Sea ice data assimilation: observational data and verification

Ocean Predict: 2019, Halifax, Canada

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MEOPAR
MARINE ENVIRONMENTAL OBSERVATION PREDICTION & RESPONSE NETWORK

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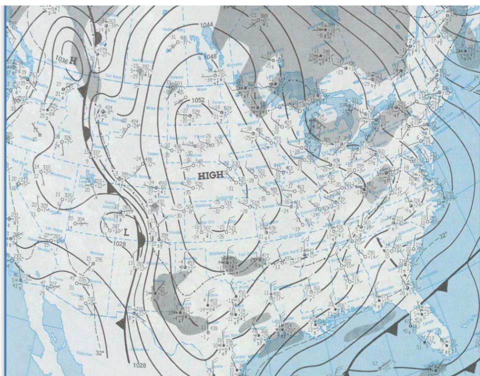
Outline

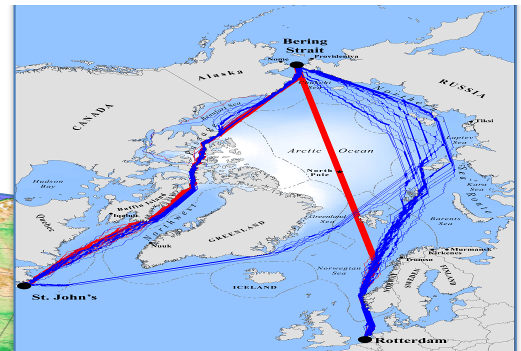
- Motivation for sea ice forecasting/data assimilation (DA)
- Thoughts on differences between sea ice DA and ocean DA
- What observations are using for ice concentration estimation?
- How can we assess/verify our sea ice concentration analyses?
- Future work

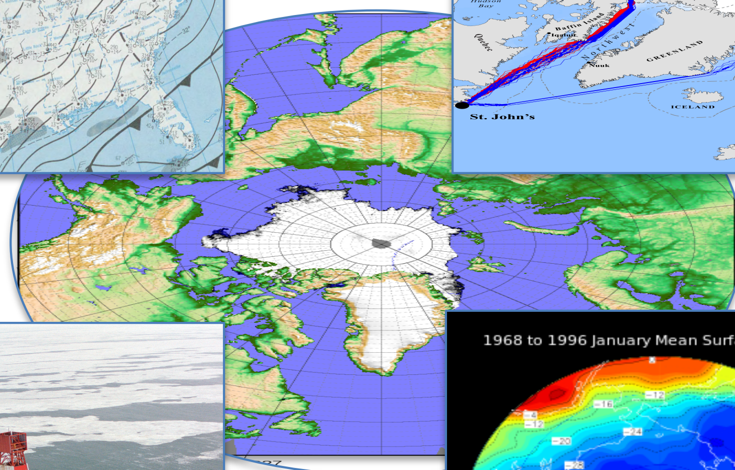
Motivation for Sea Ice Forecasting

Climate/Weather forecasting

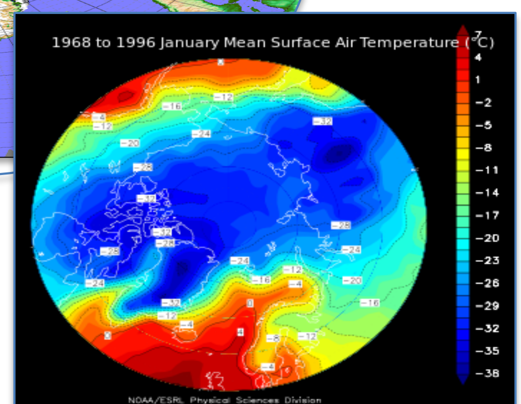


Shipping/Navigation





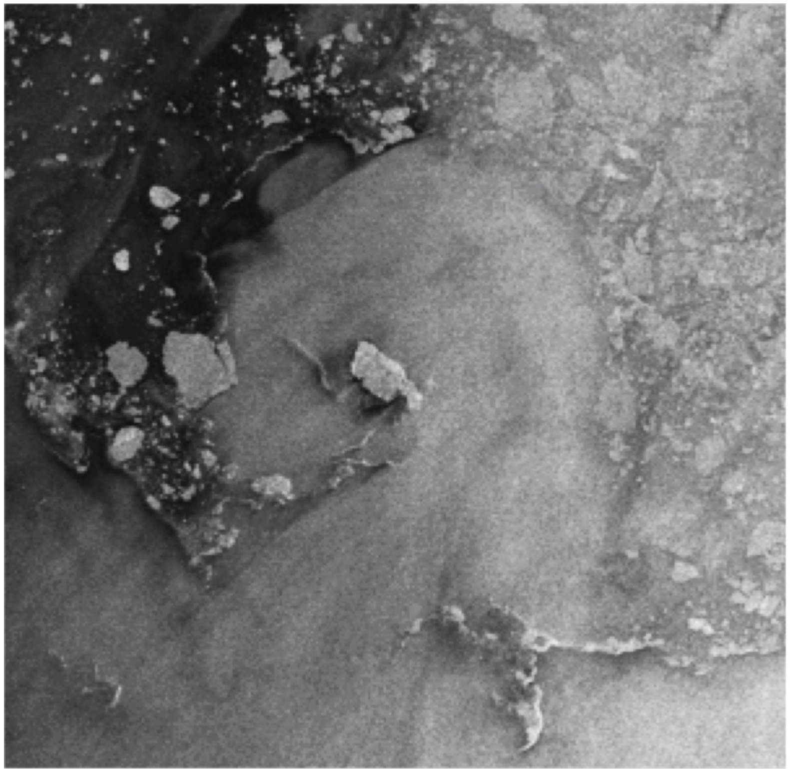
Off shore engineering



Environment monitoring

Features of sea ice

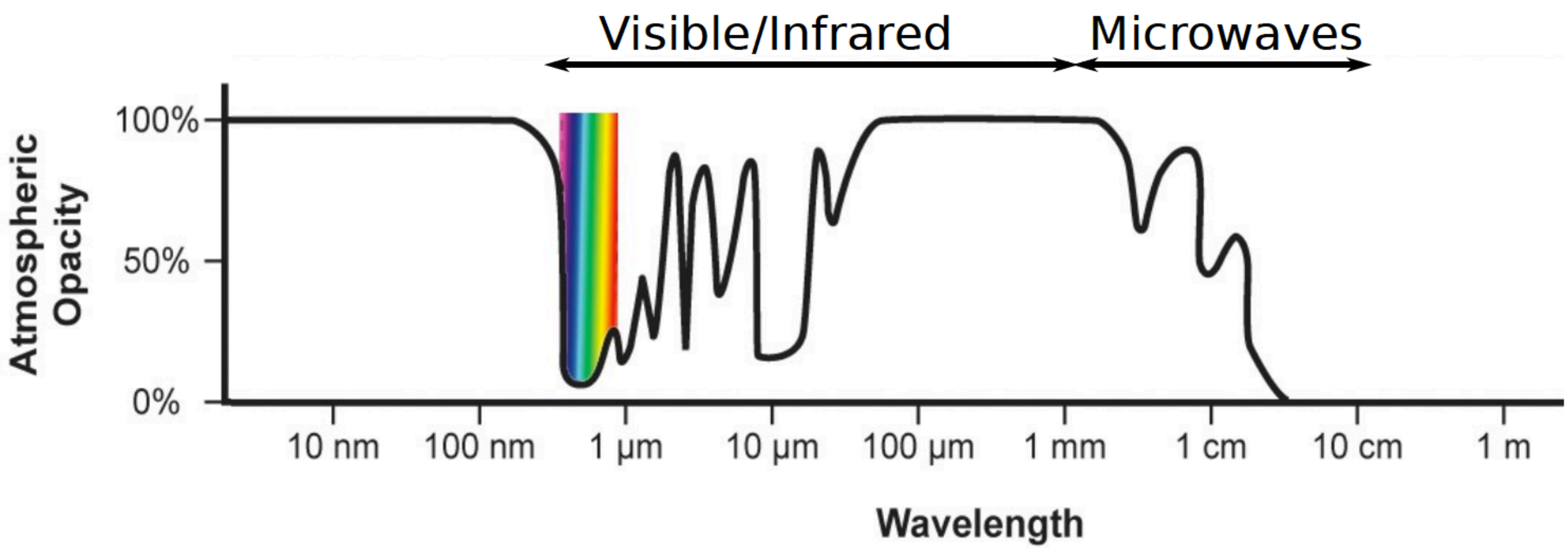
- Sea ice exhibits properties of both a continuous medium (eg. fluid) and a discontinuous medium (brittle solid)
- Sea ice is strongly boundary driven
- Location of cracks and ice edge are important for correct fluxes to and/from the atmosphere and ocean



Assimilation of passive microwave data on the Canadian East Coast

- Specified
  - Analysis carried out by minimizing a cost function (3D-Var)
  - Coupled ice-ocean model used for forecasts
- We need to choose
  - An observation vector (y)
  - Forward model, H(x)
  - A state vector (x)
  - Background error covariance matrix (B)
  - Observation error covariance matrix (R)

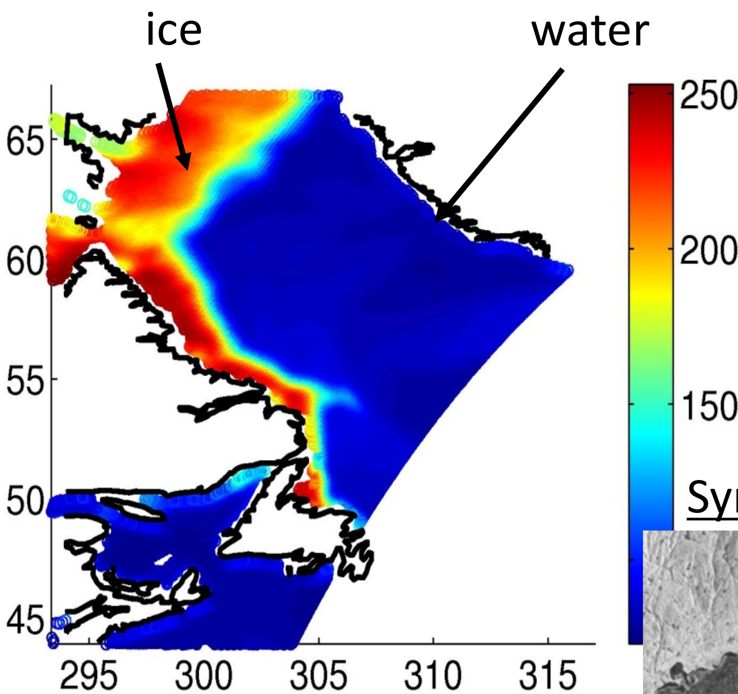
Electromagnetic Spectrum



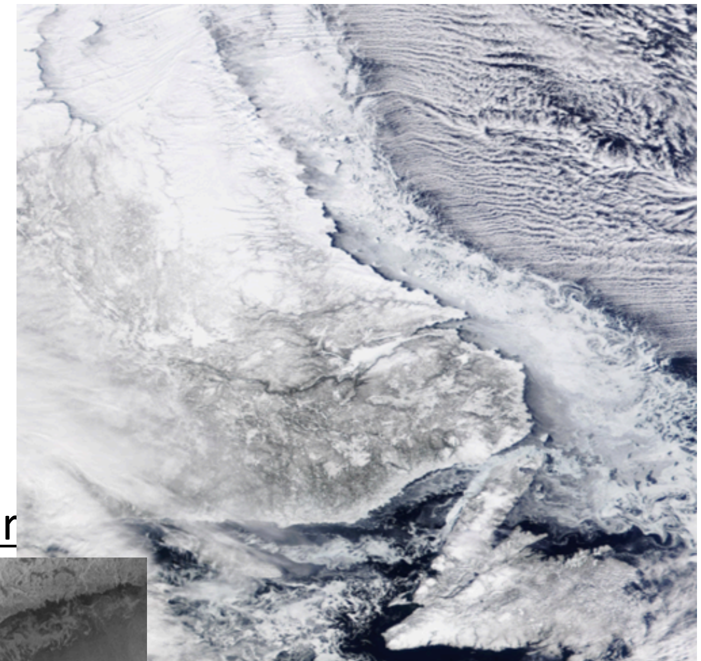
$\left.\begin{array}{l}\text{passive microwave (5-55km)}\\ \text{visible infrared (1km)}\\ \text{active microwave (50m)}\end{array}\right\}$ sensors have multiple channels

Choosing our observations

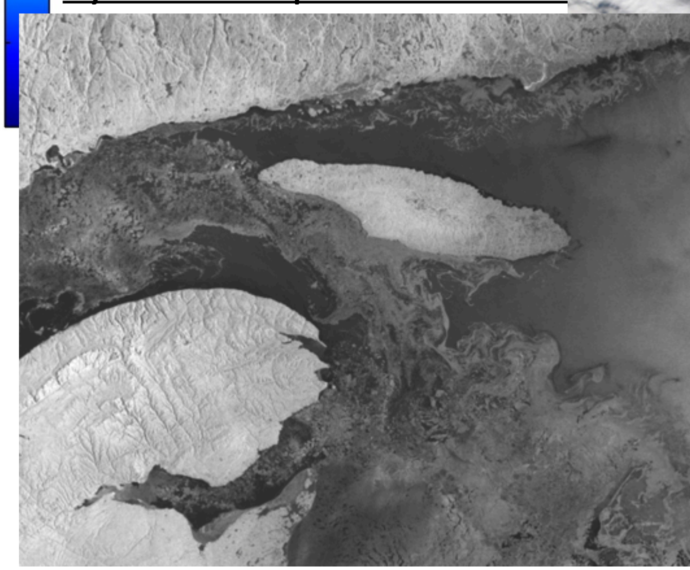
Passive microwave (PM)



Visual/Reflectance



Synthetic aperture radar



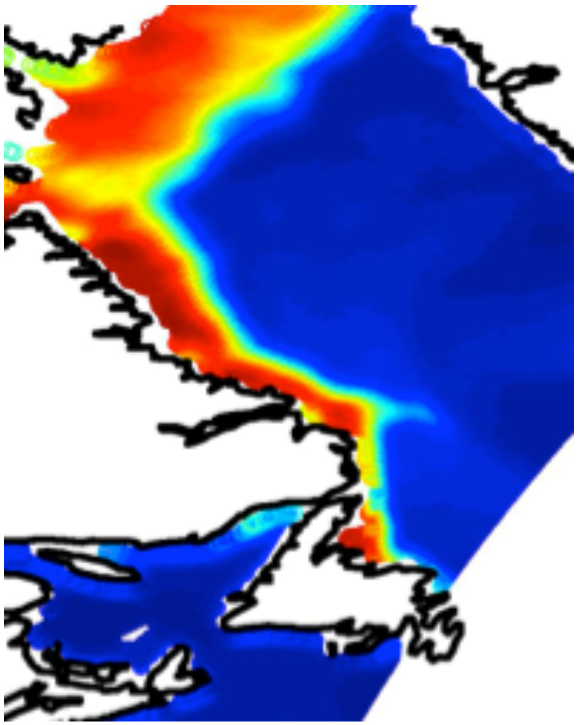
Passive microwave observations

AMSR-E Performance Characteristics

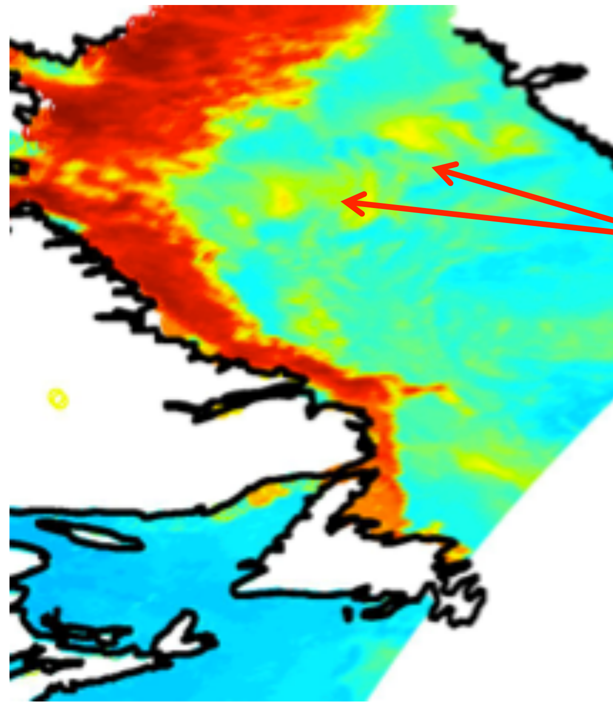
Polarization	Horizontal and vertical					
Incidence angle	55°					
Cross-polarization	Less than -20 dB					
Swath	1445 km					
Dynamic Range (K)	2.7 to 340					
Precision	1 K (1σ)					
Quantifying Bit Number	12-bit	10-bit				
Center Frequency (GHz)	6.925	10.65	18.7	23.8	36.5	89.0
Bandwidth (MHz)	350	100	200	400	1000	3000
Sensitivity (K)	0.3	0.6				1.1
Mean Spatial Resolution (km)	56	38	21	24	12	5.4
IFOV (km)	74 x 43	51 x 30	27 x 16	31 x 18	14 x 8	6 x 4
Sampling Interval (km)	10 x 10					5 x 5
Integration Time (msec)	2.6					1.3
Main Beam Efficiency (%)	95.3	95.0	96.3	96.4	95.3	96.0
Beamwidth (degrees)	2.2	1.4	0.8	0.9	0.4	0.18

- Which channels should I use?

Brightness temperature data



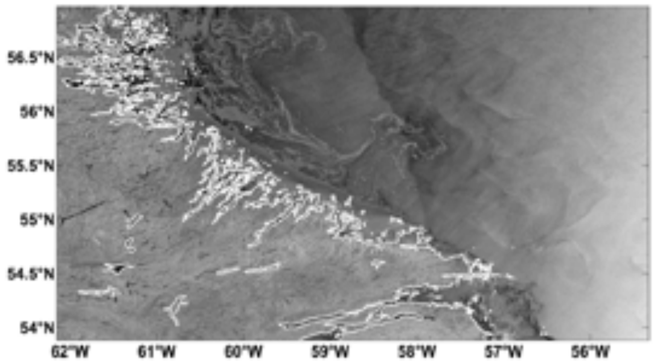
6.9GHz
coarse resolution

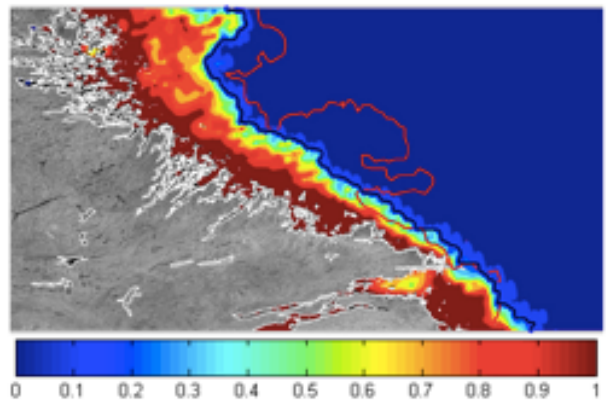


36.5GHz
higher resolution

Sea ice concentration from passive microwave: challenges due to weather

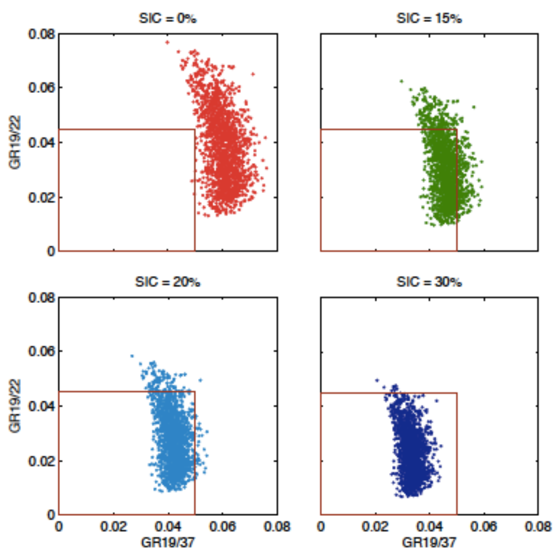
- Sea ice concentration retrievals sensitive to atmosphere (windspeed, moisture)
- Weather filters used to remove spurious ice – reduces ice concentration in MIZ





Ice edge from Image analysis chart

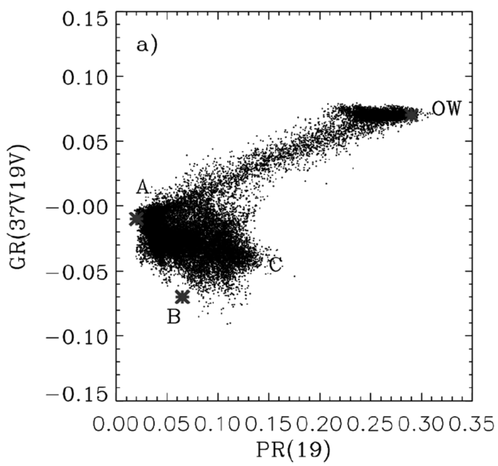
Liu et al. 2016



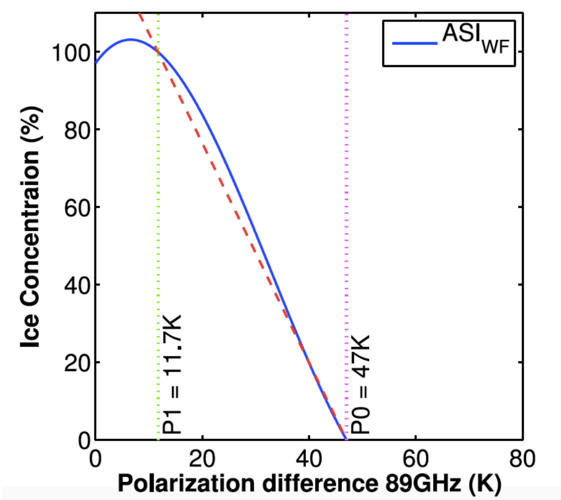
Ivanova et al. 2015

- A significant number of points with SIC$\neq 0$ can be flagged as weather

Ice concentration retrievals



Markus et al. 2009



Lu et al. 2018

- Ice concentration retrieval algorithms generally use either linear or non-linear interpolation between ice and water tie points
- Tie points can be fixed or seasonally varying
- Either weather filters are used or a correction is made
- There are many algorithms! (Ivanova 2014, Lavergne 2019, Andersen 2006, 2007…)

Data assimilation methodology

$$J(\boldsymbol{x}) = \left(\boldsymbol{x} - \boldsymbol{x}^b\right)^T \boldsymbol{B}^{-1} \left(\boldsymbol{x} - \boldsymbol{x}^b\right) + (\boldsymbol{y} - H(\boldsymbol{x}))^T \boldsymbol{R}^{-1} (\boldsymbol{y} - H(\boldsymbol{x}))$$

<u>For assimilation of ice concentration</u>

- Y is the ice concentration
- H is a linear interpolation operator

<u>For direct assimilation of brightness temperatures</u>

- Y is the observed brightness temperature
- H is a radiative transfer model (Wentz, 2000)

Forward model: $T_B = H(x)$

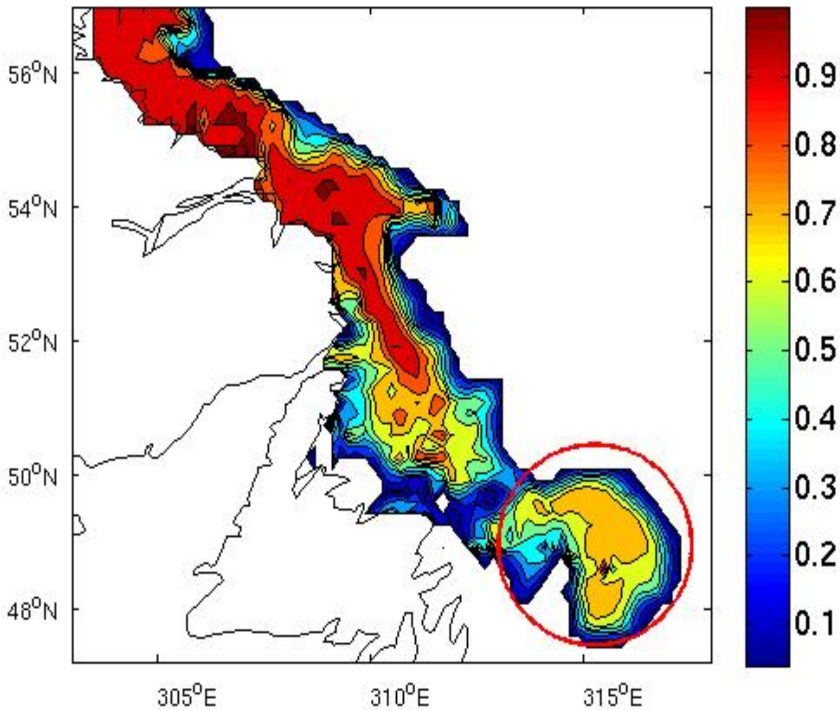
$$T_B = T_{BU} + \tau\left(C_{ice}\varepsilon_{ice}T_{ice} + (1 - C_{ice})\left(\varepsilon_{ow}T_{ow} + \Omega\right)\right)$$

- T_B is the brightness temperature
- τ is the atmospheric transmissivity
- C_{ice} is the ice concentration
- T_{ice}, T_{ow} is the ice temperature and sea surface temperature
- ε_{ice}, ε_{ow} are the ice and open water emissivity
- Ω is the scattering integral (function of windspeed)

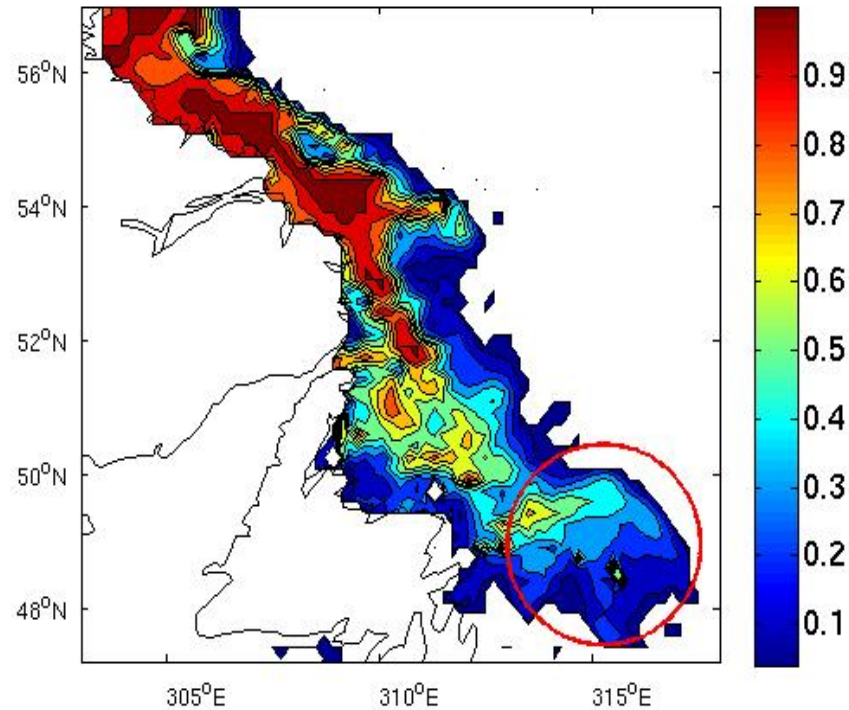
- Low frequency, 100% ice cover: $T_B = \varepsilon_{ice} T_{ice}$

Ice concentration retrievals

Result from assimilation of ice Concentration observations



Result from assimilation of brightness temperatures

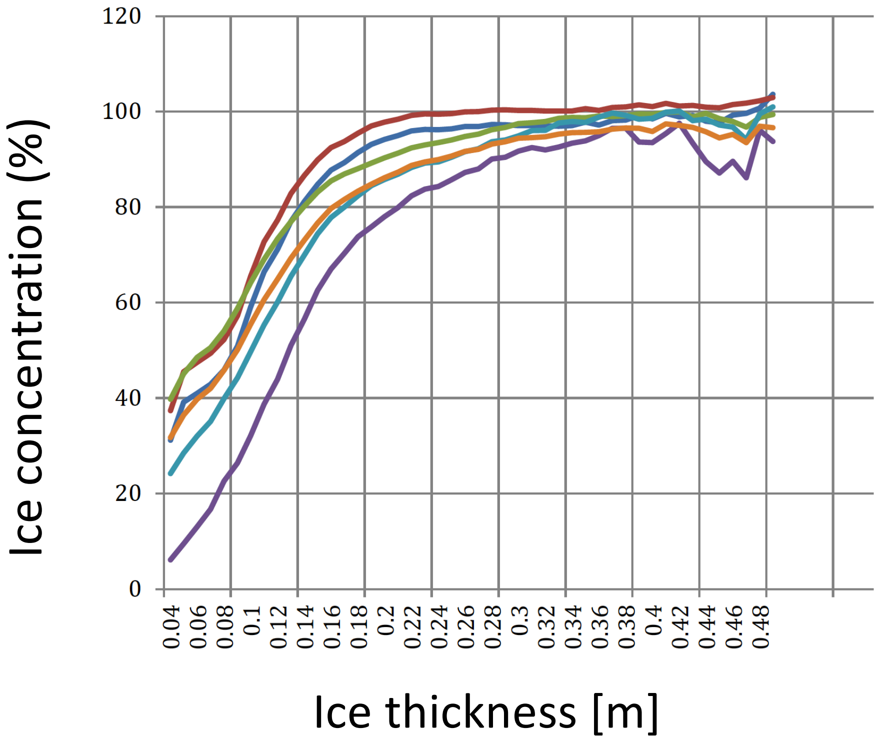


- Reduction in spurious ice due to weather effects

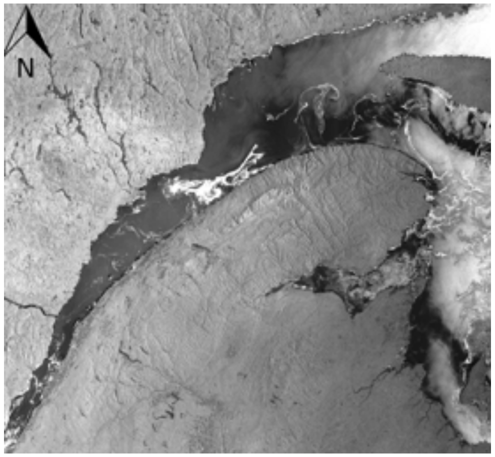
Scott et al. MWR 2012

Sea ice concentration from passive microwave: challenges due to thin ice

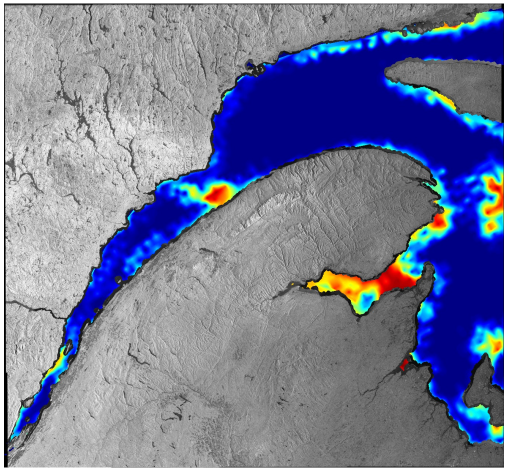
- Sea ice concentration is significantly underestimated when ice is thin



Ivanova et al. 2013

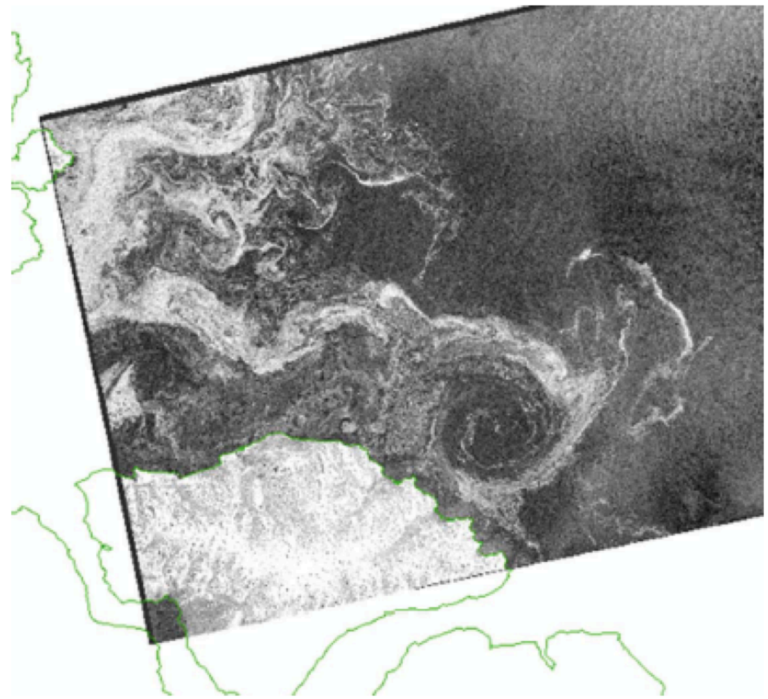


SAR image during freeze-up



Ice concentration from PM

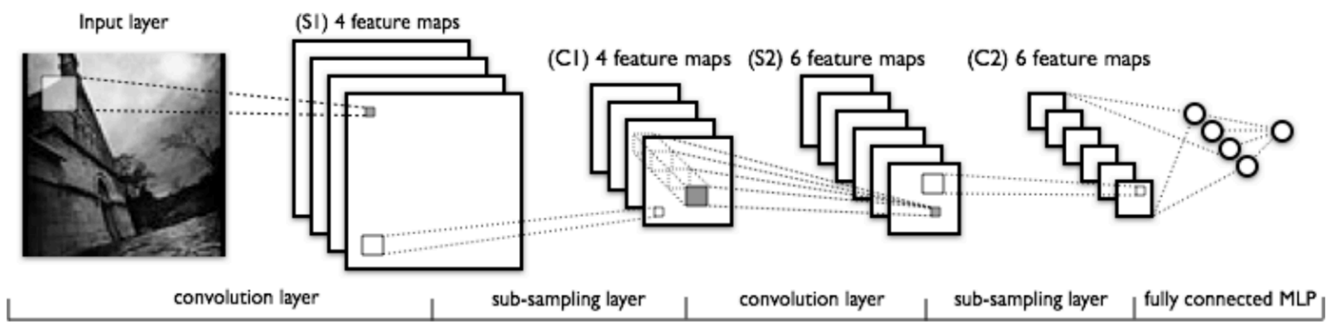
Other data sources: SAR



- As forecasting systems go to higher resolution – assimilation of high resolution data becomes more important

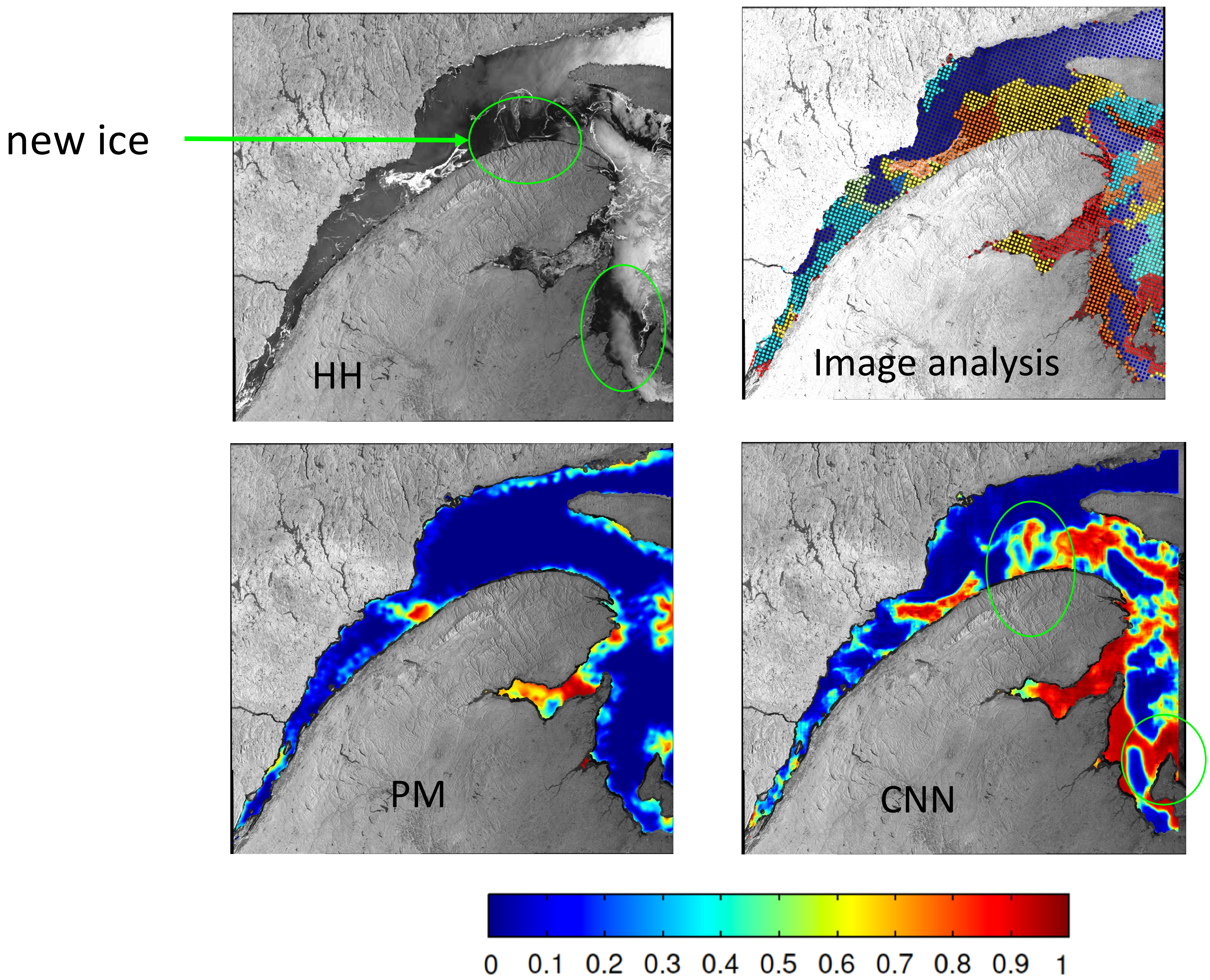
Estimating ice concentration from SAR?

- We have used convolutional neural networks to learn ice concentration from SAR (Wang, 2016)



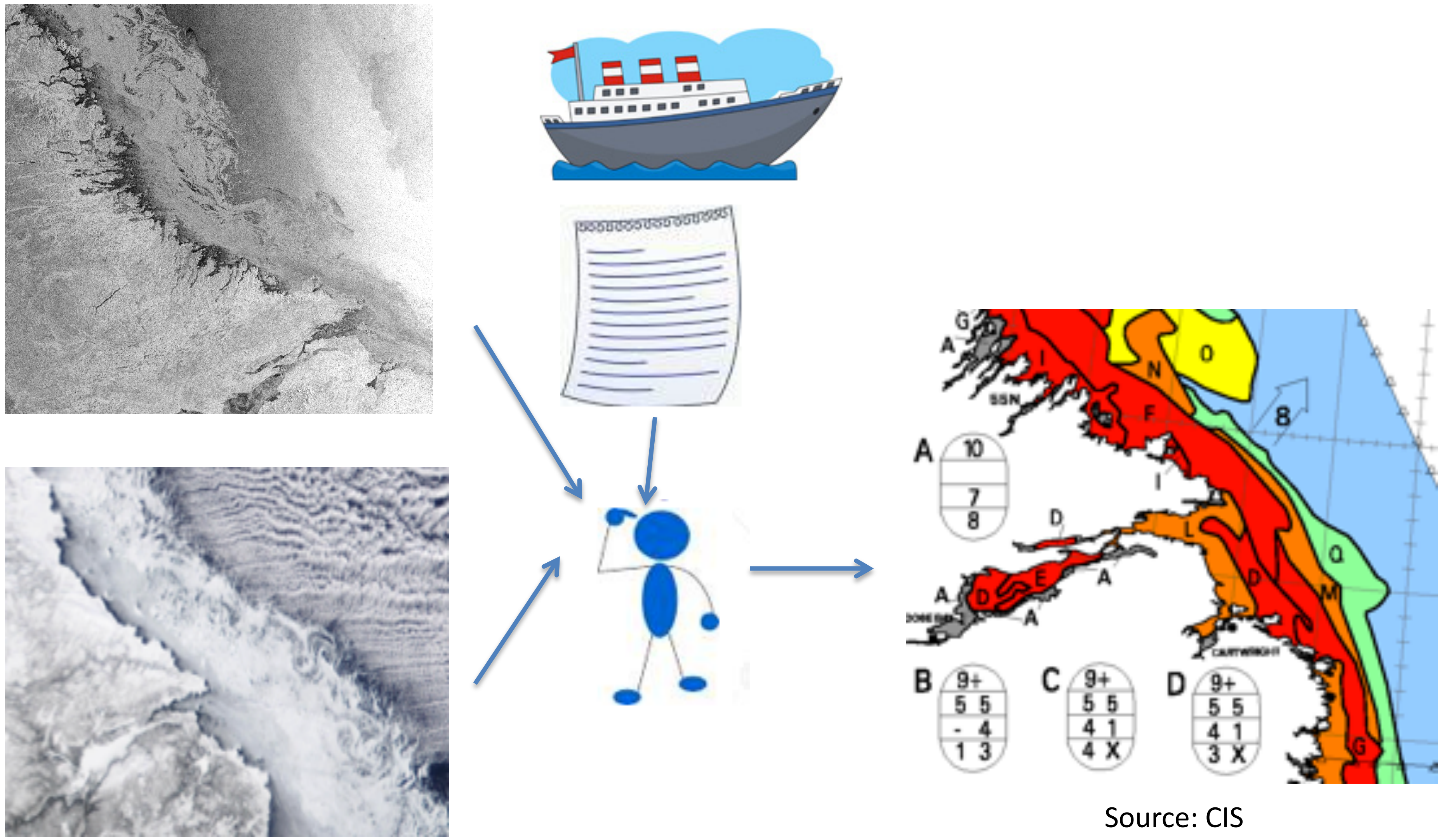
- A CNN consists of multiple layers
- Each layer has 3 operations:
  - Convolution filter
  - Nonlinear activation
  - Subsampling (averaging)

Sea ice concentration from SAR



Assessing SIC estimates

- Most SIC products are from PM data and may have similar errors
- Usually a manual analysis is used as the ‘truth’ (ice chart, IMS)



Source: CIS

Assessing SIC estimates

- Threshold is applied to ice concentration from DA to produce ice/water
- Contingency tables are used to calculate scores for ice and water (Smith et al. 2016, Buehner et al. 2015)

	Ice in verification	**Water in verification**
Ice in forecast	Hit ice	False alarm
Water in forecast	Miss	Hit water

- Proportion correct ice $= \frac{hit\ ice}{hit\ ice + miss}$
- Proportion correct water $= \frac{hit\ water}{hit\ water + false\ alarm}$

Another way to assess SIC estimates?

- It is hard to find a data set that can represent the 'truth'
- Instead of relying on a true sea ice concentration, we rank the datasets using triple collocation (McColl et al. 2016)
- Using three datasets, define the vector

$$\boldsymbol{v} = \begin{bmatrix} \sqrt{\dfrac{Q_{12}Q_{13}}{Q_{23}}} \\ \sqrt{\dfrac{Q_{12}Q_{23}}{Q_{13}}} \\ \sqrt{\dfrac{Q_{23}Q_{13}}{Q_{12}}} \end{bmatrix}$$

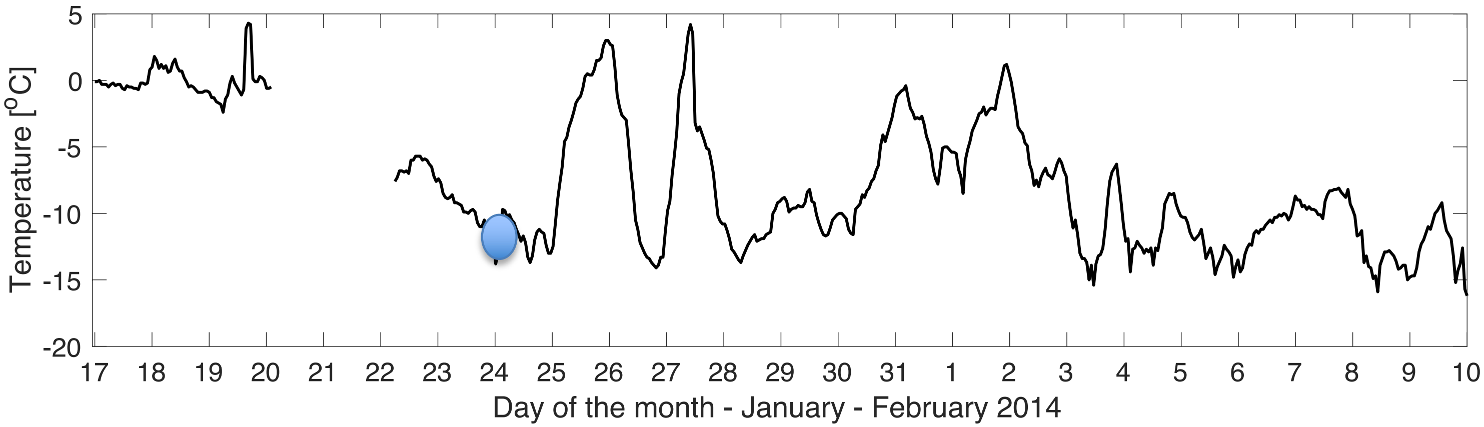
- Dataset with highest $\boldsymbol{v}$ value has strongest correlation with the other two
- One piece of information is used to make one estimate: rank datasets

Assessing SIC estimates

- It can also be shown (Parisi, 2014, Jaffe 2015) if we have three pieces of information (mean, second and third order correlation), we can estimate three items:
  - Proportion correct ice
  - Proportion correct water
  - Dataset imbalance (relative number of zeros and ones)

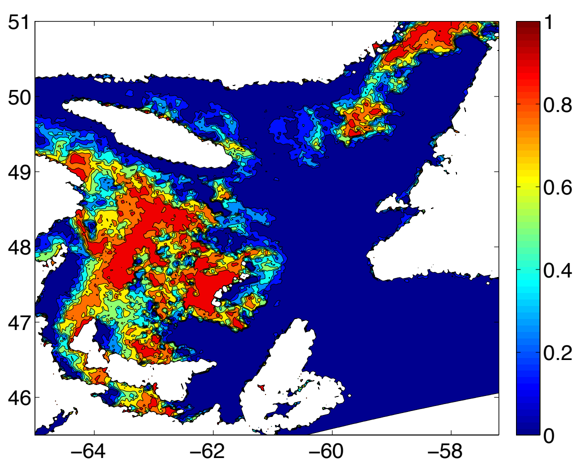
- Provides another way to compare datasets without needing to define a `truth’
- Here we test this using three data sets in the Gulf of Saint Lawrence
  - Passive microwave retrieval
  - Ice ocean model output
  - SAR-sea ice concentration (using CNN)

Gulf of Saint Lawrence: Freeze up 2014

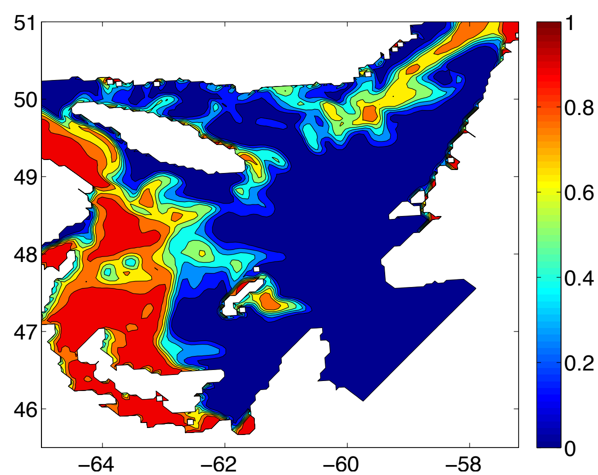


Temperature from weather station

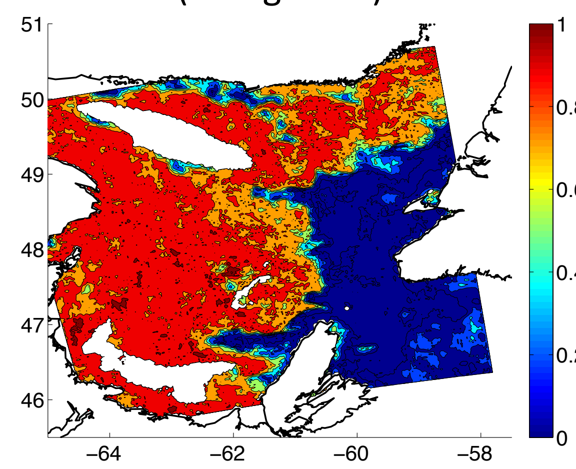
PM (Spreen 2008)



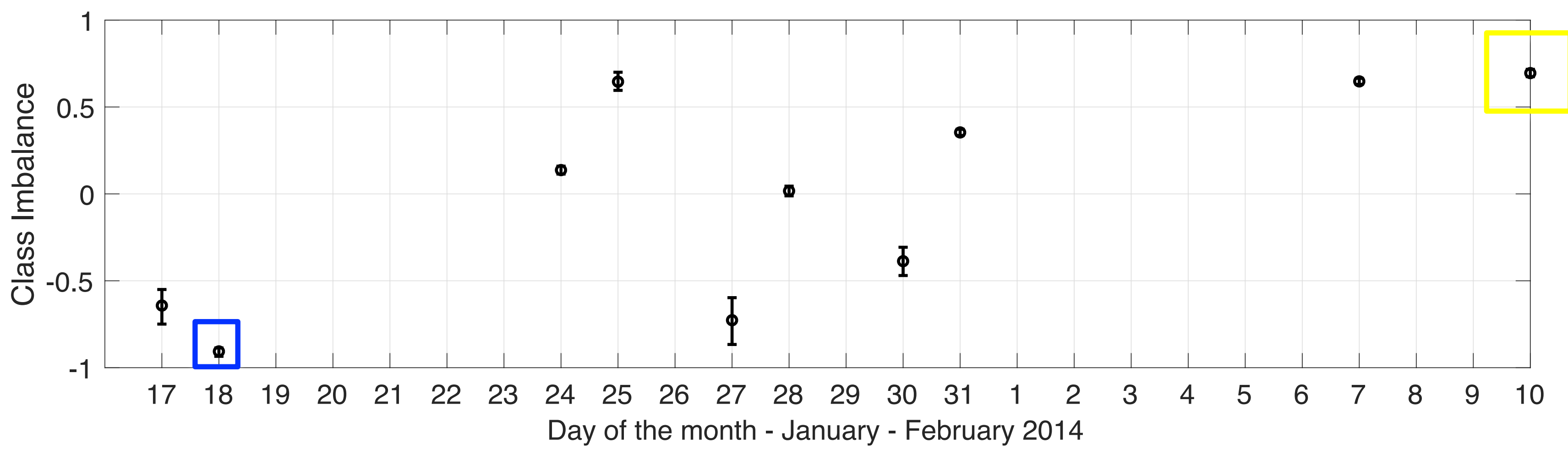
Ice ocean model (Smith, 2012)

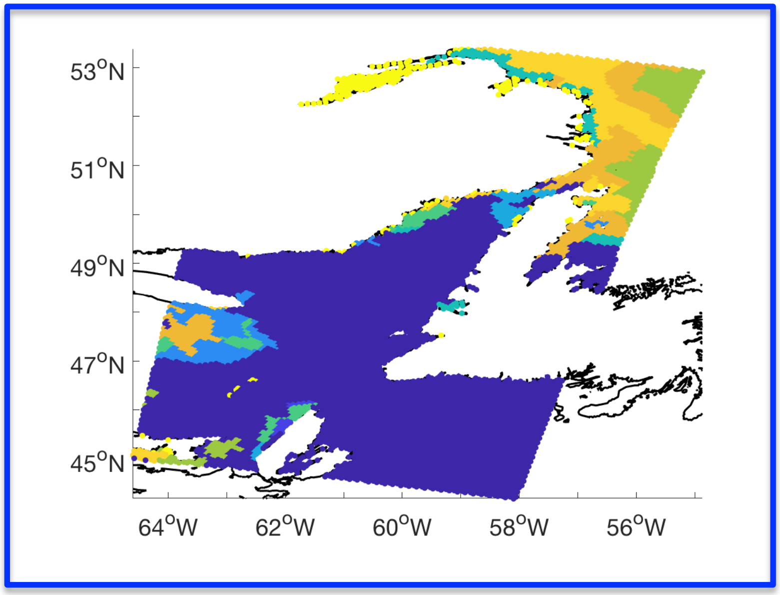


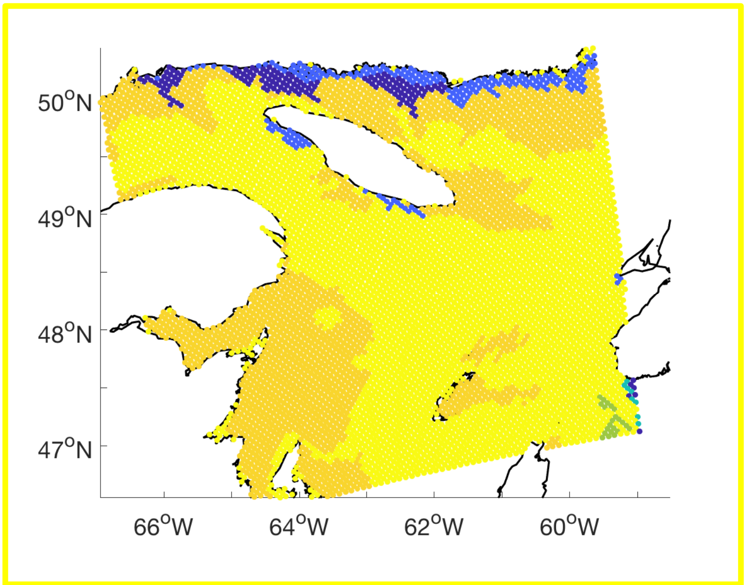
SAR (Wang 2017)



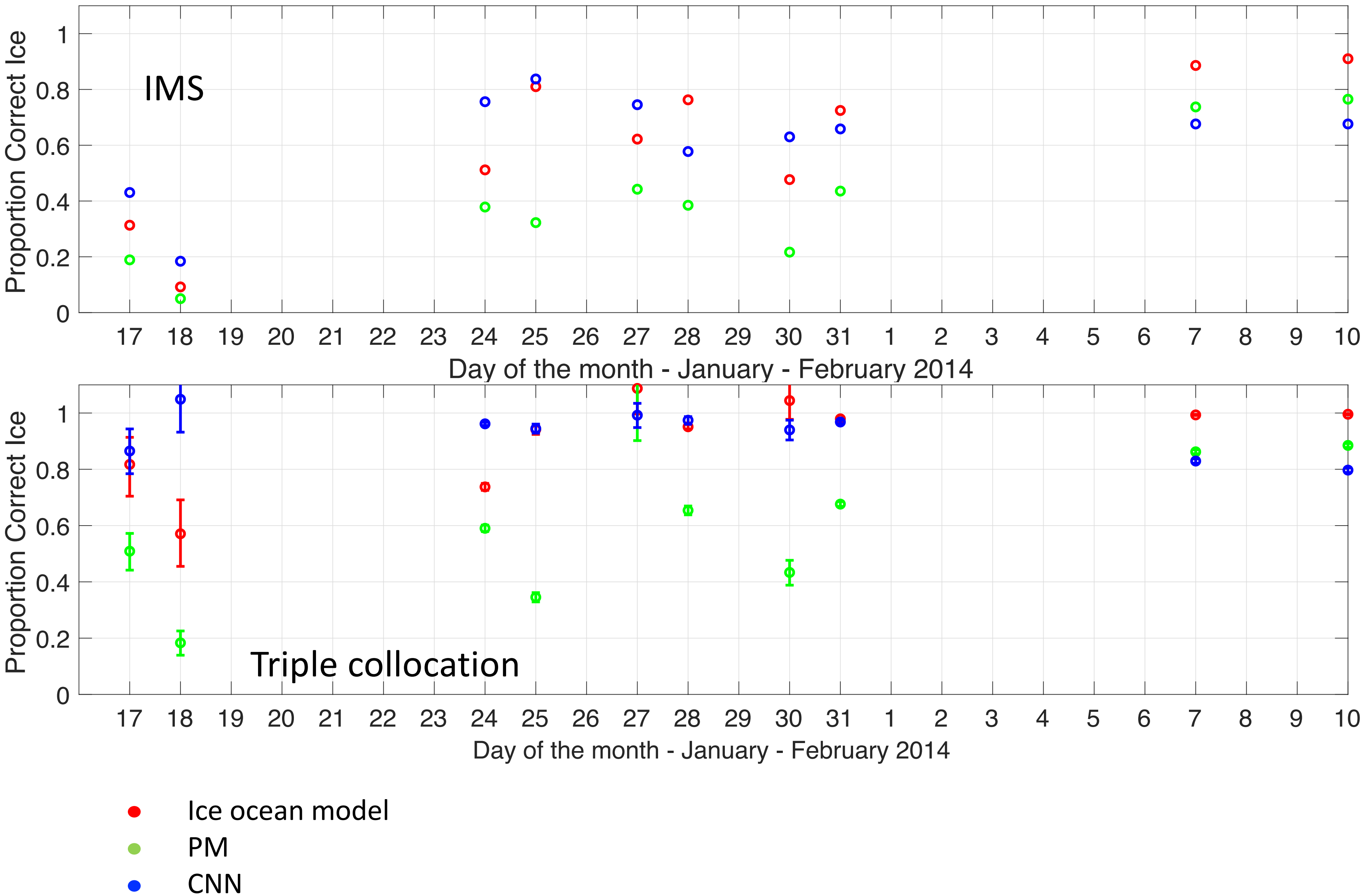
Assessing SIC estimates



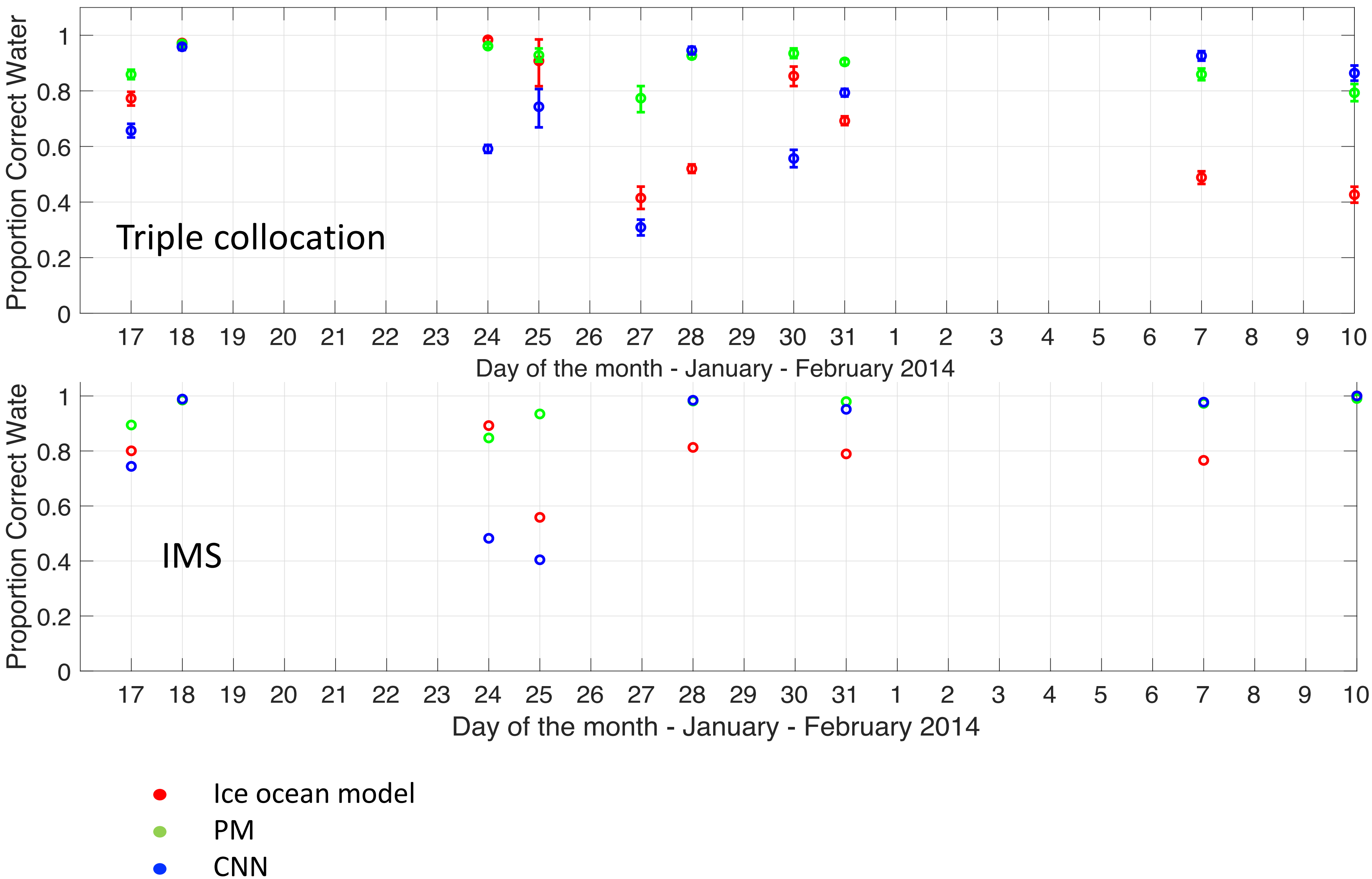




Assessing proportion correct ice



Assessing proportion correct water



Future work

- Assessment of triple collocation in the Arctic
- Work toward improved SIC retrievals in marginal ice zones
- Assimilation and verification of other sea ice parameters
  - Ice thickness and velocity

References

Jaffee et al., 2016, Estimating the accuracies of multiple classifiers without labeled data, Proceedings of the 18th International Conference on Artificial Intelligence and Statistics, 38, 407-415.

Ivanova et al., 2015, Inter-comparison and evaluation of sea ice algorithms: towards further identification of challenges and optimal approach using passive microwave observations, The Cryosphere Discussions, 9, 1797-1817

Mc Coll et al., 2016, Triple collocation for binary and categorical variables: Application to validating Landscape free-thaw retrievals, Remote Sensing of Environment, 176, 31-42

Parisi et. al., 2014, Ranking and combining multiple predictors without labelled data PNAS, vol. 111, no. 4 1253-1258

Scott et al., 2012, Direct assimilation of AMSR-E brightness temperatures for estimating sea ice concentration, Monthly Weather Review, 140, 997-1013.

Smith et al., 2016, Sea ice verification in the Canadian Global Ice Ocean Prediction System, Quarterly Journal of the Royal Meteorological Society, 142, 659-671.

Wang et al., 2017, Sea ice concentration estimation during freeze-up from SAR imagery using a convolutional neural network, Remote Sensing, 9, 408.

Wentz, 2000, AMSR Ocean Algorithm, Remote Sensing Systems.