Impact of Missing Views in Multi-view Model Predictions for Vegetation Application

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1. Motivation

- MVL is key for model the complex and heterogeneous EO data sources.
- Some EO sources may not be available: remote sensors have a finite lifetime, satellite missions can fail.
- Re-training the model is not an option.

Our focus: **evaluate** how the predictions of different MVL models are affected.

2. Methodology

We consider a **view** as an entire data source, while MVL a multi-source scenario.

Fusion strategies [1]:
➢ **Input**, **Feature**, **Ensemble**.

Missing views techniques:
➢ **Impute**: Fill in the missing view with the average from the training data.
  ○ Using **concatenation** in the fusion
➢ **Exemplar**: Search for the missing view in the training data using the available views in a shared space (obtained with **CCA embeddings**).
➢ **Ignore**: Omit the missing views in the aggregation step of the fusion.
  ○ Using **average** in the fusion

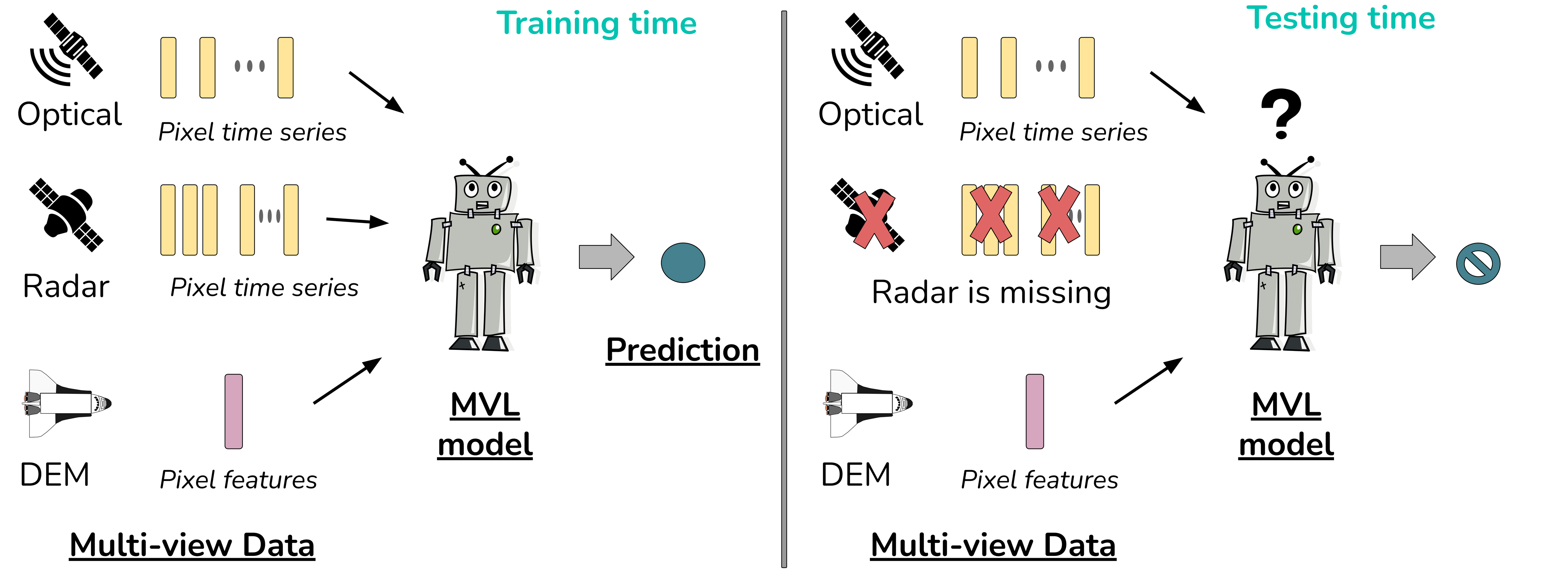
3. Dataset

- **CH-M** [2]: crop-type classification growing in a location (10 classes).
- **LFMC** [3]: predict the vegetation water per dry biomass in a location.

4. Experimental Setting

- 10-fold cross-validation with missing views in the validation fold.

Predictive quality:
- Classification: Average accuracy (AA)
- Regression: Coef. of Determination (R2)



	Samples	Years	Where	Pixel	Temporal views	Static Views
CH-M	29642	2016 - 2022	Global	10 m	Optical, Radar	Topographic
LFMC	2578	2015 - 2019	USA	250 m	Optical Radar	Topographic, land-cover class ,canopy height, soil

5. Results

T1. AA for missing views scenarios on the CH-M.		No Missing	Radar	Optical	Weather + static	Radar + weather+static	Optical + weather+static
Impute	Input-concat	**0.738**	0.641	0.296	0.534	0.534	0.142
	Feature-concat	**0.727**	0.624	0.290	0.558	0.390	0.159
Exemplar	Feature-cca	**0.727**	0.285	0.384	0.094	0.107	0.100
Ignore	Feature-avg	0.726	**0.674**	**0.542**	**0.582**	**0.529**	**0.306**
	Ensemble-avg	0.715	**0.708**	**0.613**	**0.711**	**0.715**	**0.523**

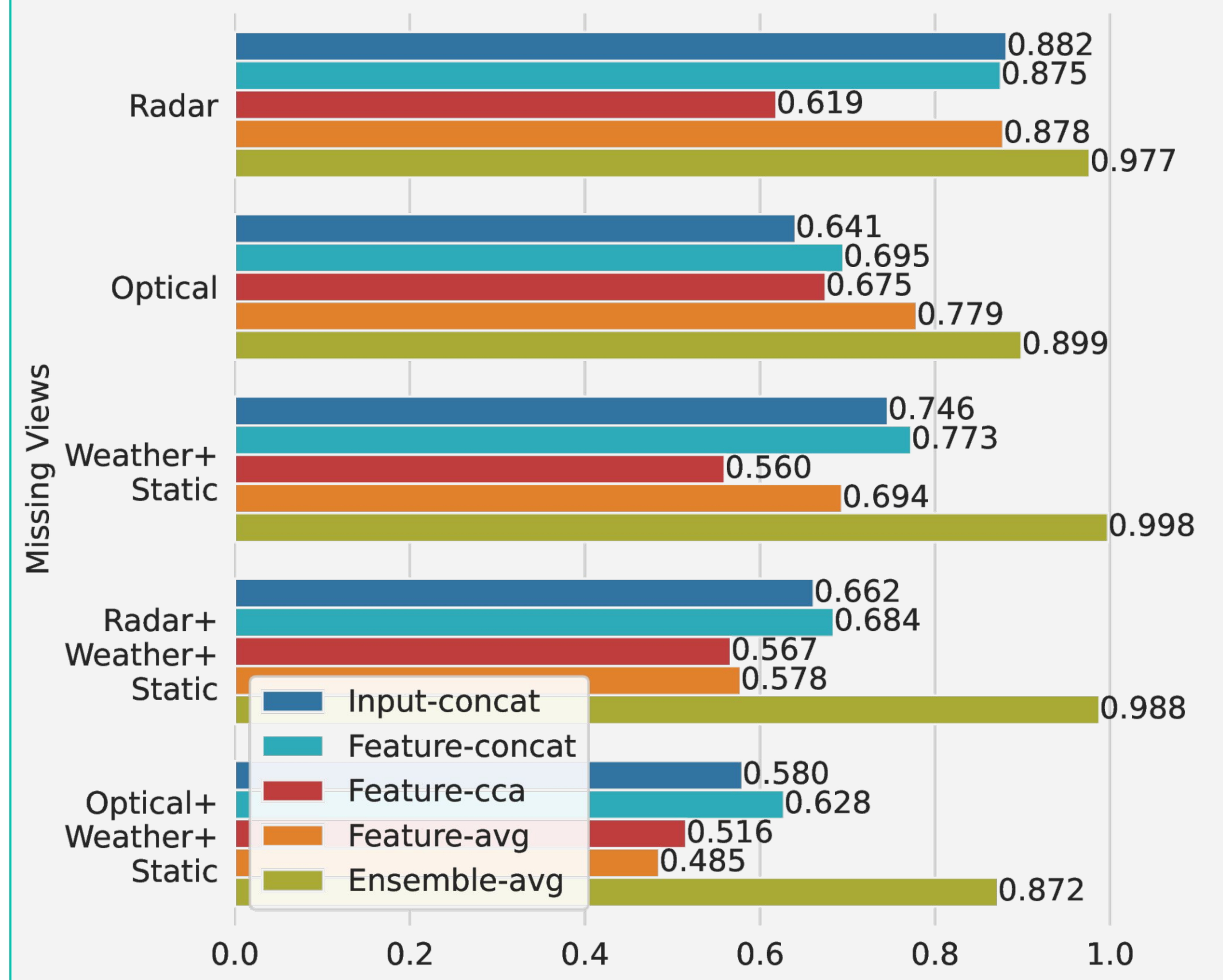
T2. R2 for missing views scenarios on the LFMC.		No Missing	Radar	Optical	Static	Radar + Static	Optical + Static
Impute	Input-concat	**0.717**	**0.650**	0.060	0.060	0.165	-0.047
	Feature-concat	0.667	0.599	**0.274**	**0.352**	**0.290**	**0.081**
Exemplar	Feature-cca	0.667	†	-0.260	†	†	†
Ignore	Feature-avg	**0.683**	**0.618**	0.142	†	†	†
	Ensemble-avg	0.312	0.292	**0.243**	**0.407**	**0.392**	**0.239**

6. Findings

1. Ignoring techniques are the least affected by missing view:
   ➢ **Ensemble-avg** with the highest robustness.
2. The impact of missing views is more severe in **regression** than classification task.
3. Missing **optical view** significantly affects predictions, as well as with static view.

On-going study
- F1. Performance Robustness Score (PRS, [4]) allow relative analysis.
- T3. **Sensor dropout** (randomly drop some EO sources) to the MVL training.

F1. PRS for missing views scenarios on the CH-M.



T3. for CH-M	No Missing	Optical	Weather + static	Radar + weather +static	Optical + weather +static
Input-concat	0.687	0.508	0.683	0.655	0.277
Feature-concat	0.659	0.510	0.591	0.515	0.292
Feature-avg	0.731	0.610	0.720	0.698	0.455

[1] *Garnot et al. 2022. Multi-modal temporal attention models for crop mapping from satellite time.*
[2] *Tseng et al. 2021. CropHarvest: A global dataset for crop-type classification.*
[3] *Rao et al. 2020. SAR-enhanced mapping of live fuel moisture content.*
[4] *Heinrich et al. 2023. Targeted adversarial attacks on wind power forecasts.*

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