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MSc Environmental Data Science and Machine Learning

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Using Deep Learning to Classify Individual Ponds of Artisanal and Small-Scale Gold Mining in Ghana

Research Background & Motivation

Why it is important to track illegal mining?

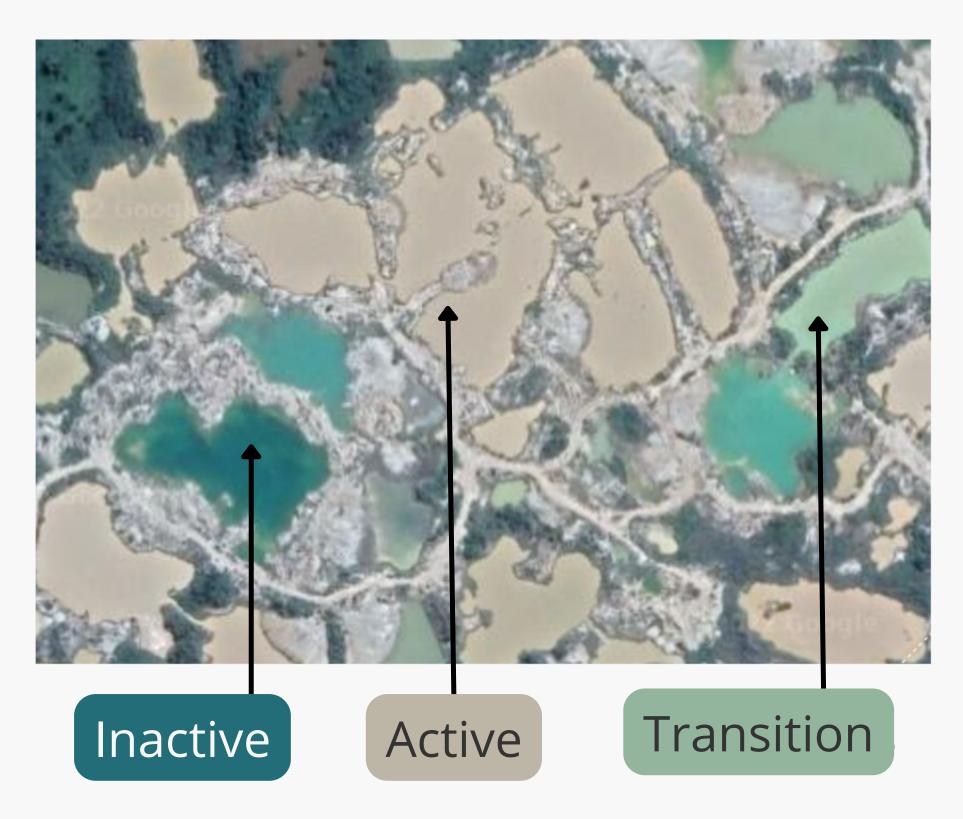
10% of national GDP

 Ghana – Africa's largest gold producer and 7th in the world.

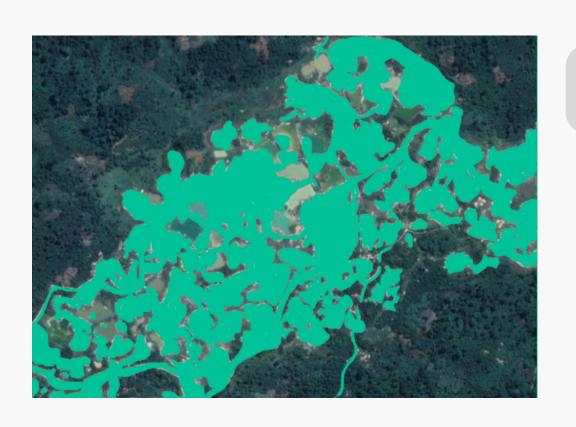
Annual tropical forest loss
 ~2600 ha yr-1

• Pollution (mercury, cionide ...)

How Gold is mined?

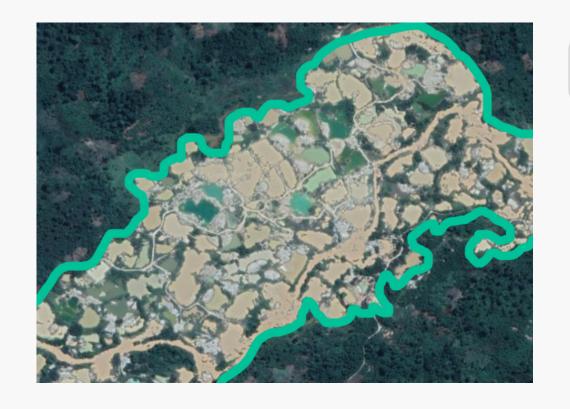


Existing Gold Mining Tracking Techniques and the Research Gap



Pixel Based Classification

Each pixel is classified individually without spatial context based on spectral signatures of proxy classes



Convolutional Neural Networks

Learn interrelationships between pixels from gridded data, so can segment whole objects. (e.g. U-Net).

Research Novelty

Segment individual mining ponds and classify activity level using U-Net algorithm.

Aim:

Detect individual gold mining ponds and classify them according to mining activity

Model Development

Adapt U-Net architecture for multi-class output.

Hyperparameter Tuning & Evaluation

Determine best combination of bands and hyperparameters to maximise F1 scores

Results

Comparison of model performance

Applications

Site to site variability
Seasonal variation in activity
Inter-annual variation in activity

Model Development - U-Net design

10 32 64

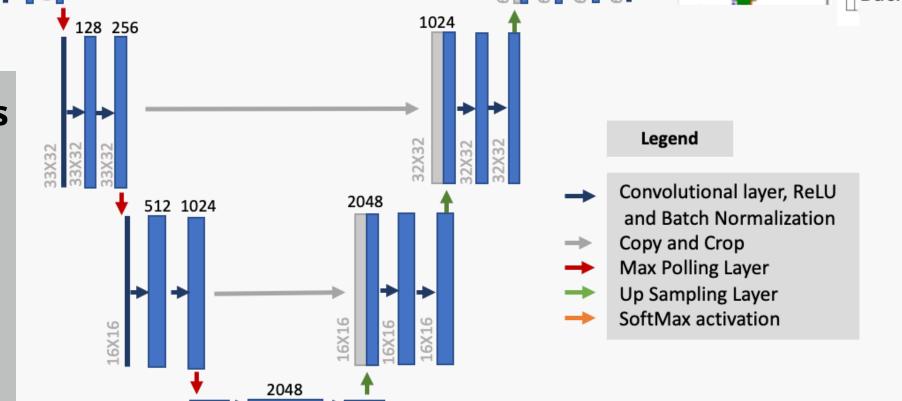
U-Net Architecture designed for 10 channel input images that predict 4 classes (active ponds, transition, inactive and background)

Input

Inp

Sentinel -2 Input Images

16 regions from Madre de Dios, Peru, 1 region in Indonesia, 1 in Myanmar and 5 from Venezuela at 2 timesteps - August 2019 & 2021



Modifications from Original Design:

Inclusion of Batch
 Normalisation

Inactive

Active

Transition

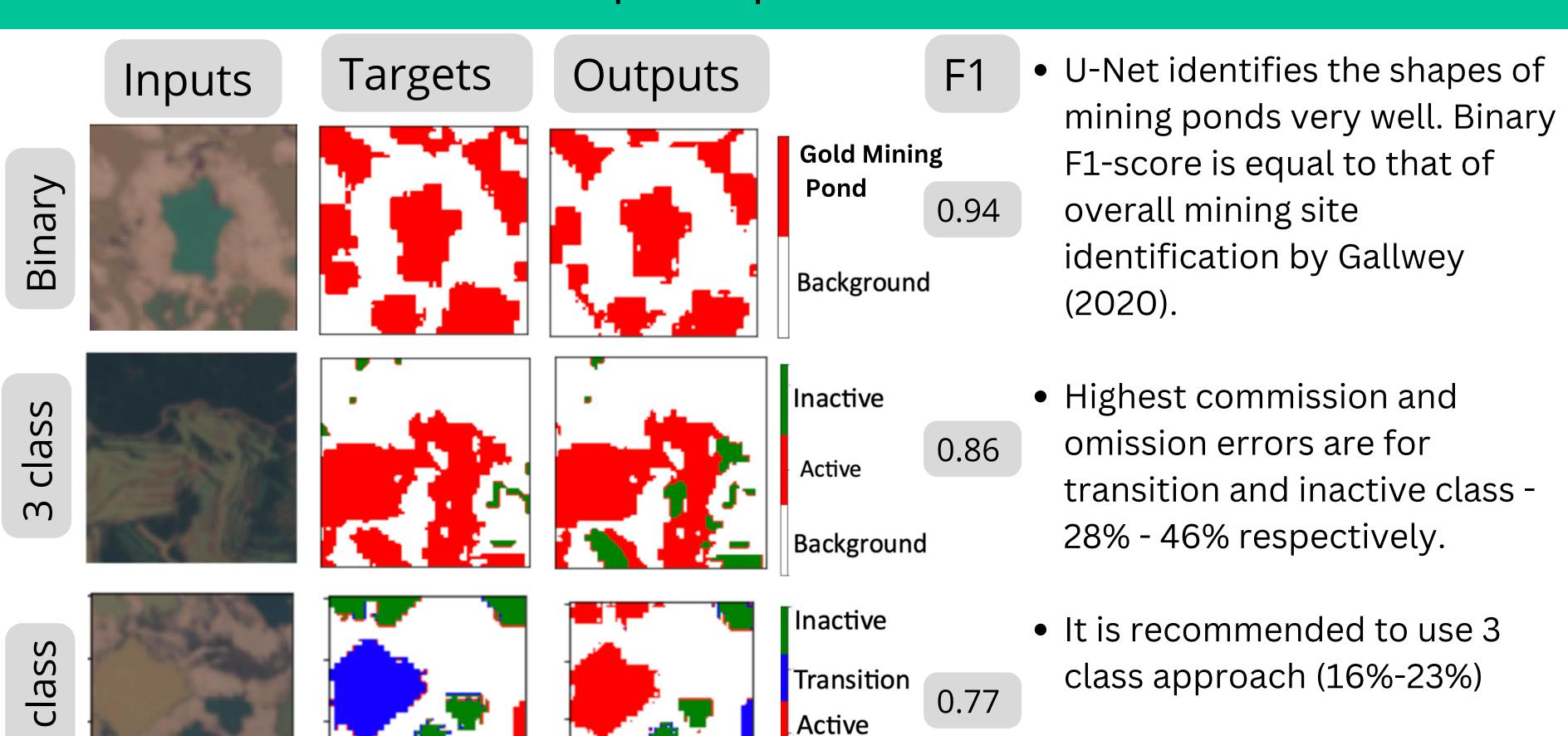
- Switch of optimiser from SGD to Adam
- Switch of loss
 function from
 CrossEntropy Loss
 to Focal Loss

Hyperparameter Tuning & Experimental Design

Performance of models improves as number of input channels increases for all target class combinations

Inputs	Targets				Hyperparameter	Role
3 channels: Red Green, Blue	Active	Transition Inactive 4 classes		Background	Start Filters	Initial depth of the image, doubled at each convolutional layer
6 channels: Red Green, Blue, NIR, SWIR1, SWIR2	Active	Inactive		Background	Blocks	Depth of the network
10 channels: Red	3 Classes				Alpha	Class weights adjuster
Green, Blue, NIR, SWIR1, SWIR2, Ultra-Blue and 3 Red Edge bands	Gold Mining Ponds Binary		Background	Gamma	Strength of focal loss regularisation	

Results: 10-channel inputs produced best results



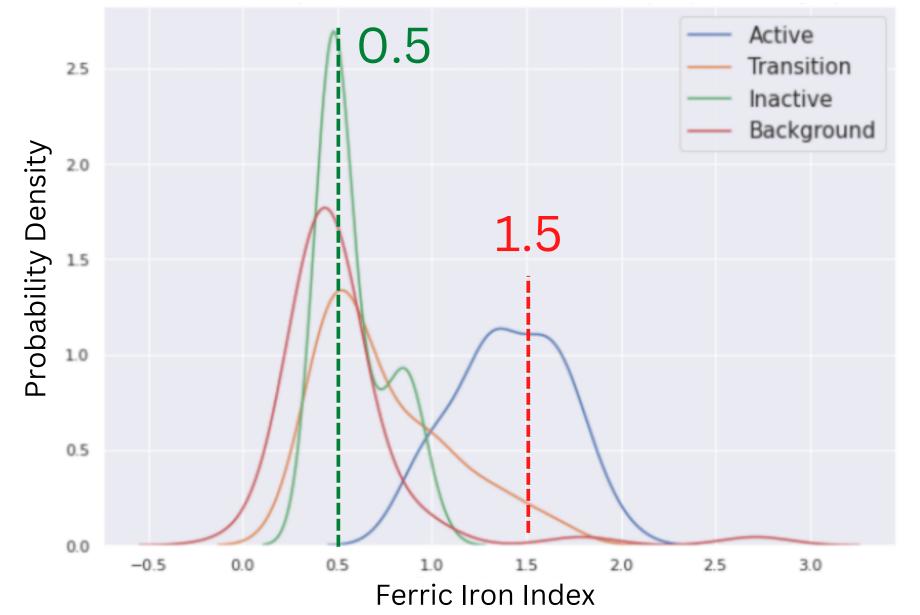
Active

Background

Application: Quantification of Water Acidification Risk due to mining activity

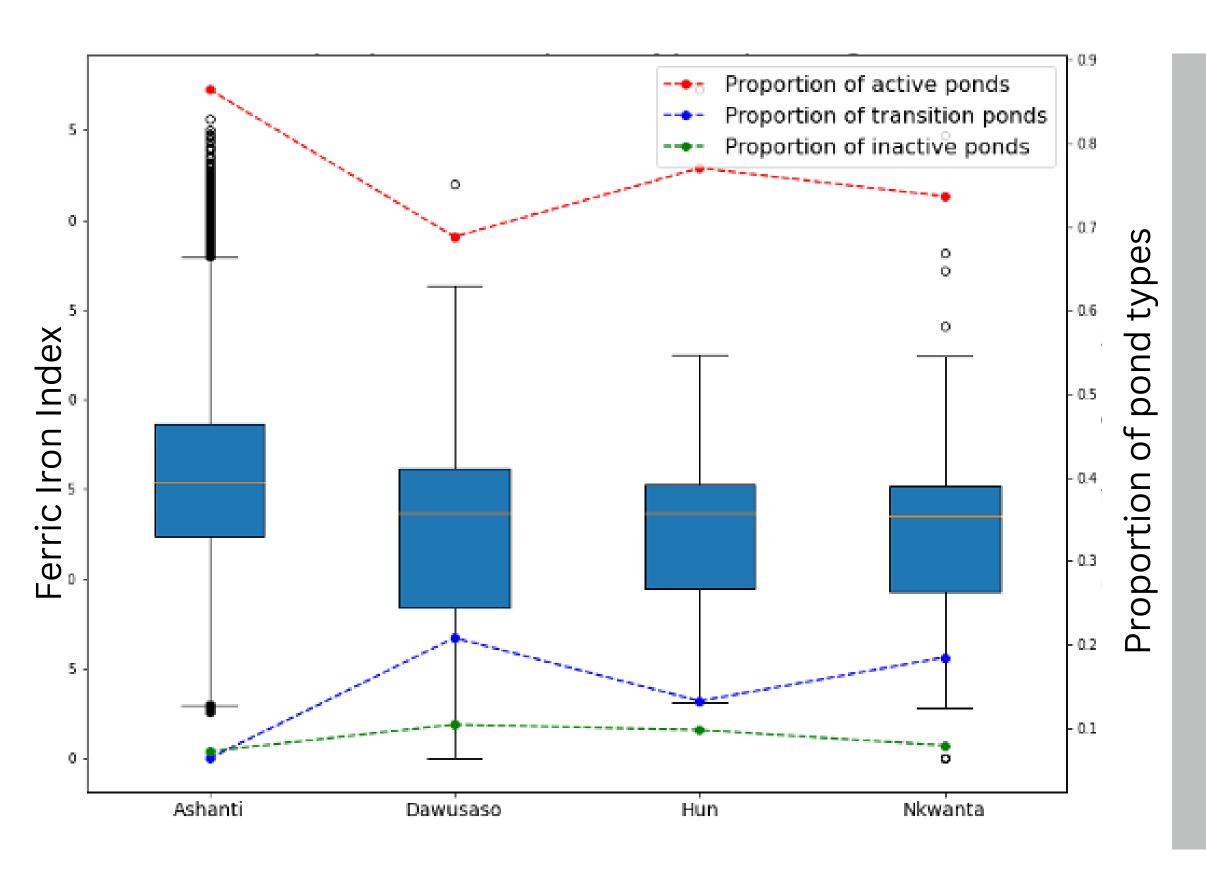
The concentration of Ferric Iron (FI) is a proxy for acidity in mine water (Akcil et al., 2006).





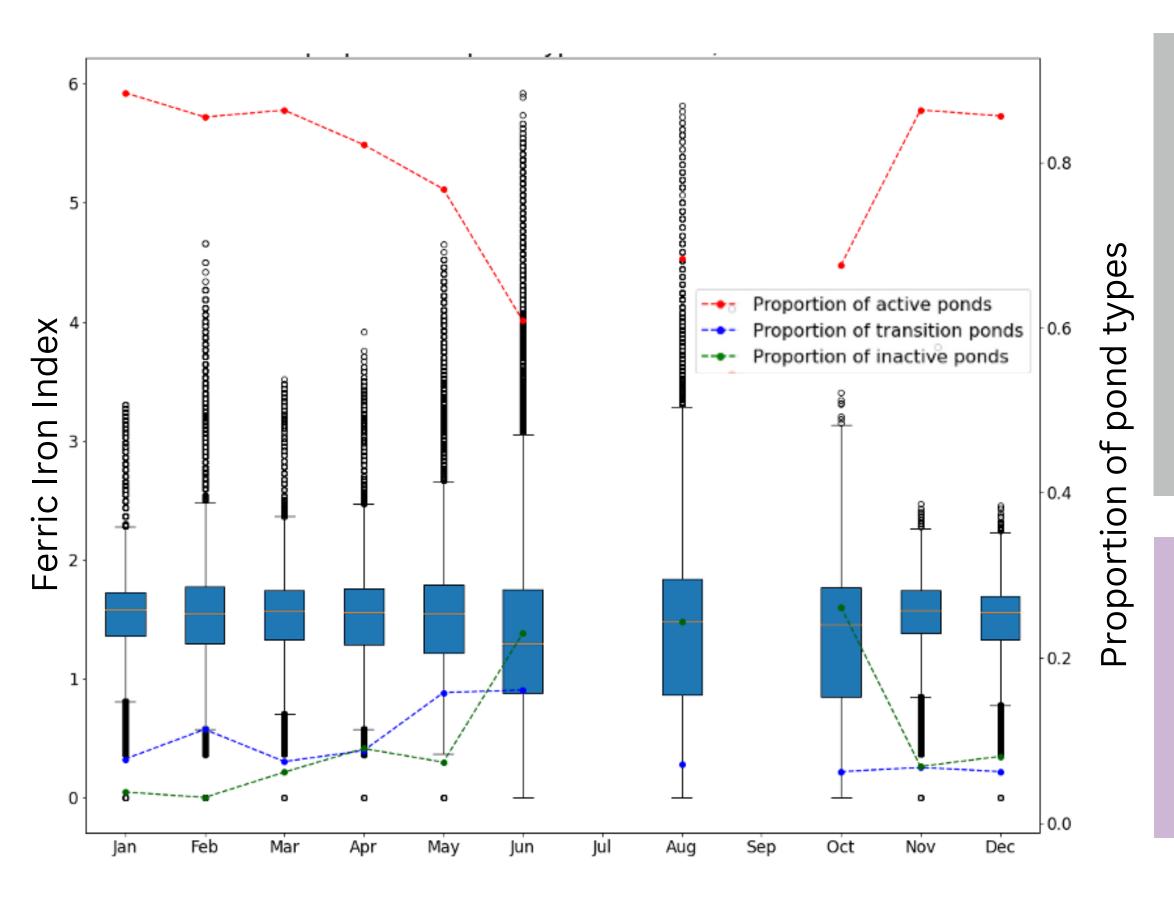
- Distribution of FI is different in active, transition, inactive and outside of mining ponds. (99% conf. lev., Kruskal-Wallis test)
- FI index is 3 times lower in transition and inactive ponds.
- Cessation of mining activity lowers FI and therefore the risk of acid mine drainage (AMD).

Application: Site to Site Comparison



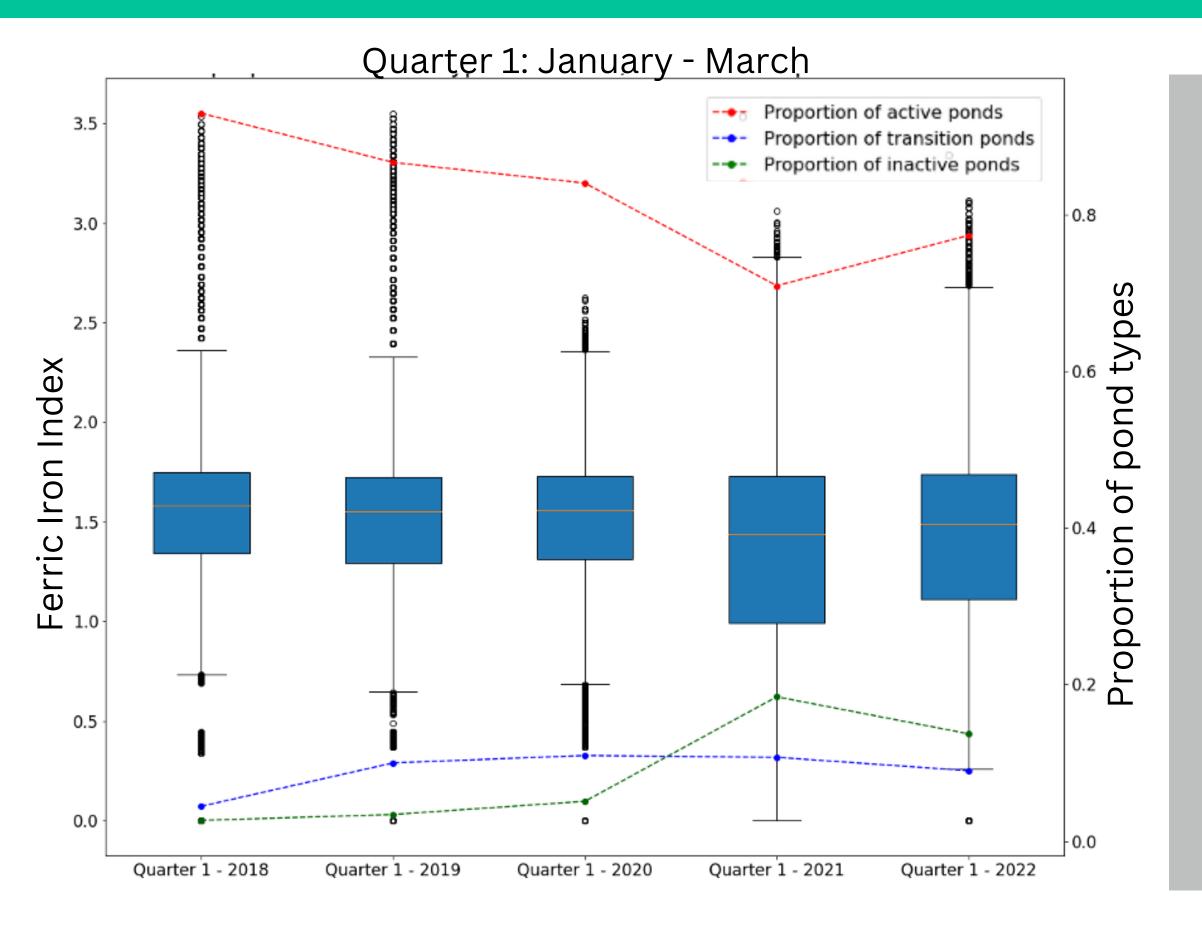
- Ashanti's proportion of active ponds is highest (88%), and the distribution of FI was skewed to larger values (Figure 6, A).
- Mean FI is 0.2 higher
- Ashanti highest risk of AMD and should be a priority site for environmental conservation and protection projects.

Application: Seasonal Evolution of Mining Activity



- Gold mining activity slows down during summer month
- Most active November March
- Mean FI index lowers from 1.7
 January March to 1.3 in June (~24% reduction).
- Lag between initial cessation of activity and FI decrease
- Strong Cloud coverage in South
 Ghana
- No Sentinel-2 cloud free data available for July and September

Application: Inter-annual evolution



- Quarter 1 most active mining season.
- Slow down of mining activity lowers FI concentration by 0.1 in 2021
- 2 year lag between slow down and MFI lowering
- Results can be used to test success of restoration projects and benchmark them agains natural environmental recovery

Conclusion

- 10-channel U-Net performed best (F1- 0.94) at detecting and classifying gold mining ponds
- Model differentiated well between active and inactive ponds, (0.86) but performed poorer in telling apart transition and inactive (0.77).
- Tool can help to select sites in most need of restoration, identify when gold mining activity is at its peak and showcase temporal evolution.
- Future development could focus on training models using high resolution and cloud free Planet data or drone assessment.

Thank You!