hindcast Modelling

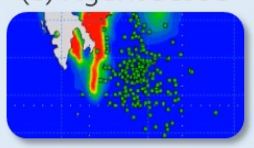
(a) Hydrodynamic



(b) Dynamic Habitat



(c) Agent Based

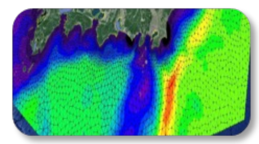


TASK 4

Environmental Risk Modelling

TASK 5

Forecast Modelling



TASK 6

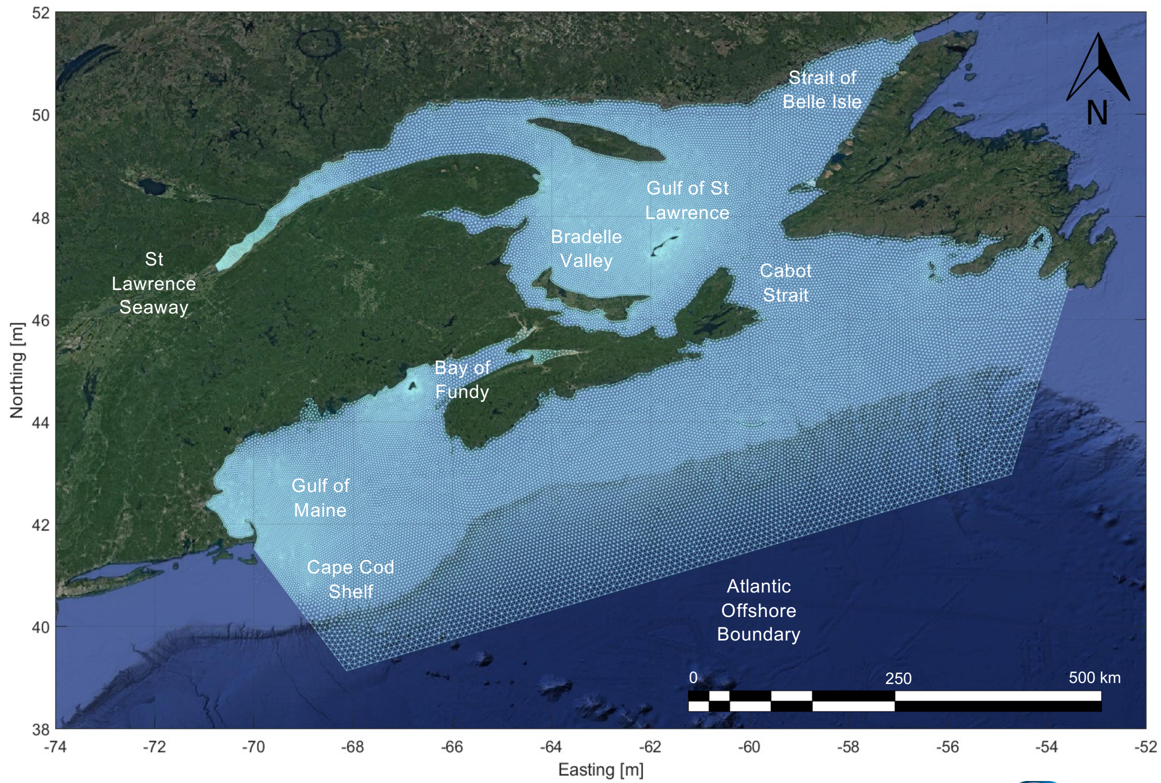
NARW Spatial & Temporal DSS

TASK 7 Reporting & Workshops

HYDRODYNAMIC MODEL

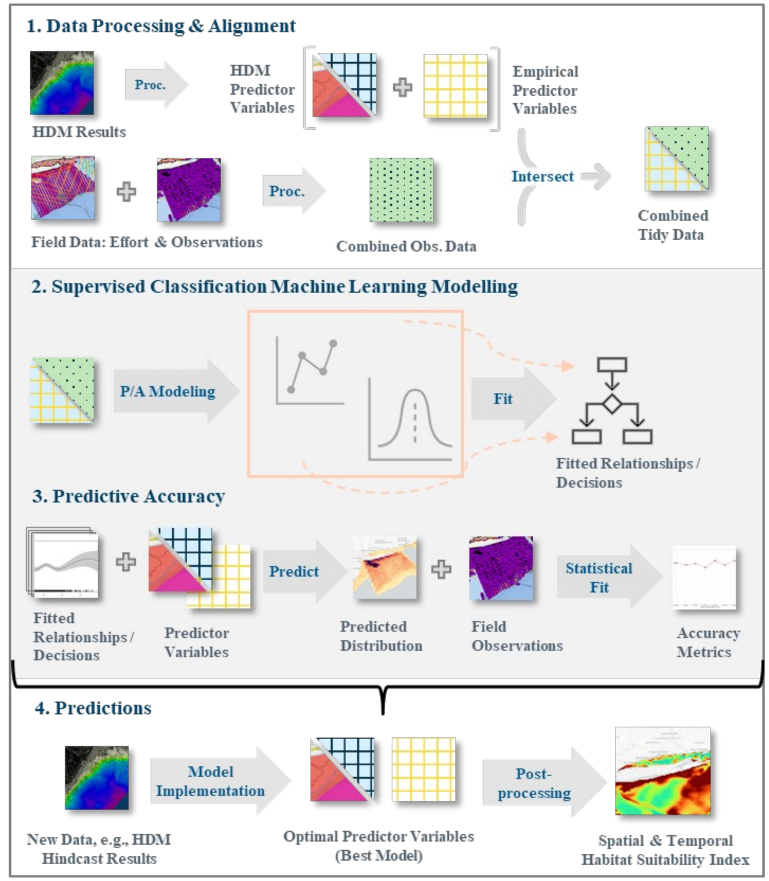
Area	Resolution (km)
Atlantic Boundary	14
Cabot Strait	7
Strait of Belle Isle	7
Gulf of Maine	5
Bradelle Valley	4.5
Bay of Fundy	8
St Lawrence	4

Sources	Dataset
Bathymetry	GEBCO, NONNA, NOAA
Boundaries	HYCOM model
Rivers	DFO & NOAA
Meteorological	NOAA CFSv2 model



DYNAMIC HABITAT MODELING

- Generalized Additive Mixed Model (GAMMs) DHM approach was originally conceived for this Project
- However, due to data constraints it was decided to use machine learning (ML)
  - ML algorithms such as Random Forests have recently been shown to outperform GAMMs
- As such, after testing various approaches, an Xtreme Gradient Boosting approach was applied



BEST MODEL, HABITAT SUITABILITY (1 YEAR), ACCURACY METRICS

Temp. - Bottom

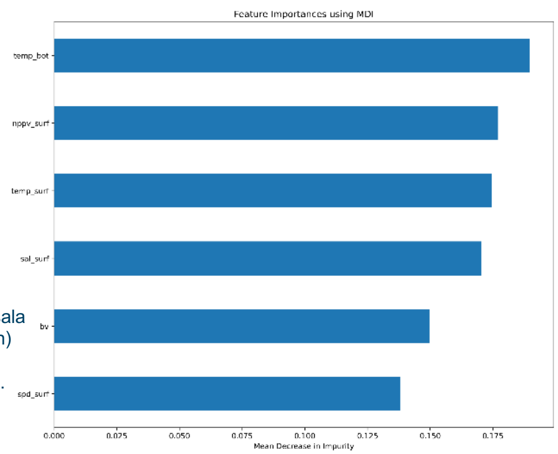
Net Primary Production - Surface

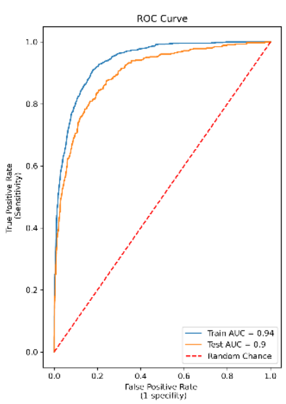
Temp. - Surface

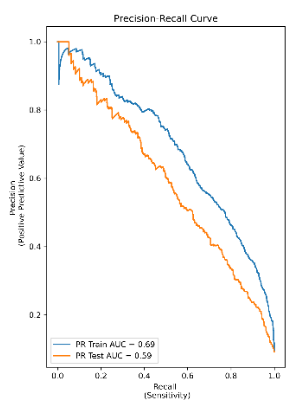
Salinity - Surface

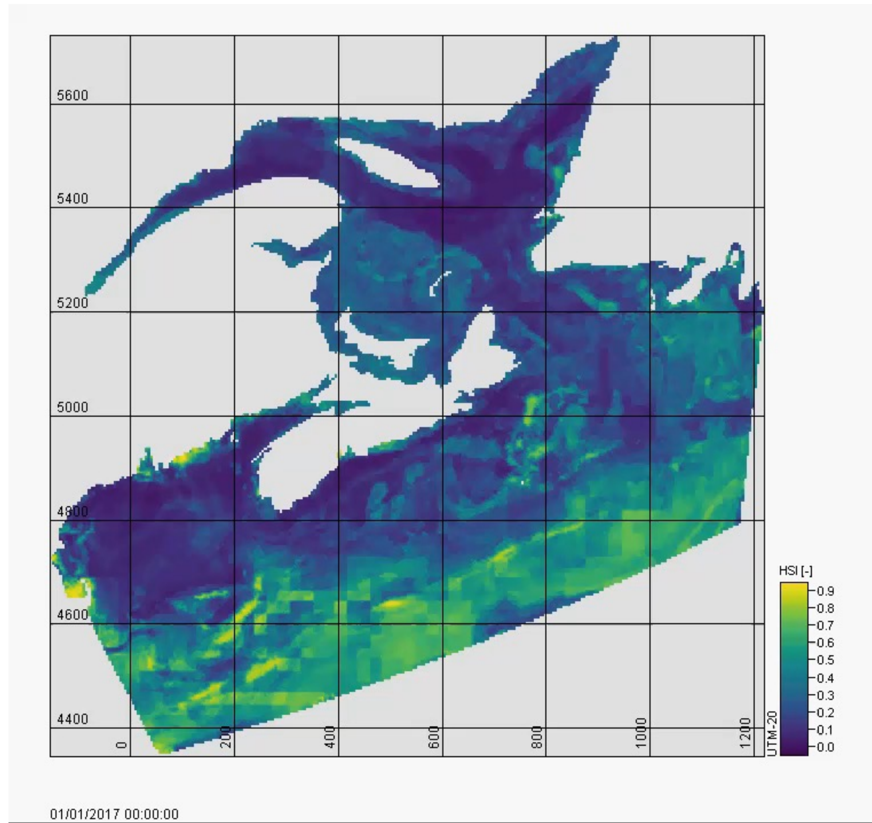
Brunt – Vaisala (stratification)

Current Spd. - Surface

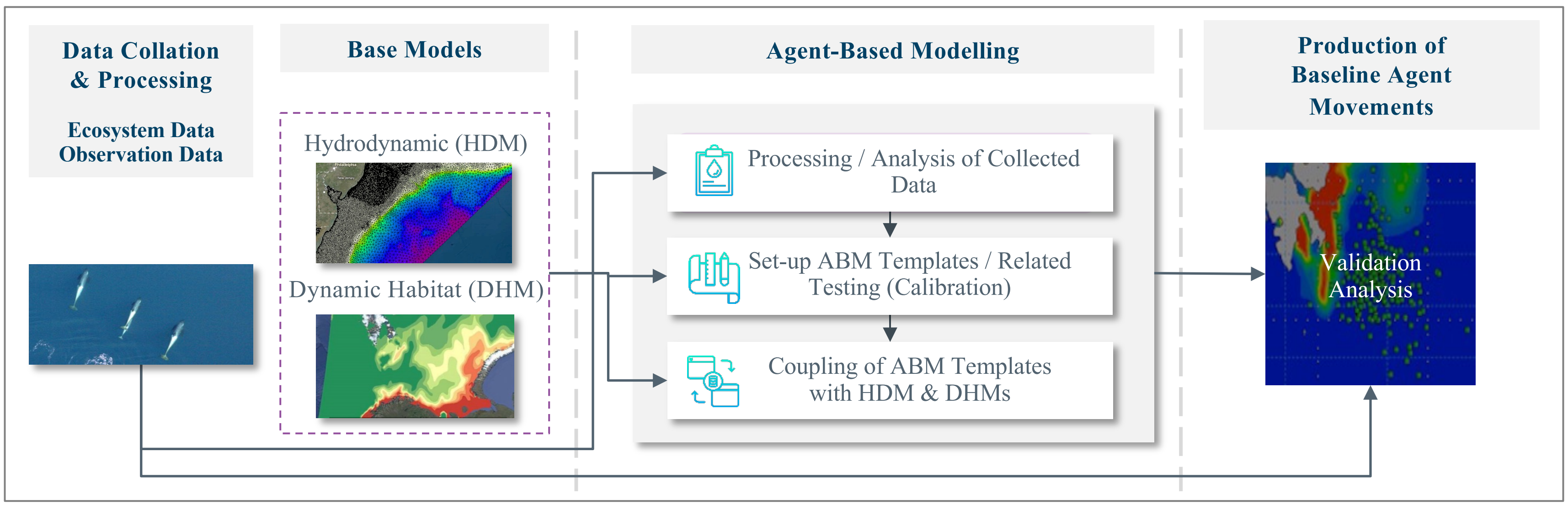








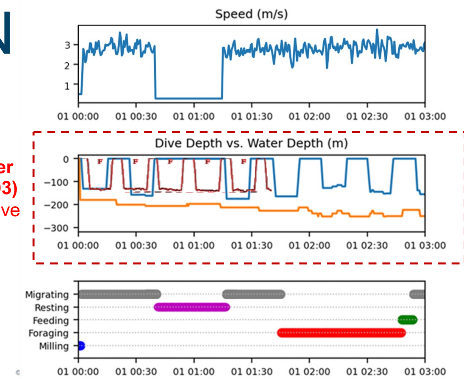
AGENT-BASED MODELING



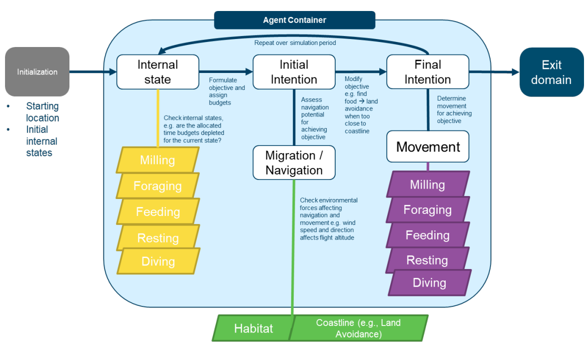
ABM SET-UP & CALIBRATION / VALIDATION

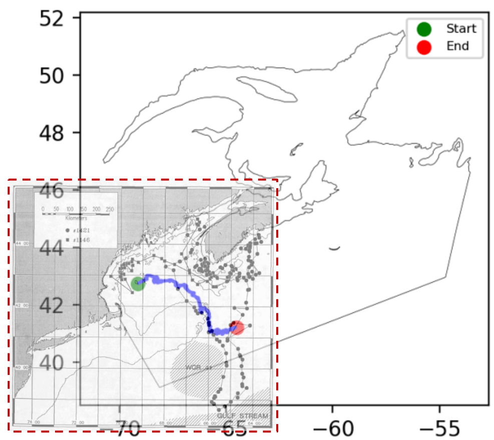
- Set-up of ABM template / initialization
- Based on extensive literature review and expert engagement (Dr. Moira Brown)
- Calibration / validation based on literature and observation datasets

Typical Whale Behaviour Over Several Hour Period

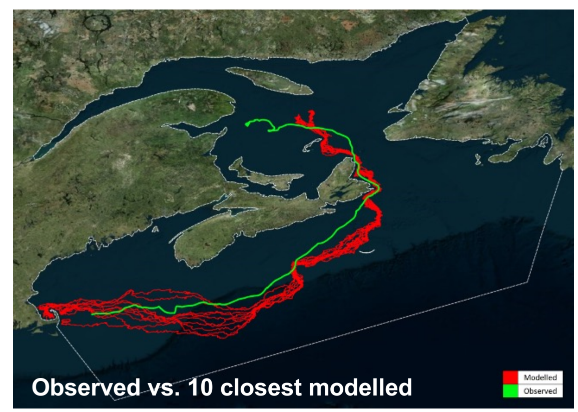


Baumgartner & Mate (2003) Recorded Dive Profile





Mate et al (1997)
Long Term (~3 week) tag data
Vs. Typical ABM Trajectory Fall Months



2019 Data Provided by Dr. Moira Brown
Long Term (~3 week) tag data
Vs. Typical ABM Trajectory Summer Months

2017 HINDCAST

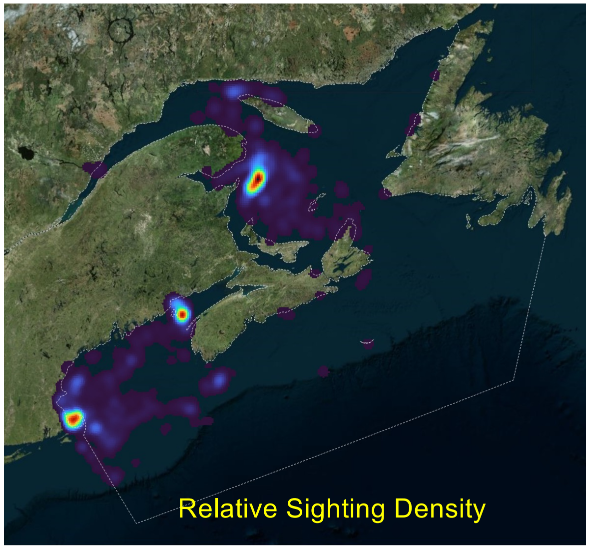
April/May

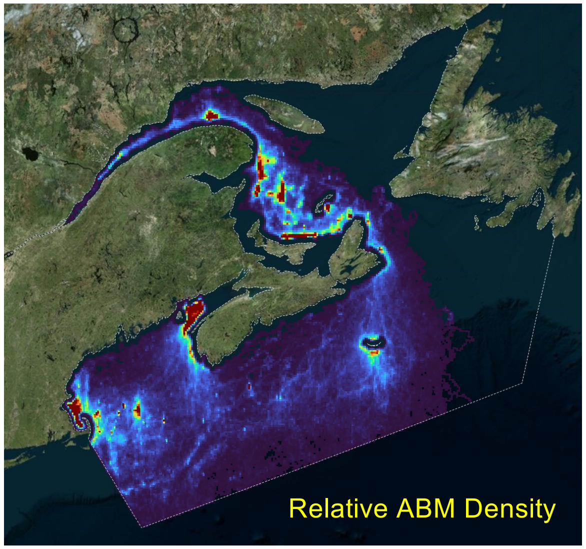
****Preliminary Hindcast Results****

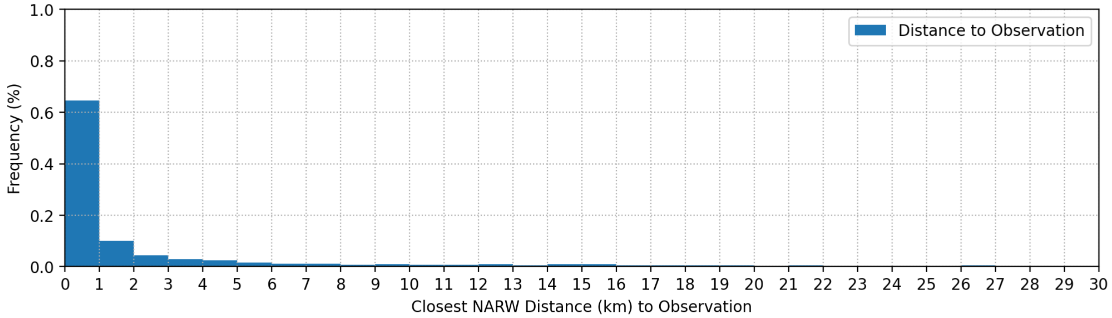
July

2017 HINDCAST

- Relative density of observations vs. ABM matches well, spatially and temporally
- Within a +/- 6 hour window:
  - ~65% of the time, our model had a NARW agent <=1 km from a known sighting
  - ~85% of the time <=5km, ~90% of the time <=10km





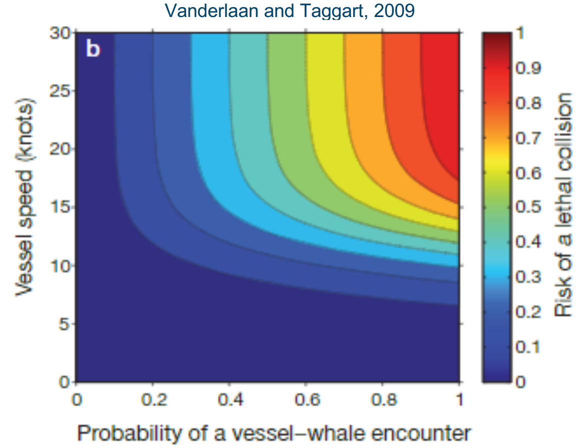


RISKS MODEL – THEORETICAL FRAMEWORK

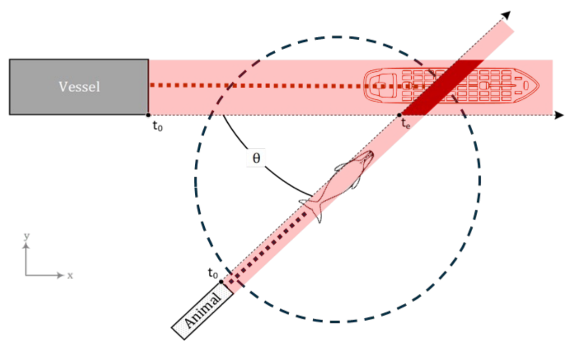
- Identifies spatiotemporal encounters, assesses risk/ lethality based on established empirical methodology
- Encounter is defined as NARW and vessel/ gear occurring at the same time within certain area
- Collision lethality depends on vessel and whale geometry, speed, direction, swimming depths and other characteristics

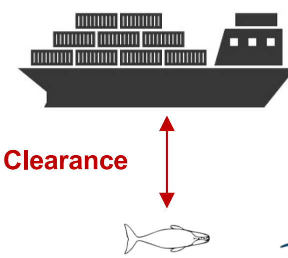
Risk = $P_{Encounter}$ x P_{Lethal}

Vanderlaan and Taggart, 2009



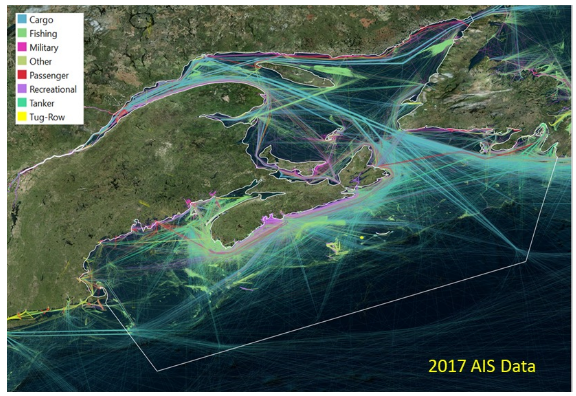
"Encounter" area

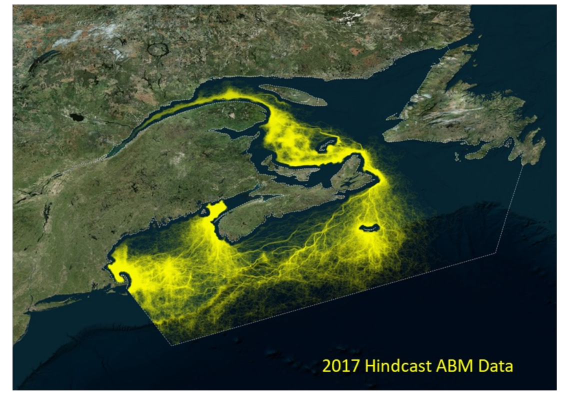


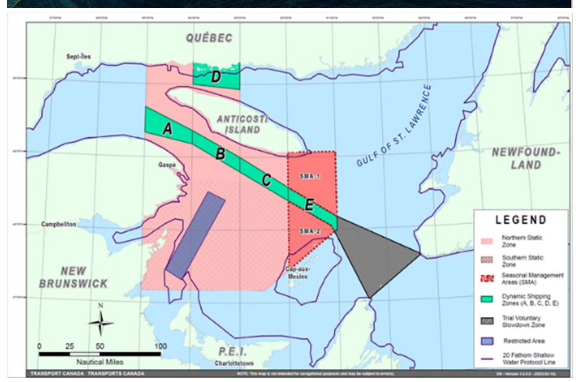


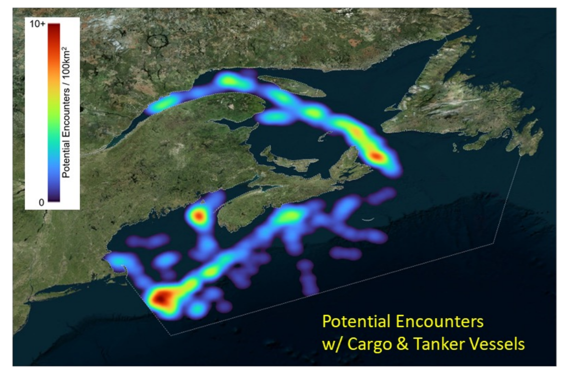
HINDCAST RISK COLLISION RESULTS

- Qualitative & quantitative risk assessment using forecasted vessel and whale positions
- Vessel to whale collision/entanglement risk over space and time
- Provide metrics and products to support existing regulatory decision-making processes

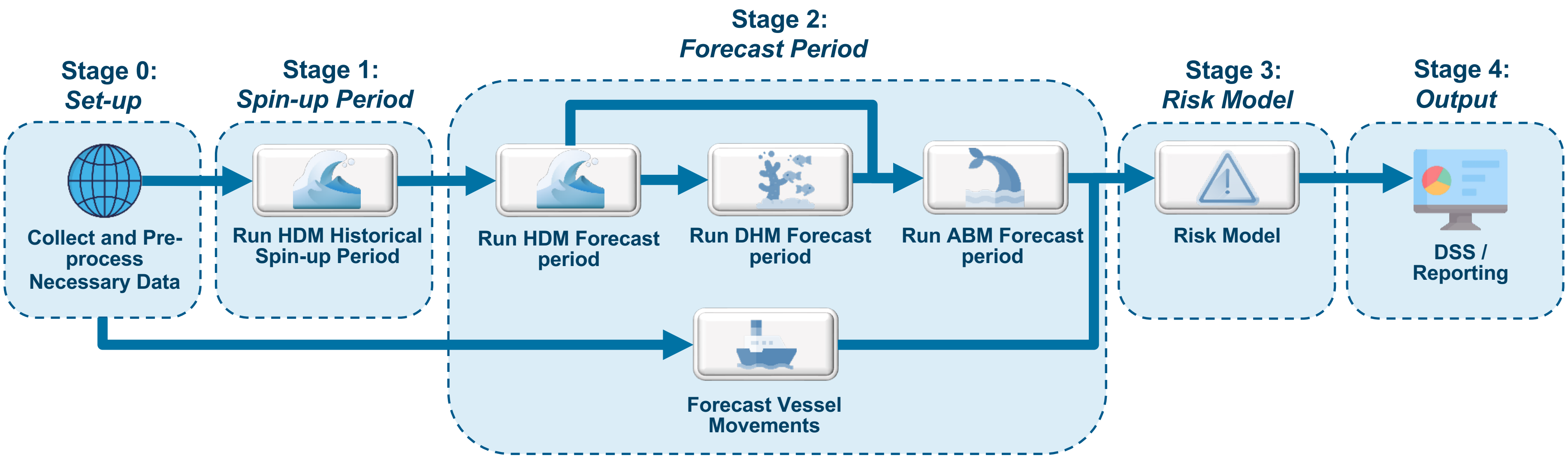








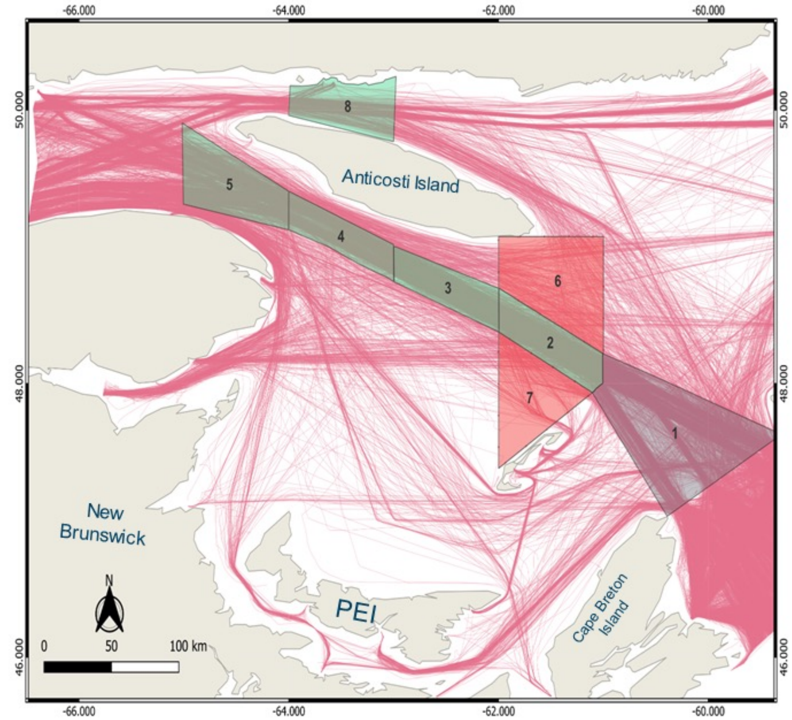
DSS – GENERAL MODELLING WORK FLOW



- Collect and process all data necessary for the model duration, generate model files
- Run HDM for historical spin-up period for stability and accuracy of forecast
- Use HDM spin-up as initial conditions for HDM forecast period
- Use output of HDM forecast as input and run DHM forecast period
- Use outputs of HDM/DHM forecasts as inputs and run ABM forecast period
- Use outputs of ABM and vessel forecasts as inputs into risk model
- DSS integration of all model forecast results (HDM, DHM, ABM, vessels, risk model)

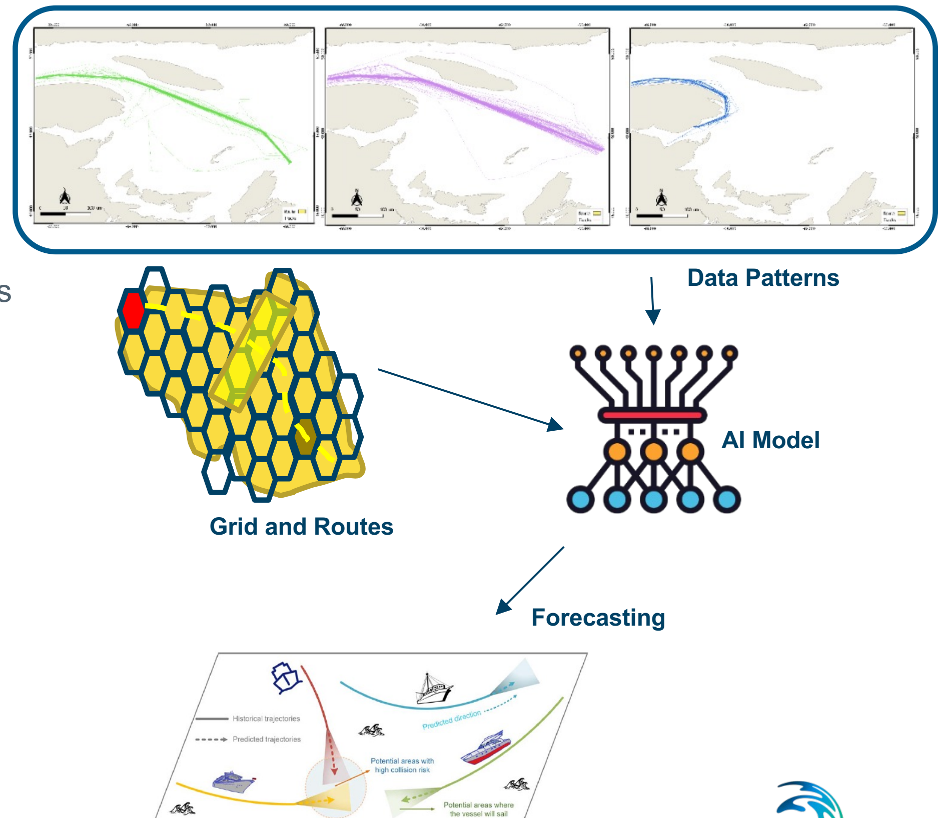
Forecasted Vessel Trajectories

- Automatic Identification System (AIS)
  - Historical dataset applied to train the forecast model
  - Real-time data feed from Transport Canada, via Spire, provides nowcast data for forecast modelling
- Machine learning based model used to forecast vessel locations up to 12 hours in the future
  - This couples with the forecasted location of the NARW to enable quantification of future collision risk in regulatory zones, thereby allowing for refined decision-making input

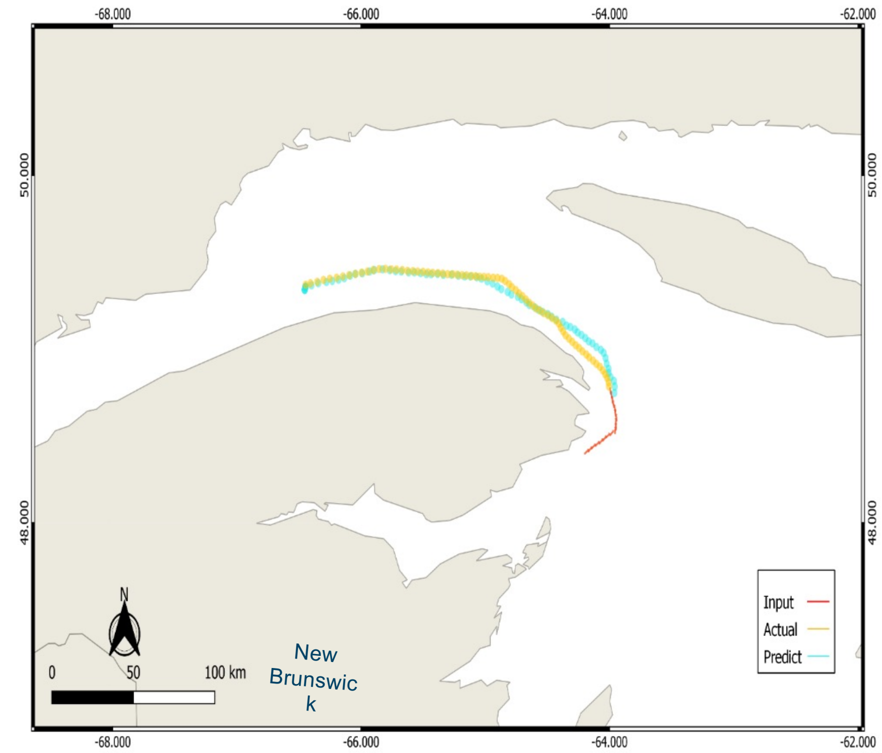


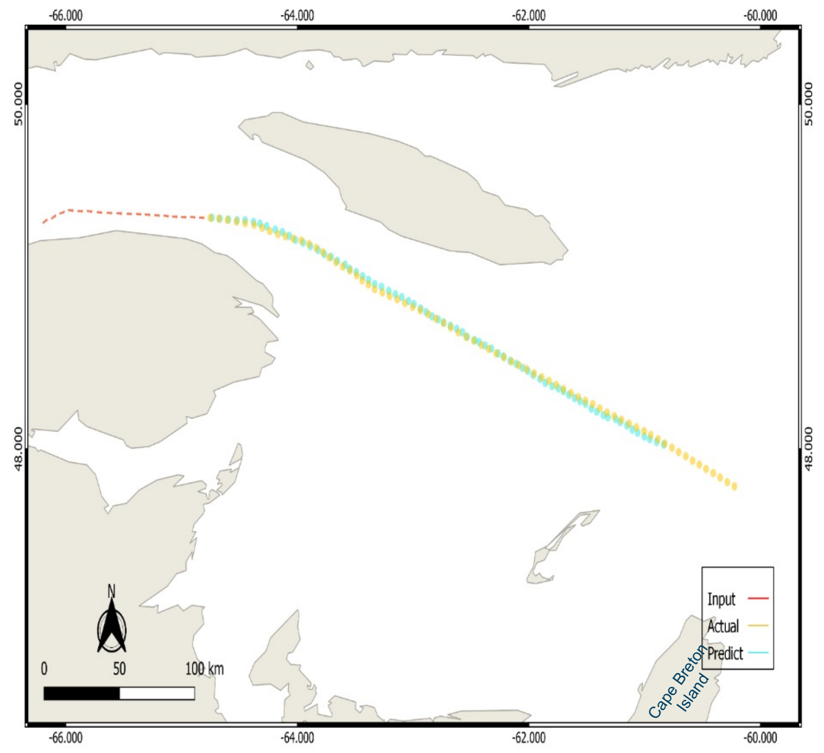
Artificial Intelligence to Model Routes

- Deep Learning Model
  - AI sequential to sequential generative model learns existing pattern from data
  - Adopted a Transformer architecture of deep learning to train the model
  - Transformer architecture of deep learning model enables rapid data learning
- Parameter Selection and Optimization
- 3 hours for each trajectory as input feed of model
- Target:
  - Short-term trajectory (1h) forecasting is fast and reliable
  - The model is gradually trained over increasing time-spans
  - The model was trained and is optimized to forecast the vessel position for the subsequent 12 hours



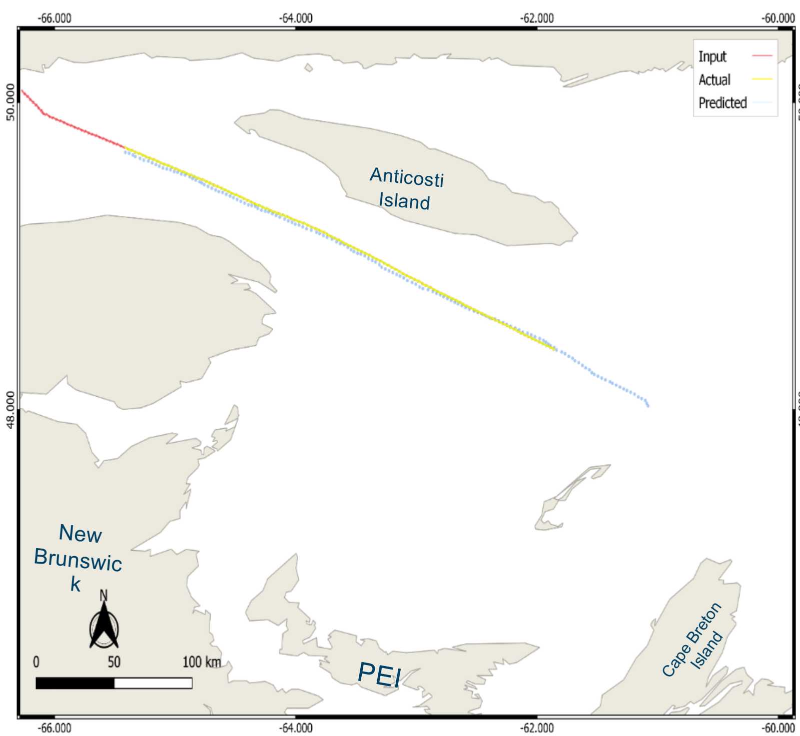
Forecasting Samples

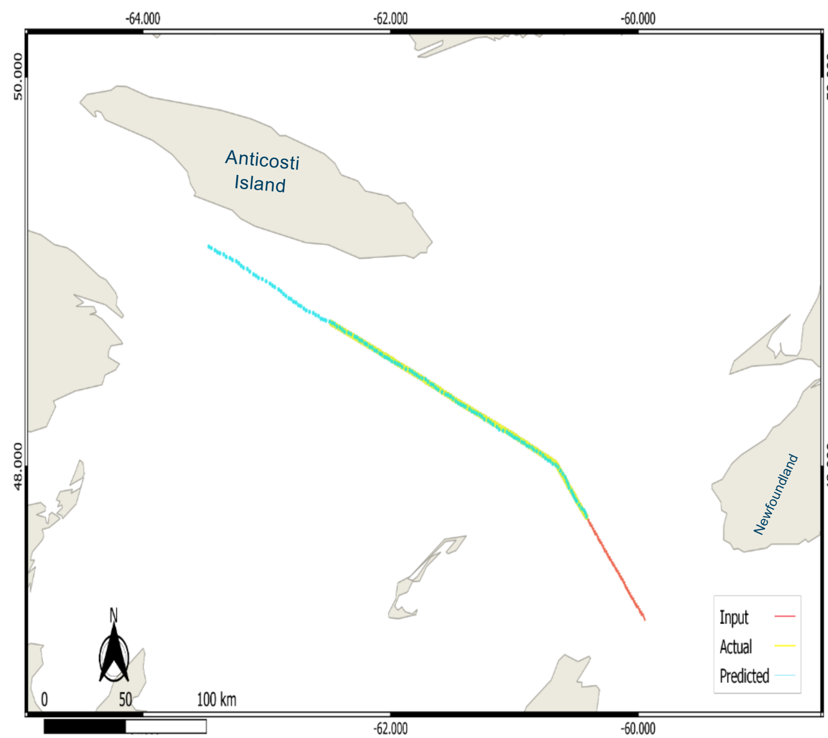




Institute for Big Data Analytics

Forecasting Samples

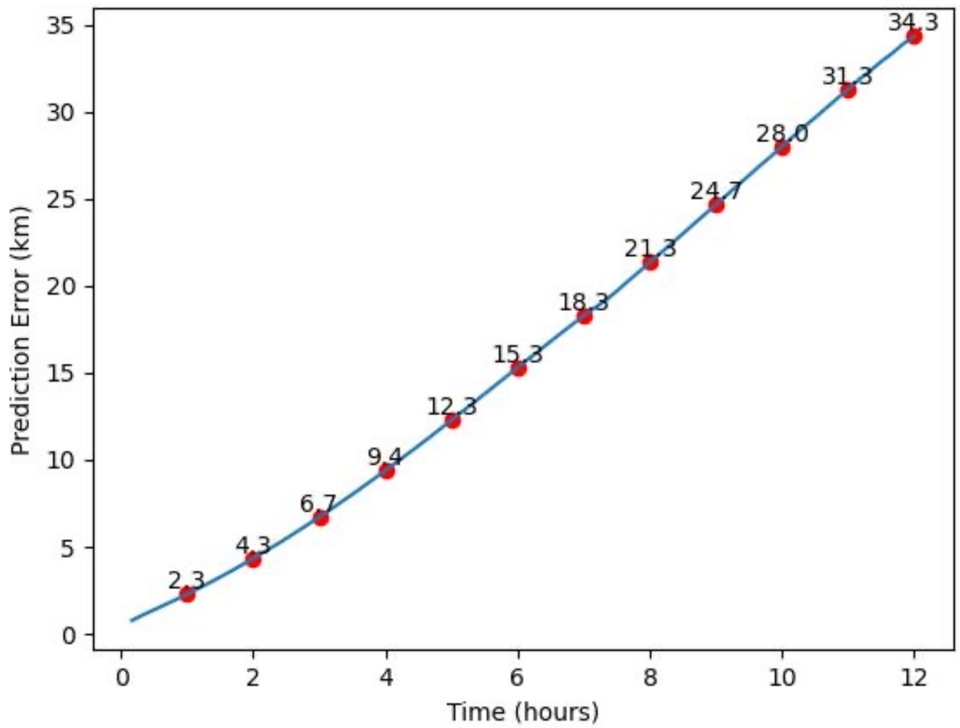




Prediction Accuracy Evaluation

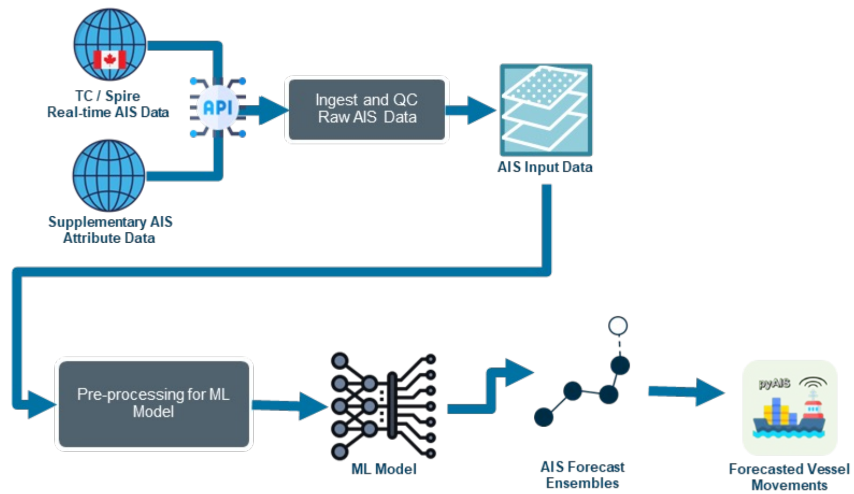
- RMSE: Root mean square error
  - For next 12 hours, the error of 24 sequential predicted positions (lat., long.) is calculated with actual positions.
- MTC: Mean of Trajectory Coverage
  - Percentage of actual points covered wrt to 2KM radius of predicted points
- DTW: Dynamic Time Wrapping
  - Measure the calculated error in movement pattern

RMSE	**27.8 (KM)**
MTC	**81.1 (%)**
DTW	**0.28 (Deg)**

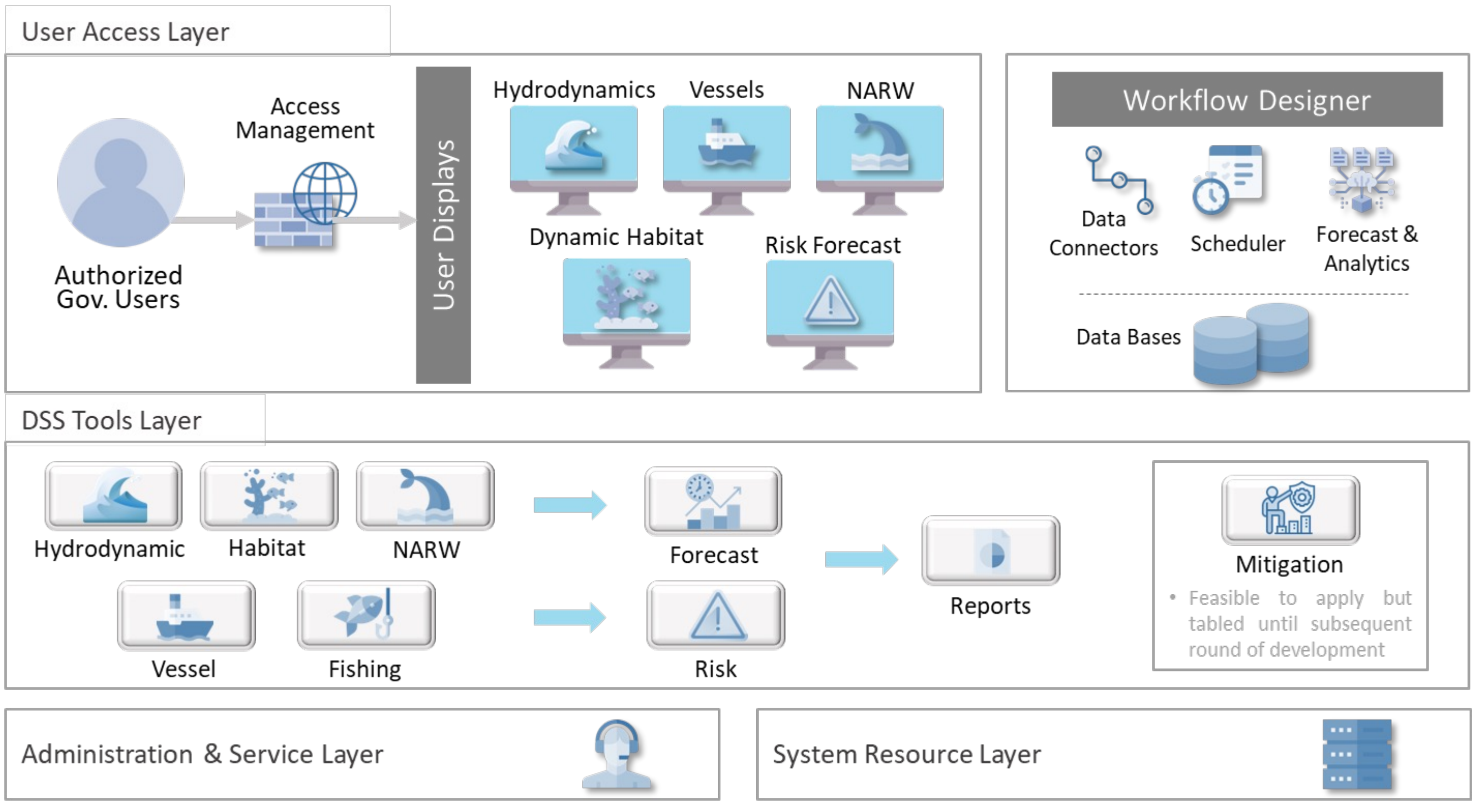


Vessel Forecast / Backend Integration - Progress

- Vessel forecast backend operational
- Spire real-time TCP data feed established
- Continuously streaming raw AIS data
- Forecast occurs on demand
- Automatically QC's data and replaces missing attributes (vessel type most important)
- Prepares raw data for ML model
- Generates forecast ensembles with ML model
- Passes forecasts to Risk Model



DSS AIMED AT ENHANCING REGULATORY MECHANISMS



Thank you

Key modelling contributions / supervisory support from:

Reinier Tromp
Dr. Mohammad Madani
Henrik Skov
Michael Bell
Jonas Brandi Mortensen
Derek Eden
Aline Kaji
Dr. Jay Kumar
Felix-Antoine Audet
Dr. Guillaume Clouette-Gauthier

Dr. Moira Brown
Tom Foster
Dr. Ron Pelot
Dr. Gesche Winkler