# Warsaw University of Technology

# Model fusion for multimodal prediction of plant species composition



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#### **#TLDR**

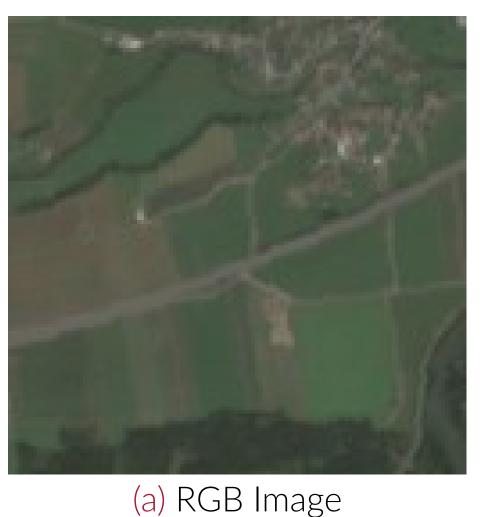
- We develop a model to predict plant species presence across space and time.
- We employ a multi-modal neural network combining ViT and ResNet architectures, processing satellite images, climate time series, and environmental maps for species prediction.
- We use **Focal Loss** to focus learning on rare species, addressing the challenge of presence-only data and improving model robustness.

## **GeoLifeCLEF 2024 Competition**

- Prediction of plant species composition across space and time.
- Learning from a small amount of high quality presence-absence multi-label data and a large number of presence-only single-label samples.

#### Multimodal data

Provided datasets included species distribution as well as geographic and environmental data.





(b) NIR Image

Figure 1. Satellite image patches for sample location

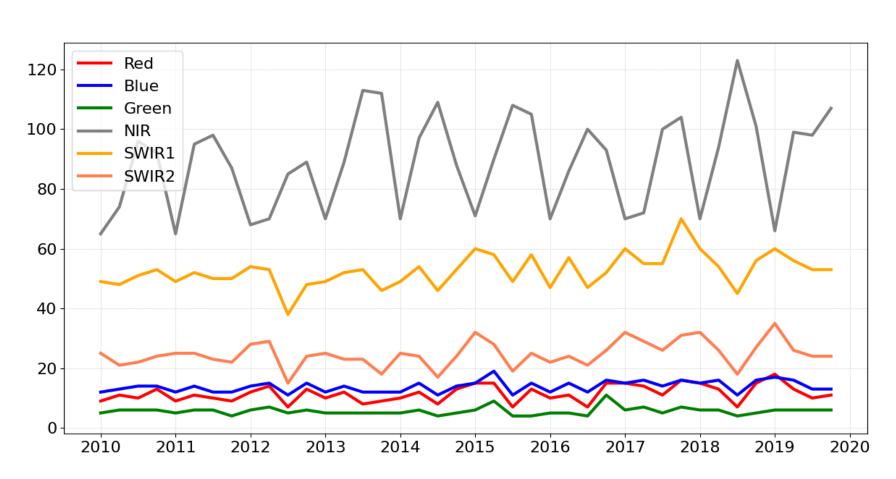


Figure 2. Satellite time series for sample location

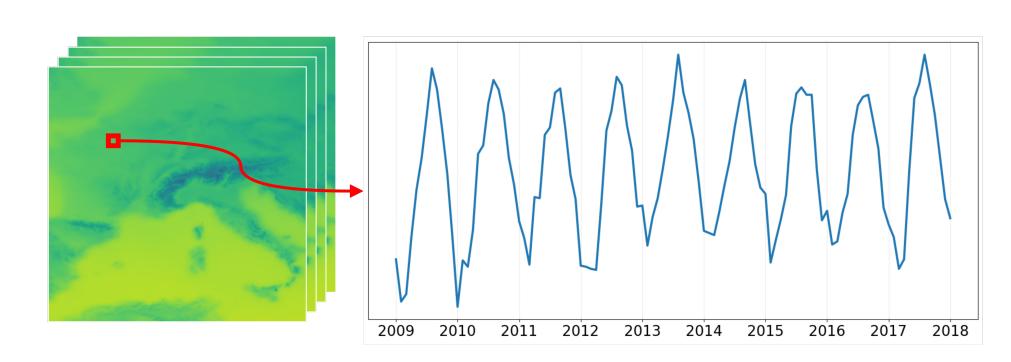


Figure 3. Mean daily temperature series for sample location

# **Top 25**

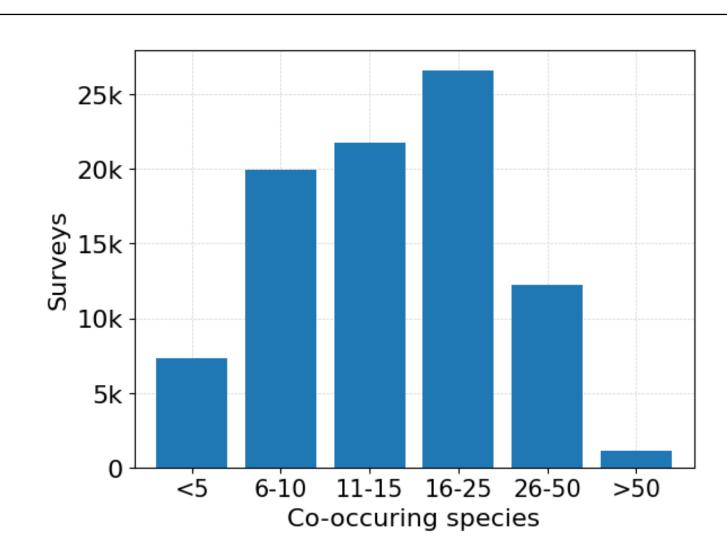
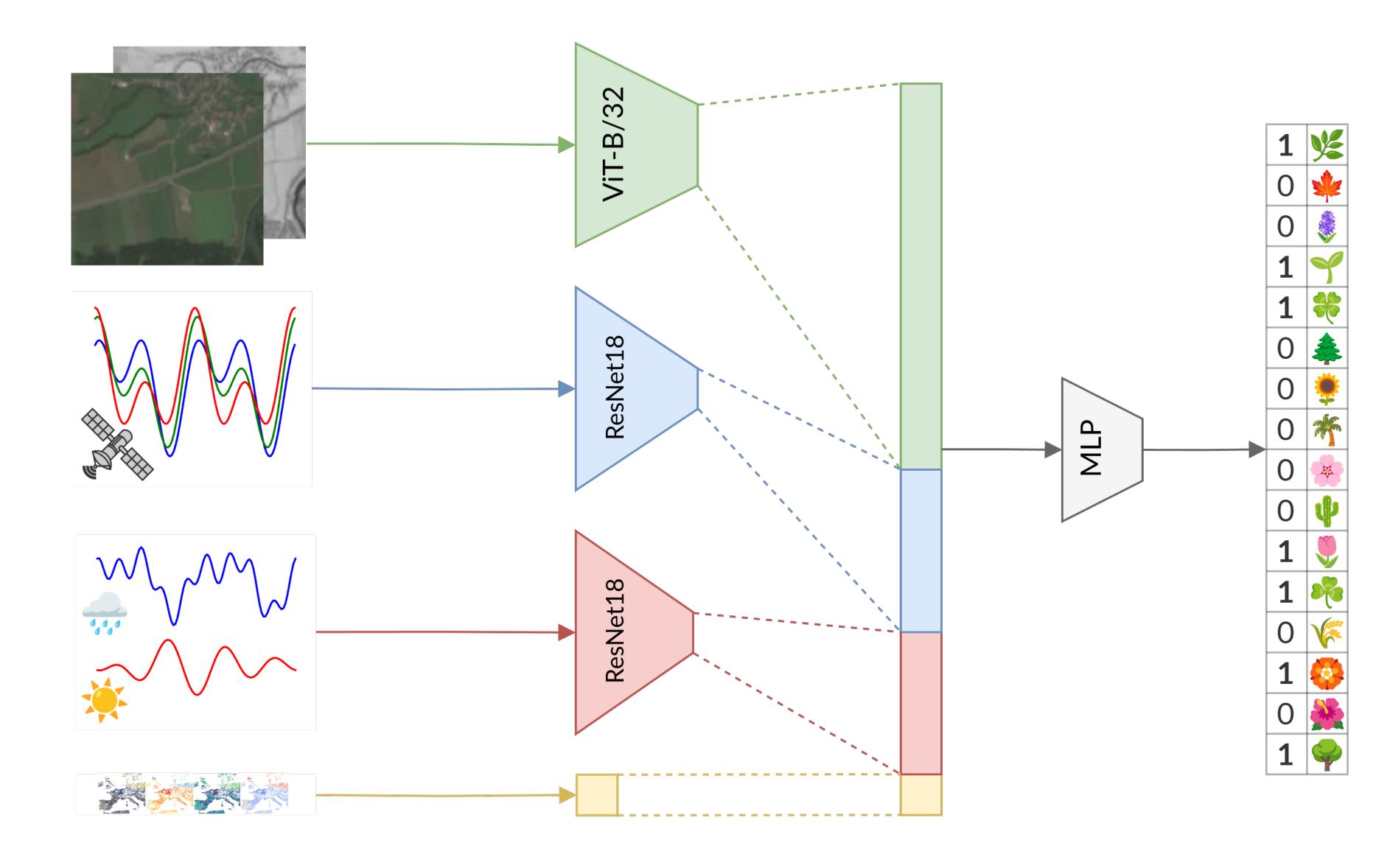


Figure 4. Species distribution across surveys

#### Multi-modal feature fusion - one to rule them all!

Each modality is processed by separate model:

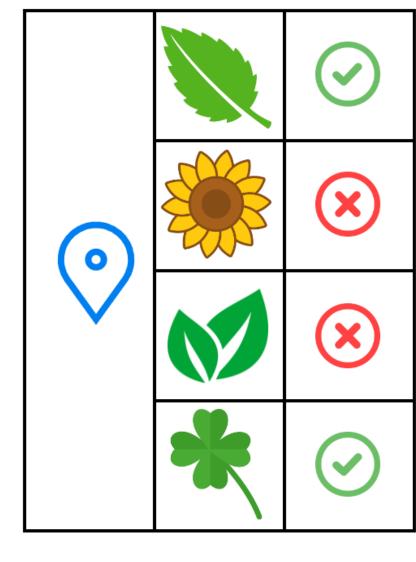
- Visual Transformer processes RGB and NIR images of the area.
- ResNets extract essential information from lansat and bioclimatic time series.
- Standalone features are fed directly to the head classifier.

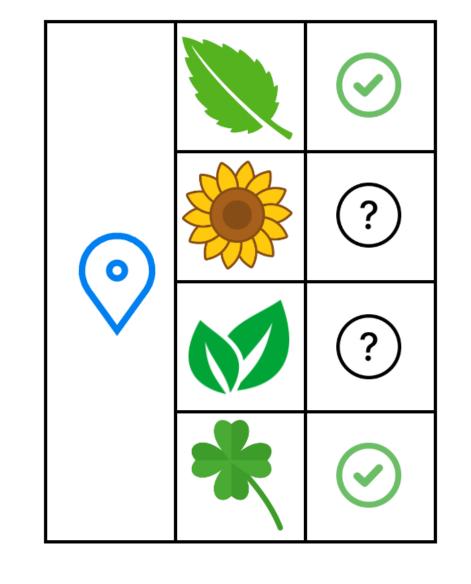


## Flower, are you there?

Presence-Only (PO): species observations with unknown absences; easier to obtain.

Presence-Absence (PA): species observations and confirmed absences; harder to obtain.





(a) Presence Absence

(b) Presence Only

Figure 5. Comparison of training datasets

# Focus on the positives!

Significant label imbalance - on average:

333%

more negative than positive labels per sample location.

$$FL(p_t) = -\alpha (1 - p_t)^{\gamma} log(p_t)$$

Focal Loss brings focus to rare, positive labels, thanks to modulating factor  $\gamma \geq 0$ :

- misclassfied example  $(p_t \longrightarrow 0)$  loss unaffected,
- correct example  $(p_t \longrightarrow 1)$  loss downweighted.

# Arranging time series into cubes

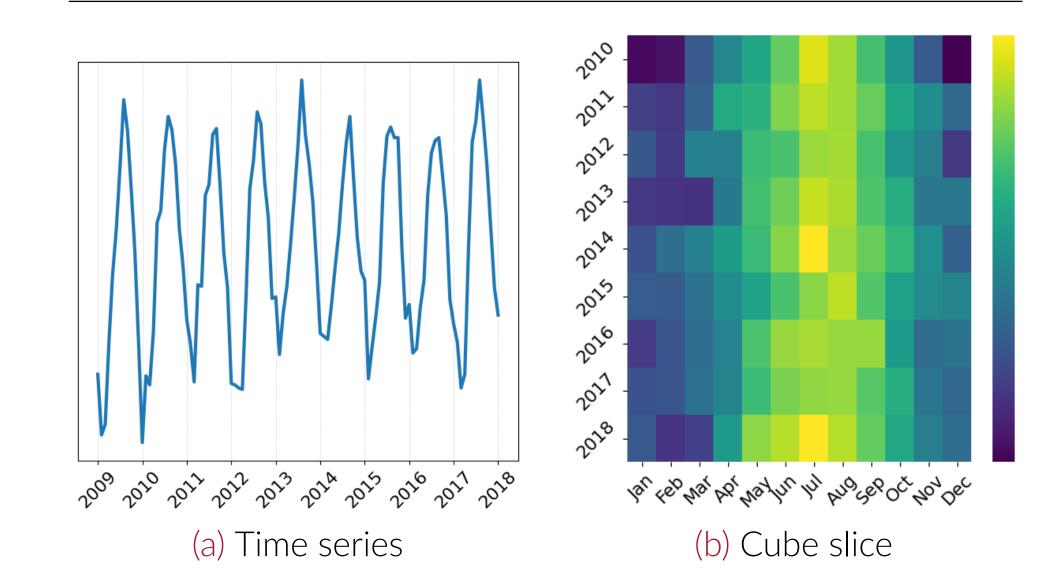


Figure 6. Transformed mean daily temperature data

- Landsat and bioclimatic time series reshaped into cubes (variables, quarters/months, years).
- Cubes to be treated as image-like tensors for use in ResNet.

#### **Take-Away Points**

The final model was verified in the GeoLifeCLEF 2024 CVPR competition, securing 13th place, indicating promising results.

- Combining specialized models significantly improves performance.
- Loss functions need to be well-adjusted to reflect specific challenges.
- Creative data preprocessing provides additional performance boost.

#### Learn more!





(a) GitHub repo

(b) Contest website