Predicting Stream Drying

Assessing **land use effects** through **remote sensing** and **deep learning**

Presenter: Giulia Domingues Pedro
Contact: giulia.domingues@usp.br

Co-authors:
Matheus Pinheiro Ferreira (ESALQ/USP);
Paula Caroline dos Reis Oliveira (ESALQ/USP);
Silvio Frosini de Barros Ferraz (ESALQ/USP).

DecisionES 2025
Porto Seguro BR
Jun 30th to Jul 4th
Symposium on Ecosystem Services, Forest Management and Decision Making

USP
ESALQ
Luiz de Queiroz College of Agriculture
University of São Paulo

FAPESP
SÃO PAULO RESEARCH FOUNDATION

Forest Hydrology Laboratory

What is my **motivation**?

- My PhD project focuses on evaluating **stream health** using **geospatial data**;
- During fieldwork, I could observe the **true situation of streams** in the region I study.

What is my **motivation**?

- My PhD project focuses on evaluating **stream health** using **geospatial data**;
- During fieldwork, I could observe the **true situation of streams** in the region I study.
- Most streams were extremely degraded and **alarmingly dry**.

What is my **motivation**?

- My PhD project focuses on evaluating **stream health** using **geospatial data**;
- During fieldwork, I could observe the **true situation of streams** in the region I study.
- Most streams were extremely degraded and **alarmingly dry**.

A critical factor: **stream dryness**

- **Climate and land-use changes** can reduce base flow, **causing perennial streams to dry up**;
- Many rivers are expected to stop flowing during parts of the year in the coming decades (Messager et al., 2021);
- **Intermittent rivers and ephemeral streams (IRES)** are **less studied** and it's extension largely unknown (Messager et al., 2021).

Photo: Giulia Domingues Pedro

A critical factor: **stream dryness**

- IRES: excluded from management and laws;
- USA: remove IRES from environmental laws, risking even less protection (Messager et al., 2021);
- Brazilian Native Vegetation Protection Law: protects perennial and intermittent rivers — but not ephemeral ones;
- **Non-perennial rivers and streams are being degraded at an alarming rate** (Acuña et al., 2014).

Photo: Giulia Domingues Pedro

When and where **streams are drying?**

- **When?**
  - Only during the dry season;
  - Permanent flow loss.
- **Where?**
  - Often in watersheds degraded by land-use change.
- Mapping and monitoring is essential to understand their dynamics (Messager et al., 2021).

Photo: Giulia Domingues Pedro

We need **new approaches**

- **Remote Sensing**
  - Large-scale, repeatable coverage;
  - Multi-temporal monitoring, low field costs.

- **Deep Learning**
  - Detection of complex patterns;
  - Learns and adapts with more data.

- Together, they might offer a solid approach to **monitor stream drying patterns**.

Photo: Giulia Domingues Pedro

Additional challenge: **headwater streams**

- Remote sensing can't see everything;
- **Predicting stream conditions from the contribution area** (landscape) is a valuable strategy.

Photo: Giulia Domingues Pedro

Can stream drying be effectively assessed using only geospatial data?

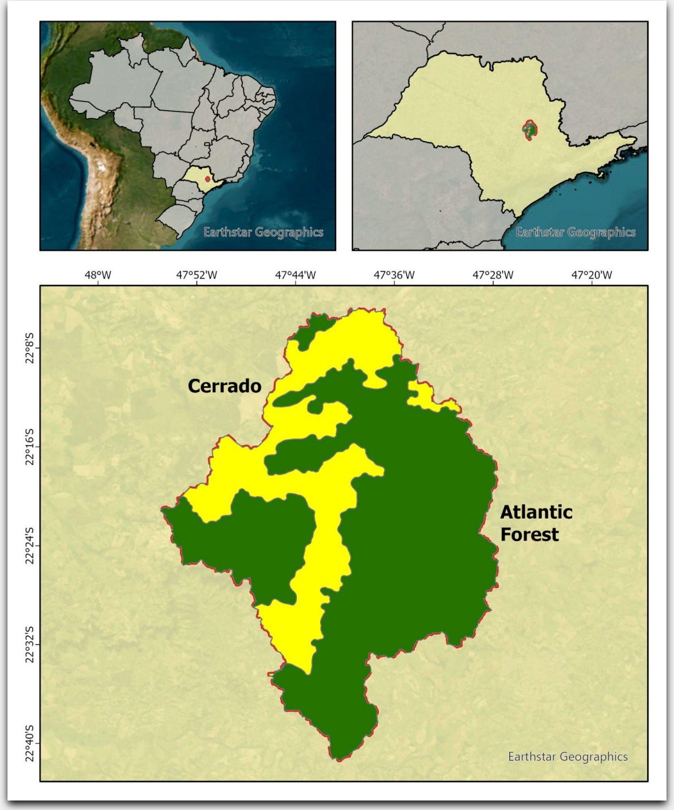

Photo: Giulia Domingues Pedro

Objectives

- To predict the likelihood of stream drying based on the contribution area (**remote sensing**);
- To develop and train a **deep neural network model** capable of performing this prediction with high accuracy.

The **Corumbataí** watershed

- Transition zone between two biomes: **Atlantic Forest and Cerrado** (“Brazilian savanna”);

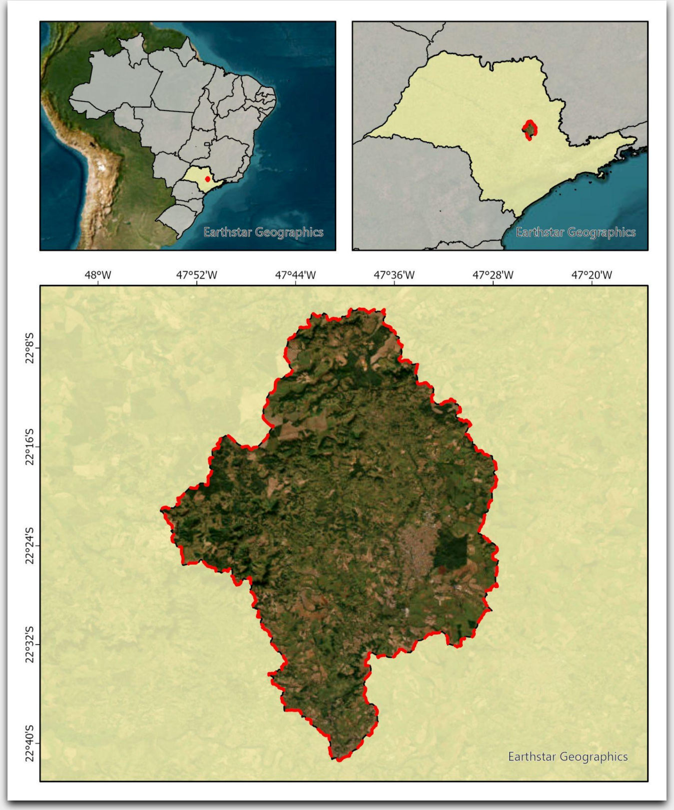


Photos: Giulia Domingues Pedro

The **Corumbataí** watershed

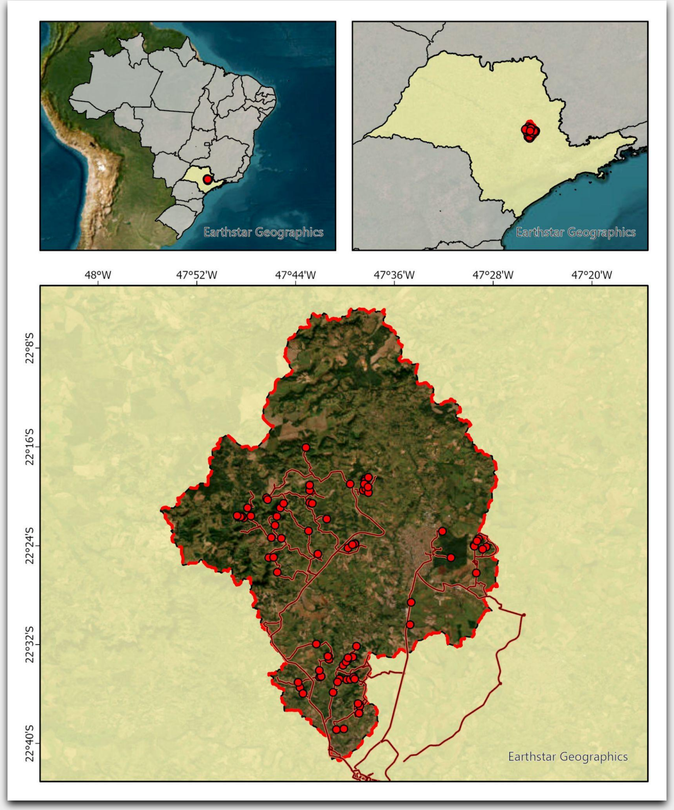
- Important for agricultural and industrial development;
- **Highly impacted** by intensive agriculture, particularly **sugarcane crops** and **cattle ranching**.

Photos: Giulia Domingues Pedro

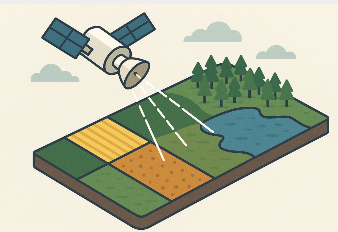


First step: **Fieldwork**

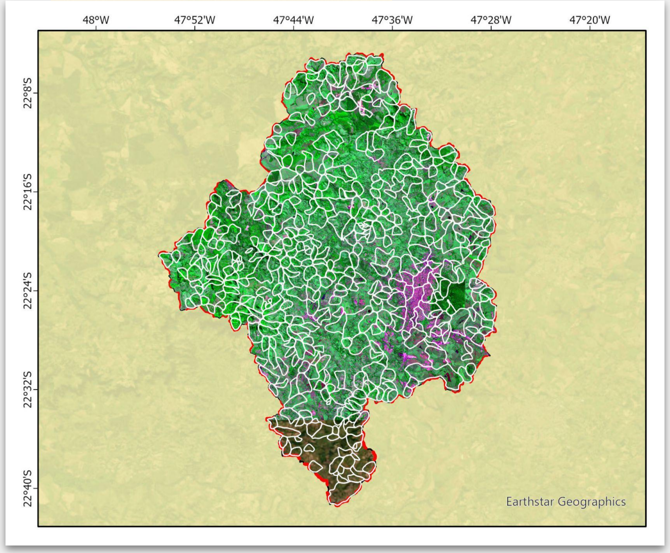
- During April and May, we visited **83 streams** in the Corumbataí basin and classified them as *Dry* or *Not Dry*;
- Streams up to 3rd order (Strahler's classification).



Remote sensing data

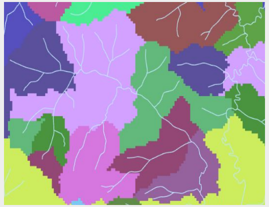


- Planet: RGB, NIR; 5 m;
- Sentinel 2: Vegetation indices (NDVI, NDWI_VEG, MNDWI; 10 m);
- **Dry season**;
- Digital Elevation Model (DEM) to generate watersheds (SRTM, 30 m).



Fluxogram

Watersheds
DEM (SRTM 30 m)
+ ArcGIS Hydrology Tools

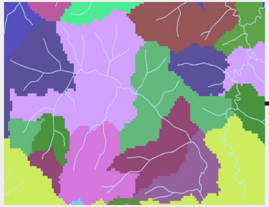


+

Multiband raster
Stacking spectral and
index layers
Planet and Sentinel

Fluxogram

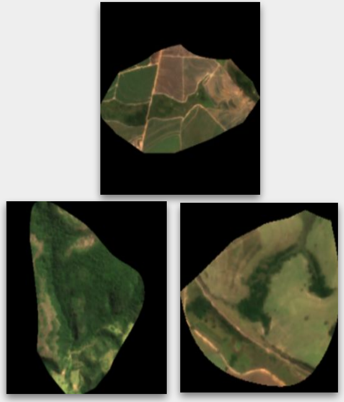
Watersheds
DEM (SRTM 30 m)
+ ArcGIS Hydrology Tools



+

Multiband raster
Stacking spectral and index layers
Planet and Sentinel

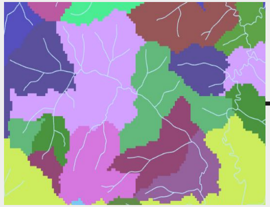
Training patches



Number of images per class:
Dry: 21
NotDry: 65

Fluxogram

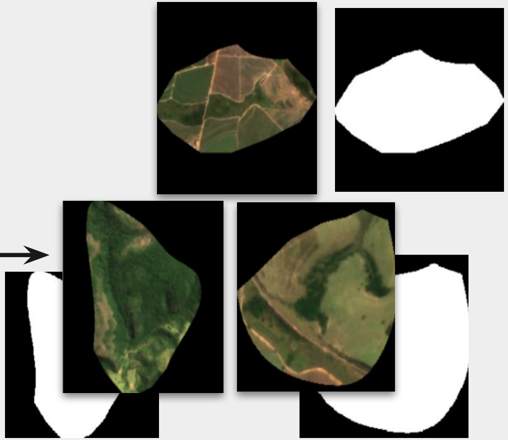
Watersheds
DEM (SRTM 30 m)
+ ArcGIS Hydrology Tools



+

Multiband raster
Stacking spectral and
index layers
Planet and Sentinel

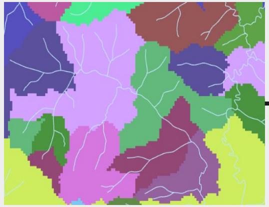
Training patches
+ attention masks



Number of images per class:
Dry: 21
NotDry: 65

Fluxogram

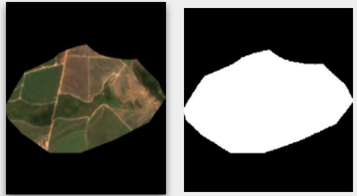
Watersheds
DEM (SRTM 30 m)
+ ArcGIS Hydrology Tools



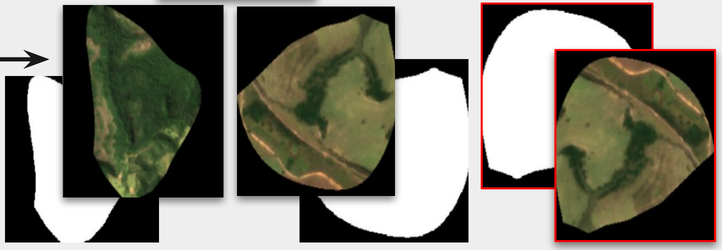
+

Multiband raster
Stacking spectral and index layers
Planet and Sentinel

Training patches
+ attention masks



Images artificially generated

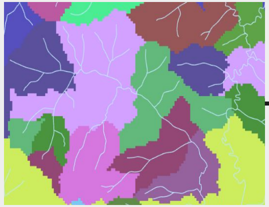


Rotation
Gaussian noise

Number of images per class:
Dry: 21 **+ 29 = 50**
NotDry: 65

Fluxogram

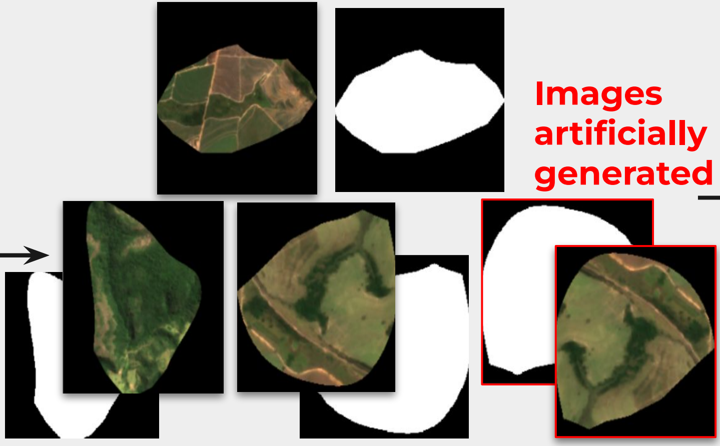
Watersheds
DEM (SRTM 30 m)
+ ArcGIS Hydrology Tools



+

Multiband raster
Stacking spectral and index layers
Planet and Sentinel

Training patches
+ attention masks



Images artificially generated

Rotation
Gaussian noise

Number of images per class:
Dry: 21 **+ 29 = 50**
NotDry: 65

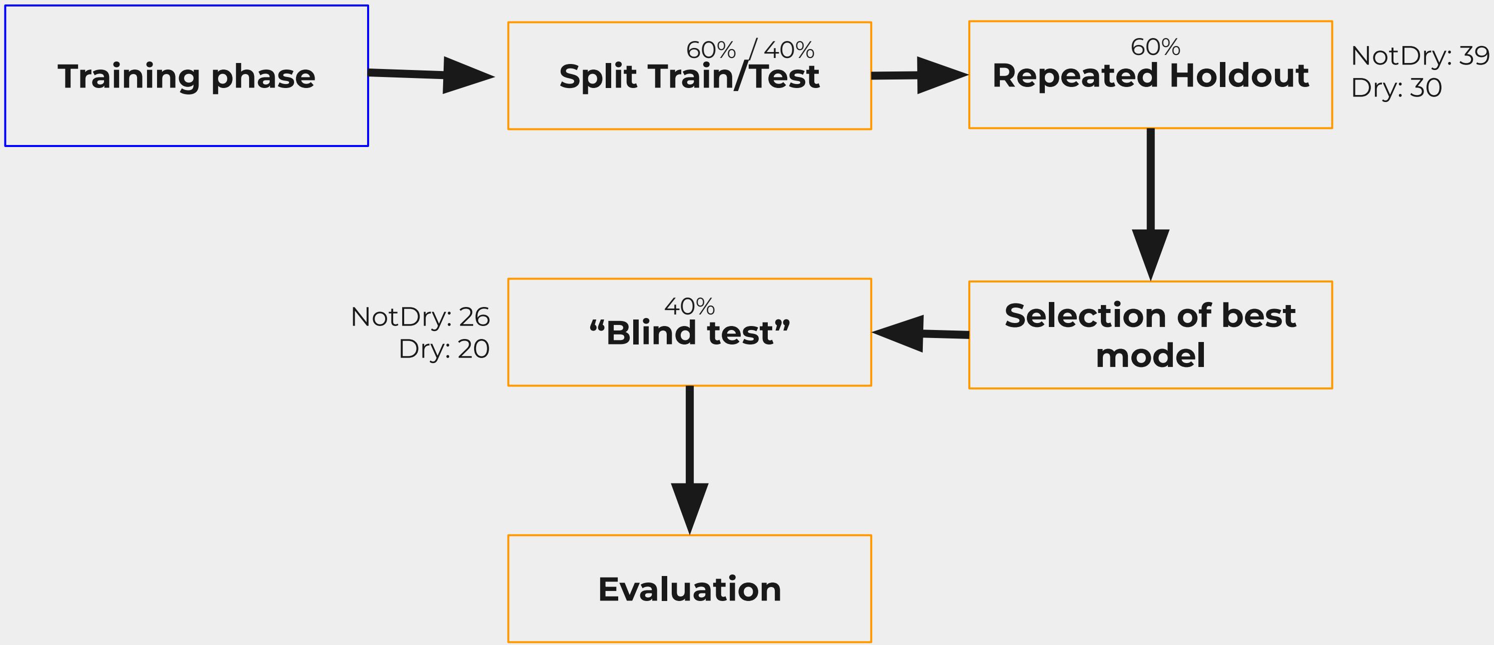
ResNet18

Training phase

Fluxogram

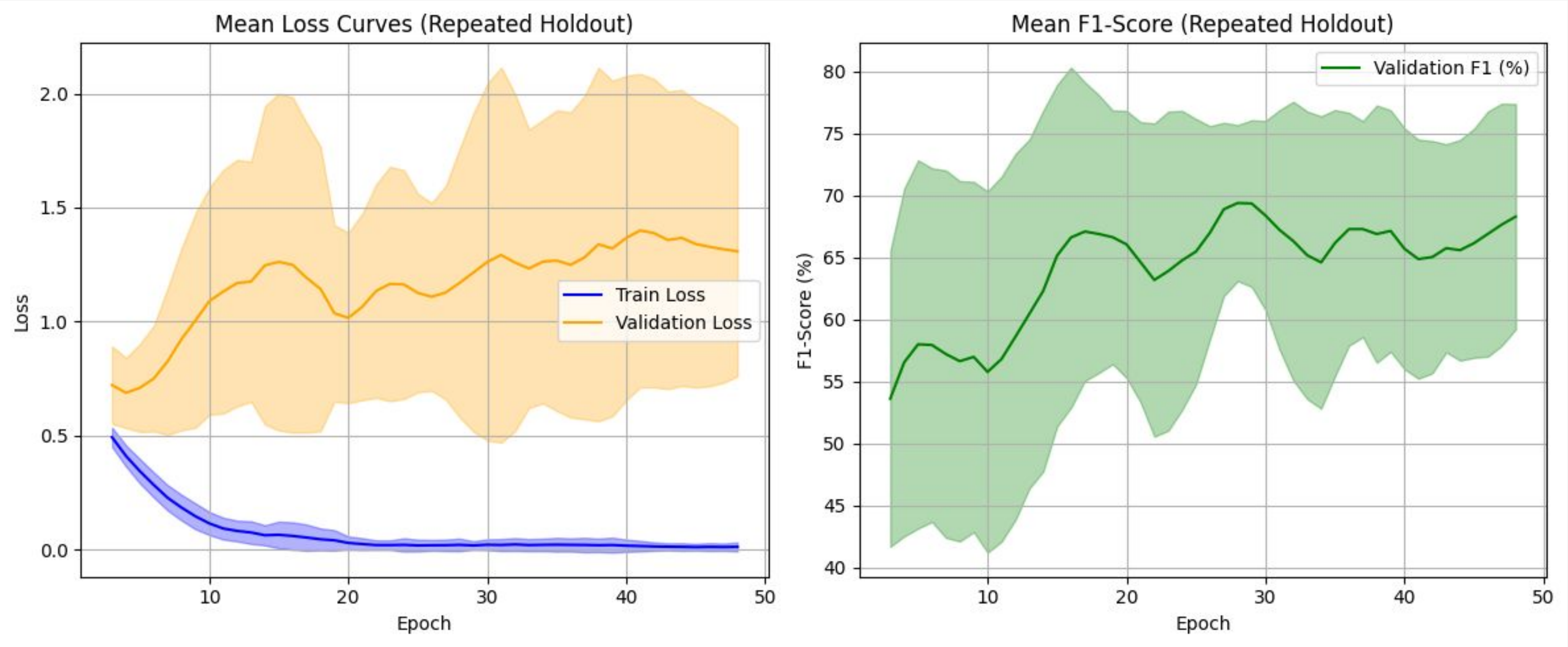

Training phase
60% / 40%
Split Train/Test
60%
Repeated Holdout
NotDry: 39
Dry: 30

Fluxogram


Training phase
60% / 40%
Split Train/Test
60%
Repeated Holdout
NotDry: 39
Dry: 30
Selection of best model
40%
“Blind test”
NotDry: 26
Dry: 20
Evaluation

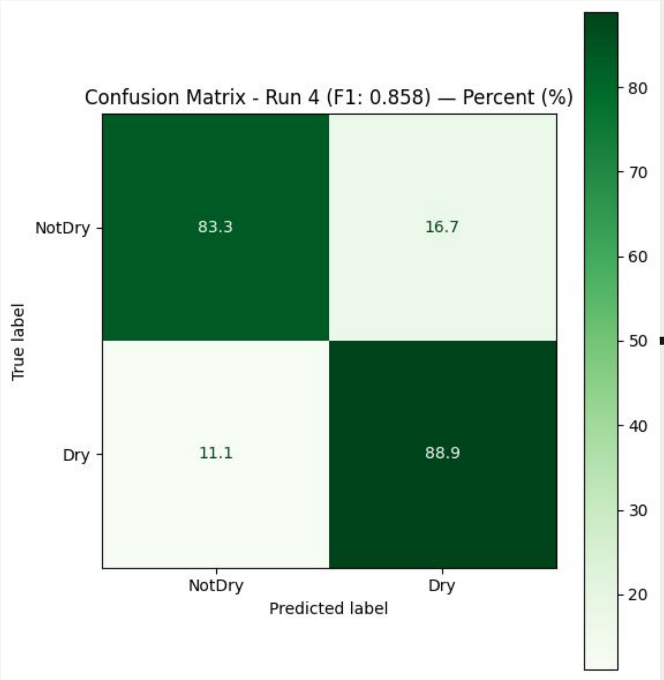
Results

- Training and Validation Trends



Results

- Confusion Matrices – **Best Run**



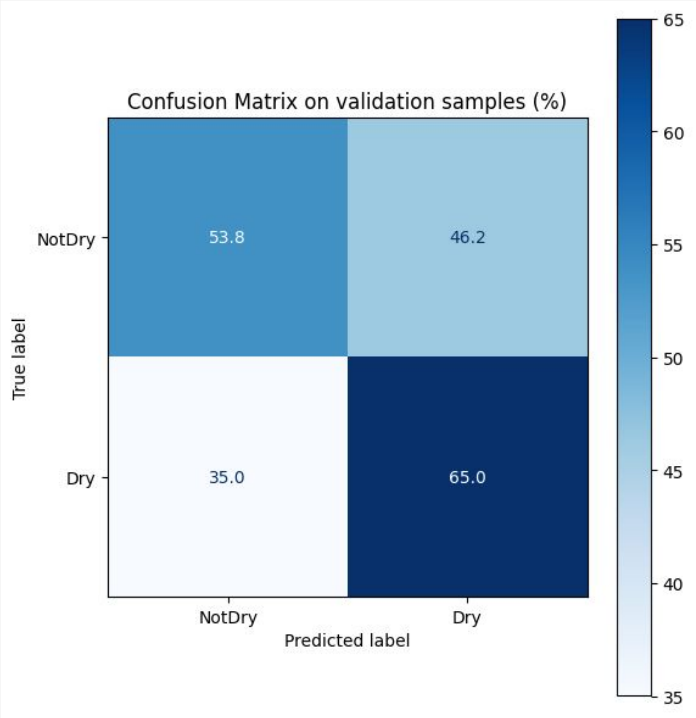
Best model

40%

"Blind test"

Results

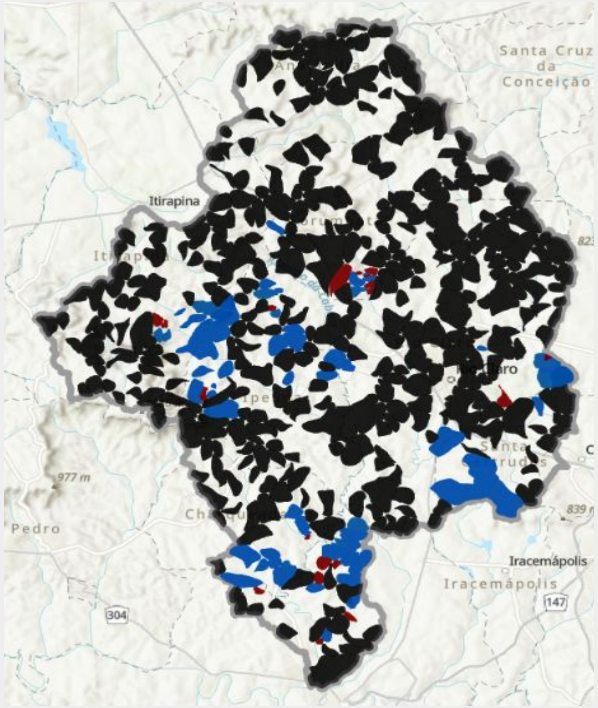
- Blind Test (40%)



Class	Precision	Recall	f1-score	support
NotDry	0.667	0.538	0.596	26
Dry	0.520	0.650	0.578	20
Accuracy			**0.587**	**46**

Results

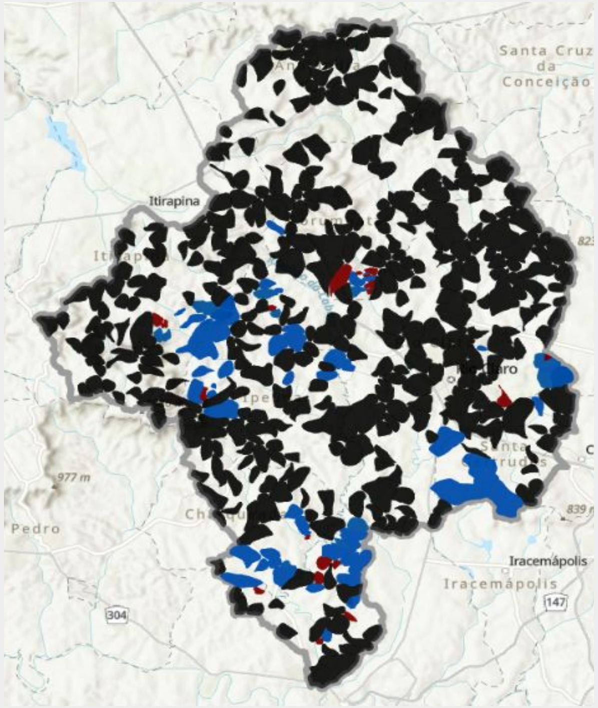
- Corumbataí watershed

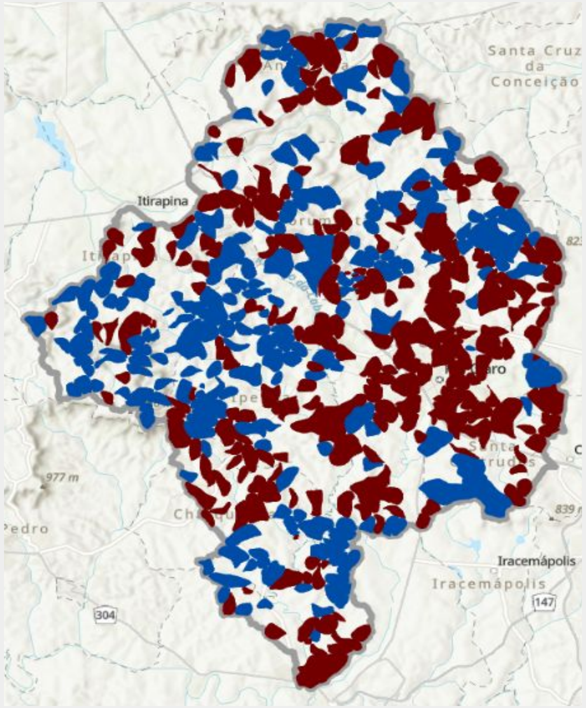


- NotDry
- Dry
- Unknown

Results

- Corumbataí watershed

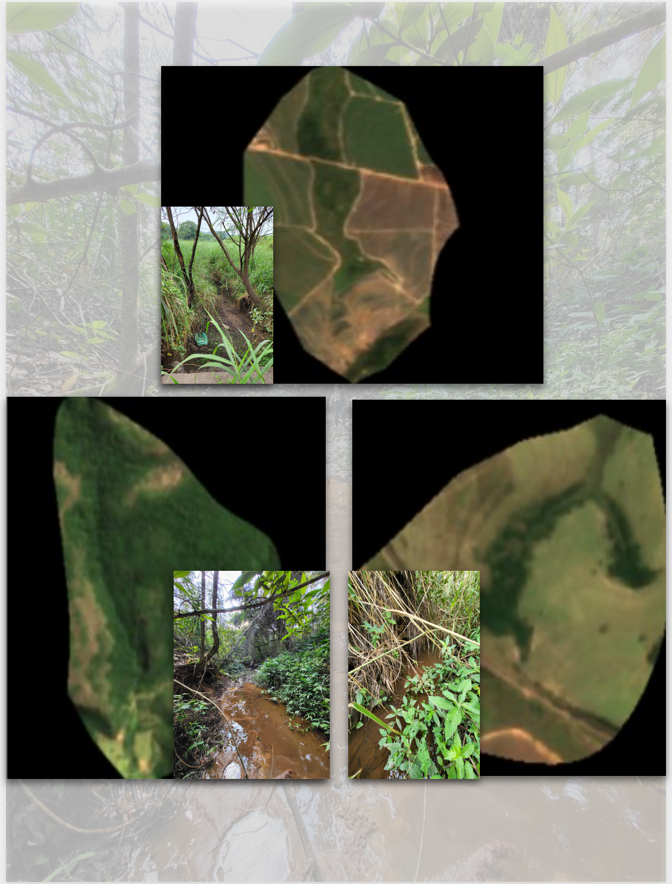




- NotDry
- Dry
- Unknown

Conclusions

- ResNet architectures: good potential to classify dry vs. non-dry watersheds;
- The “blind” testing showed **generalization challenges** and lower accuracy;
- Remote sensing with AI is a **promising approach** for monitoring intermittent streams, even with limited data.



Final Considerations

- Initial step in a larger project using remote sensing and AI to assess stream health;
- The mere presence of water does not guarantee a healthy stream;
- It remains unclear whether streamflow is more strongly influenced by:
  - Morphometric variables;
  - Soil and climate conditions; or
  - Land use.

Next Steps

- Include morphometric and edaphoclimatic variables;
- Improve the DEM for watershed delineation;
    - Airborne LiDAR data from São Paulo State (*coming soon*!).
- Test other ResNet architectures;
- Increase the sample size and evaluate the rainy season (to assess intermittency or total dryness);
- Investigate what the model is prioritizing during training (attribute maps, etc).

Thank you!

Presenter: Giulia Domingues Pedro
Contact: giulia.domingues@usp.br

Co-authors:
Matheus Pinheiro Ferreira (ESALQ/USP);
Paula Caroline dos Reis Oliveira (ESALQ/USP);
Silvio Frosini de Barros Ferraz (ESALQ/USP).

DecisionES 2025
Porto Seguro
Jun 30th to Jul 4th BR
Symposium on Ecosystem Services, Forest Management and Decision Making

USP

ESALQ
Luiz de Queiroz College of Agriculture
University of São Paulo

FAPESP
SÃO PAULO RESEARCH FOUNDATION

Forest Hydrology Laboratory