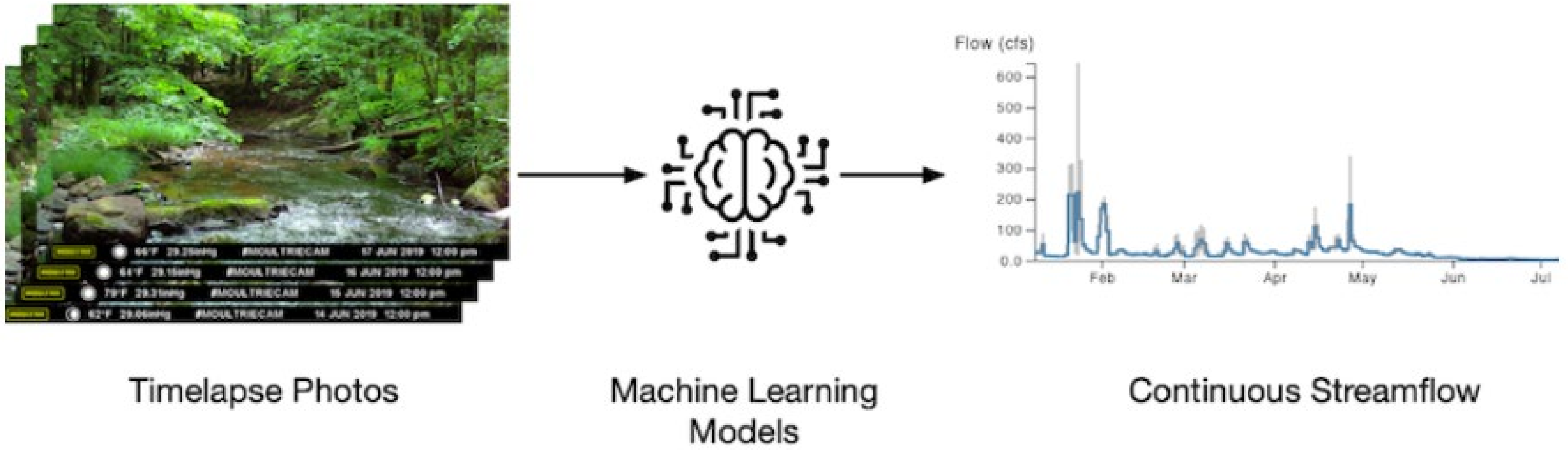
Streamflow Monitoring with Machine Learning Modeling

Regional - ORD Applied Research



USGS and EPA ORD, R1, R2, R3, R5, R6, R7, R8

USGS EPA

Use of brand names is not an endorsement

Background/ Problem

Streams are highly vulnerable to increases in droughts and floods.

It is very **difficult to assess impacts** due to the lack of gages.

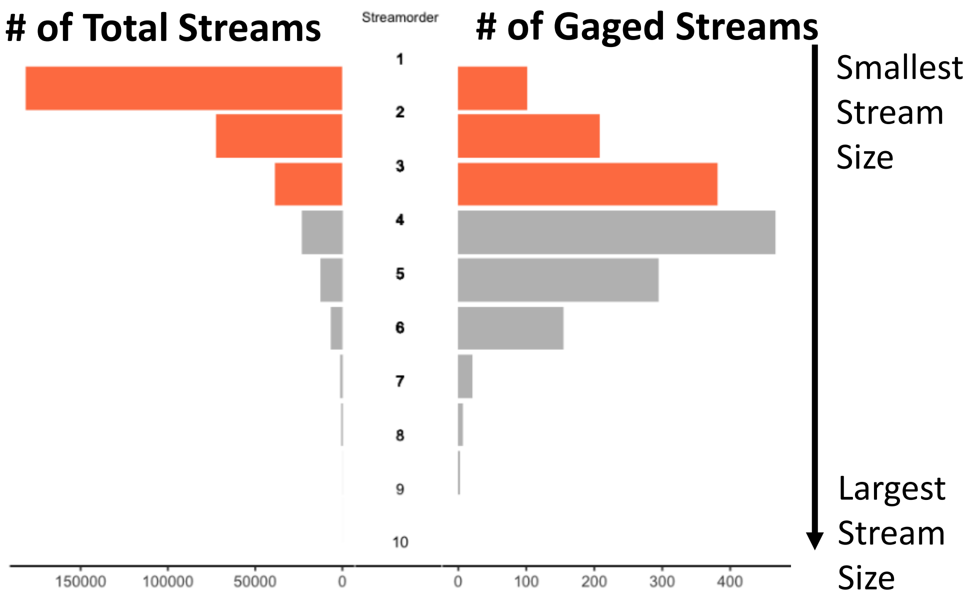
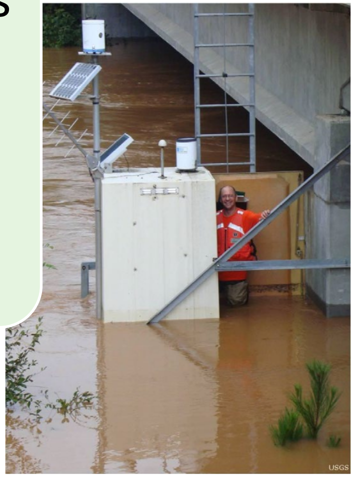


Figure 2: Relative # of USGS gages by stream order for the NE U.S. Headwaters in orange. Source: USGS NWIS and NHD+ Provided by: USGS.

How can we get data in small streams?

Images from time-lapse trail cameras & machine learning modeling

Regular stream gages or hydrological equipment are **difficult to maintain and expensive.**

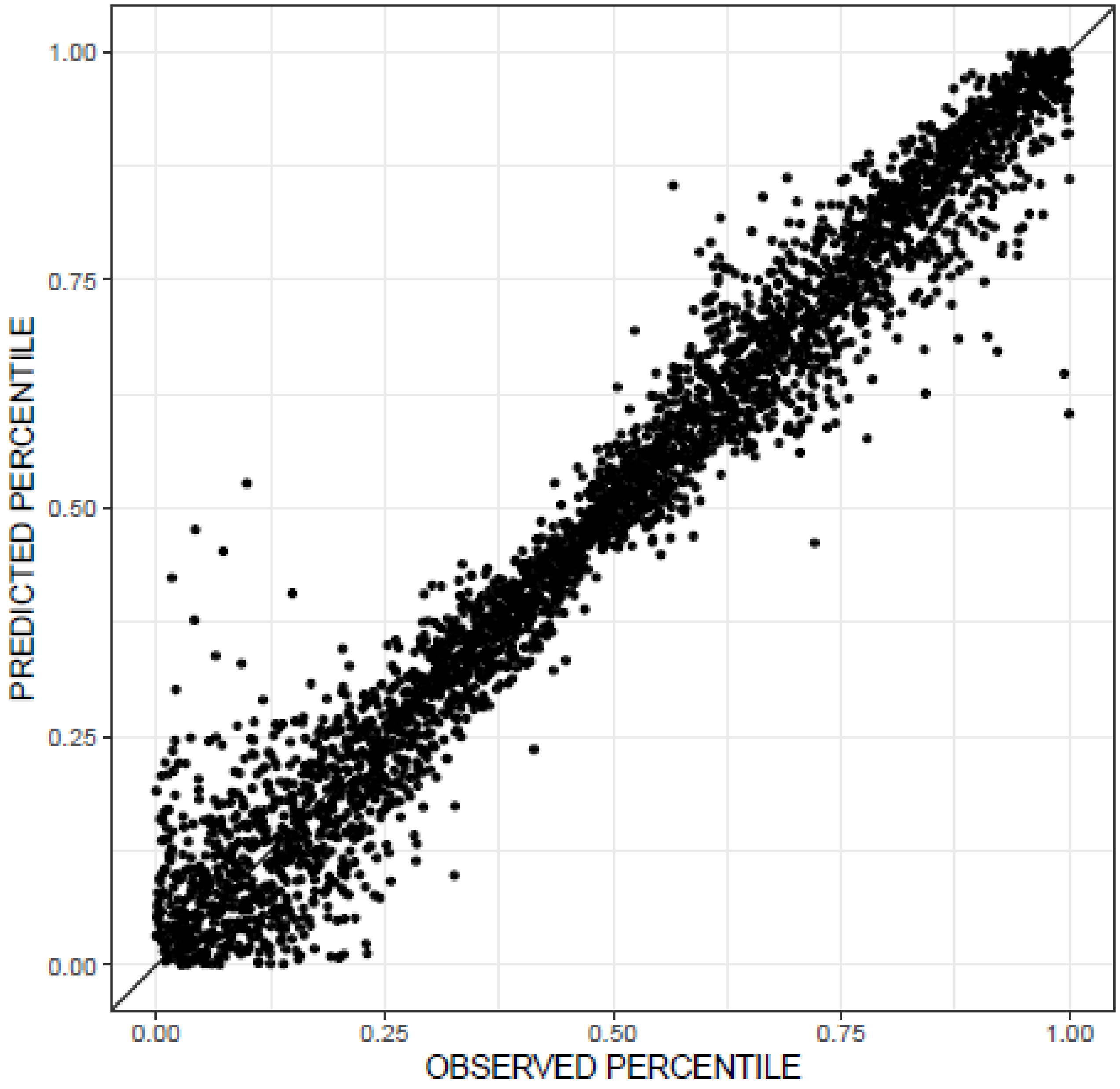


Project Context

3 key things needed:

1. Input data for models
2. Database of images
   Flow Photo Explorer*
3. Machine Learning models to estimate stream flow
   With local flow data*
   Without local flow data

2018 Innovation Project Products



Machine Learning Modeling Results for Discharge*
Provided by USGS and Conservation Science Partners, Inc.

Flow Photo Explorer

Free, public, interactive, web-based & integrated database platform.

Provided by USGS

2022-2023 Project Objectives & Approach

1. <u>Test a novel human-assisted ranking-based machine learning model</u> for estimating flow from photos **when hydrological data is not available** for a variety of different stream types

A person visually compares pairs of images and annotates which image has higher flow in each pair.

Which image has higher flow?

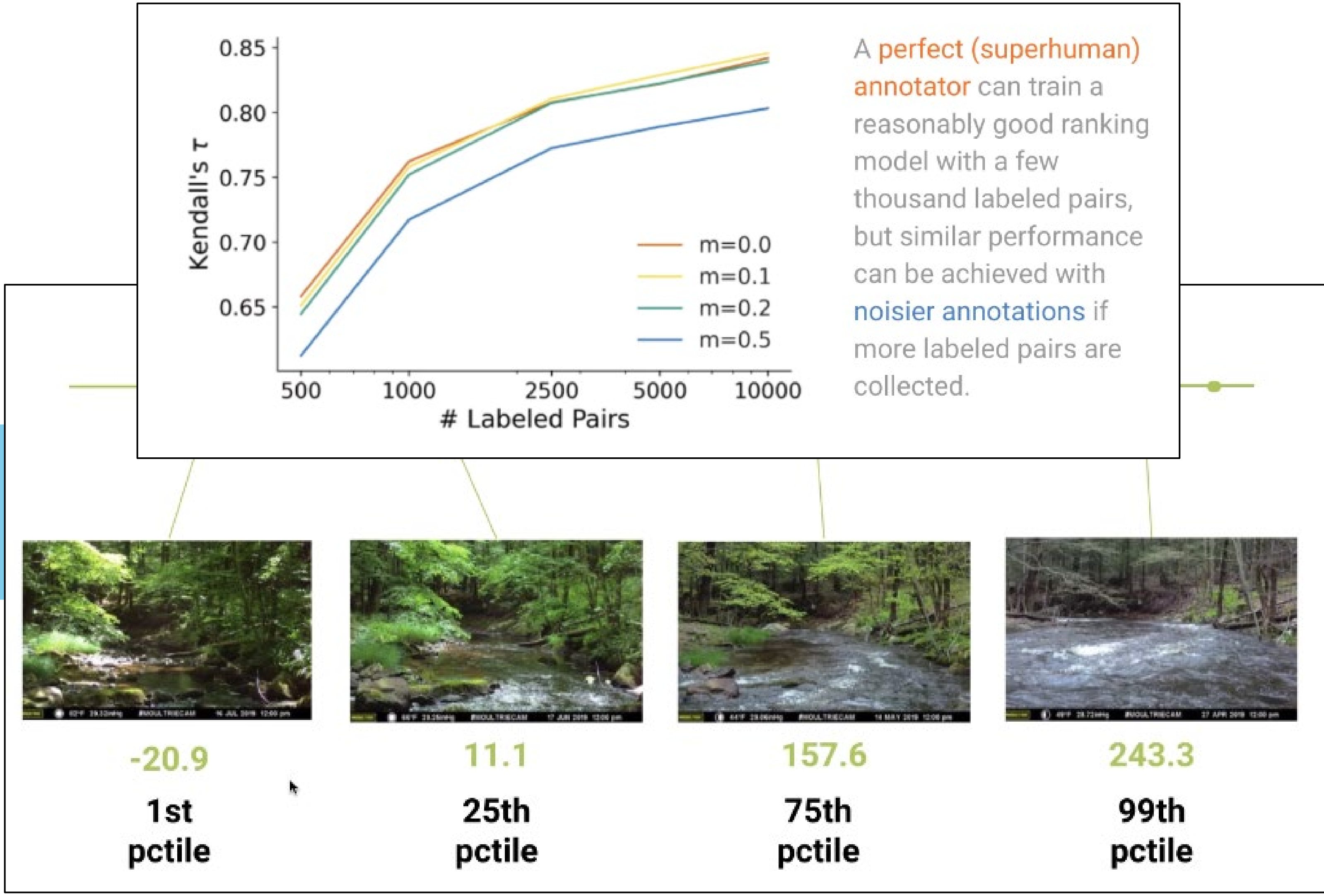
Can be done by stakeholders, citizen volunteers, Agency personnel, etc.

2022-2023 Project Objectives & Approach

1. Test a novel human-assisted ranking-based machine learning model

A person visually compares pairs of images and annotates which image has higher flow in each pair.

Based on these human annotations, a deep learning model will be trained in order to predict which image has more flow.



Provided by Amrita Gupta, Microsoft AI for Good

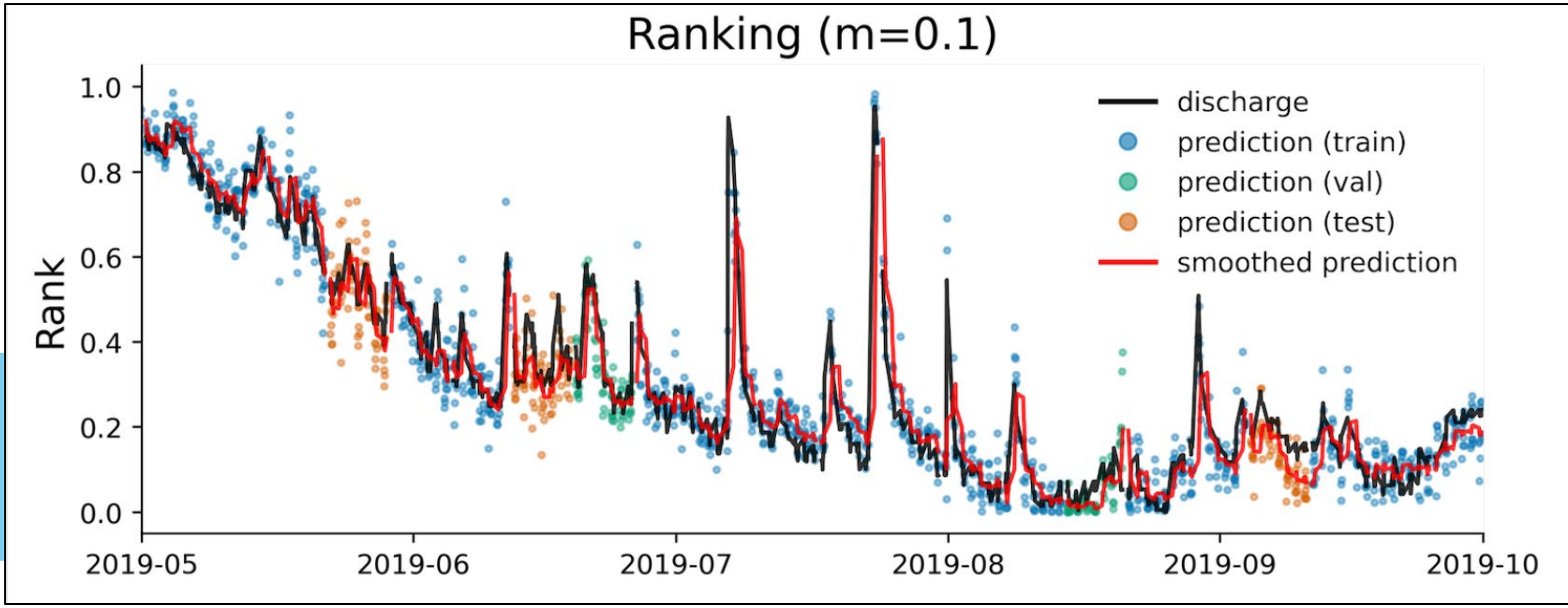
2022-2023 Project Objectives & Approach

1. <u>Test a novel human-assisted ranking-based machine learning model</u>

A person visually compares pairs of images and annotates which image has higher flow in each pair.

Based on these human annotations, a deep learning model will be trained in order to predict which image has more flow.

Use the fitted model to assign flow estimates to all images collected at a given location.



Provided by Amrita Gupta, Microsoft AI for Good

Towards Continuous Streamflow Monitoring with Time-Lapse Cameras and Deep Learning

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ABSTRACT

Effective water resources management depends on monitoring the volume of water flowing through streams and rivers, but collecting continuous discharge measurements using traditional streamflow gages is prohibitively expensive. Time-lapse cameras offer a low-cost option for streamflow monitoring, but training models for predicting streamflow directly from images requires streamflow data to use as labels, which are often unavailable. We address this data gap by proposing the alternative task of Streamflow Rank Estimation (SRE), in which the goal is to predict *relative* measures of streamflow such as percentile rank rather than *absolute* flow. In particular, we use a learning-to-rank framework to train SRE models using pairs of stream images ranked in order of discharge by an annotator, obviating the need for discharge training data and thus facilitating monitoring streamflow conditions at streams without gages. We also demonstrate a technique for converting SRE model predictions to stream discharge estimates given an estimated streamflow distribution. Using data and images from six small US streams, we compare the performance of SRE with conventional regression models trained to predict absolute discharge. Our results show that SRE performs nearly as well as regression models on relative flow prediction. Further, we observe that the accuracy of absolute discharge estimates obtained by mapping SRE model predictions through a discharge distribution largely depends on how well the assumed discharge distribution matches the field observed data.

ACM Reference Format:

Amrita Gupta, Tony Chang, Jeffrey D. Walker, and Benjamin H. Letcher. 2022. Towards Continuous Streamflow Monitoring with Time-Lapse Cameras and Deep Learning. In *ACM SIGCAS/SIGCHI Conference on Computing and Sustainable Societies (COMPASS) (COMPASS '22), June 29-July 1, 2022, Seattle, WA, USA.* ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3530190.3534805

1 INTRODUCTION

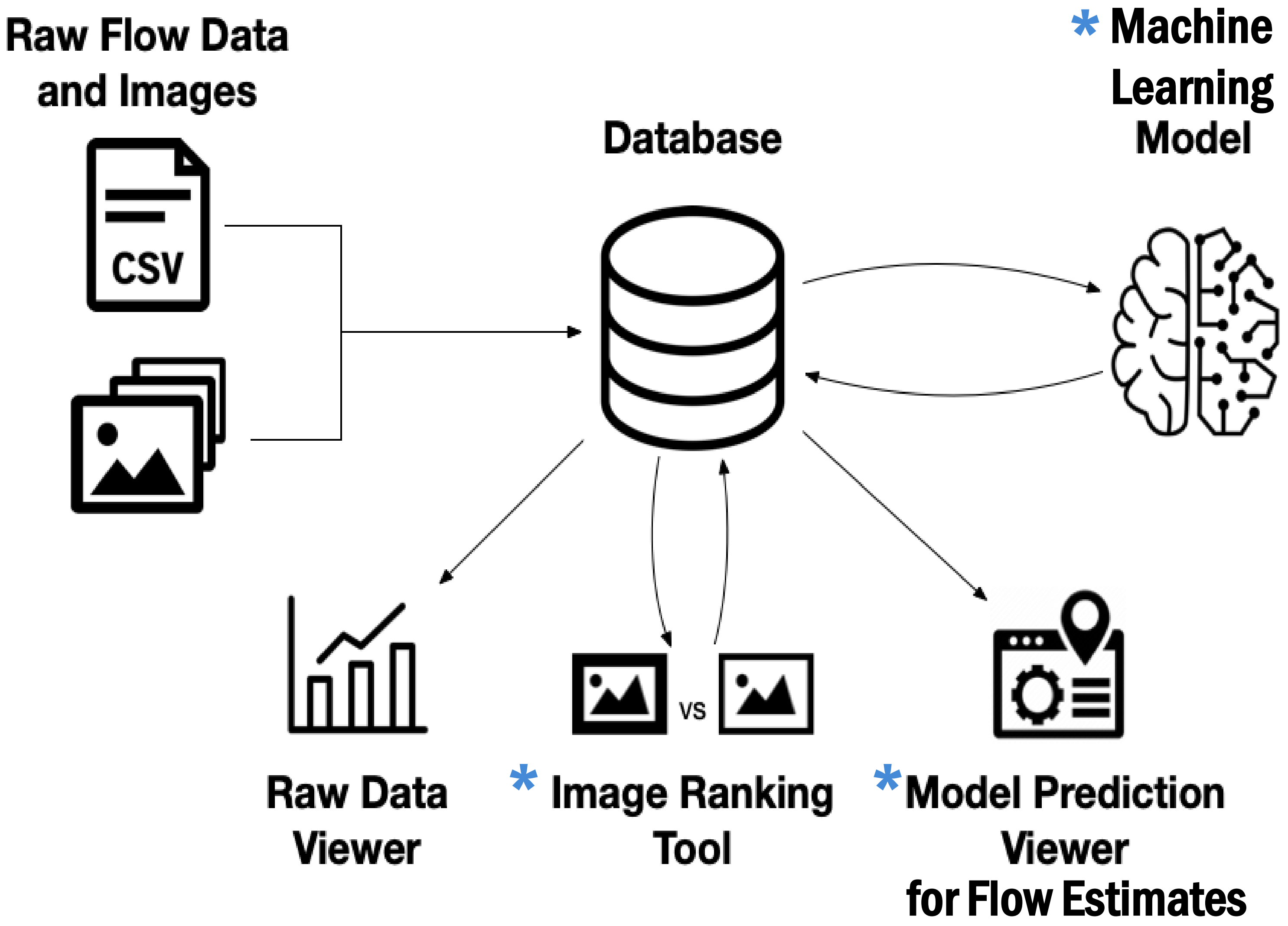
Streamflow refers to the volume of water flowing through the cross-section of a river channel per unit time. Also known as discharge, streamflow varies due to natural processes like rainfall, snowmelt, and groundwater seepage, as well as anthropogenic activities like water withdrawals, irrigation returns, and land-use change. It is an essential quantity underpinning short-term and long-term water resources management decisions [13], flood and drought warning systems [26, 41], and aquatic ecosystem health assessments [8]. Streamflow is also a key indicator of climate change [1], and thus tracking the trends and other changes in the magnitude and timing of streamflow is important for understanding the impacts of climate change on water availability, natural hazards, and aquatic habitats [28]. In short, effective management and climate adaptation of our valuable water resources depends on the widespread availability of streamflow monitoring data.

Research Objectives & Approach

2. <u>Enhance Flow Photo Explorer</u>

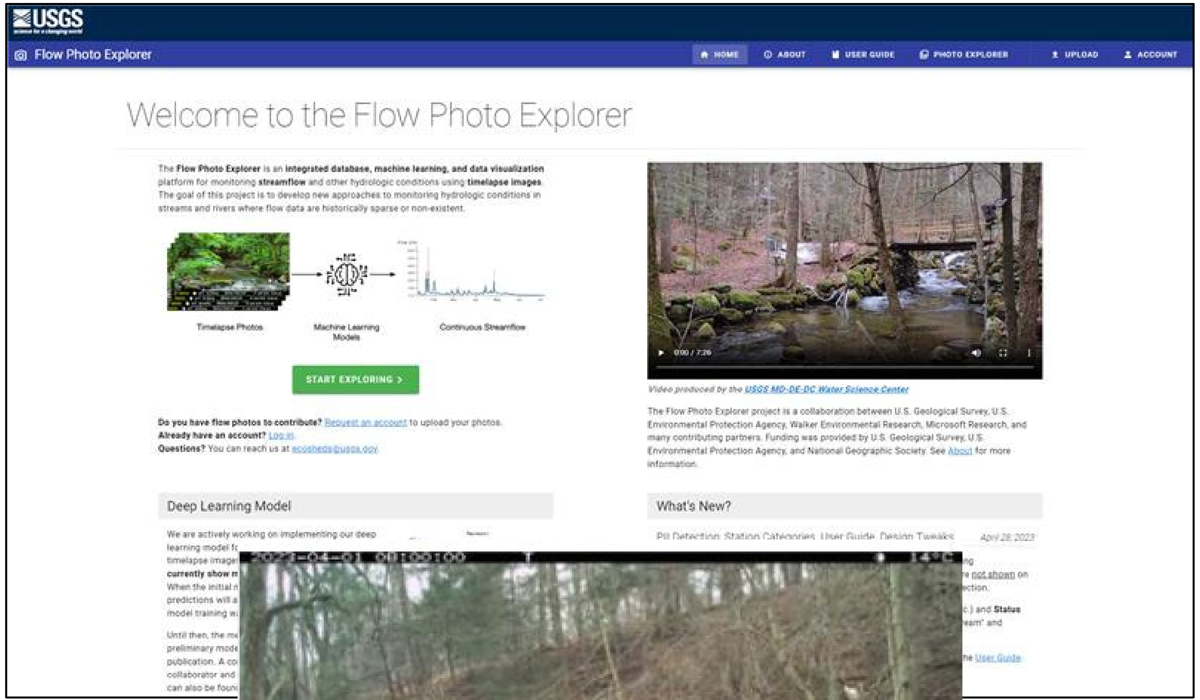
Add tools for users to supply input data for model training and to explore model predictions.

*New for this ROAR project



Provided by USGS

Latest Updates



1. **Redesigned Homepage**, includes "What's New“, project video, and updated User Guide.

2. **PII detector,** will screen images, and prevent anything with confidence > 0.8 for person or vehicle from appearing.

3. Stations have **Waterbody Type** and **Status** (*Active* vs Discontinued)

Stream / Canal / Ditch / Tidal Stream / Wetland

Lake, Reservoir, Impoundment / Estuary / Ocean / Coastal

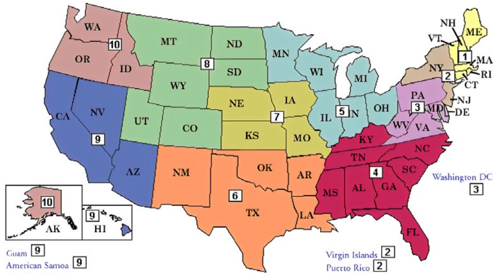
Roles

Silvio O. Conte Research Laboratory & Contractors

- Develop the machine learning modeling
- Enhance Flow Photo Explorer

- Participate in development
- Ensure protocols and equipment are in place
- Lead coordination and communication

Roles



State, Tribal, & Other Collaborators:

- Collect trail camera continuous photos and upload into Flow Photo Explorer
- Provide feedback on developing products
- Rank photos for flow status
- Optionally attend tri-weekly meetings

Anticipated Results and Impact

1. Interactive data & modeling tool for widespread use
2. Removal of cost & expertise barriers for streamflow characterization
3. Information for stakeholder decisions across many applications:
    - Effects of hydromodifications or their removal (relating to BIL)
    - Effects of installed BMPS or restoration projects
    - WOTUS implications
    - Water quality criteria
    - Assessment decisions
    - Citizen Science and/or ecological studies
    - Tracking flow with extreme weather events/Climate change impacts

What's your use case?

Participation

Supplies Needed

Trail Camera with timelapse mode

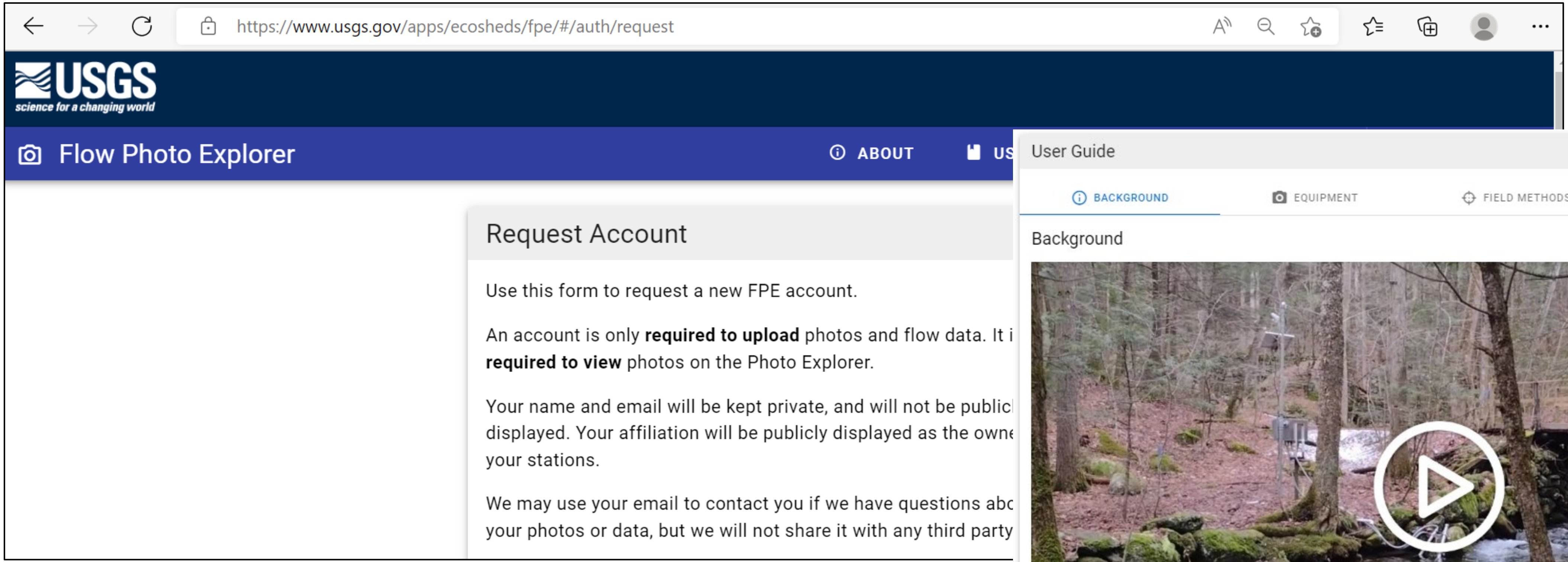
Optional camera mount/ Security housing

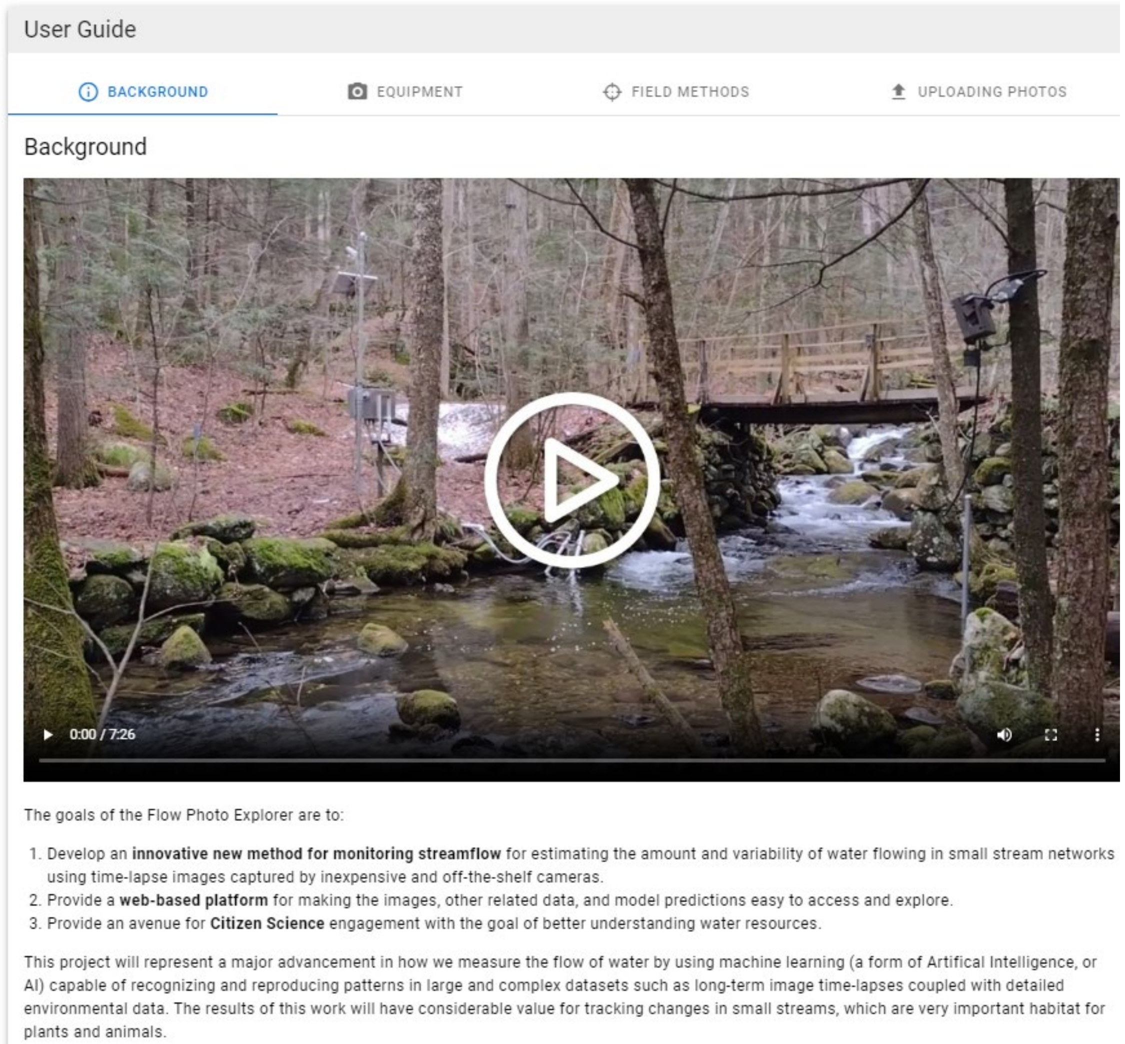
Memory card

Batteries
(or solar panel)

Cable lock

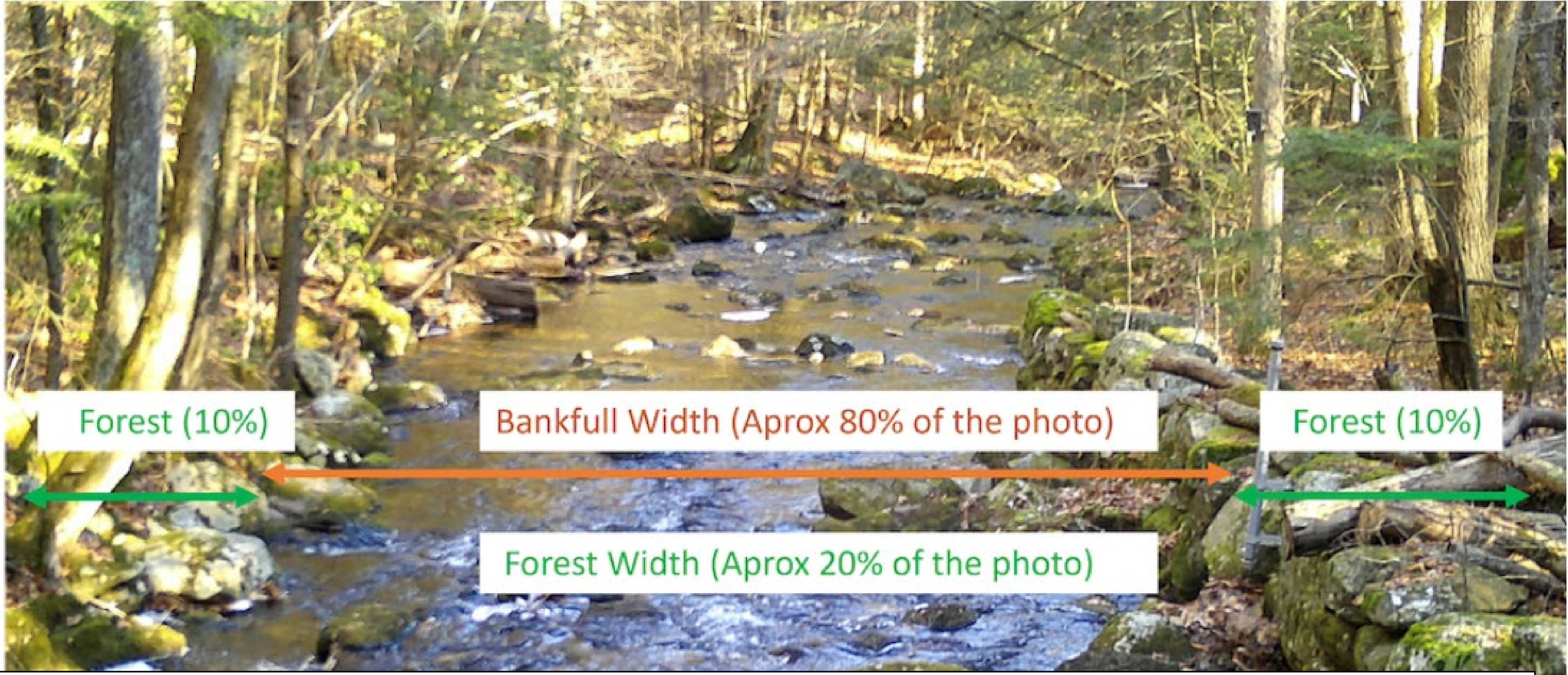
Set up a Flow Photo Explorer account. Create a station.





Review the User Guide on FPE.

General Steps

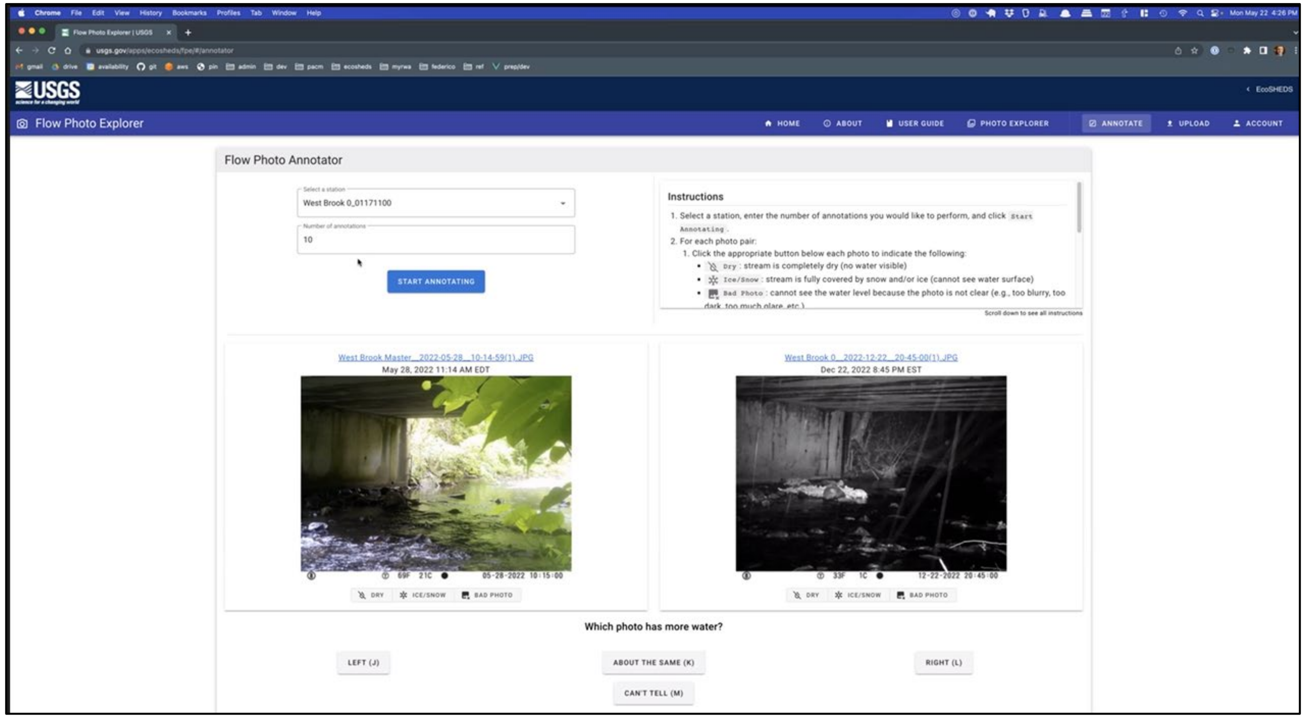


1. Select a site location and install a trail camera.
2. Configure camera with ideal timelapse interval of 15 minutes. Note if daylight savings or standard time.
3. Download images after a period of time (usually 1-3 months) and upload with metadata to FPE website.
4. Participate in the pair-wise image ranking.

Next Steps

1. **Near Future**
   - Ranking Tool on web site
   - Testing ranking by different users

> FPE does not currently show model predictions, only observed data, until the ranking tool is available and modeling complete for that site.



Screenshot from Jeff Walker

2. **Long-Term**
   - Proposal for lakes and wetlands

Photos from Tetra Tech

Contact Us

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Flow Photo Explorer Website

Modeling Publication & Presentation