

# servir-aces: A Python Package for Training Machine Learning Models for Remote Sensing Applications

Biplov Bhandari<sup>1,2</sup> and Timothy Mayer<sup>1,2</sup>

<sup>1</sup> Earth System Science Center, The University of Alabama in Huntsville, 320 Sparkman Drive, Huntsville, AL 35805, USA <sup>2</sup> SERVIR Science Coordination Office, NASA Marshall Space Flight Center, 320 Sparkman Drive, Huntsville, AL 35805, USA

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

## Software

- [Review](#)
- [Repository](#)
- [Archive](#)

Editor: [Open Journals](#)

## Reviewers:

- [@openjournals](#)

Submitted: 01 January 1970

Published: unpublished

## License

Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](#)).

## Summary

**servir-aces** Agricultural Classification and Estimation Service (ACES) is a Python package for generating training data using highly parallelized [apache-beam](#) and [Google Earth Engine \(GEE\)](#) ([Gorelick et al., 2017](#)) workflows as well as for training various Machine Learning (ML) and Deep Learning (DL) models for Remote Sensing Applications ([Mayer et al., 2023](#)), ([Bhandari & Mayer, 2024](#)).

## Statement of Need

Despite robust platforms, specialized technical knowledge is required to setup and run various ML/DL models, leading many practitioners, scientists, and domain experts to find it difficult to implement them. The **servir-aces** Python package is created to fill this gap. **servir-aces** significantly lowers the barrier for users to export training data and both train and run DL models using cloud-based technology with their GEE workflows. Several examples are provided via a runnable notebook to make it easier for scientists utilize this emerging field of DL.

With petabytes of data available via GEE, and integration of the TensorFlow (TF) platform, models trained in TF can be easily loaded into GEE. This package provides functionalities for 1) data processing; 2) data loading from GEE; 3) feature extraction, 4) model training, and 5) model inference. The combination of TF and GEE has enabled several large scale ML and DL Remote Sensing applications. Some of them include Wetland Area Mapping ([Bakkestuen et al., 2023](#)), Crop Type Mapping ([Poortinga et al., 2021](#)), Surface Water Mapping ([Mayer et al., 2021](#)), and Urban Mapping ([Parekh et al., 2021](#)).

## servir-aces Audience

**servir-aces** is intended for development practitioner, researchers, and students who would like to utilize various freely available Earth Observation (EO) data using cloud-based GEE and TF ecosystem to perform large scale ML/DL related Remote Sensing applications.

We also provide several notebook examples to showcase the usage of the **servir-aces**. Here we show how **servir-aces** can be used for crop-mapping related application. Ideally, the same process can be repeated for any kind of the image segmentation task.

## servir-aces Functionality

The major high-level functionality of the **servir-aces** packages are: - Data loading and processing from GEE. - Generation of training data for various ML and DL models. - Training and evaluation

of ML/DL Models. - Inferences of the trained ML/DL models. - Support for remote sensing feature extraction. - Integration with Apache Beam for data processing and parallelization.

The key functionality of **servir-aces** is organized into several modules:

- **data\_processor**: this module provides functionality for data input/output and preprocessing for the image segmentation project.
- **model\_builder**: this module provides functionality for creating and compiling various Neural Network Models, including DNN, CNN, U-Net.
- **model\_trainer**: this module provides functionality for training, building, compiling, and running specified deep learning models.
- **metrics**: this module provides a host of statistical metrics, standard within the field, for evaluating model performance and provide utility functions for plotting and visualizing model metrics during training.
- **ee\_utils**: this module for providing utility functions to handle GEE API information and authentication requests.
- **remote\_sensing**: this module provides various static methods to compute Remote Sensing indices for analysis.

## **servir-aces Funding**

This research was funded through the US Agency for International Development (USAID) and NASA initiative Cooperative Agreement Number: AID486-A-14-00002. Individuals affiliated with the University of Alabama in Huntsville (UAH) are funded through the NASA Applied Sciences Capacity Building Program, NASA Cooperative Agreement: 80MSFC22M004.

## **servir-aces Acknowledgement**

The authors would like to thank NASA's Applied Sciences Program and Capacity Building Program, specifically Dr. Nancy Searby. We also want to thank the **SERVIR** program especially Dan Irwin, Dr. Ashutosh Limaye, and Eric Anderson. Additionally, we would like to thank the USAID especially Dr. Pete Epanchin. We would also like to thank UAH specifically Dr. Rob Griffin and the **Lab for Applied Science (LAS)** as well as **SERVIR's Geospatial Artificial Intelligence Working Group (Geo-AI WG)** for their support and collaboration over the years. Finally, we are indebted to Dr Nick Clinton from the Google Earth Outreach Team for the support.

## **References**

- Bakkestuen, V., Venter, Z., Ganerød, A. J., & Framstad, E. (2023). Delineation of wetland areas in south norway from sentinel-2 imagery and LiDAR using TensorFlow, u-net, and google earth engine. *Remote Sensing*, 15(5), 1203.
- Bhandari, B., & Mayer, T. (2024). Comparing deep learning models for rice mapping in bhutan using high resolution satellite imagery. *ISPRS Open Journal of Photogrammetry and Remote Sensing*, to appear, to appear.
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google earth engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27.
- Mayer, T., Bhandari, B., Martínez, F. G., Walker, K., Jiménez, S. A., Kruskopf, M., Maganini, M., Phalke, A., Wangchen, T., Phuntsho, L., & others. (2023). Employing the agricultural

- 79 classification and estimation service (ACES) for mapping smallholder rice farms in bhutan.  
80 *Frontiers in Environmental Science*, 11, 1137835.
- 81 Mayer, T., Poortinga, A., Bhandari, B., Nicolau, A. P., Markert, K., Thwal, N. S., Markert,  
82 A., Haag, A., Kilbride, J., Chishtie, F., & others. (2021). Deep learning approach for  
83 sentinel-1 surface water mapping leveraging google earth engine. *ISPRS Open Journal of*  
84 *Photogrammetry and Remote Sensing*, 2, 100005.
- 85 Parekh, J. R., Poortinga, A., Bhandari, B., Mayer, T., Saah, D., & Chishtie, F. (2021).  
86 Automatic detection of impervious surfaces from remotely sensed data using deep learning.  
87 *Remote Sensing*, 13(16), 3166.
- 88 Poortinga, A., Thwal, N. S., Khanal, N., Mayer, T., Bhandari, B., Markert, K., Nicolau, A. P.,  
89 Dilger, J., Tenneson, K., Clinton, N., & others. (2021). Mapping sugarcane in thailand  
90 using transfer learning, a lightweight convolutional neural network, NICFI high resolution  
91 satellite imagery and google earth engine. *ISPRS Open Journal of Photogrammetry and*  
92 *Remote Sensing*, 1, 100003.

DRAFT