

# The 22nd International Conference on Pervasive Computing and Communications (PerCom 2024)



## “Stitching Satellites to the Edge: Pervasive and Efficient Federated LEO Satellite Learning”

March 13, 2024, Biarritz, France

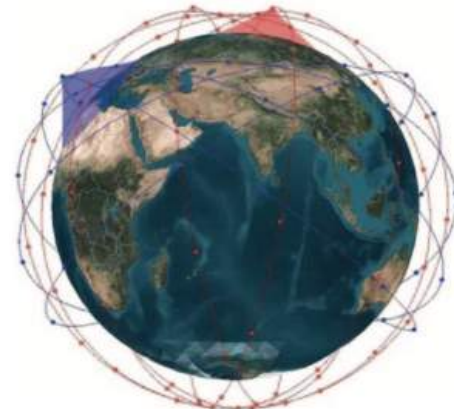
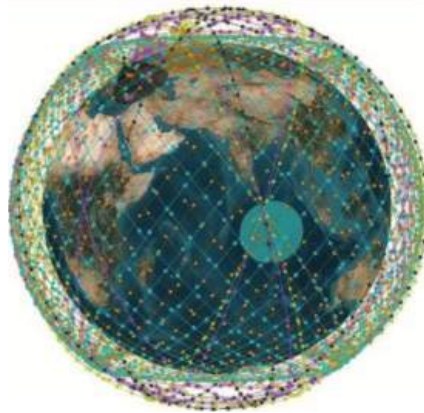
**Mohamed Elmahallawy and Tie Luo**

Computer Science Department, Missouri University of Science and Technology, USA



## Low Earth Orbit (LEO) Satellite Networks

The **recent surge** of interest and investment in large-scale LEO satellites



Industry

**SPACEX**  
STARLINK

**amazon**  
Project Kuiper

**eutelsat**  
ONEWEB

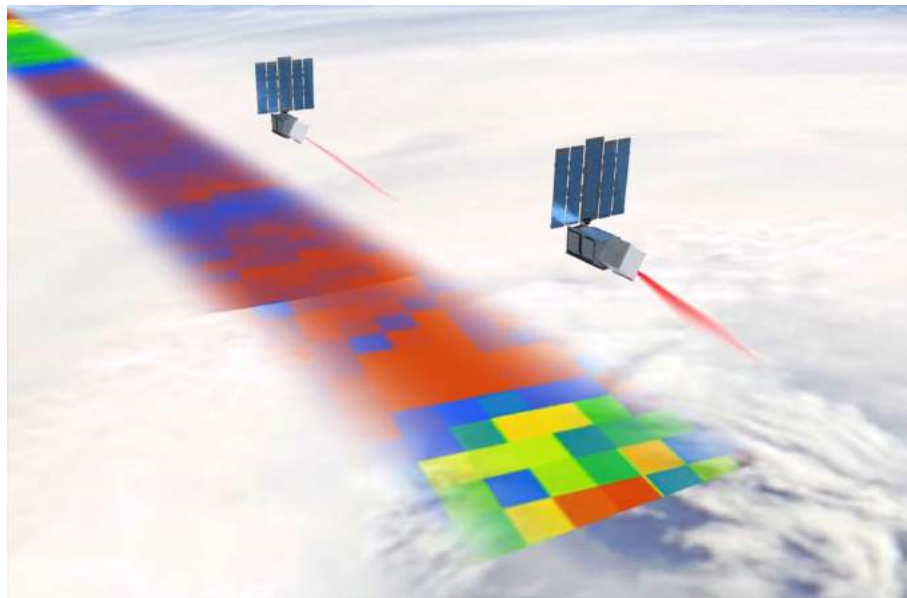
Government



**esa**  
European Space Agency

# Low Earth Orbit (LEO) Satellite Networks

Enable **novel applications** empowered by machine learning, such as:



**5 petabytes** of image data per day (2019)!

## Disaster Detection



## Border Monitoring



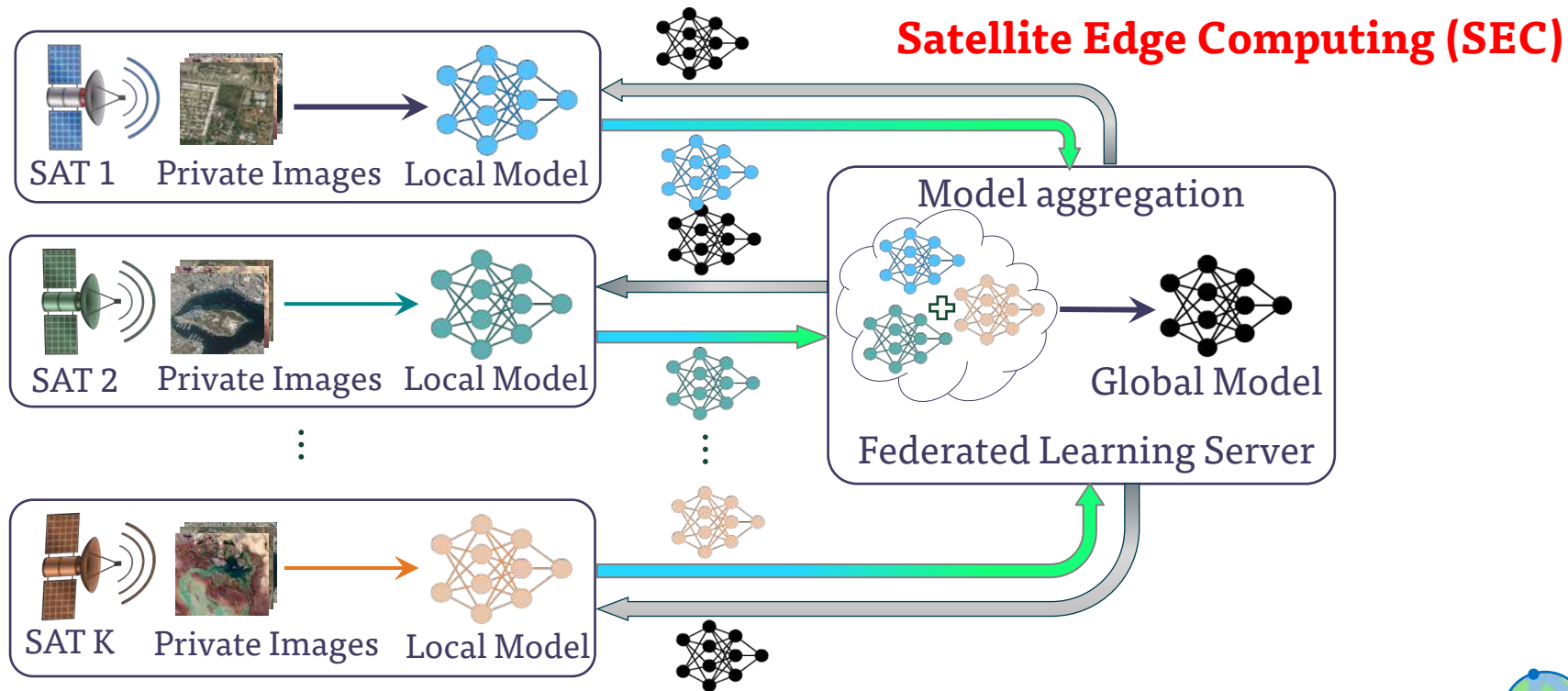
# Low Earth Orbit Satellite Networks

Conventional (i.e., centralized) ML:

- Download high-resolution satellite images to a ground station (GS)
- This is **impractical** because:
  - **Bandwidth**
    - **50~500MB** (vs. 5 petabytes satellite data!)
  - **Privacy**
    - **Raw data** transmission

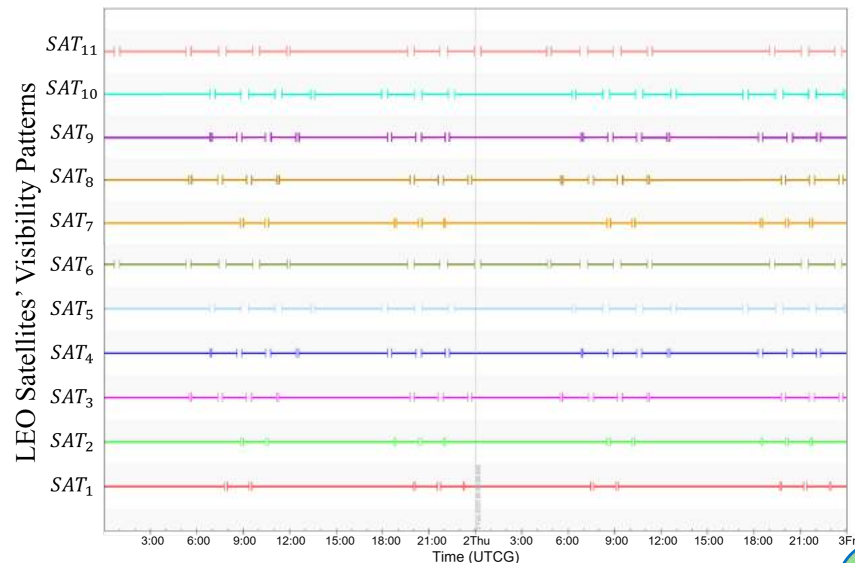


## Introducing Federated Learning (FL) into LEO Networks



## Challenges in SEC

- ✗ Limited computation and storage
  - LEO satellites cannot train large-scale ML models onboard
  - Overlooked by existing FL-LEO literature
- ✗ **Sporadic** and **irregular** visibility pattern
  - The **iterative** FL process will converge after several **days** or even **weeks**



A visiting pattern over 2 days of a LEO network consisting of 11 satellites that communicate with a GS in Rolla, MO, USA

## Contributions

- We propose an innovative framework FL to enable satellite edge computing (SEC)

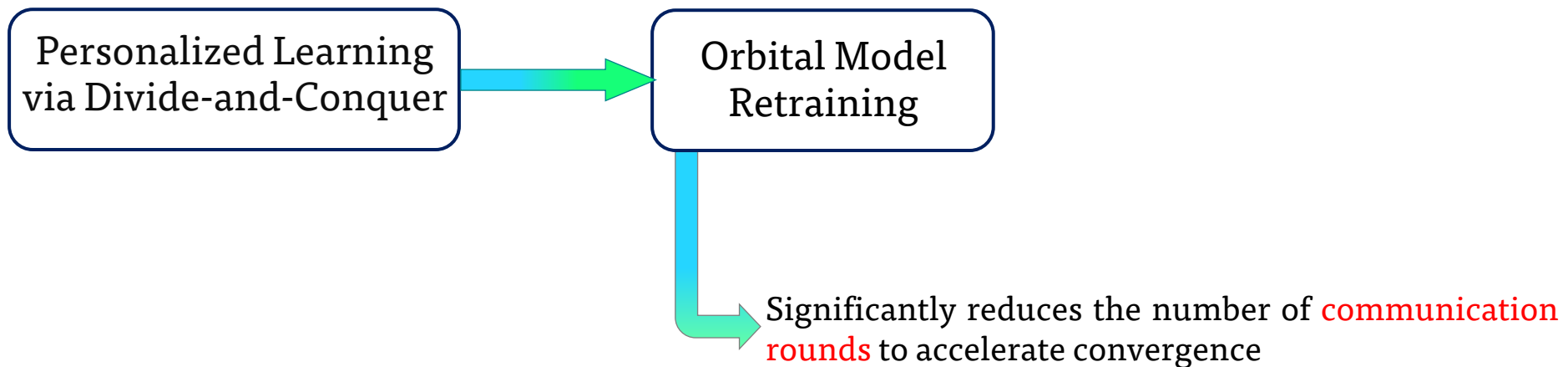
Personalized Learning  
via Divide-and-Conquer

Enables satellites to train **lightweight ML** models, addressing the computation and memory limitations.



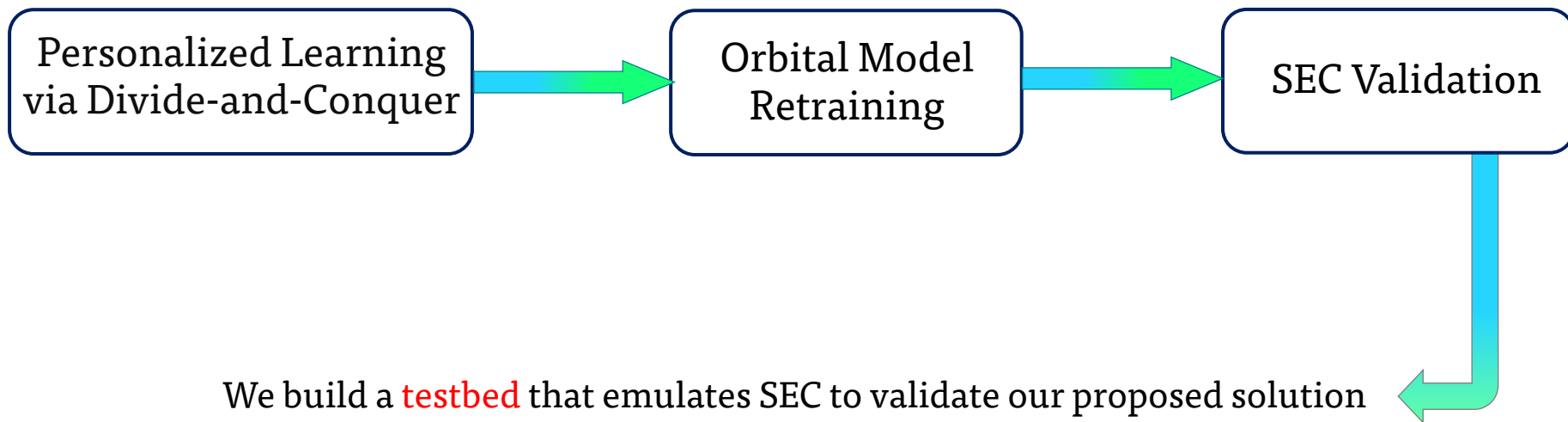
## Contributions

- We propose an innovative framework FL to enable satellite edge computing (SEC)



## Contributions

- We propose an innovative framework FL to enable satellite edge computing (SEC)



- LEO satellites collaboratively train a global ML model to minimize the global loss as:

Data size of satellite's  $n$

$$\min_{w \in \mathbb{R}^d} F(w) = \sum_{n \in \mathcal{N}} \frac{m_n}{m} F_n(w)$$

Data size of all satellites

loss function of a satellite  $n$

$$F_n(w) = \frac{1}{m_n} \sum_{x \in D_n} f_n(w; x)$$

- Each satellite  $n$  trains a local model by minimizing  $F_n(w)$  through SGD:

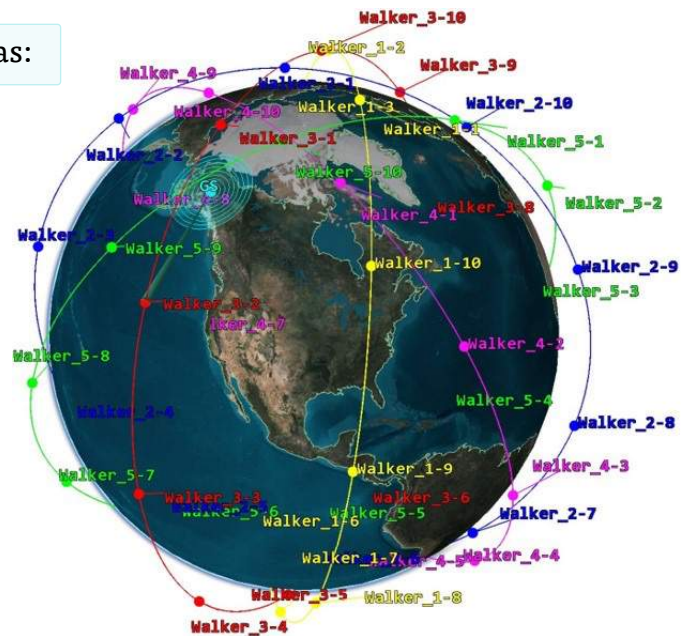
Global iteration index

learning rate

$$w_n^{\beta, j+1} = w_n^{\beta, j} - \frac{\eta}{b} \sum_{i=1}^b \nabla f_n(w_n^{\beta, j}; x_n^i), \quad i = 0, 1, 2, \dots, I-1$$

Mini-batch size

Local model of satellite  $i$  at the  $j$ -the local iteration

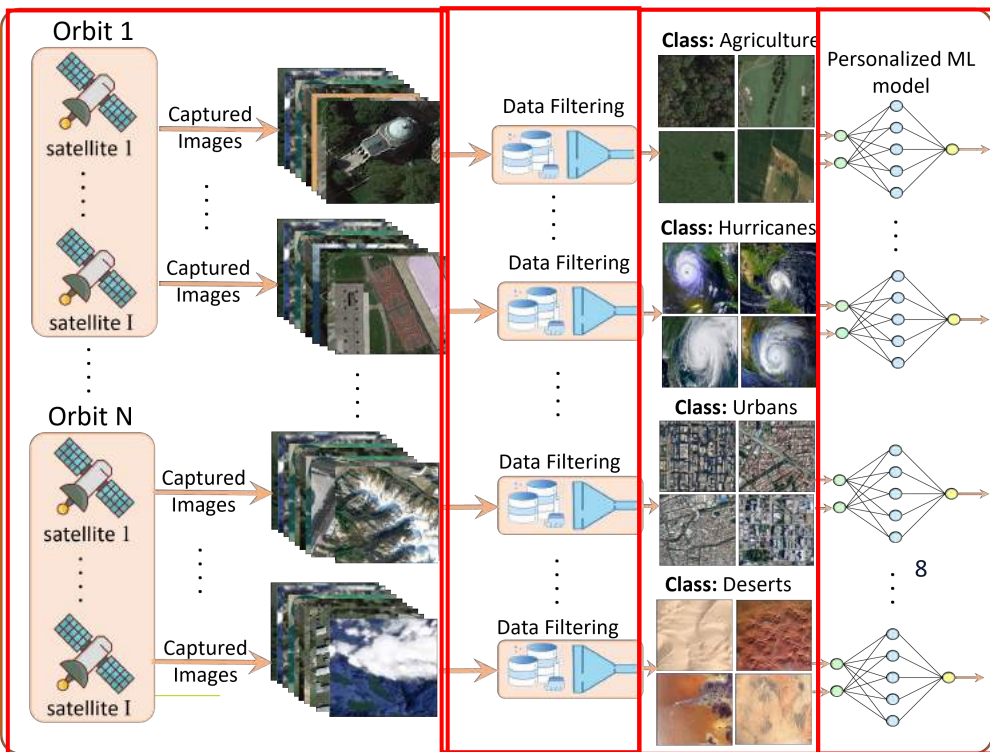


LEO network of  $N$  satellites

- The server aggregates all the satellites' local models into a global model:

$$w^{\beta+1} = \sum_{n \in \mathcal{N}} \frac{m_n}{m} w_n^{\beta}$$

### 1. Personalized Learning via Divide-and-Conquer



Converting multi-class classification problem into binary classification

#### Before Training

- ✓ Each satellite **filters** its collected images for a **single target class**:

$$D_i^{\text{filtered}} = \{X_i \mid (X_i, y) \in D_i, \pi_i(y) = 1\}$$

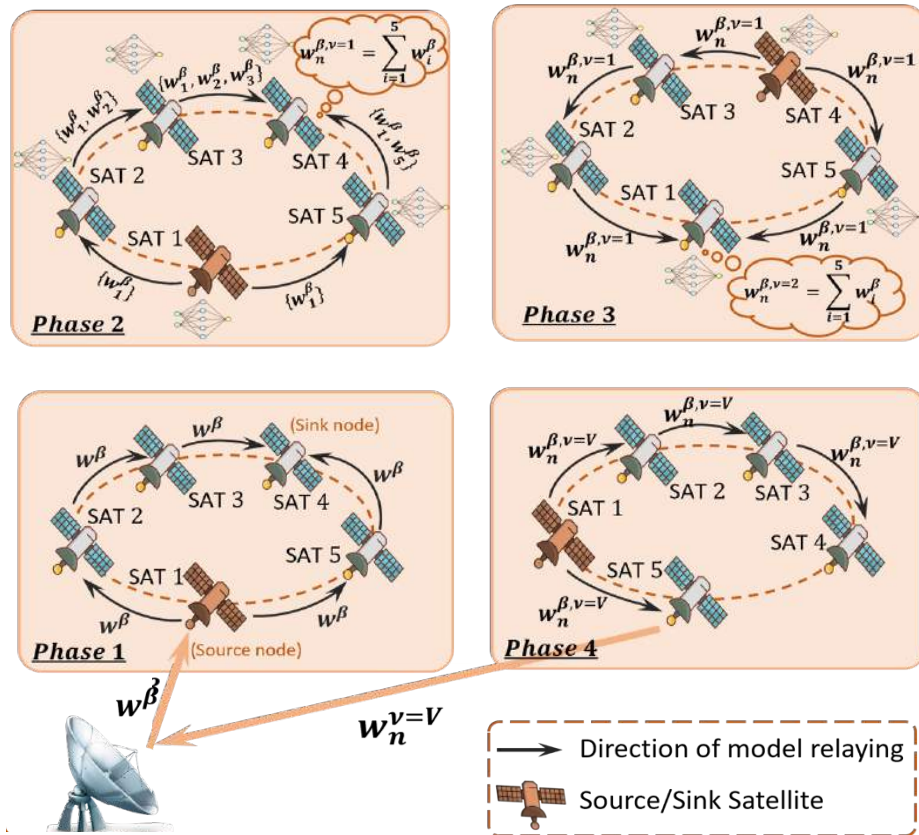
- ✓ This converts the original complex **multi-class** problem into a **binary classification** problem.

$$t_{\text{train}}^i = \frac{\nu_i \cdot J \cdot c_{\text{process}} + c_{\text{overhead}}}{f_i}, \quad \text{where } \nu_i = \left\lceil \frac{m_i^{\text{filtered}}}{\kappa} \right\rceil$$

#### During training

- ✓ Each satellite trains a **personalized** ML model by employing the **one-vs-all** strategy.

## 2. Orbital Model Retraining



### Objective

Convert the binary classification tasks **back** to the original multi-class problem

### Phase 1:

Distribute global model to all satellites within each orbit

### Phase 2:

**Sink satellite** aggregates all binary models received from satellites in the same orbit, forming an “orbital model”

### Phase 3:

**Retrain** the orbital model for several orbital rounds: essentially FL in an **extreme non-IID** scenario

$$w_n^{\beta,v+1} = \sum_{i \in \mathcal{I}_n} \frac{m_i^{\text{filtered}}}{m_{\mathcal{I}_n}} w_i^{J,v}, \text{ where } m_{\mathcal{I}_n} = \sum_{i \in \mathcal{I}_n} m_i^{\text{filtered}}$$

### Phase 4:

The first visible satellite to the FL server (ground station) transmits orbital model to server

# Evaluation

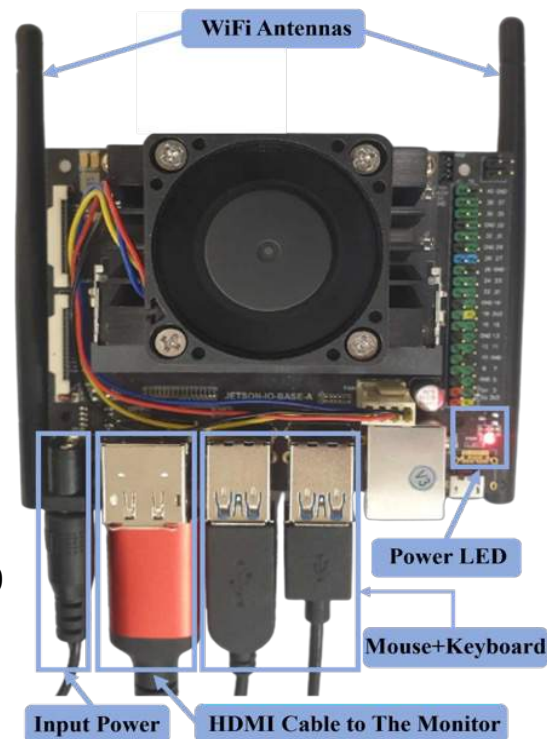
## Experimental Setup

### ▪ LEO Satellite Network

- Two LEO networks of **60** satellites evenly distributed over **6 orbits**, one with inclination of  $45^\circ$  and the other 5 with inclination of  $85^\circ$
- STK simulator was used to generate **satellite visibility pattern**
- Ground station is positioned in Rolla, MO, USA as the FL server

### ▪ Satellite Training (Testbed)

- **Jetson Nano** with NVIDIA Maxwell GPU to **emulate** each satellite
- Dataset: **EuroSat** (high-resolution **real-satellite images**) containing 10 classes of land cover
- Each satellite trains a **VGG-16** model
- Also uses MNIST, CIFAR-10, and CIFAR-100 datasets for comparison with SOTA



# Evaluation

## Results 1: Convergence

### Comparing with SOTA

TABLE III: Comparison of convergence time and accuracy under non-IID settings (near-polar Constellation).

	FL-LEO Approaches	Accuracy (%)			Convergence time (h)
		MNIST	CIFAR-10	CIFAR-100	
Sync FL	FedAvg [3]	79.41	70.68	61.66	60 ( $\mathcal{P}\mathcal{S}$ located anywhere)
	FedISL [7]	82.76	73.62	66.57	8 ( $\mathcal{P}\mathcal{S}$ located at the NP)
	FedISL [7]	61.06	52.11	47.99	72 ( $\mathcal{P}\mathcal{S}$ located anywhere)
	NomaFedHAP [8]	82.73	77.36	62.81	24 ( $\mathcal{P}\mathcal{S}$ located anywhere)
Async FL	FedAsync [25]	70.36	61.81	56.37	48 ( $\mathcal{P}\mathcal{S}$ located anywhere)
	FedSpace [6]	52.67	39.41	36.04	72 (satellite uploads some of its data)
	AsyncFLEO [14]	79.49	69.88	61.43	9 (sink satellite has sufficient visible period)
	<b>Ours</b>	<b>94.64</b>	<b>89.69</b>	<b>82.65</b>	<b>2.13</b> ( $\mathcal{P}\mathcal{S}$ located anywhere)

### Classification results (EuroSat)



Fig. 6: Twenty randomly selected images from a Eurostat test set of 5400 samples, illustrating the predicted vs. ground truth labels. Blue and red color represent correct and incorrect predictions, respectively.

# Evaluation

## Results 1: Convergence

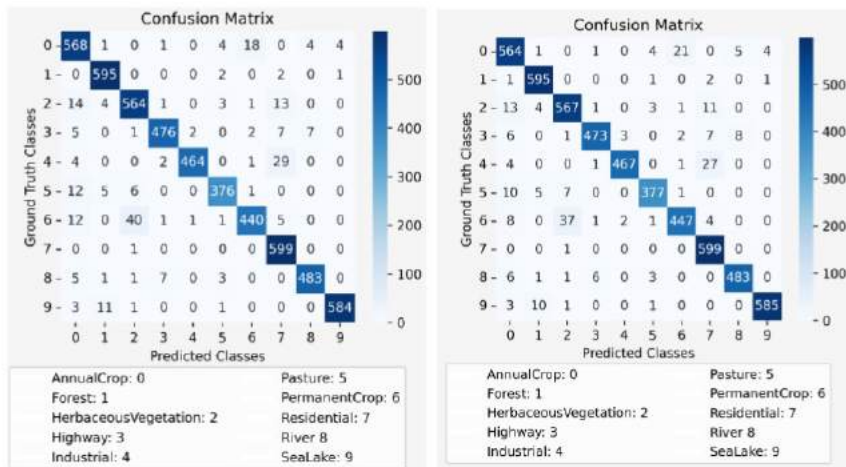
### Individual class accuracy for EuroSat

TABLE IV: Evaluation of our approach on EuroSat Dataset.

Class \ Metric	# of images	Near-polar constellation (85°)				Inclined constellation (45°)			
		ACC(%)	PC (%)	RC (%)	F1 (%)	ACC(%)	PC (%)	RC (%)	F1(%)
AnnualCrop	600	97.63	92.06	94.67	93.34	98.39	91.71	94.0	92.84
Forest	600	98.19	96.73	98.67	97.69	99.52	96.59	99.17	97.86
HerbaceousVegetation	600	99.32	93.05	93.67	93.36	98.5	92.12	94.5	93.33
Highway	500	99.61	97.74	95.0	96.35	99.31	97.93	94.60	96.24
Industrial	500	98.89	98.95	93.80	96.30	99.30	98.94	93.40	96.09
Pasture	400	99.23	96.42	94.25	95.32	99.33	96.67	94.25	95.44
PermanentCrop	500	97.46	95.14	90.0	92.50	98.54	94.50	89.40	91.88
Residential	600	99.01	91.45	99.83	95.46	99.04	92.15	99.83	95.84
River	500	99.56	98.17	96.60	97.38	99.44	97.37	96.60	96.99
SeaLake	600	99.11	98.66	98.0	98.33	99.63	99.15	97.50	98.32

Better visibility

Less visibility



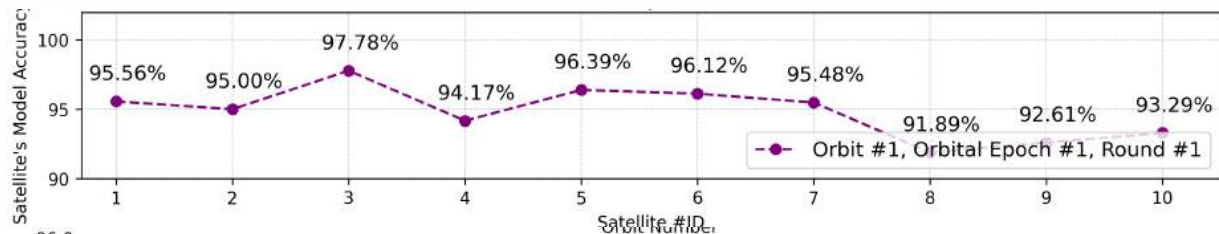
(a) Near-polar constellation (85°). (b) Inclined constellation (45°).

Fig. 5: Confusion matrix that compares 10 predicted and ground-truth classes for 5400 test images.

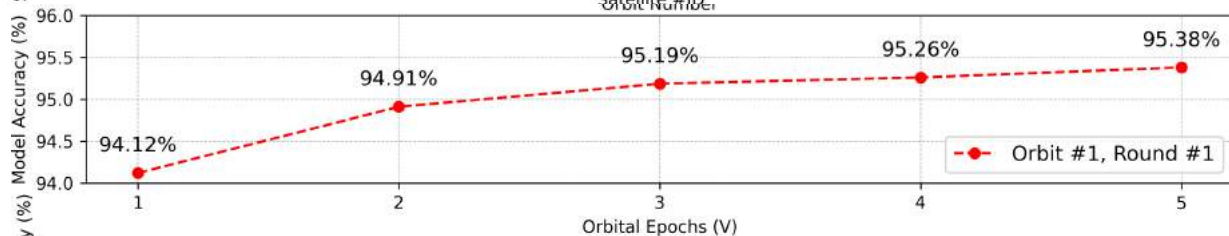


# Evaluation

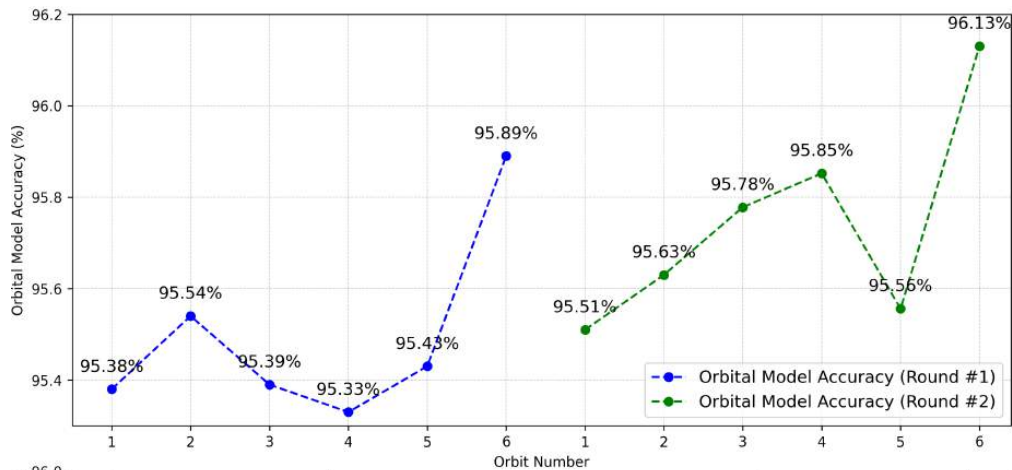
Binary Model Accuracy



Orbital Model Accuracy



Global Model Accuracy



# Evaluation

## Results 2: Computation and Communication overhead; Energy Consumption

### A. Computation Overhead

- Measured by floating-point operations per second (**FLOPS**)

### B. Communication Overhead

- Measured by size of the global model

### C. Energy Consumption

- Jetson Nano experienced GPU usage of **17--58%** during training on various datasets
- Energy consumption ranged between **merely 1.38--2.25 watts** for each local model, demonstrating the advantage of being highly **lightweight**

TABLE V: Comparison of computation and communication overheads of our approach in different settings.

(a) Computation overhead.		(b) Communication overhead.	
Model	FLOPS (G)	Dataset	Size (MB)
CNN using MNIST	11.91	MNIST	0.437
CNN using CIFAR-10	15.58	CIFAR-10	0.798
CNN using CIFAR-100	28.13	CIFAR-100	7.76
VGG-16 using EuroSat	43.84	EuroSat	26.68

# From Lab to Space

- **Recent Launch** (March 6, 2024)

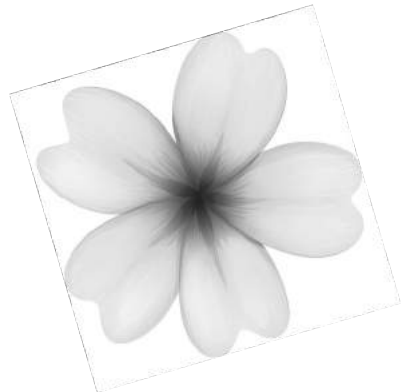
- SpaceX launched an LEO satellite developed by **Missouri University of Science and Technology**, tasked with capturing Earth images.
- Equipped with Raspberry Pi

- **Future Launch** (Feb. 2026)

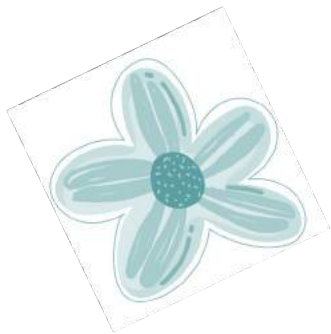
- Currently working on building two other LEO satellites: *Missouri Rolla* (MR) and *Missouri Rolla Second* (MRS).
- MR and MRS will be equipped with Jetson Nano to train ML models onboard



*Thank You*



*Questions?*



# Take-Home Message

- AI-driven **satellite edge computing (SEC)** is coming.
- Federated learning integrated with LEO satellite networks (**FL-LEO**) is a promising approach but with challenges of computational and storage limitations
- We propose a solution to tackle this challenge in FL-LEO to **enable SEC**
  - Personalized ML model via divide-and-conquer
  - Orbital model retraining
- Validated by testbed

*Thank You*

*Questions?*

Funded by:



Acknowledgement:



### Secure and Efficient Federated Learning in LEO Constellations using Decentralized Key Generation and On-Orbit Model Aggregation

Mohamed Elshahhat<sup>1</sup>, Tie Luo<sup>2</sup>, Mohamed I. Bebak<sup>3</sup>  
<sup>1</sup>Computer Science Department, Missouri University of Science and Technology, Rolla, MO 65401, USA  
<sup>2</sup>School of Computer and Cyber Sciences, Angewandte Informatik, FH Kaiserslautern, Germany  
<sup>3</sup>Faculty of Engineering, Mansoura University, Mansoura, Egypt

# Security & Privacy Preserving

Recent satellite-based machine learning has advanced significantly, but remains vulnerable to adversarial attacks. This paper introduces a secure and efficient federated learning framework for LEO constellations. The framework consists of a decentralized key generation and on-orbit model aggregation protocol. The key generation phase is performed on the ground stations, while the model aggregation is performed on-board the satellites. The proposed framework ensures the confidentiality of the model updates and the integrity of the aggregated model. The framework is evaluated using a realistic LEO constellation scenario, demonstrating its effectiveness in preserving the security and efficiency of the federated learning process.

### Secure and Privacy-Preserving Federated Learning for Low Earth Orbit Satellite Networks

Mohamed Elshahhat<sup>1</sup>, Tie Luo, Senior Member, IEEE, Mohamed I. Bebak, Member, IEEE

Secure federated learning (SFL) is a promising approach for training machine learning models on data distributed across multiple devices. However, SFL is vulnerable to adversarial attacks, particularly in the context of satellite networks. This paper introduces a secure and privacy-preserving federated learning framework for Low Earth Orbit (LEO) satellite networks. The framework consists of a secure key generation and on-orbit model aggregation protocol. The key generation phase is performed on the ground stations, while the model aggregation is performed on-board the satellites. The proposed framework ensures the confidentiality of the model updates and the integrity of the aggregated model. The framework is evaluated using a realistic LEO constellation scenario, demonstrating its effectiveness in preserving the security and efficiency of the federated learning process.

### Secure Aggregation Is Myopic: Preserving Long-Term Federated Satellite Learning

Department of Computer Science, Missouri University of Science and Technology, Rolla, MO 65401, USA  
Email: {mshahhat, tie@missouri.edu}

All papers are available at <https://tluoocs.github.io>

### Communication-Efficient Federated Learning for LEO Satellite Networks Integrated with HAPs Using Hybrid NOMA-OFDM

Mohamed Elshahhat<sup>1</sup>, Student Member, IEEE, Tie Luo<sup>2</sup>, Senior Member, IEEE, and Khalid Ramadan<sup>3</sup>

# Computing & Communication

Hybrid NOMA-OFDM is a promising approach for integrated satellite and HAP networks. This paper introduces a communication-efficient federated learning framework for LEO satellite networks integrated with HAPs using Hybrid NOMA-OFDM. The framework consists of a decentralized key generation and on-orbit model aggregation protocol. The key generation phase is performed on the ground stations, while the model aggregation is performed on-board the satellites. The proposed framework ensures the confidentiality of the model updates and the integrity of the aggregated model. The framework is evaluated using a realistic LEO constellation scenario, demonstrating its effectiveness in preserving the security and efficiency of the federated learning process.

### Stitching Satellites to the Edge: Pervasive Efficient Federated LEO Satellite

Mohamed Elshahhat<sup>1</sup>, Tie Luo, Senior Member, IEEE, Mohamed I. Bebak, Member, IEEE

Stitching satellites to the edge is a promising approach for pervasive computing and communications. This paper introduces a pervasive efficient federated learning framework for LEO satellite networks. The framework consists of a decentralized key generation and on-orbit model aggregation protocol. The key generation phase is performed on the ground stations, while the model aggregation is performed on-board the satellites. The proposed framework ensures the confidentiality of the model updates and the integrity of the aggregated model. The framework is evaluated using a realistic LEO constellation scenario, demonstrating its effectiveness in preserving the security and efficiency of the federated learning process.

### One-Shot Federated Learning for LEO Constellations that Reduces Convergence Time from Days to 90 Minutes

Mohamed Elshahhat<sup>1</sup>, Tie Luo, Senior Member, IEEE, Mohamed I. Bebak, Member, IEEE

One-shot federated learning (OSFL) is a promising approach for reducing convergence time in federated learning. This paper introduces a one-shot federated learning framework for LEO constellations. The framework consists of a decentralized key generation and on-orbit model aggregation protocol. The key generation phase is performed on the ground stations, while the model aggregation is performed on-board the satellites. The proposed framework ensures the confidentiality of the model updates and the integrity of the aggregated model. The framework is evaluated using a realistic LEO constellation scenario, demonstrating its effectiveness in reducing convergence time from days to 90 minutes.

### AsyncFLEO: Asynchronous Federated Learning of Satellite Constellations with High-Altitude

Mohamed Elshahhat<sup>1</sup> and Tie Luo<sup>2</sup>  
<sup>1</sup>Computer Science Department, Missouri University of Science and Technology, Rolla, MO 65401, USA  
<sup>2</sup>School of Computer and Cyber Sciences, Angewandte Informatik, FH Kaiserslautern, Germany

Asynchronous federated learning (AFL) is a promising approach for satellite constellations with high-altitude. This paper introduces an asynchronous federated learning framework for satellite constellations with high-altitude. The framework consists of a decentralized key generation and on-orbit model aggregation protocol. The key generation phase is performed on the ground stations, while the model aggregation is performed on-board the satellites. The proposed framework ensures the confidentiality of the model updates and the integrity of the aggregated model. The framework is evaluated using a realistic satellite constellation scenario, demonstrating its effectiveness in preserving the security and efficiency of the federated learning process.

### FedHAP: Fast Federated Learning for LEO Constellations using Collaborative

Mohamed Elshahhat<sup>1</sup> and Tie Luo<sup>2</sup>  
<sup>1</sup>Computer Science Department, Missouri University of Science and Technology, Rolla, MO 65401, USA  
<sup>2</sup>School of Computer and Cyber Sciences, Angewandte Informatik, FH Kaiserslautern, Germany

Fast federated learning (FFL) is a promising approach for LEO constellations using collaborative. This paper introduces a fast federated learning framework for LEO constellations using collaborative. The framework consists of a decentralized key generation and on-orbit model aggregation protocol. The key generation phase is performed on the ground stations, while the model aggregation is performed on-board the satellites. The proposed framework ensures the confidentiality of the model updates and the integrity of the aggregated model. The framework is evaluated using a realistic LEO constellation scenario, demonstrating its effectiveness in preserving the security and efficiency of the federated learning process.

### Optimizing Federated Learning in LEO Satellite Constellations via Intra-Plane Model Propagation and Sink Satellite Scheduling

Mohamed Elshahhat<sup>1</sup>, Tie Luo<sup>2</sup>, Senior Member, IEEE, Mohamed I. Bebak, Member, IEEE

Optimizing federated learning (OFL) is a promising approach for LEO satellite constellations via intra-plane model propagation and sink satellite scheduling. This paper introduces an optimizing federated learning framework for LEO satellite constellations via intra-plane model propagation and sink satellite scheduling. The framework consists of a decentralized key generation and on-orbit model aggregation protocol. The key generation phase is performed on the ground stations, while the model aggregation is performed on-board the satellites. The proposed framework ensures the confidentiality of the model updates and the integrity of the aggregated model. The framework is evaluated using a realistic LEO constellation scenario, demonstrating its effectiveness in preserving the security and efficiency of the federated learning process.

# Convergence Speed & Efficiency

It is not end here, it just started