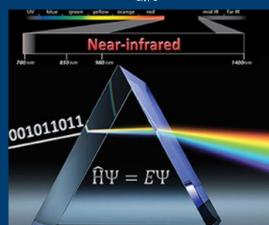
#### Science, Service, Stewardship





A revolutionary approach for improving age determination efficiency in fish using Fourier transform near infrared spectroscopy (FT-NIRS)

FT-NIRS 2023 Workshop 3-7 April

Envisioning the future of production fish ageing: end-to-end integration of the FT-NIRS age estimation enterprise

Thomas Helser, Irina Benson, Esther Goldstein, Beth Matta, Brenna Groom, Jon Short

Many thanks to AGP staff

## NOAA FISHERIES SERVICE



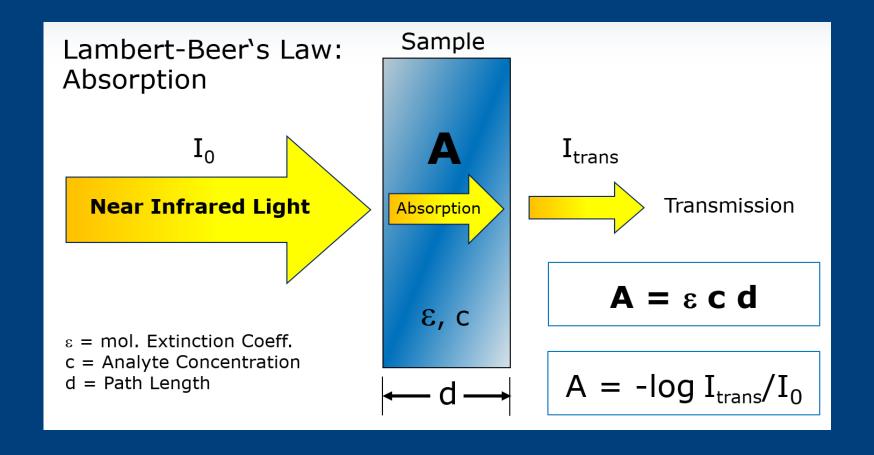


Envisioning the future of production fish ageing: end-to-end integration of the FT-NIRS age estimation enterprise

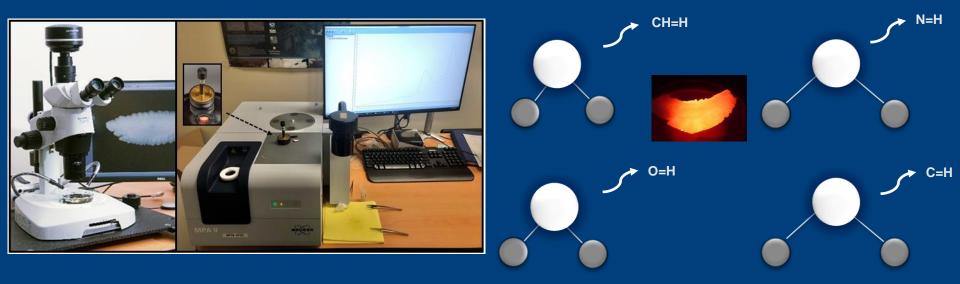
## Where to begin?

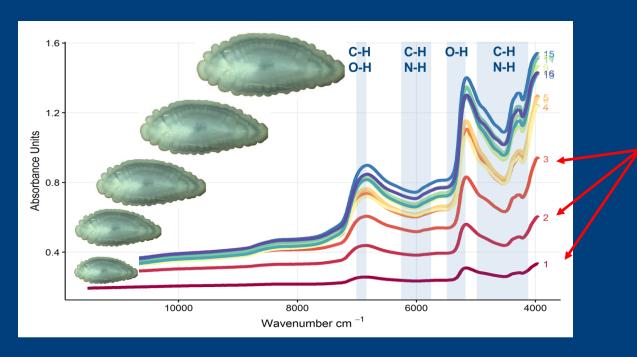
- Some background of FT-NIRS & age prediction
- ➤ How does FT-NIRS age estimation fit into the TMA process (maintain consistency in both TMA and FT-NIRS)
- Describe a (*hypothetical*) system of process control and data quality control from end-to-end (reporting examples)
- Emulate the future process: 1) build predictive model on data from past (2014-2018) and predict ages from future collections (2019 and 2021)

## Interaction of electromagnetic radiation and matter



## NIR Spectroscopy: measurement of intra-molecular vibrations



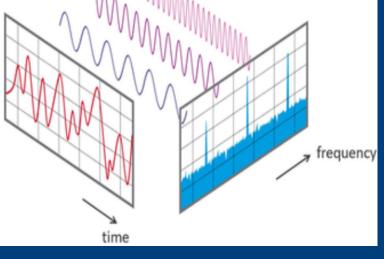


Different ages have different absorbance profiles

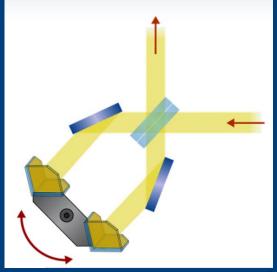
### How are the molecular motions detected and measured?

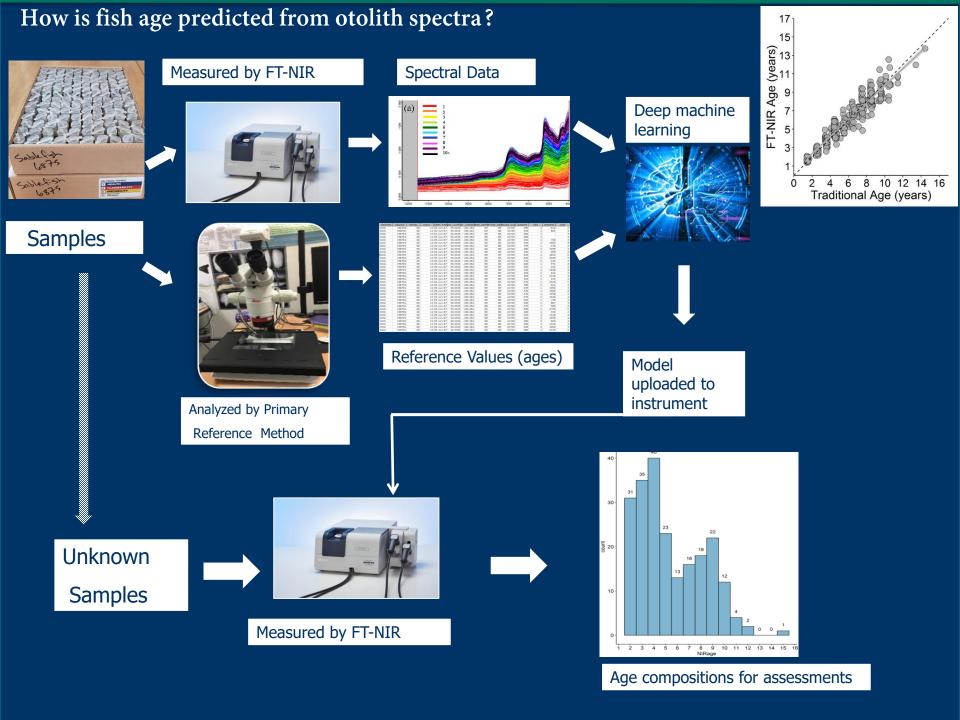
### Fourier transform near infrared spectrometer





## Interferometer







Proceedings of the Research Workshop on the Rapid Estimation of Fish Age Using Fourier Transform Near-Infrared Spectroscopy (FT-NIRS)

ICES JOURNAL OF MARINE SCIENCE JOURNAL DU CONSEIL

> Age estimation of red snapper (Lutjanus campechanus) using FT-NIR spectroscopy: Towards a feasibility for fisheries management





A transformative approach to ageing fish otoliths using Fourier transform near infrared spectroscopy; a case study of eastern Bering Sea walleye pollock (Gadus chalcogrammus)



Ageing fish at the molecular level using Fou transform near infrared spectroscopy (FT-NIRS): A case study of Pacific cod



#### MARINE & FRESHWATER RESEARCH



OPEN ACCESS | Article

The future of fish age estimation: deep machine learning coupled with Fourier transform near-infrared spectroscopy of otoliths

Irina M. Benson 📴, Thomas E. Helser 📴, Giovanni Marchetti 🚭, and Beverly K. Barnett 📴

Resource Ecology and Fisheries Management Division, Alaska Fisheries Science Center, National Marine Fisheries Service, NOAA, 7600 Sand Point Way NE, Seattle, WA 98115, USA; Google LLC, 1600 Amphitheatre Parkway, Mountain View, CA 94043, USA; Fisheries Assessment, Technology, and Engineering Support Division, Biology and Life History Branch, SoutheastFisheries Science Center, Panama City Laboratory, National Marine Fisheries Service, NOAA, 3500 Delwood Beach Rd, Panama City, FL 32408, USA



## NOAA **FISHERIES**

Original Research Article

Fourier transform near infrared spectroscopy as a tool to predict spawning status in Alaskan fishes with variable reproductive strategies

Todd TenBrink , Sandra Neidetcher, Morgan Arrington, Irina Benson, o, Christina Conrath<sup>3</sup> and Thomas Helser



SSAGE

OPEN ACCESS

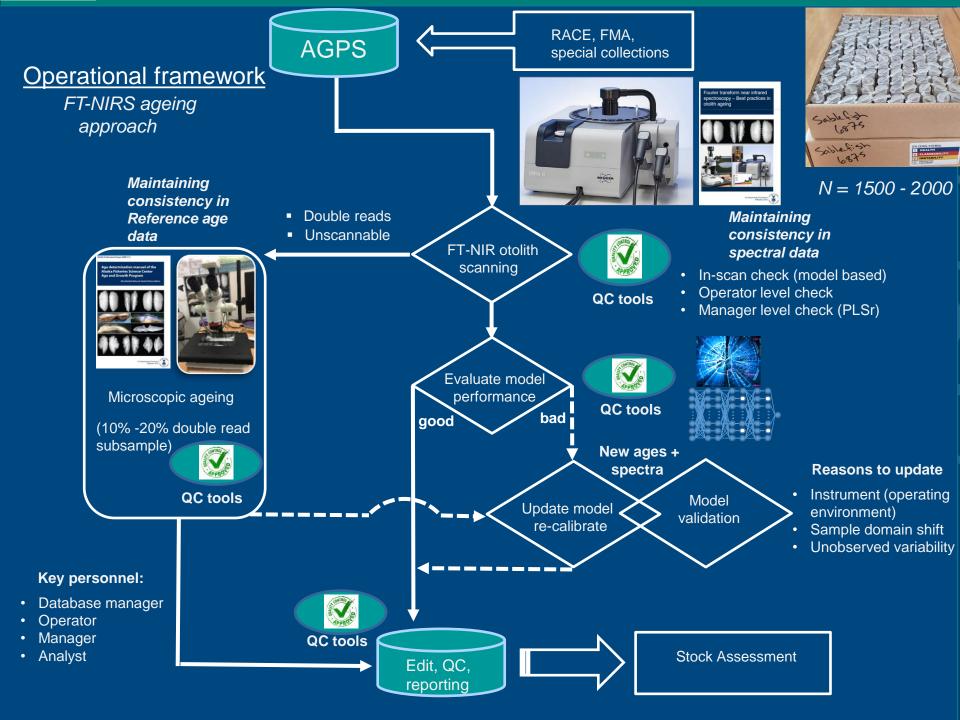
frontiers in Marine Science

Rapid and Reliable Assessment of Fish Physiological Condition for **Fisheries Research and Management Using Fourier Transform** Near-Infrared Spectroscopy

Esther D. Goldstein<sup>1\*</sup>, Thomas E. Helser<sup>1</sup>, Johanna J. Vollenwelder<sup>2</sup>, Ashwin Sreenivasan3 and Fletcher F. Sewall2







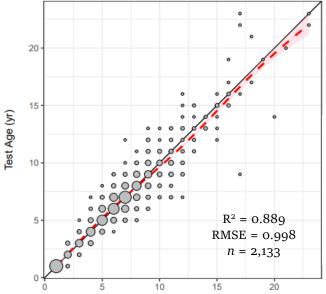


- Using otoliths from past EBS 2014-2018 surveys build a predictive CNN model.
- Predict ages for 2019 & 2021 using FT-NIRS (2014 – 2018) model



## EBS walleye pollock (2014-2018) Age data



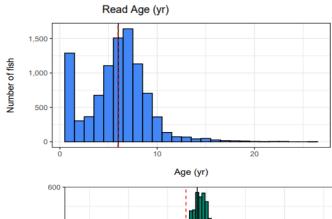


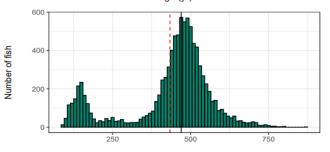
Precision statistic	Value
Percent agreement (PA)	66.9%
Average percent error (APE)	3.05%
Coefficient of variation (CV)	4.32%
Total number of fish in ageing collection	9603
Number of fish unaged	58
Number of fish in precision-testing sample	2133
Number of fish aged by two readers	2133
Percentage of fish with paired age readings	22
(a) Bias direction	5.83

minus bias	371 otoliths	17.4%
plus bias	335 otoliths	15.7%
complete agreement	1427 otoliths	66.9%

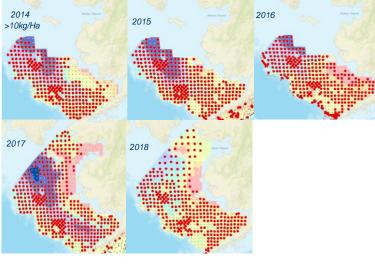
#### (b) Tests of symmetry

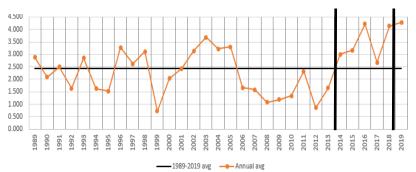
Test name	$\mathbf{d}\mathbf{f}$	Test statistic	$\boldsymbol{p}$
Bowker's	48	55.72	0.21
Evans-Hoenig	7	4.79	0.69



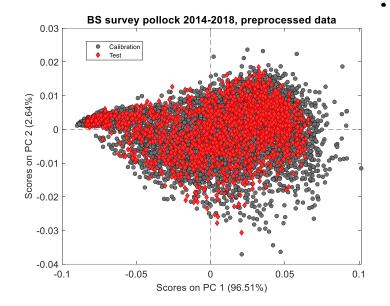






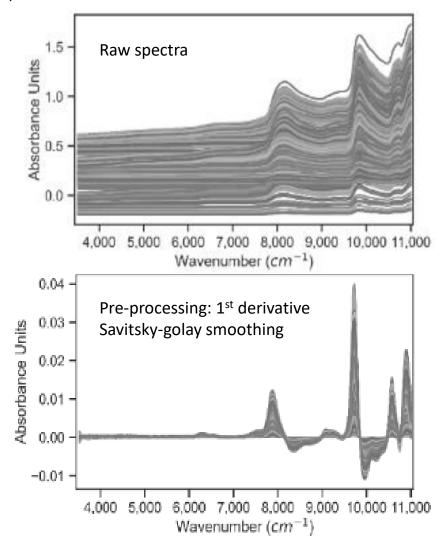


## EBS walleye pollock base model (2014-2018) Otolith spectra



Features	Subset	Values
Mean fish age*	train	5.72 (3.3)
(standard deviation)	test	5.82 (3.14)
Fish age range*	train	1 – 23
	test	1 – 23
Fish length range	train	90 – 870
	test	100 - 800
Latitude range	train	53.13822 - 65.25117
	test	53.15808 - 65.23351
Gear depth range	train	18 - 695.79
	test	18 - 640
Gear temperature range	train	-1.6 – 9.9
	test	-1.6 – 9.6

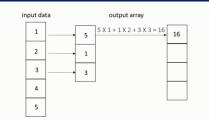
- n = 8,617
- Onion algorithm to split train & test (applied to each year)



### **Convolutional Neural Network**

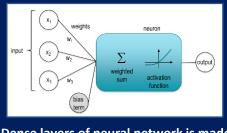




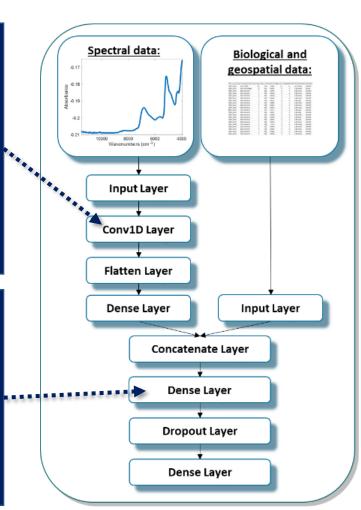


Deep learning networks will have multiple kernels and will produce multiple output arrays.

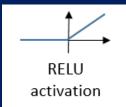
## Neurons are core processing units of the network.



Dense layers of neural network is made up of layers of neurons.

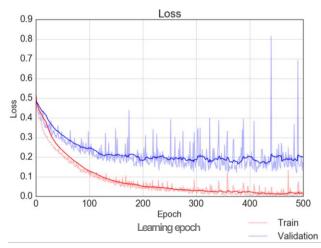


Non-linear activation functions introduce non-linear properties into network.



We used Rectified linear unit (RELU) functions which outputs the input directly if it is positive, for negative input outputs zero.

To implement our models we employed Python using TensorFlow with Keras API and hyperband optimization (HB) for hyperparameter tuning.



#### **Predictive results from CNN**

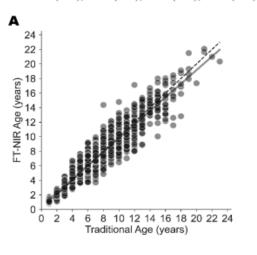


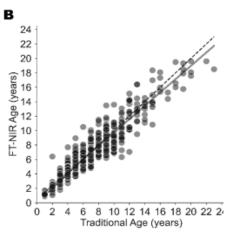
## Walleye pollock (Gadus chalcogrammus)

Table 3. Prediction results of multi-modal CNN and PLS models.

Model	Number of otoliths			$\mathbb{R}^2$		RMSE	RMSE	
	Train	Test	Outliers*	Train	Test	Train	Test	
CNN				0.93	0.92	0.83	0.91	
PLS with all spectral wavenumbers	6866	1751	12	0.89	0.87	0.99	1.14	
PLS with selected spectral wavenumbers				0.90	0.87	0.97	1.12	

<sup>\*</sup>Spectral outliers removed for each collection year: 2014 (n=3); 2015 (n=1); 2016 (n=3); 2017 (n=1); 2018 (n=4)





 $R^2 = 0.92 \text{ RMSE}_p = 0.91 \text{ years}$ 

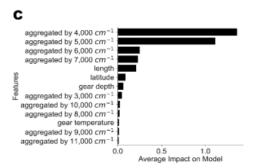


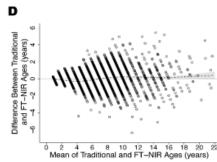
## Canadian Journal of Fisheries and Aquatic Sciences

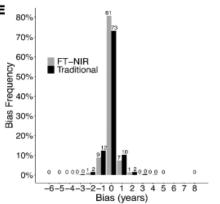
The future of fish age estimation: deep machine learning coupled with Fourier transform near infrared spectroscopy of otoliths.

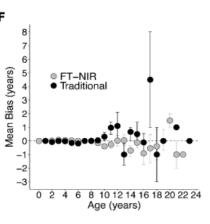
Benson, Irina; NOAA Fisheries Alaska Fisheries Science Center, Resource Ecology and Fisheries Management Division Helser, Thomas; NOAA Fisheries Alaska Fisheries Science Center, Resource Ecology and Fisheries Management Division Marchetti, Giovanni; Google LLC

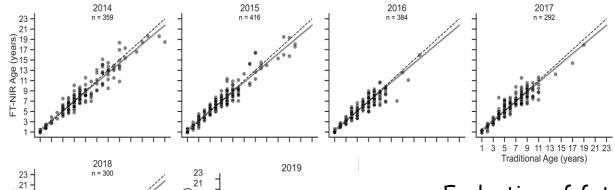
Barnett, Beverly; NOAA Fisheries Southeast Fisheries Science Center, Fisheries Assessment, Technology, and Engineering Support Division, Biology and Life History Branch, Panama City Facility

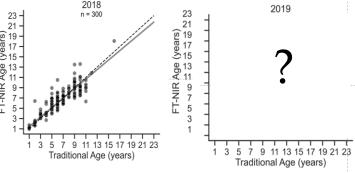












#### Dropout as a Bayesian Approximation: Representing Model Uncertainty in Deep Learning

Proceedings of the 33<sup>rd</sup> International Conference on Machine Learning, New York, NY, USA, 2016. JMLR: W&CP volume 48. Copyright 2016 by the author(s).

nature > nature reviews physics > viewpoint > article

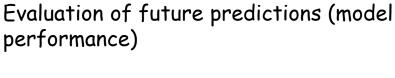
Viewpoint | Published: 22 August 2022

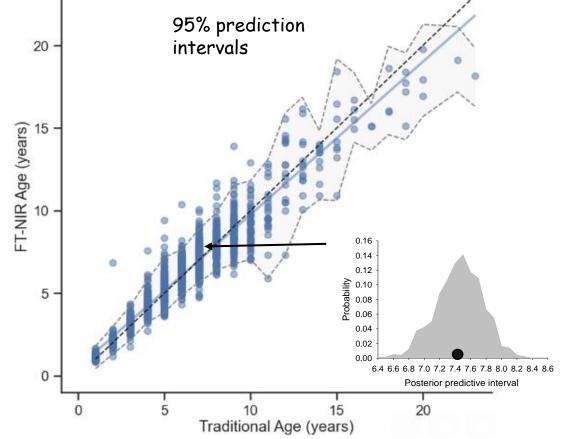
#### Bayesian uncertainty quantification for machinelearned models in physics

Yarin Gal ☑, Petros Koumoutsakos ☑, François Lanusse ☑, Gilles Louppe ☑ & Costas Papadimitriou ☑

Nature Reviews Physics 4, 573-577 (2022) Cite this article

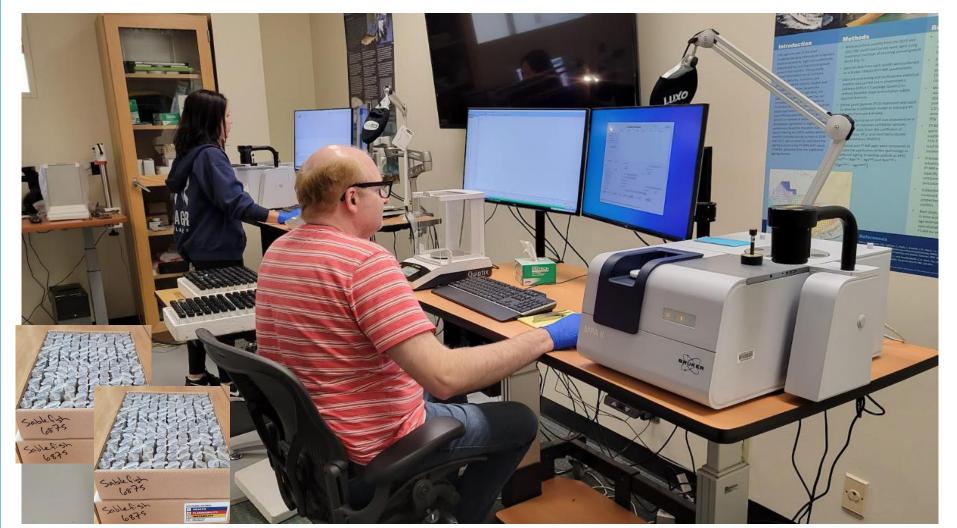
4138 Accesses | 23 Altmetric | Metrics







## PART I: Collection of pollock otolith NIR spectra (Still in 2019, but jump to the future to 2021)



## Consistency in otolith spectra



FT-NIR otolith scanning



## QA/QC standardized reports ex. 2019 survey walleye pollock

Analysis by session	Total scans	Unscannable	Broken	Crystallized	Other issue	Outliers	Extreme	Unusual
NIR_162201901201A	138	2	2	3	5	2	3	4
NIR_162201901201B	261	11	1	10	16	2	12	6
NIR_162201901201C	140	0	4	4	5	1	9	4
NIR_162201901201D	140	0	0	6	9	1	12	6
NIR_162201901201E	85	0	0	1	2	0	7	2
NIR_94201901201A	124	7	6	6	4	0	10	6
NIR_94201901201B	236	44	13	10	30	1	24	4
NIR_94201901201C	138	2	0	7	7	1	11	4
NIR_94201901201D	138	2	2	6	7	1	11	2
NIR_94201901201E	78	0	0	0	3	0	4	4
Separate analysis on combined 2019 scan sessions	1478	68	28	53	88	5	82	42

Future scan sessions - standardized at ~ 2 boxes (200+ otos)

Higher efficiency may be realized (w/o weighing otoliths)

Outliers - Rescan or traditional ageing

Extreme - Pass QA/QC if there are no issues based on metadata

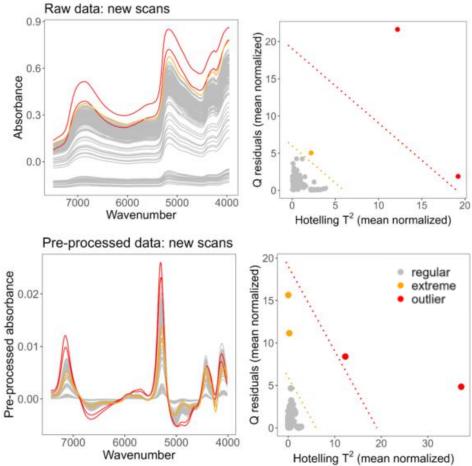
#### Unusual -

- Confirm outliers
- Possibly add data to calibration model
  - o 2019 warm year
  - o Many small fish

Include time-flow stats to monitor utilization and efficiency:

- 10 operators
- 1.66 2.43 hrs/session
- 30 50 scans/person/hour (as high as 67 scans/hour)

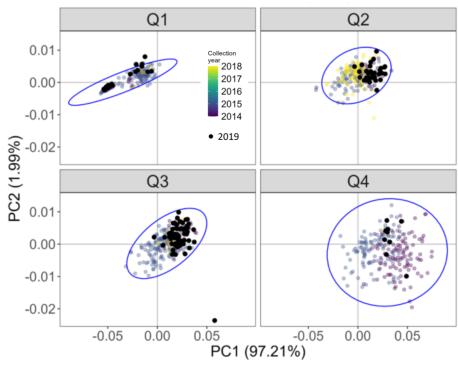
## **QA/QC** standardized reports ex. 2019 survey walleye Pollock Session NIR\_162201901201A



Part 1: Extremes & Outliers
PCA by scan session

- Extreme: determine cause (small otolith, broken, etc.)
   Significance level = 0.05
- Outliers: rescan or age traditionally.
  Significance level = 0.01





#### Part 2: Unusual spectra

New scans vs. past scans

- PCAs with all data
- 99% data ellipse by length quartile

→ outliers & specimens that expand data domain



# PART II: Processing 2019 & 2021 age data (only ageing 20% of entire collection)



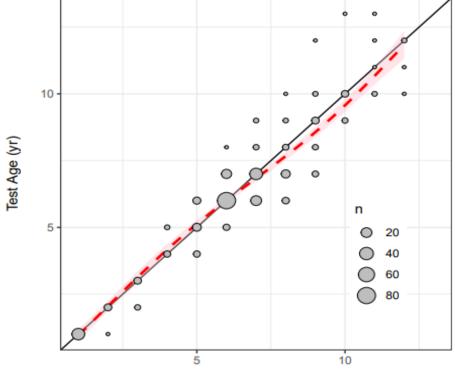
## Consistency in Reference age data (assumes 20% double reads)

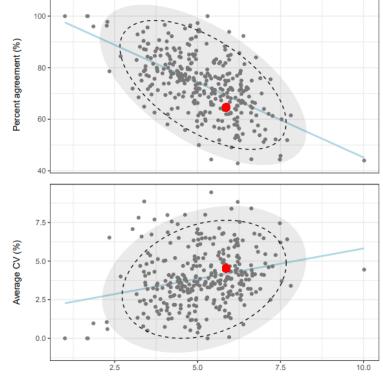


QC tools

Table 1: Precision statistics for the Walleye Pollock 2019 Bering Sea Survey collection.

Precision statistic	Value					
Percent agreement (PA) Average percent error (APE)	64.61% 3.2%		(a) Bias direction			
Coefficient of variation (CV) Total number of fish in ageing collection	4.53% $1552$	minus bia plus bias		2 otoliths 13.6 7 otoliths 21.8		
Number of fish unaged Number of fish in precision-testing sample	13 308	(b)	(b) Tests of symmetry			
Number of fish aged by two readers	308	Test name	df	Test statistic	c <i>p</i>	
Percentage of fish with paired age readings Average read age (paired reads only)	20 5.95	Bowker's Evans-Hoenig	17 3	23.44 9.1	0.14 0.03	
Average test age (paired reads only)	5.86					





Read Age (yr)

Average test age (yr)

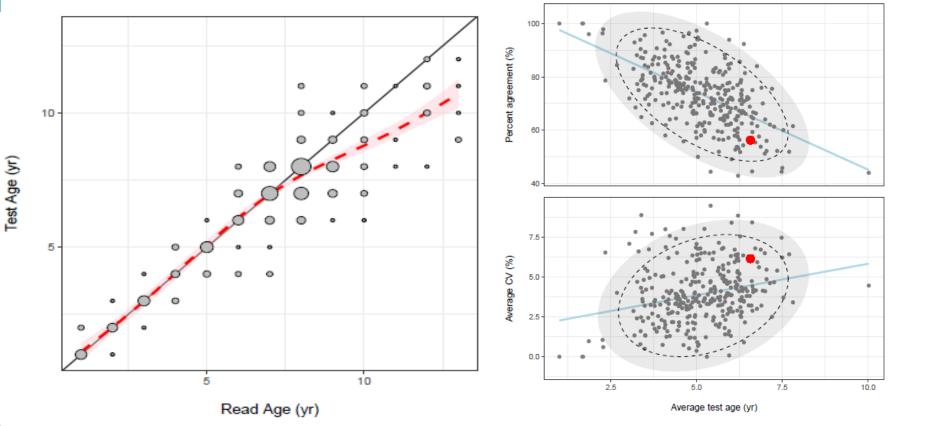
## Consistency in Reference age data (assumes 20% double reads)



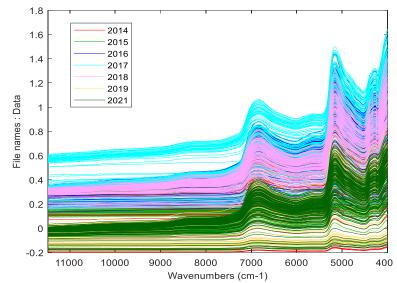
QC tools

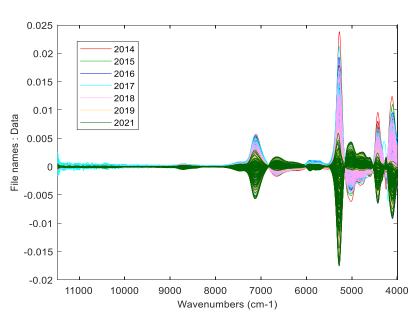
Table 1: Precision statistics for the Walleye Pollock 2021 Bering Sea Survey collection.

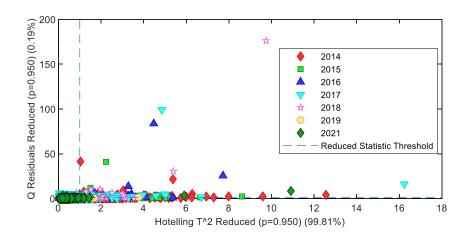
Precision statistic	Value				
Percent agreement (PA) Average percent error (APE)	56.27% 4.34%	(a) Bias direction			
Coefficient of variation (CV) Total number of fish in ageing collection Number of fish unaged	6.14% 1535 7	plus bias 112 otol		5 otoliths 12 otoliths 02 otoliths	12.5% 31.2% 56.3%
Number of fish in precision-testing sample	359	(b) Tests of symmetry			
Number of fish aged by two readers Percentage of fish with paired age readings	359 23%	Test name	df Te	est statistic	c <i>p</i>
Average read age (paired reads only) Average test age (paired reads only)	6.89 6.57	Downer b		.09 .57	0.01 0

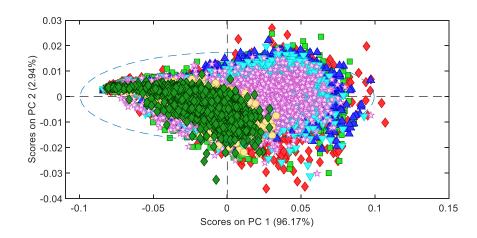


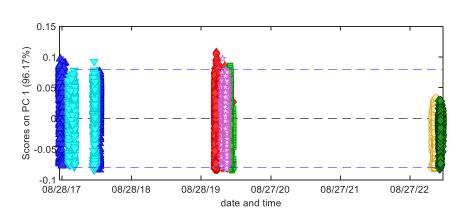






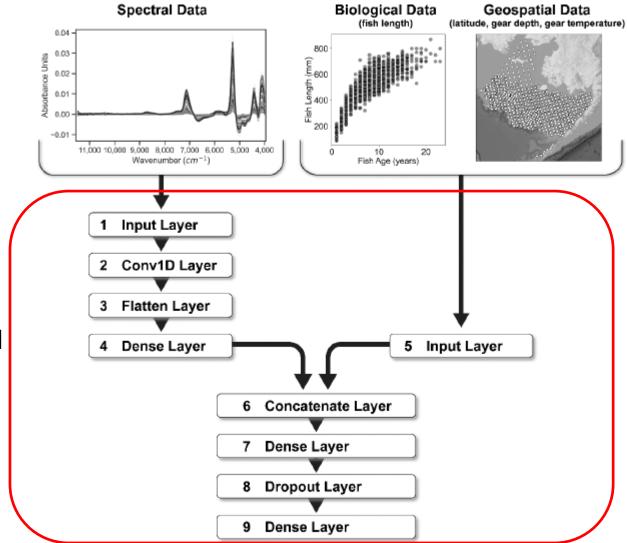






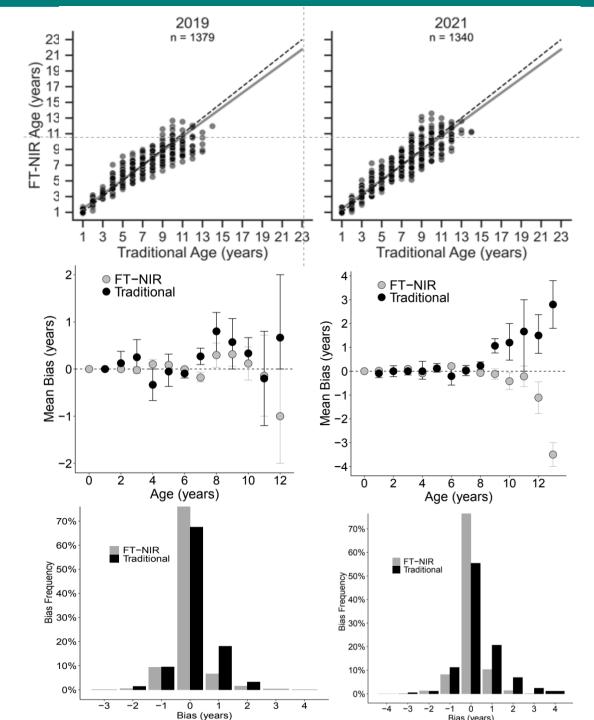


# Predicting 2019 & 2021 (ages, spectra & metadata)



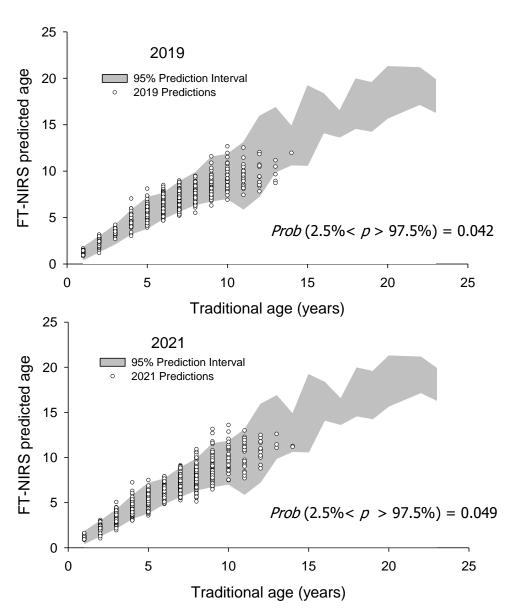
2014-2018 CNN base model



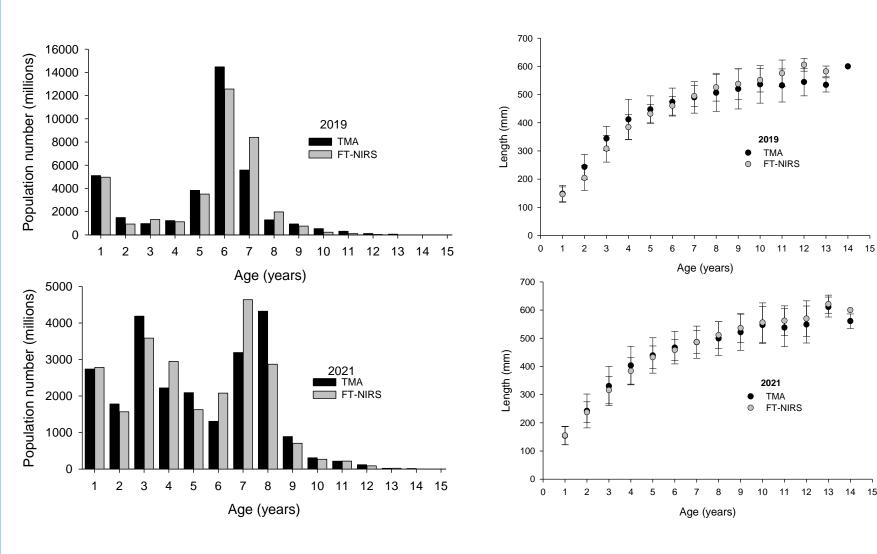




## Assessing CNN model performance of future predictions



## Age data products for stock assessments







Envisioning the future of production fish ageing: end-to-end integration of the FT-NIRS age estimation enterprise

## Talking points?

- Define the "bar" for successful application
- Ageing imprecision for use in stock assessments (TMA + NIR)
- FT-NIRS age data performance in stock assessments model updating to accommodate unseen variability
- FT-NIRS operational transition and technological deployment
- ➤ Utility function evaluate trade offs between TMA samples (double reads + outliers + issue otoliths) and FT-NIRS efficiency gains



#### The Future:

- Continue to investigate ageing error and bias effects on models (enhance predictive models to accommodate "known" age fish)
- > Improve database interface and architecture (employ time-flow statistics for cost-benefit analysis)
- Broaden simulation framework to accommodate larger range of species & life histories
- Leverage cloud computing and machine learning (take advantage of other data types)
- > Develop predictive model tool box (R, ADMB, OPUS, Python) standardization
- > Better define staff needs and skill sets required for future operationalization
- > Think more about operational transition and technological deployment (where possible)
- Communicate to stake holders

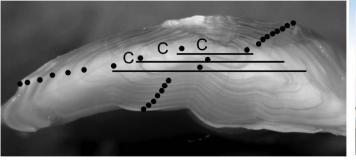
Questions?

## Strategic Initiative work flow

2022 2025 2021 •Instrument optimization (AFSC, Jan-Mar 2019) for otoliths Application Development •FT-NIRS Workshop (April 2019; SI planning over 5 years) Otolith spectra acquisition (3 species per region x 5-year time depth Predictive model development (calibration/validation) Discovery switchback Proceedings of the Process control, quality control, fault Research Workshop on **Application** detection the Rapid Estimation of **Fish Age Using Fourier Implementation** Transform Near-Infrared Standards, best practices (simulation) Spectroscopy (FT-NIRS) Al/Deep machine learning Discovery •Build scientific basis of tech. (publish) switchback **NEFSC** Stock Assessment La Jolla Lab Panama City Integration **SWFSC SEFSC**  Evaluation of assessment model outputs to FT-NIRS data Santa Cruz Lab Beaufort Lab •Provide FT-NIRS precision & reliability metrics Deployment of **NWFSC** technology Integrating technology into current production setting

(species-specific)

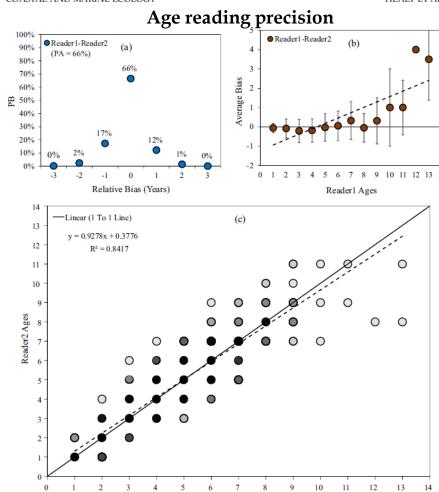
### Pacific cod otolith (transverse section)





COASTAL AND MARINE ECOLOGY

HEALY ET AL.



Reader1 Ages

