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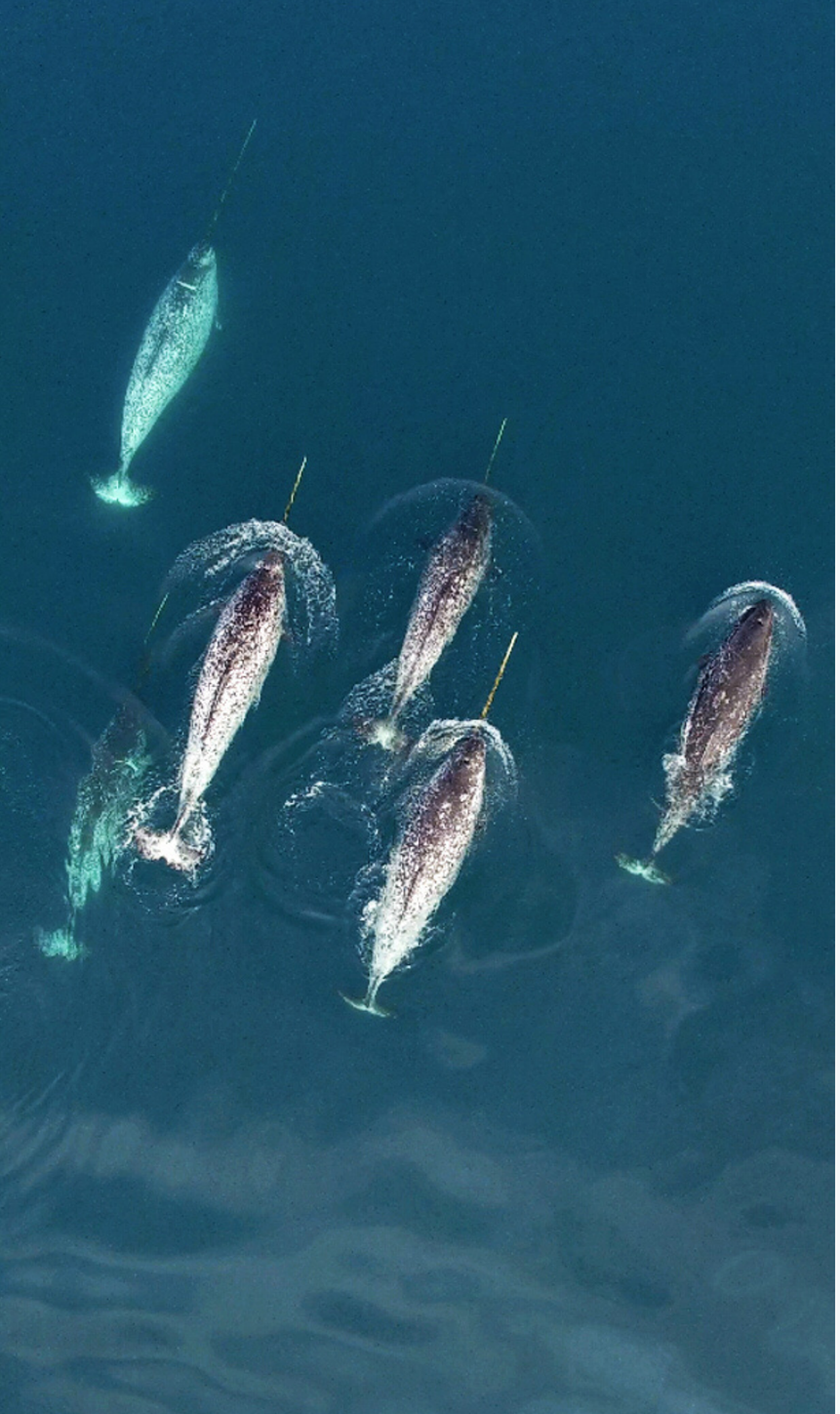
Scaling marine mammal monitoring using AI: A human-in-the-loop solution to analyze aerial datasets

Justine Boulent, PhD
Lead AI Researcher



Presentation outline

1. A few words about Whale Seeker
2. Marine wildlife monitoring context
3. Case study: a human-in-the-loop solution to scale marine mammal monitoring applied to the detection of beluga whales
4. Perspectives and conclusion

1. Whale Seeker: meet the founders!

Leveraging AI to deliver better and faster marine wildlife detection data.

Emily Charry-Tissier

CEO | Biologist
Co-founder

Antoine Gagné

CTO | Software Developer
Co-founder

Bertrand Charry

Lead Marine Biologist
Co-founder

1. Whale Seeker: meet the team!

Emily Charry-Tissier

CEO | Biologist
Co-founder

Antoine Gagné

CTO | AI & Software
Co-founder

Bertrand Charry

Lead Marine Biologist
Co-founder

Justine Boulent

Lead AI Researcher

Arnaud Pourchez

Data Engineer - MLops

Bento Gonçalves

AI Researcher

Marcela Quintero

Head of Marketing

Marina Galvao

Head of Science
Communication

Christine Fürthaller

Head of Growth

1. Whale Seeker: rewards and certifications

Certified
Certifiée B Entreprise
Corporation

SOLAR IMPULSE
EFFICIENT SOLUTION
LABEL
™

< >
Montréal Declaration
Responsible AI_
</ >

IRCAI GLOBAL TOP 100
AI
OUTSTANDING PROJECT 2022

GLOBAL TOP 100
OUTSTANDING PROJECT

AI solutions for Sustainable Development

unesco
Centre
Under the auspices
of UNESCO

IRC AI
International Research Centre
on Artificial Intelligence
under the auspices of UNESCO

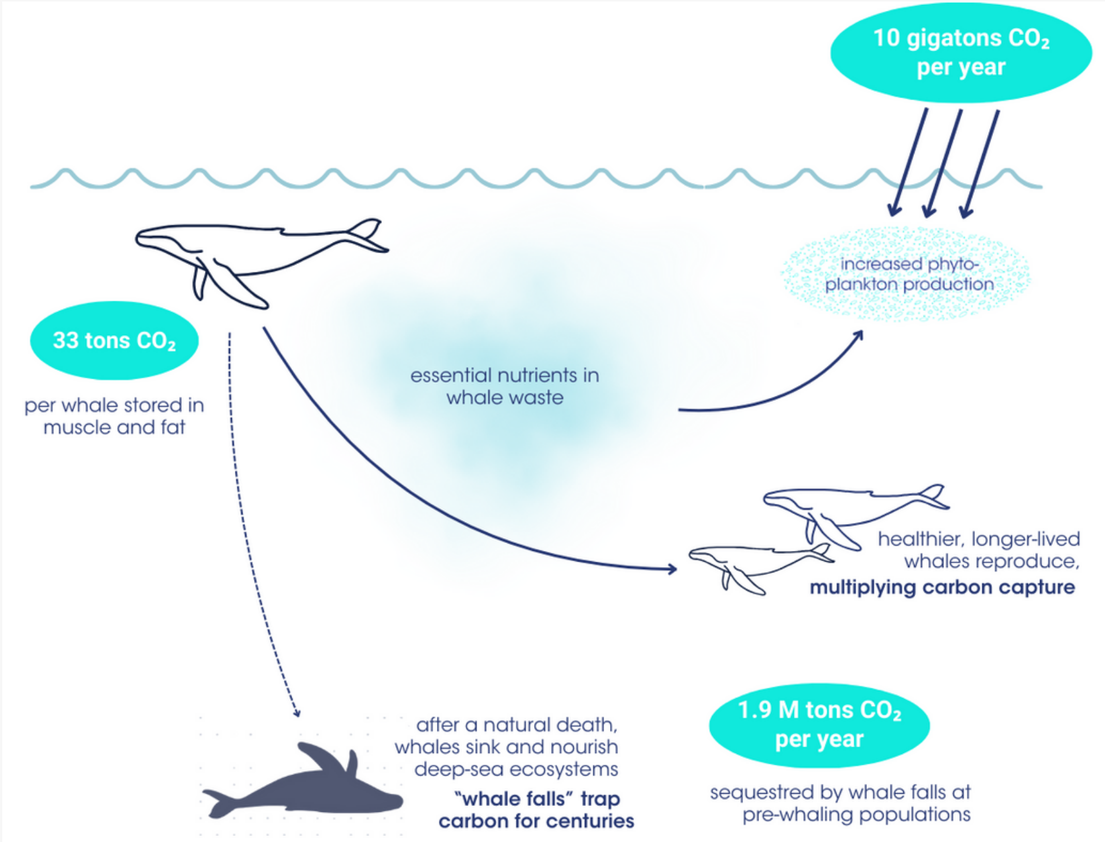
2. Marine wildlife monitoring

- **Whales, a unique opportunity against climate change**

Key ecosystem services:

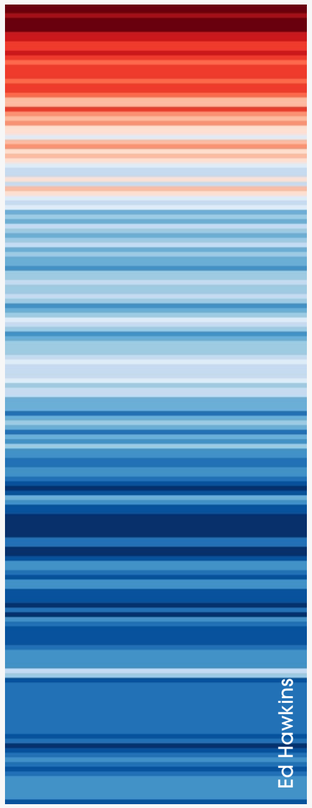
- Carbon sequestration
- Gardeners of the oceans

⟶ Value estimated at $ 2 million



2. Marine wildlife monitoring

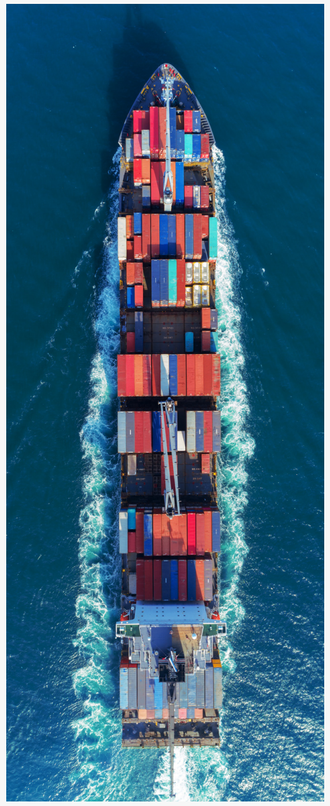
- Main threats



CLIMATE CHANGE

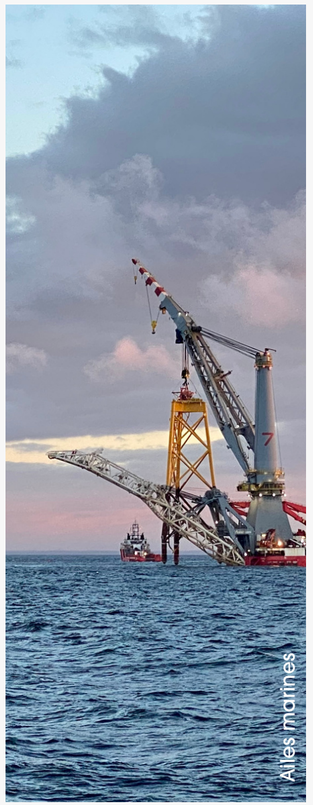
WATER POLLUTION

WHALING



OCEAN TRAFFIC

FISHNET ENTANGLEMENTS



OFFSHORE PROJECTS

2. Marine wildlife monitoring

- **Maritime activity regulations and marine mammal monitoring**

  Regulations for maritime activities:
  - Fishing: Seasonal area closures
  - Traffic: Speed reductions
  - Offshore projects (energy, dredging, unexploded explosive ordnance...): Environmental impact assessments

National Geographic Creative/Alamy Stock Photo

2. Marine wildlife monitoring

- **Maritime activity regulations and marine mammal monitoring**

  Regulations for maritime activities:
  - Fishing: Seasonal area closures
  - Traffic: Speed reductions
  - Offshore projects (energy, dredging, unexploded explosive ordnance...): Environmental impact assessments

  ⟶ Need for cost-efficient, standardized and reliable wildlife data

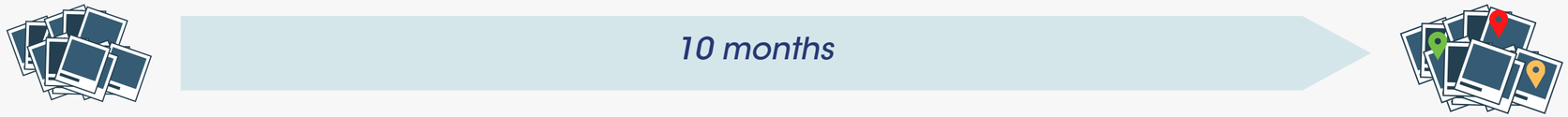
National Geographic Creative/Alamy Stock Photo

2. Marine wildlife monitoring

- **The challenges around marine wildlife data**

Data analysis = the bottleneck

- Manual analysis still the norm
- Lack of standardisation
- Time-consuming. Ex: 5,300 images for a beluga survey = about 10 months of manual analysis



2. Marine wildlife monitoring

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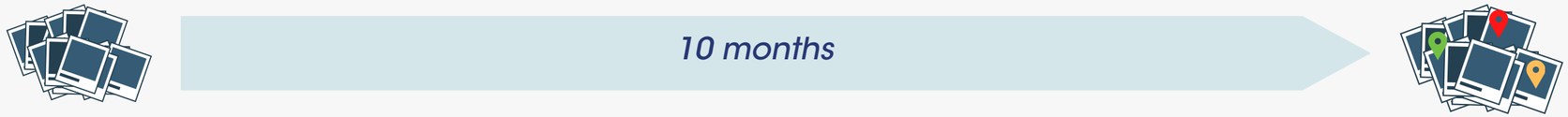


→ AI to accelerate image analysis

2. Marine wildlife monitoring

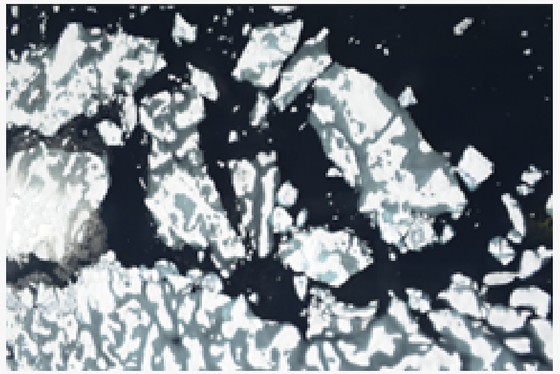
- **The challenges of AI for marine wildlife detection**
  - Remote sensing imagery: huge images, variation in specifications and quality.



2. Marine wildlife monitoring

- **The challenges of AI for marine wildlife detection**
  - Remote sensing imagery
  - Marine environment: dynamic (waves, tides, weather...) and diverse (geographical areas, natural and anthropogenic objects...)






2. Marine wildlife monitoring

- **The challenges of AI for marine wildlife detection**
  - Remote sensing imagery
  - Marine environment
  - Marine wildlife: underwater, occlusion, behavior variability, camouflaging capabilities...

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- **The challenges of AI for marine wildlife detection**
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  - Marine wildlife: underwater, occlusion, behavior variability, camouflaging capabilities...

⟶ A unique AI model cannot be the solution for now

3. Case study: HITL for beluga survey analysis

frontiers | Frontiers in Marine Science

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Pêches et Océans Canada

Scaling whale monitoring using deep learning: A human-in-the-loop solution for analyzing aerial datasets

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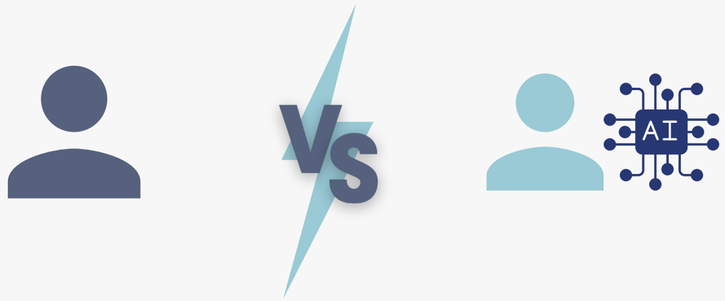
3. Case study: HITL for beluga survey analysis

- Objective



Compare manual analysis with the AI-assisted analysis

3. Case study: Material and Methods

- **Data: Cumberland Sound beluga population survey (2017)**
  - Threatened population of belugas
  - Aerial survey by Fisheries and Oceans Canada (DFO)
  - 5334 images

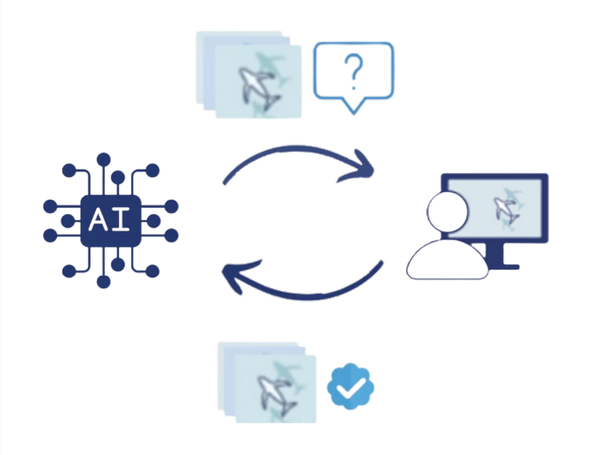
Manual analysis by a photo-analyst

4572 belugas detected

8 to 12 months of work

3. Case study: HITL for beluga survey analysis

- **Human-in-the-loop AI approach**
  - All images are not equally valuable
  - Query significant samples to be annotated
  - Iterative process: Query - Annotate - Train - Evaluate



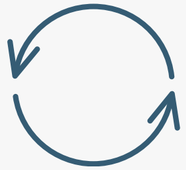
3. Case study: Material and Methods

- **Pipeline for whale detection**

1

Automated preliminary analysis

2



Active learning loop

3

Human review

3. Case study: Material and Methods

1 Automated preliminary analysis

Goal: avoid a cold start to the active learning loop and define "interesting" images

3. Case study: Material and Methods

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Output, for each image:

3. Case study: Material and Methods

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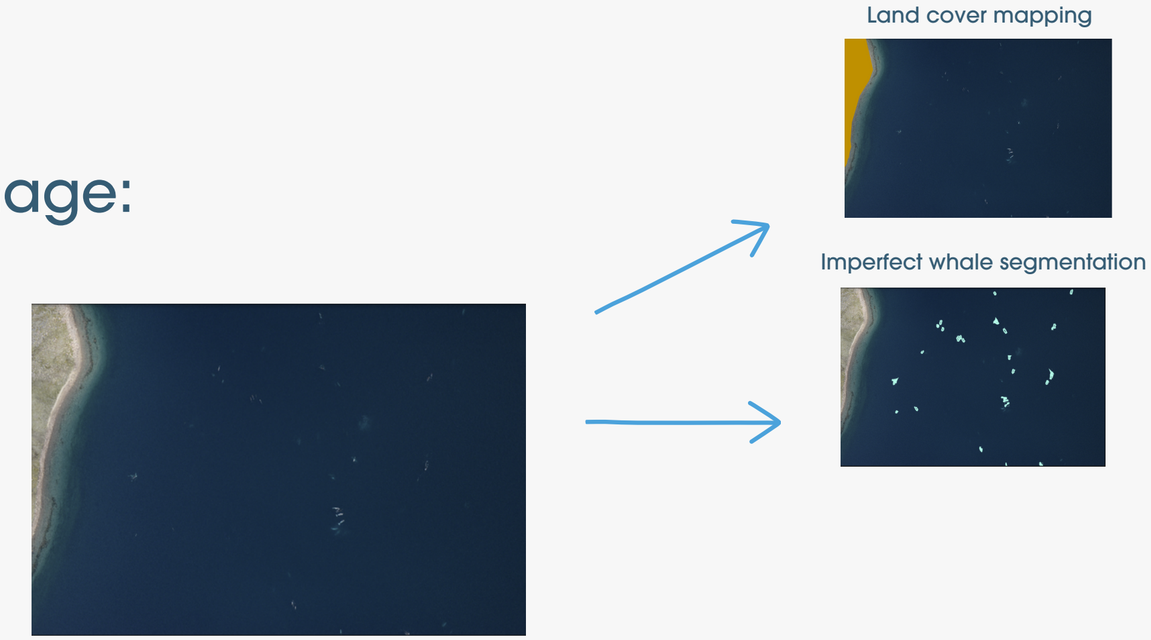

3. Case study: Material and Methods

1 Automated preliminary analysis

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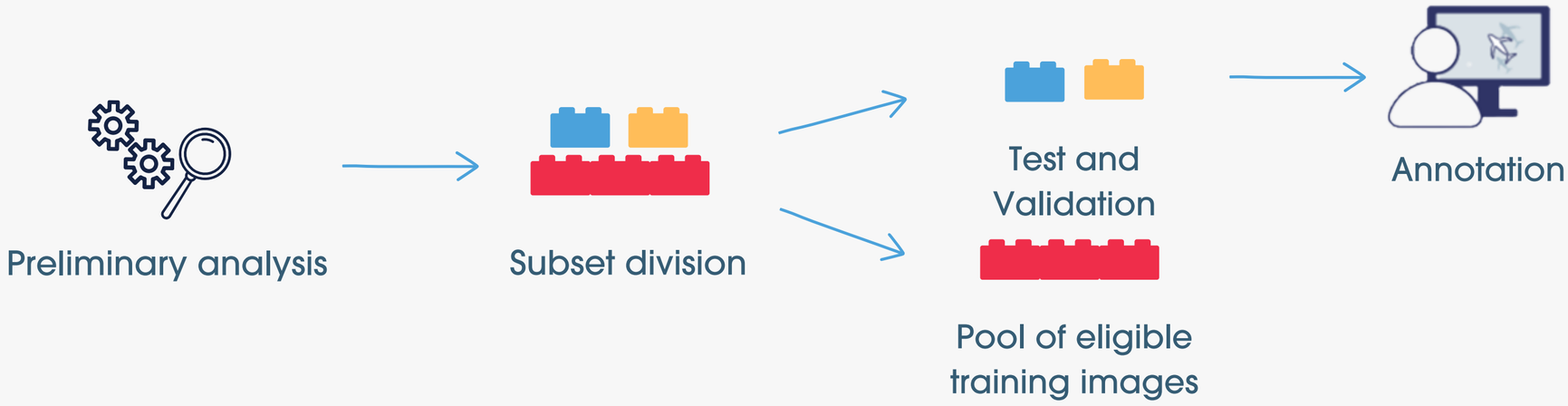
Output, for each image:

3. Case study: Material and Methods

2 Active learning loop

Goal: train the model until its performance meets our expectations



3. Case study: Material and Methods

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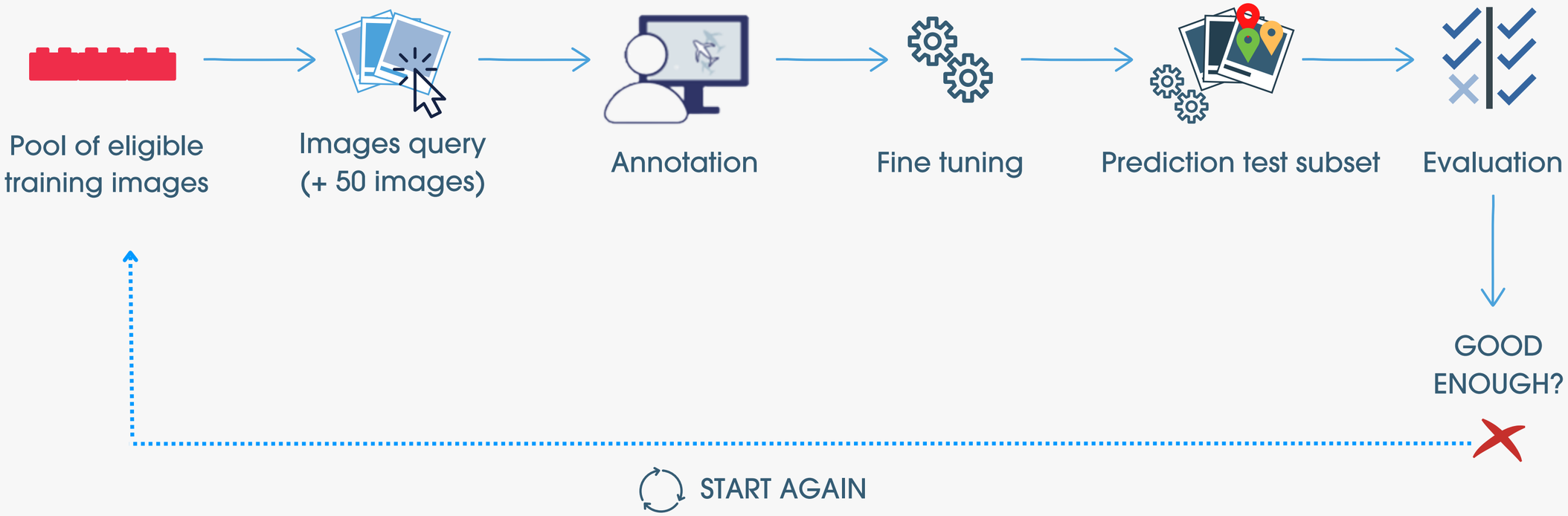
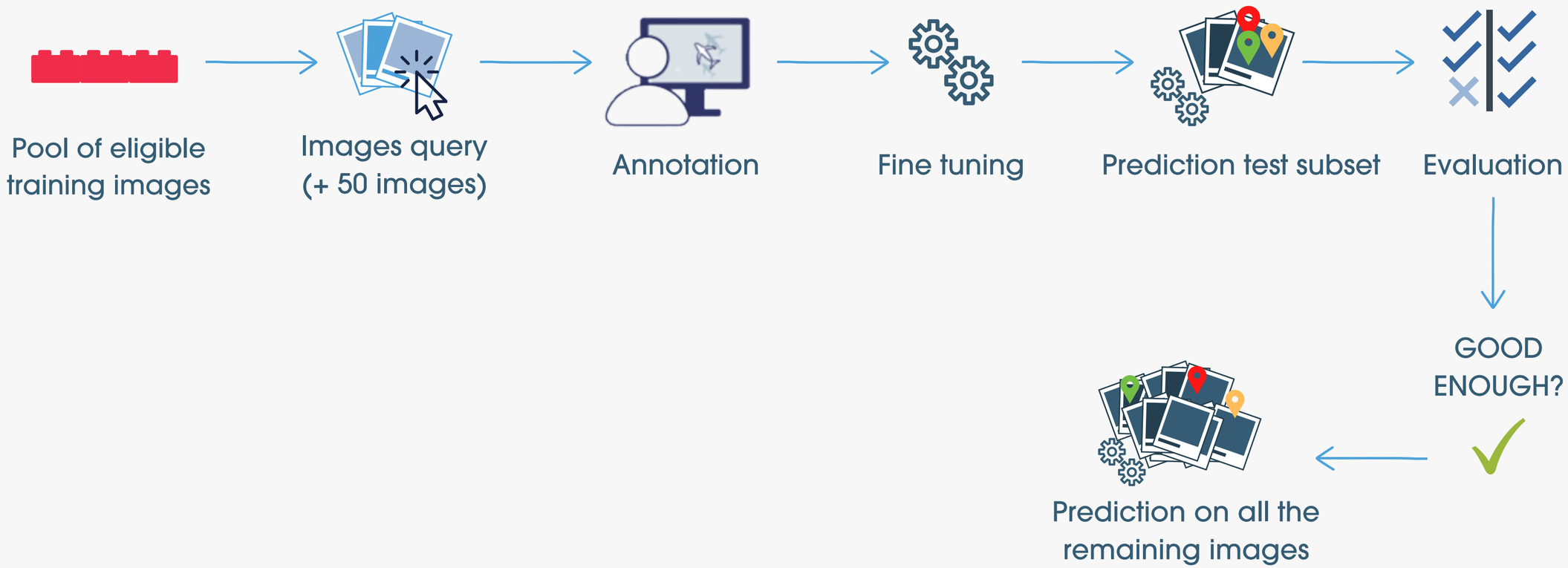


3. Case study: Material and Methods

2 Active learning loop

Goal: train the model until it is good enough



3. Case study: Material and Methods

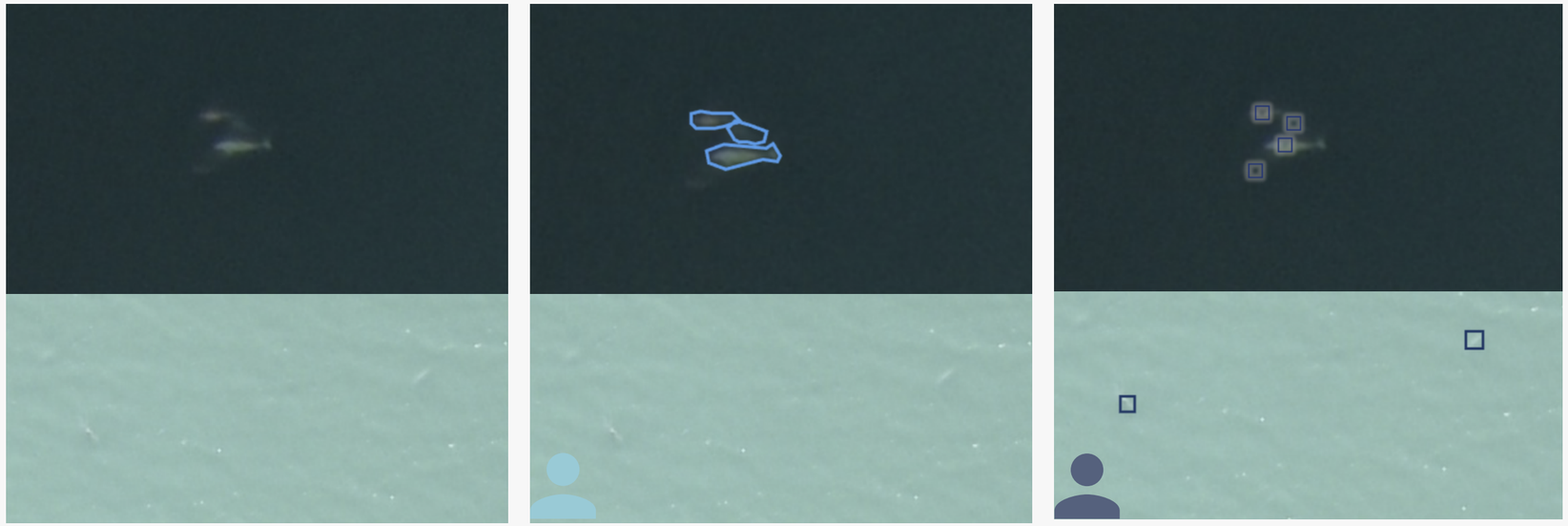
3 Human review of the predictions

Goal: ensure the detections' high quality

- Manual revision of the predictions
- Only the images with predictions are verified

3. Case study: Material and Methods

- **Metrics**
  - Ground truth = annotations by a photo-analyst
  - Inter-observer variability



3. Case study: Material and Methods

- **Metrics**

$$Inter - observer\ agreement = \frac{Detections_{ObsA,ObsB}}{Detections_{ObsA,ObsB} + Detections_{ObsA} + Detections_{ObsB}}$$

Detections ObsA, ObsB represents the number of whales detected by both Observers,

Detections ObsA represents the number of detections made only by Observer A,

Detections ObsB represents the number of detections made only by Observer B.

3. Case study: Material and Methods

- **Inter-observer agreement for our case study**

Three annotating Observers:

Observer 1: Marine mammal expert from Whale Seeker


Observer 2: Marine mammal expert from Whale Seeker


Observer 3: Marine mammal expert from Fisheries and Oceans Canada

3. Case study: Material and Methods

- **Inter-observer agreement for our case study**

Three annotating Observers:

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Observer 2: Marine mammal expert from Whale Seeker


Observer 3: Marine mammal expert from Fisheries and Oceans Canada

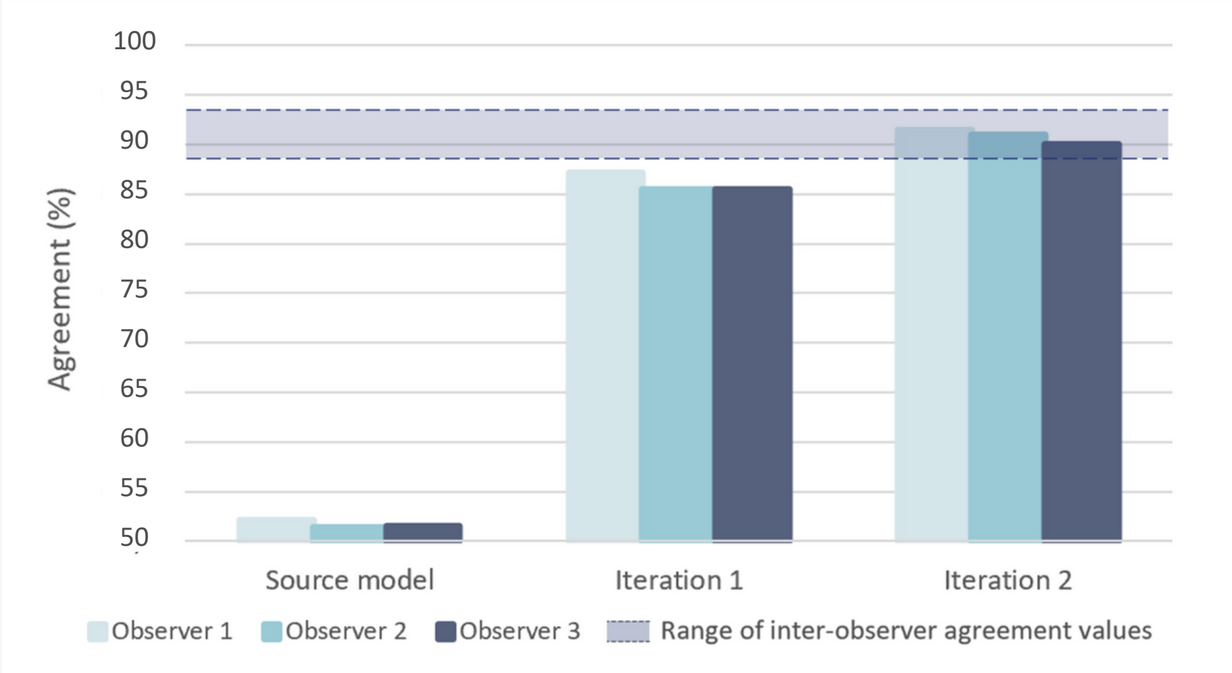
Inter-observer agreement on the test subset:

From 88,6% to 93%

→ Minimum value expected for the model on the test subset

3. Case study: Results

- **Results of the training loop on the test subset**
  - Minimum value expected exceeded on iteration 2 (= 100 training images)
  - Model-Observer agreement: from 90% to 91.4%



3. Case study: Results

- **Results of the entire dataset**

Manual analysis

4,572 belugas detected

Vs

AI-assisted analysis

4,298 belugas detected

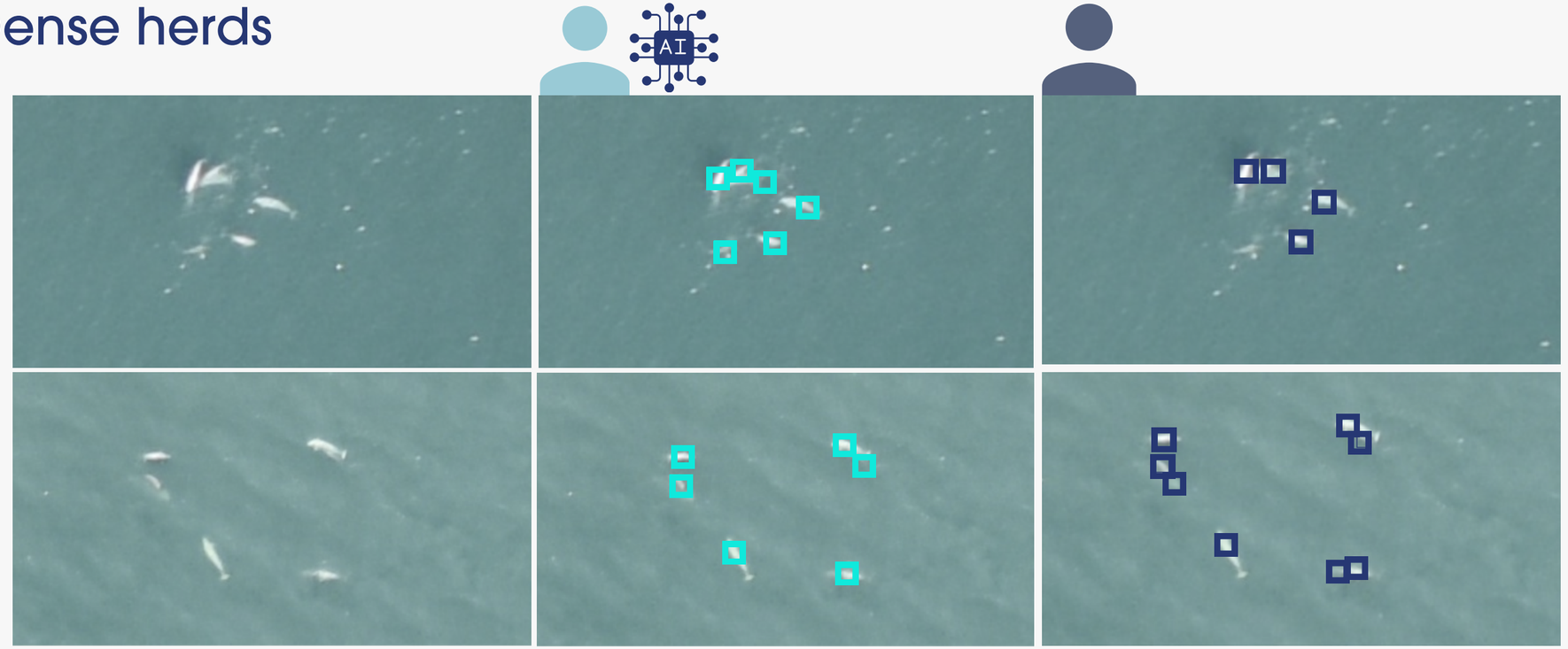
→ 84% of mutual agreement

3. Case study: Results

- **Results of the entire dataset**

Main sources of disagreement:

  - Depth
  - Dense herds



3. Case study: Results

- **Time-tracking: hours spent on the analysis by the marine mammal experts**

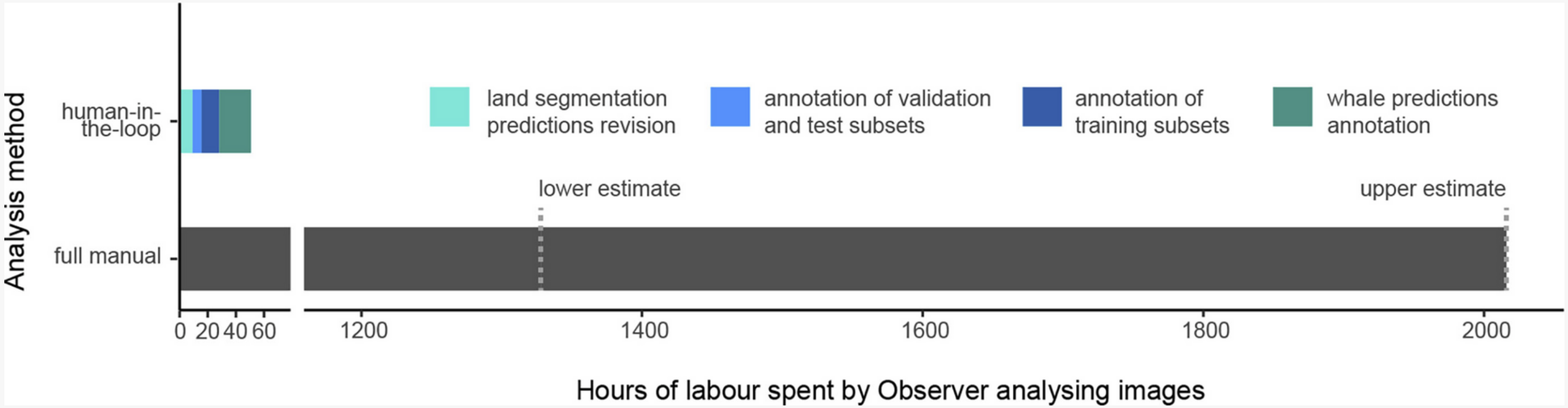
Manual analysis

1,300 to 2,020 hours

VS

AI-assisted analysis

53 hours



3. Case study: Conclusion

- **Active learning = effective approach to leverage AI**

  ➡ Ending the image analysis bottleneck

3. Case study: Conclusion

- **Active learning = effective approach to leverage AI**

  ➡ Ending the image analysis bottleneck

- **Need for better protocol standardisation, for multiple observer analysis**

  ➡ Can be done with the help of AI

4. Conclusion and perspectives

- From drone to satellite: several data sources available
- AI as a solution to provide better wildlife monitoring
- Not a miracle solution: algorithm must be maintained, evaluated, improved

Thanks!

Meet us at our stand: N656

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