FORTY: A Benchmark for Forest Type Mapping and Geospatial Foundation Models

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Yuchang Jiang, Maxim Neumann

Introduction

Where are the forests?

FAO's definition: …trees higher than 5m…canopy cover more than 10%...
⇒ focus more on forest coverage: forest vs non-forest

Besides 'where', what kinds of forests?

Forest classes: natural forests, planted forests, tree crops…
⇒ focus more on detailed forest type mapping

+ Better deforestation risk and degradation monitoring
+ Better biodiversity monitoring
+ support for EU Deforestation Regulation (EUDR) compliance

…

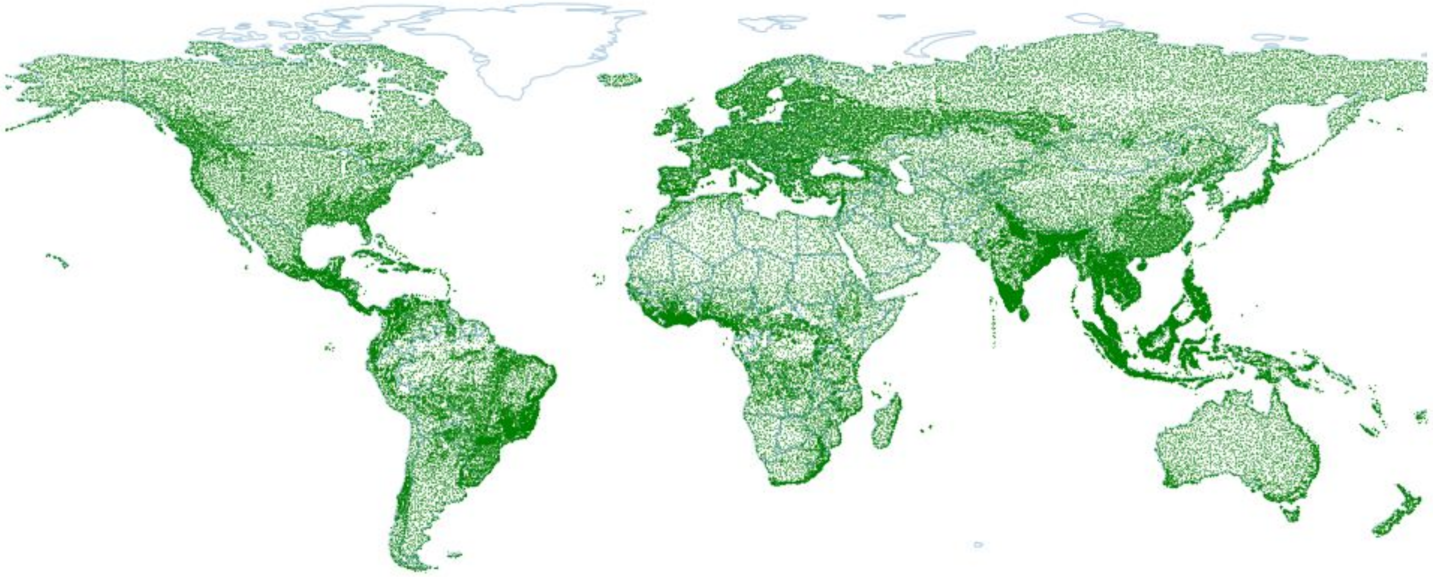
so we propose

FORTY: a DL benchmark for forest type mapping

FORTY Dataset

a global-scale multi-modal multi-temporal DL benchmark

- 200,000 samples with 1280m x 1280m coverage at 10 m resolution
- annotated with per-pixel labels
- classes
  - **forest classes: (1) natural forest, (2) planted forest, (3) tree crops**
  - non-forest classes: (4) other vegetation, (5) built, (6) water, (7) ice, (8) bare ground



FORTY Dataset: reference data

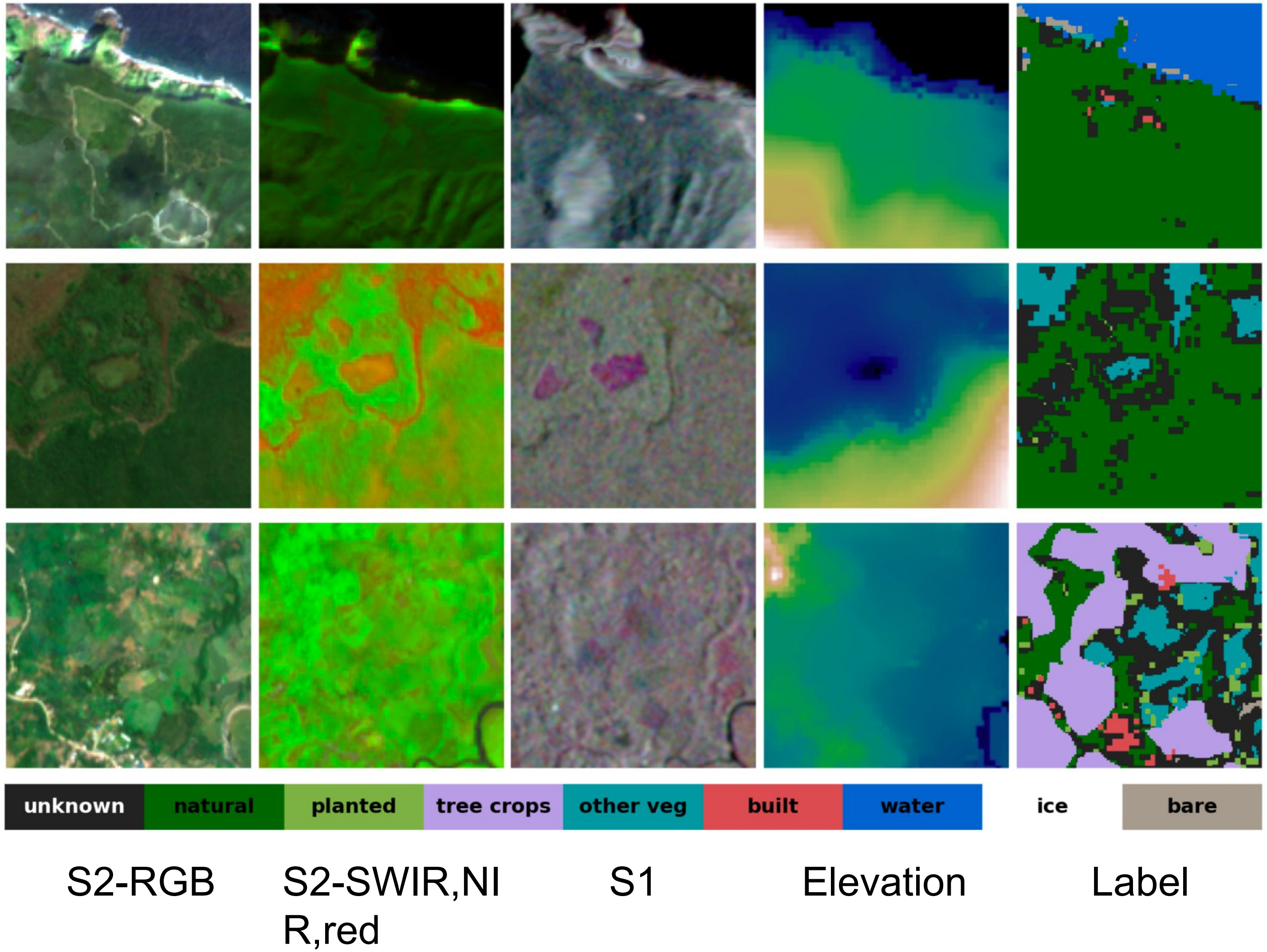
Collect and merge diverse publicly available data sources

some main data sources:

FORTY Dataset: satellite data

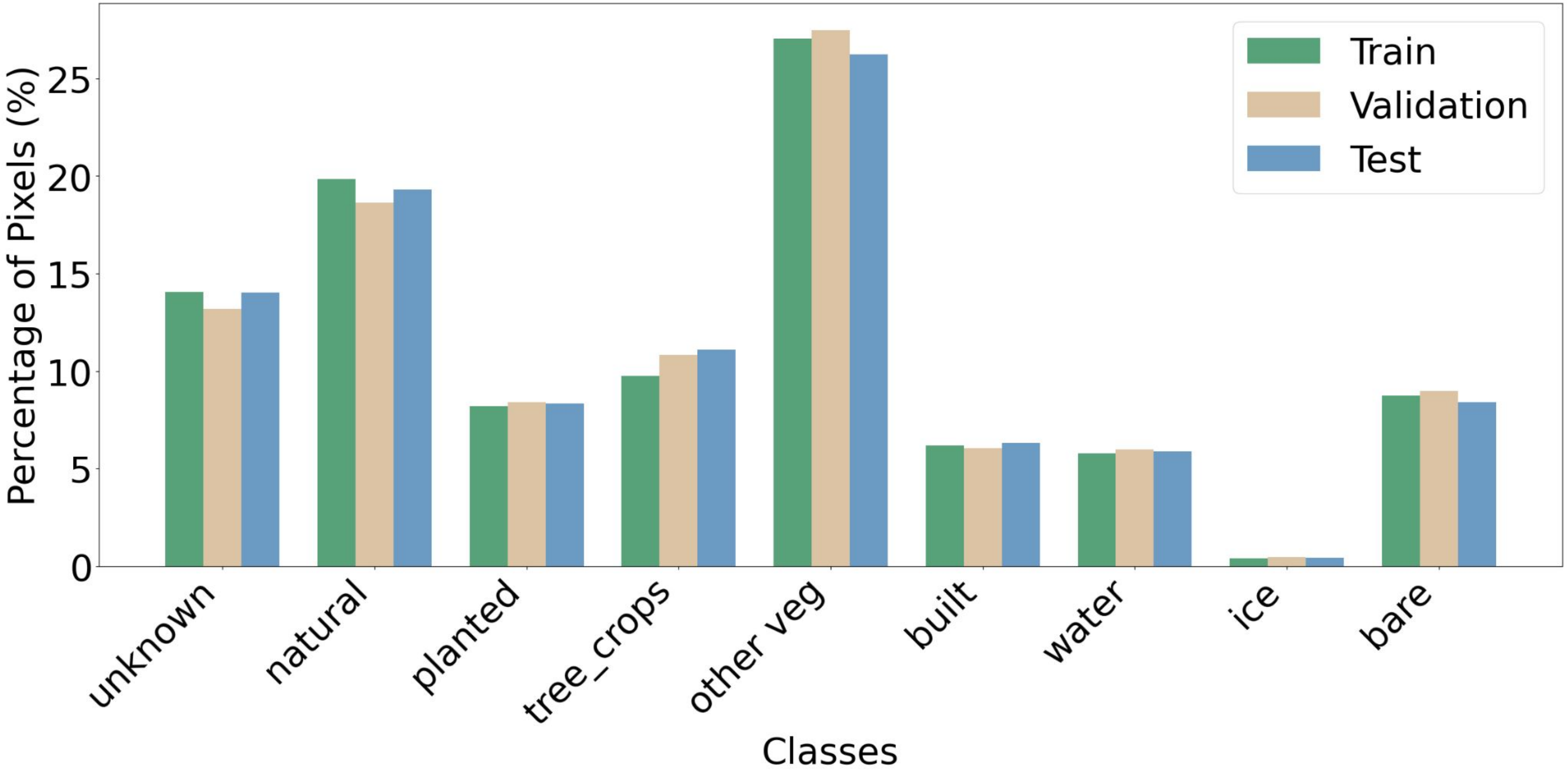
- **Sentinel-2:**
  - 10m resolution
  - monthly/seasonal/yearly in 2018-2020
- **Sentinel-1:**
  - 10m resolution
  - monthly/seasonal/yearly in 2018-2020

- **Climate (TerraClimate [1]):**
  - ~4km resolution
  - monthly/seasonal/yearly in 2018-2020
- **Elevation (FABDEM [2]):**
  - 30m resolution
  - non-temporal dataset



FORTY Dataset: dataset analysis

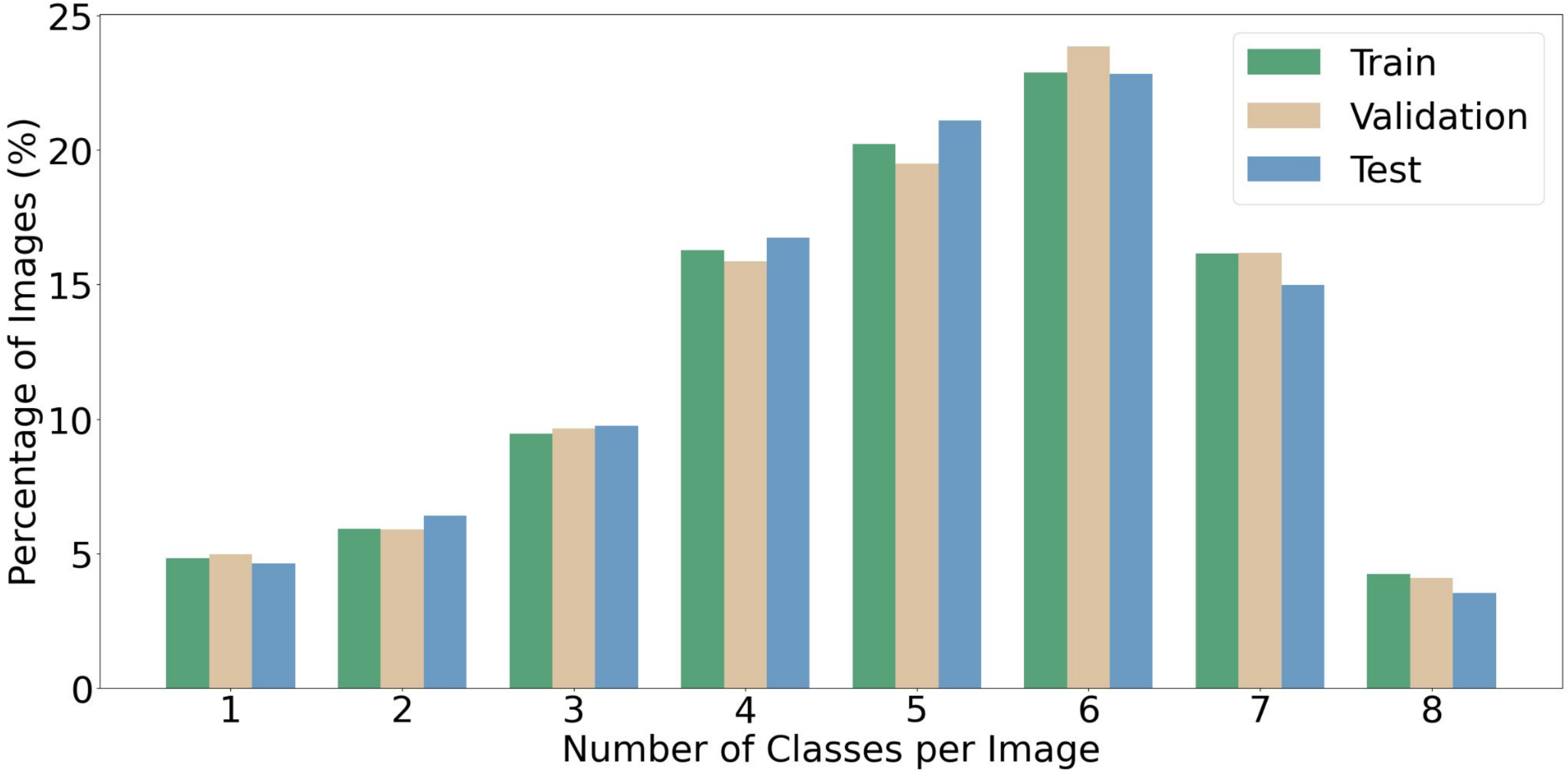
- Geographically split the dataset into train:val:test = 8:1:1
- Classes distribution
  - balanced at sample-level
  - imbalanced at pixel-level ⇒



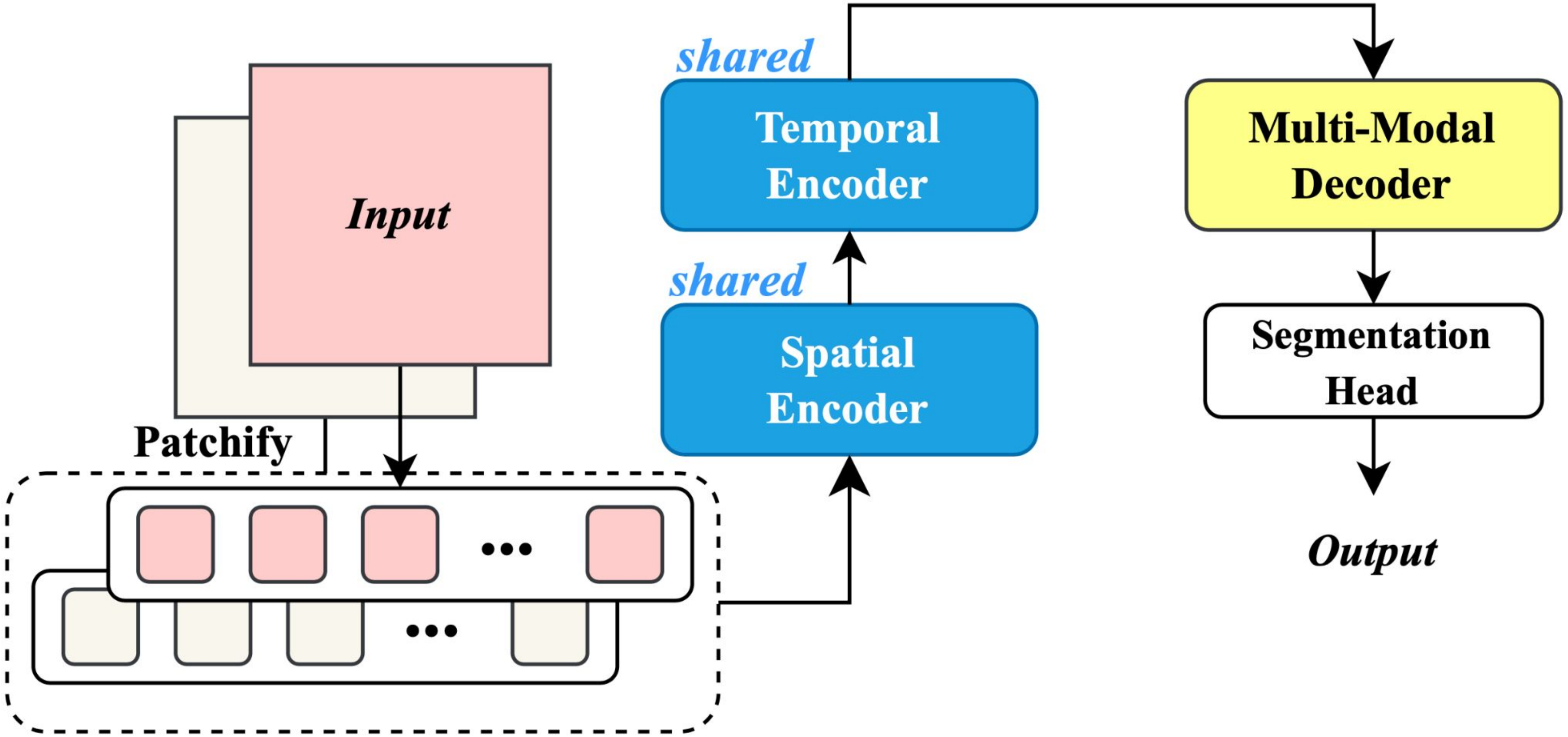
Distribution of Classes at Pixel-Level

FORTY Dataset: dataset analysis

- Most samples contain at least 4 different classes
- Provide rich segmentation labels for model training



Multi-modal Temporal Spatial ViT (MTSViT)



Experiment Results

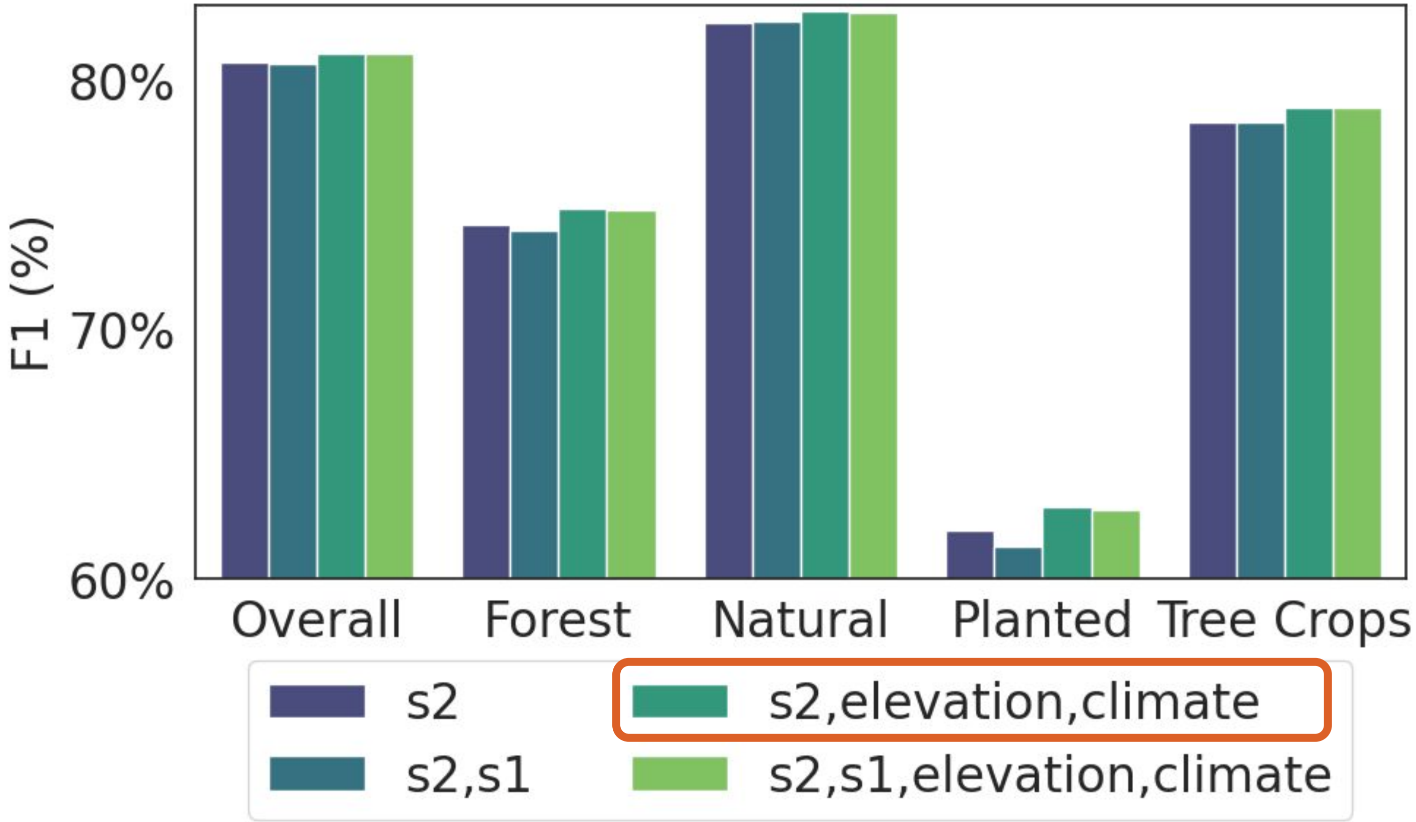
- inputs: seasonal Sentinel-2, climate, and elevation from 2020
- baselines: UNet3D[3], UTAE[4], TSViT[5]

TABLE I: Results (F1 score and standard deviation) on the test set using Sentinel-2, climate, and elevation data over 1 year: (*Overall*), for the 3 *Forest* classes, and for the individual classes: natural (*N*), planted (*P*), and tree crops (*TC*).

	Overall	**Forest**	**N**	**P**	**TC**
UNet3D	32.4 (1.3)	24.2 (5.3)	56.2 (8.3)	7.5 (8.8)	8.8 (12.1)
UTAE	49.4 (0.8)	37.7 (5.0)	71.4 (0.0)	13.8 (5.4)	27.8 (9.6)
TSViT	79.6 (0.1)	73.1 (0.1)	81.8 (0.0)	60.2 (0.3)	77.5 (0.2)
Ours	**81.1** (0.1)	**74.9** (0.1)	**82.8** (0.0)	**62.9** (0.3)	**78.9** (0.2)

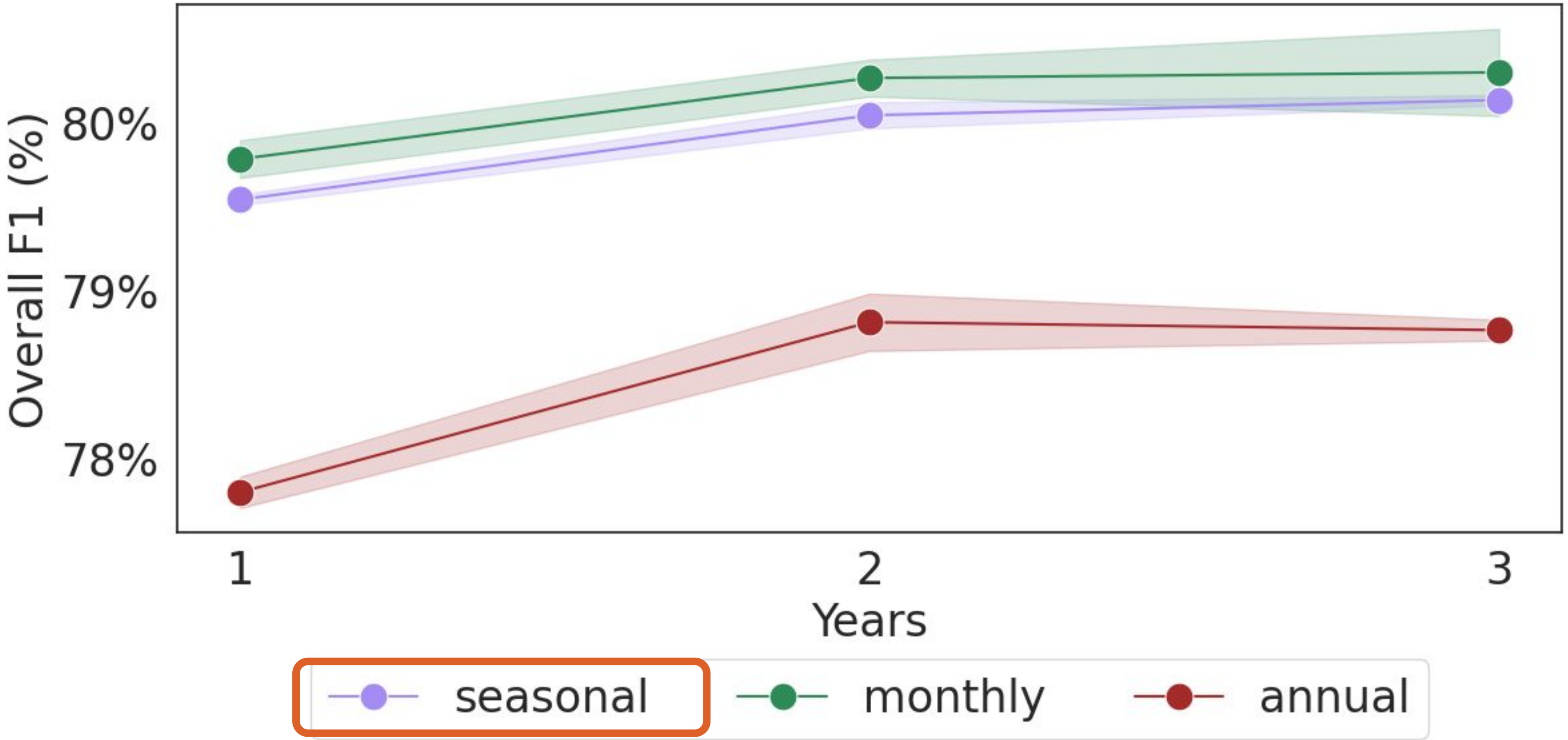
Experiment Results

- inputs: seasonal Sentinel-2, Sentinel-1, climate, and elevation from 2020
- **multi-modality ablation** based on MTSViT



Experiment Results

- inputs: monthly or seasonal or annual Sentinel-2 data from 2018, 2019, 2020
- **multi-temporal ablation** based on MTSViT

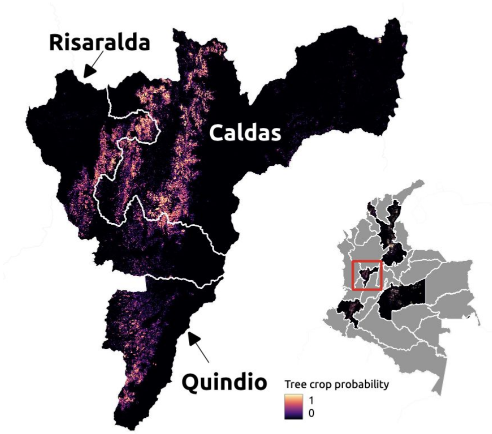


Applications of FORTY?

summary
- global-scale, 200k samples, per-pixel label
- multi-modalities: Sentinel-2, Sentinel-1, Climate, Elevation
- temporal: monthly, seasonal, yearly in 2018, 2019, 2020

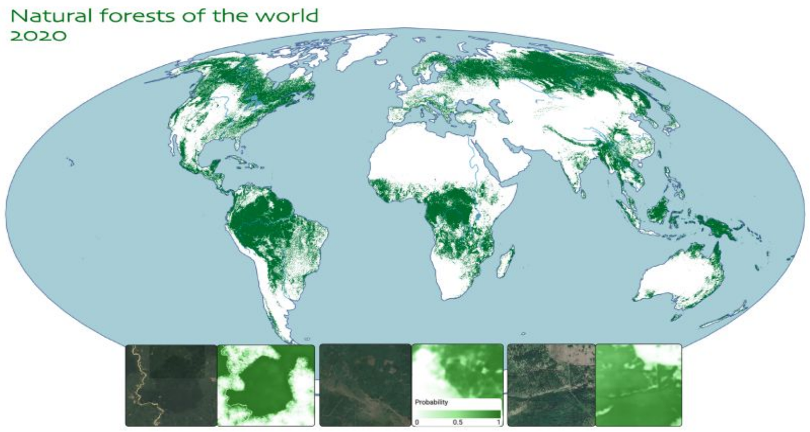
- testbase of geospatial models
- contribute to forest related applications, e.g. already contributed to our other works

A High-Resolution **Tree Crop** Map of South America



in review at *Remote Sensing of Environment*

Natural Forests of the World – A 2020 Baseline for Deforestation and Degradation Monitoring



in review at *Nature Scientific Data*

University of Zurich[UZH]

EcoVision

Google DeepMind

Stay tuned!

FORTY Benchmark

- dataset release (github.com/google-deepmind/forest_typology)
- evaluation on more geospatial foundation models

Code Framework

- JEO: model training and inference for geospatial remote sensing in JAX (github.com/google-deepmind/jeo)
- GeeFlow: geospatial dataset generation with GEE (github.com/google-deepmind/geeflow)

Applications and Maps

- A High-Resolution Tree Crop Map of South America (under review)
- Natural Forests of the World (under review)

Contact details

yuchang.jiang@uzh.ch
maximneumann@google.com

University of Zurich[UZH] EcoVision Google DeepMind

References

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