

# High-Resolution Global Inland Surface Water Monitoring using PlanetScope Data and Supervised Learning with Bootstrapped Noisy Labels

Sayantana Majumdar<sup>1,1</sup>, Ramesh Nair<sup>1,1</sup>, Amit Kapadia<sup>1,1</sup>, Jesus Martinez Manso<sup>1,1</sup>, Cameron Bronstein<sup>1,1</sup>, Brad Neuberg<sup>1,1</sup>, Samapriya Roy<sup>1,1</sup>, Benjamin Goldenberg<sup>1,1</sup>, Justin Davis<sup>1,1</sup>, Kelsey Jordahl<sup>1,1</sup>, Ryan Smith<sup>2,2</sup>, and Leanne Abraham<sup>1</sup>

<sup>1</sup>Planet Labs

<sup>2</sup>Missouri University of Science and Technology

November 30, 2022

## Abstract

High-resolution mapping and monitoring of global inland surface water bodies are critical to address challenges in sustainable water management practices. Planet currently operates the largest constellation of Earth Observation satellites and collects images at very high spatial (0.5 m - 5 m) and temporal (near-daily) resolutions. Here, we use PlanetScope data (resampled to 3 m) to develop a holistic and fully automated pipeline running on the Google Cloud Platform for monitoring global inland surface water. We incorporate the openly-available Global Reservoir and Dam (GRanD) data set into a three-stage supervised learning approach which initiates with an unsupervised label-generation step consisting of k-means clustering and NIR-based thresholding. We then rank the labels generated from these steps and the water labels extracted from the latest ESRI 10 m land cover data based on image contours. The best (noisy) labels having the least number of contours from this unsupervised learning stage are bootstrapped to train a deep-learning based semantic segmentation model (U-Net) on a KubeFlow pipeline. We subsequently create a new refined dataset by using these model predictions as labels which are passed to a Stochastic Gradient Descent (SGD)-based multi-temporal supervised label refinement stage (SGD classifier running on the same label for multiple input scenes). Finally, we iterate over the SGD based-supervised and U-Net-based label refinement steps to successively denoise the bootstrapped data until we obtain an acceptable test accuracy ( $F_1$  score  $> 0.9$ ). Visual inspection of the results obtained over different climatic regions, terrains, and seasons across the globe shows that our approach works quite well. We also aggregate these predictions to detect temporal changes in surface water area. However, the model predictions exhibit high uncertainty in agricultural areas and complex terrains characterized by hill shadows and clouds. This issue could potentially be mitigated using hard-negative mining. Nevertheless, with the nearly-daily imaging capability of Planet, the high-fidelity surface water maps developed using this proposed supervised learning approach could be beneficial to the global water community for dealing with water security issues as part of the UN sustainable development goals.

---

# IN25C-0468 - High-Resolution Global Inland Surface Water Monitoring using PlanetScope Data and Supervised Learning with Bootstrapped Noisy Labels

---



Tuesday, 14 December 2021



16:00 - 18:00



Convention Center - Poster Hall, D-F

---

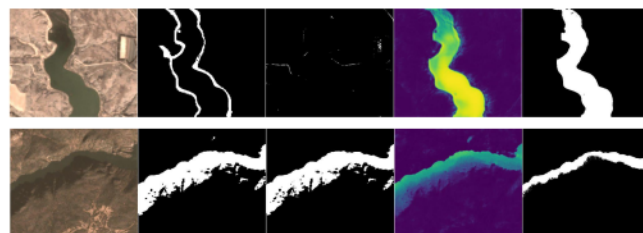
## Abstract

High-resolution mapping and monitoring of global inland surface water bodies are critical to address challenges in sustainable water management practices. Planet currently operates the largest constellation of Earth Observation satellites and collects images at very high spatial (0.5 m - 5 m) and temporal (near-daily) resolutions. Here, we use PlanetScope data (resampled to 3 m) to develop a holistic and fully automated pipeline running on the Google Cloud Platform for monitoring global inland surface water.

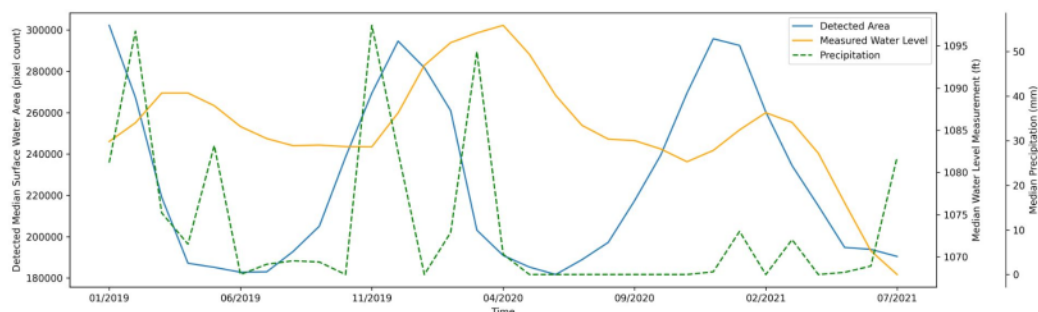
We incorporate the openly-available [Global Reservoir and Dam \(GRanD\)](#) data set into a three-stage supervised learning approach which initiates with an unsupervised label-generation step consisting of k-means clustering and NIR-based thresholding. We then rank the labels generated from these steps and the water labels extracted from the latest [ESRI 10 m land cover](#) data based on image contours. The best (noisy) labels having the least number of contours from this unsupervised learning stage are bootstrapped to train a deep-learning based semantic segmentation model ([U-Net](#)) on a KubeFlow pipeline. We subsequently create a new refined dataset by using these model predictions as labels which are passed to a Stochastic Gradient Descent (SGD)-based multi-temporal supervised label refinement stage (SGD classifier running on the same label for multiple input scenes). Finally, we iterate over the SGD based-supervised and U-Net-based label refinement steps to successively denoise the bootstrapped data until we obtain an acceptable test accuracy ( $F_1$  score > 0.9).

Visual inspection of the results obtained over different climatic regions, terrains, and seasons across the globe shows that our approach works quite well. We also aggregate these predictions to detect temporal changes in surface water area. However, the model predictions exhibit high uncertainty in agricultural areas and complex terrains characterized by hill shadows and clouds. This issue could potentially be mitigated using hard-negative mining. Nevertheless, with the nearly-daily imaging capability of Planet, the high-fidelity surface water maps developed using this proposed supervised learning approach could be beneficial to the global water community for dealing with water security issues as part of the UN sustainable development

goals.



1) visual image 2) unsupervised label 3) supervised label 4) prediction image 5) supervised refinement image



Comparing the detected surface water area with the measured water level at Lake Mead (near Hoover Dam), Nevada from 2019-2021. Here, we plot the monthly median values. The precipitation data are obtained from [PRISM](#) daily data sets (4 km resolution). We are seeing a correlation of trends between these two plots which measure two different physical quantities: a) Lake Mead elevation (water level) obtained from [Bureau of Reclamation](#) and b) the detected surface water area (pixel count) from our model predictions.

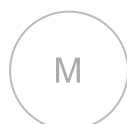
## Virtual Poster

With the pressing demands for freshwater resources associated with the rising global population and climate change, mapping and monitoring global freshwater reserves at local scales and high cadence are critical. Planet operates the largest constellation of Earth Observation satellites, collecting images at very high spatial (0.5 m - 3 m) and temporal (near-daily) resolutions. In this work, we use PlanetScope data (3 m) to develop an automated framework for monitoring global inland surface water.

We incorporate the openly-available [Global Reservoir and Dam \(GRanD\)](#) data set and [ESRI 10 m land cover](#) data into a holistic learning approach consisting of unsupervised, supervised, and segmentation modeling steps. Here, we use the Google Cloud Platform to run the entire pipeline. Visual inspection of the results obtained over different climatic regions, terrains, and seasons across the globe shows that our approach works quite well. However, we observe that the model predictions are not satisfactory in complex topographies where hill shadows and clouds are present.

Nevertheless, the nearly-daily imaging capability of Planet and the high-resolution surface water maps developed using our approach could benefit the global water community involving researchers, water managers, and other stakeholders to address the UN sustainable development goals on water security.

## First Author



Sayantan Majumdar

## Authors

---

N

[Ramesh Nair](#)  
Planet Labs

K

[Amit Kapadia](#)  
Planet Labs

M

[Jesus Martinez Manso](#)  
Planet Labs

B

[Cameron Bronstein](#)  
Planet Labs

N

[Brad Neuberg](#)  
SETI Institute

R

[Samapriya Roy](#)  
Planet Labs

G

[Benjamin Goldenberg](#)  
Planet Labs

D

[Justin Davis](#)  
Planet Labs

J

[Kelsey Jordahl](#)  
Planet Labs

S

[Ryan Glen Smith](#)  
Missouri University of  
Science and Technology

---

## View Related

### [IN25C - Commercial Earth Observation and NOAA's Low-Earth Orbiting Satellite Data for Research and Applications IV Poster](#)

**Alfreda Hall**, NASA Goddard Space Flight Center, Greenbelt, MD, United States, **Manil Maskey**, NASA Marshall Space Flight Center, MSFC, Huntsville, AL, United States, **Satya N Kalluri**, NOAA/NESDIS, Lanham, MD, United States, **Gary McWilliams**, NOAA/NESDIS JPSS Program Office, Lanham, MD, United States and **Bill Sjoberg**, GST Contractor Supporting NOAA, Lanham, MD, United States



Tuesday, 14 December 2021



16:00 - 18:00



Convention Center - Poster Hall, D-F