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

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1. Motivation

- **Multi-view learning** (MVL) is crucial for modeling heterogeneous EO sources.
- EO data 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 all the features in a specific EO data source, and compare the following MVL fusion approaches [1]:

➢ **Input**, **Feature**, **Ensemble**.

Missing views techniques explored:

➢ **Impute**: Fill in the missing view with the average value from the training data.
  - **Concatenate** as the merge function.

➢ **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.
  - **Average** as the merge function.

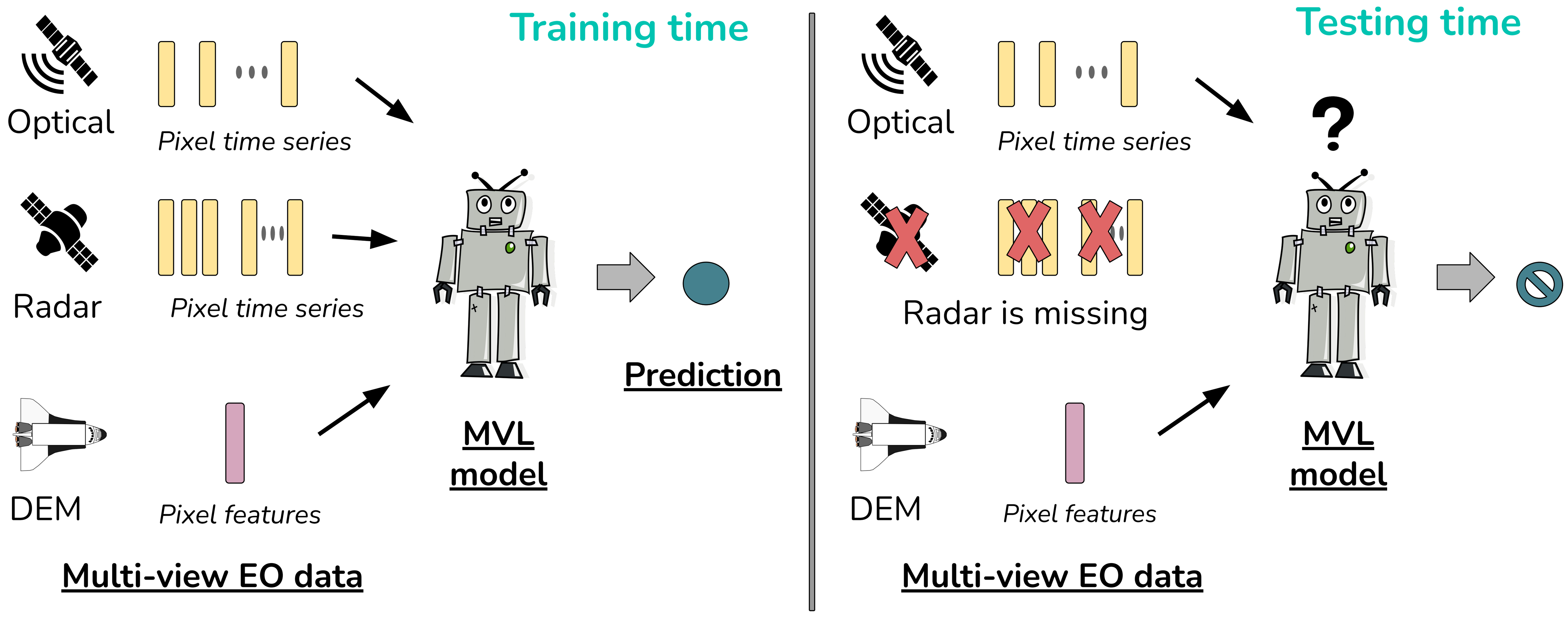
3. Experimental setting

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

Predictive quality assessment:

➢ Classification: Average accuracy (AA)

➢ Regression: Coef. of Determination (R2)



4. Datasets & Results

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

	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

T1. AA for different missing view cases 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 different missing views cases 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

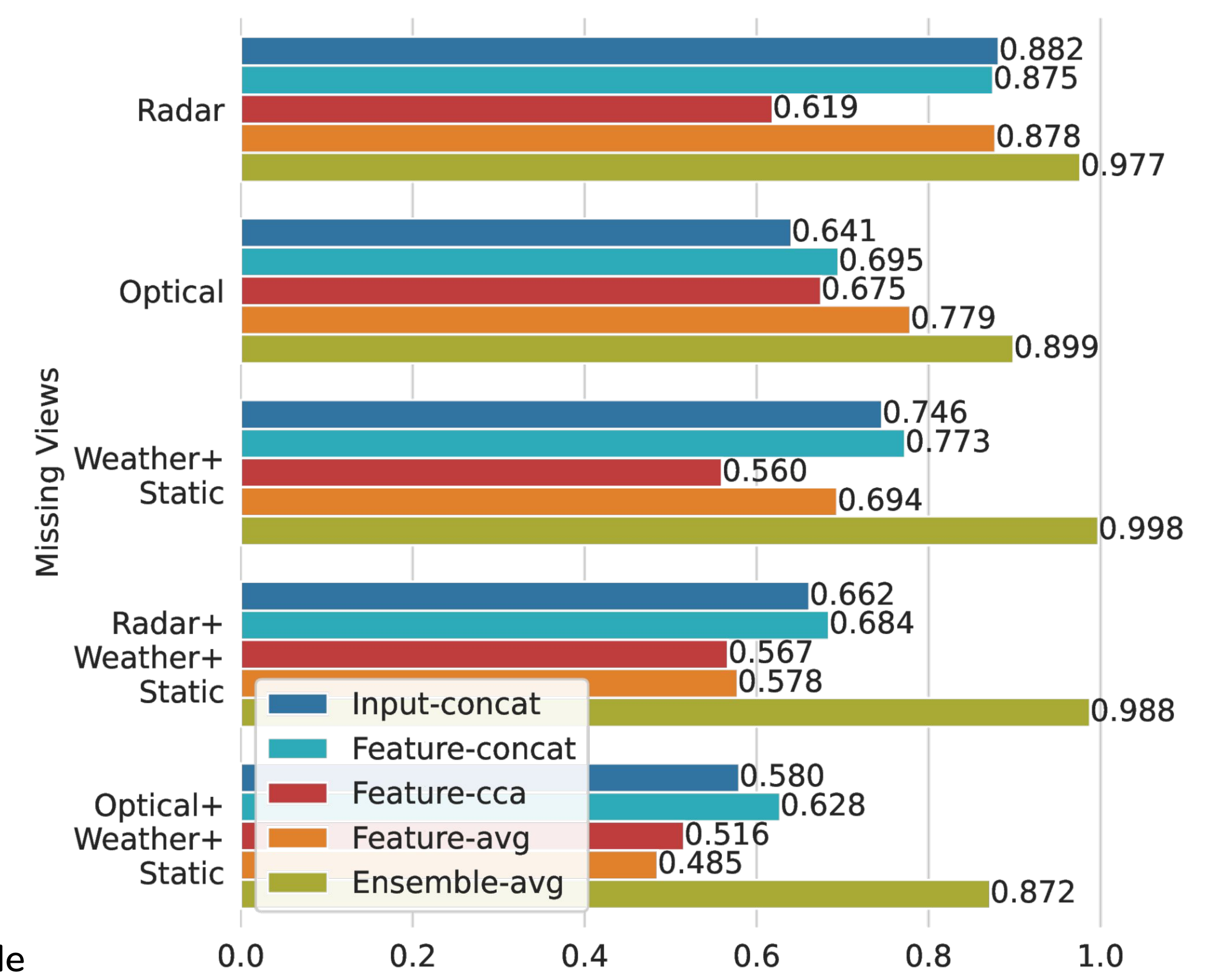
1. MVL models with ignoring techniques are the least affected by missing views:
   ➢ highest robustness: **Ensemble-avg**.
2. Impact of missing views is more severe in **regression** than classification tasks.
3. Missing **optical view** significantly affects MVL model predictions.

On-going Work

- F1. Performance Robustness Score (PRS, [4]) allow relative analysis.
  - Predictive error with missing views relative to error with all views.
- T3. **Sensor dropout** applied during training increase robustness.
  - Randomly drop (mask out) all features in a view.

T3. AA for CH-M.	No Missing	Radar	Optical	Weather + static	Radar + weather+static	Optical + weather+static
Input-concat	0.687	0.665	0.508	0.683	0.655	0.277
Feature-concat	0.659	0.612	0.510	0.591	0.515	0.292
Feature-avg	0.731	0.705	0.610	0.720	0.698	0.455

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



References

[1] Garnot et al. 2022. *Multi-modal temporal attention models for crop mapping from satellite time series.*
[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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