

Unsupervised heteromodal physics-informed representation of MRI data: tackling data harmonisation, imputation and domain shift

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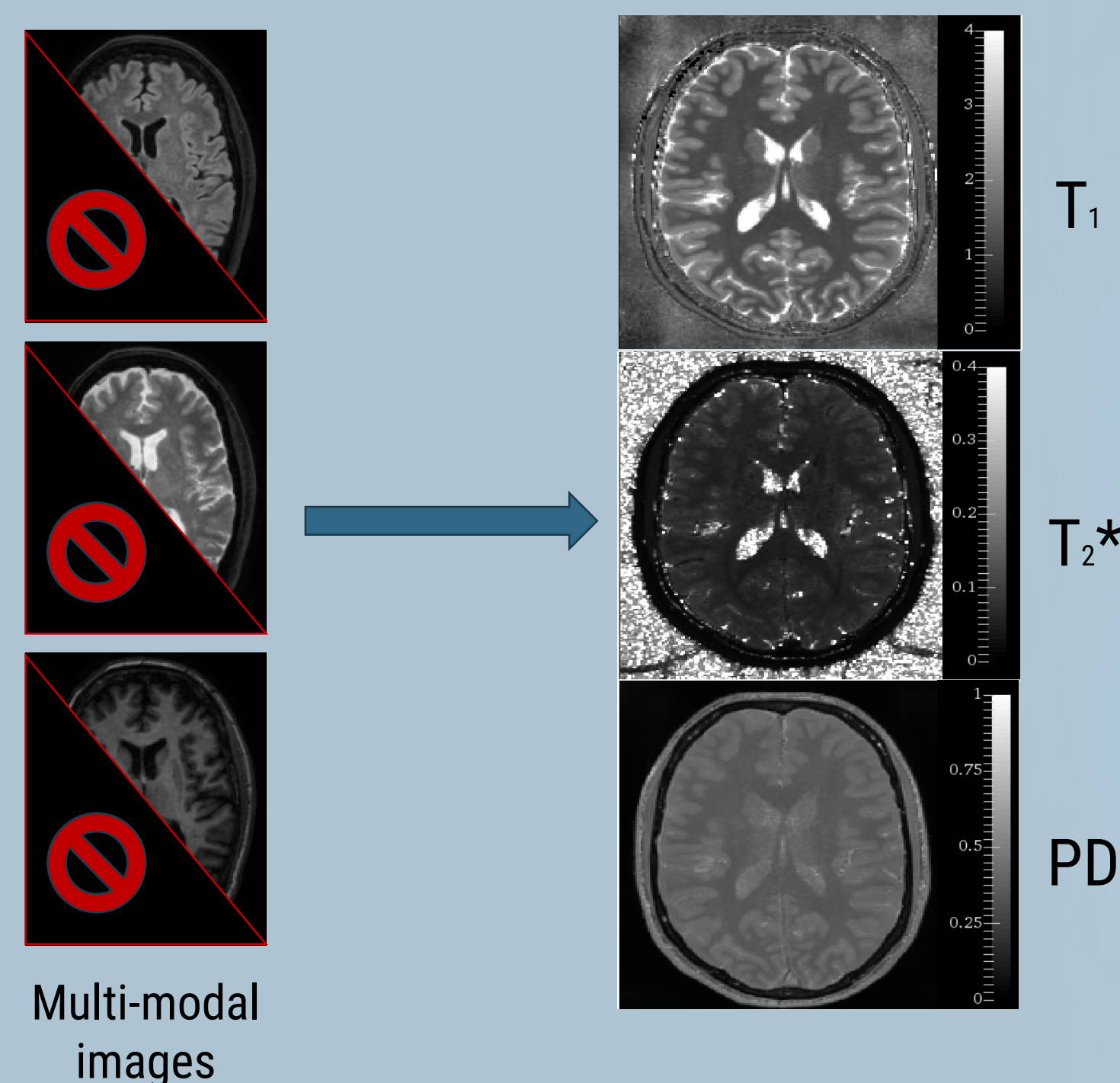
Introduction

- MRI is an excellent diagnostic tool, suitable for both **morphological and functional** imaging.

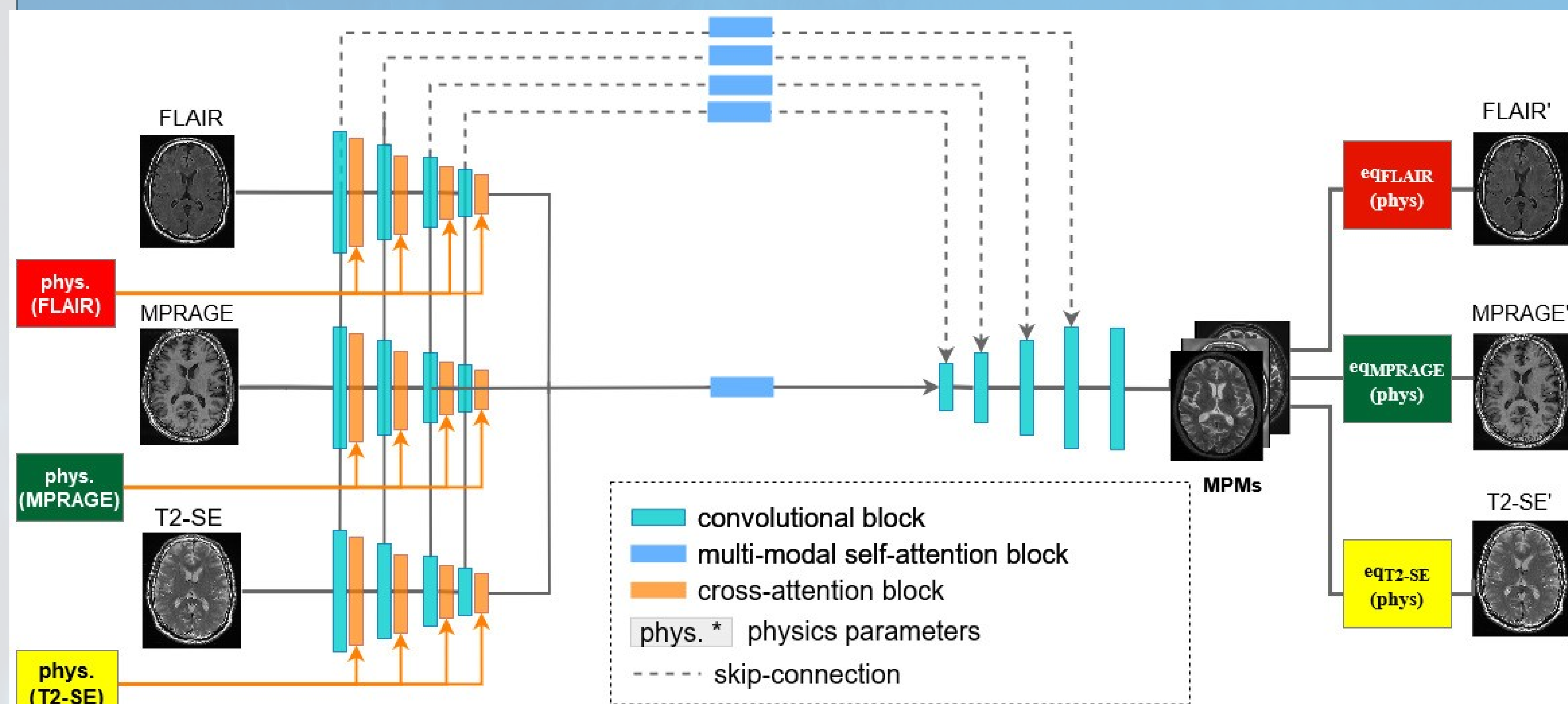
- However, MRI images acquired with different sequences, and with differing sequence parameters can **exhibit significant differences in contrast** which can result in **downstream issues** when tracking volumetric changes or identifying pathology

- **Quantitative imaging** can address these concerns **BUT** is **costly and time-consuming**, typically necessitating **multiple scanning sessions**

- We propose a **multi-modal, unsupervised, missing-data robust** MPM translation pipeline that can be applied to typical clinically acquired data



Proposed Pipeline



The main pipeline components are:

1. Three input modality branches (FLAIR, MPRAGE, T2-SE) which can be fed empty images
2. A U-Net style architecture for ingesting the images
3. Multi-modality self-attention blocks for modulating the contribution of each modality towards different components of the MPM
4. A static equation-based physics-forward model for reconstructing the original images using the output MPM: Allows for **UNSUPERVISED** training as no real MPMs required

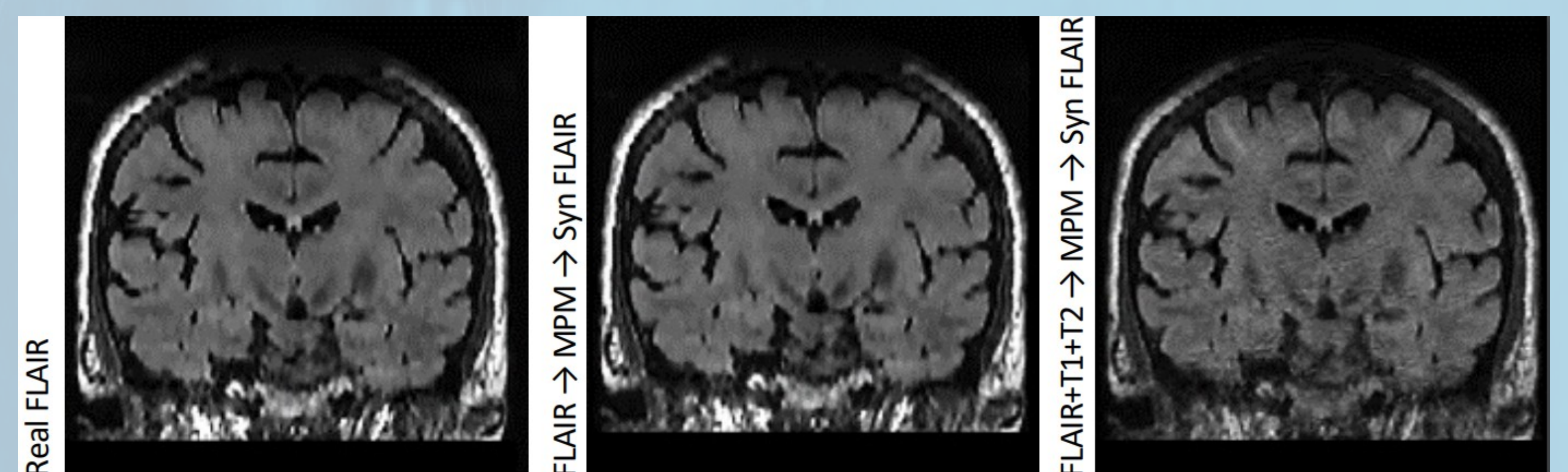
Experimental setup

- Network is trained with the **SABRE** (MPRAGE, FLAIR, T2-SE) and **Biobank** (MPRAGE, FLAIR) datasets

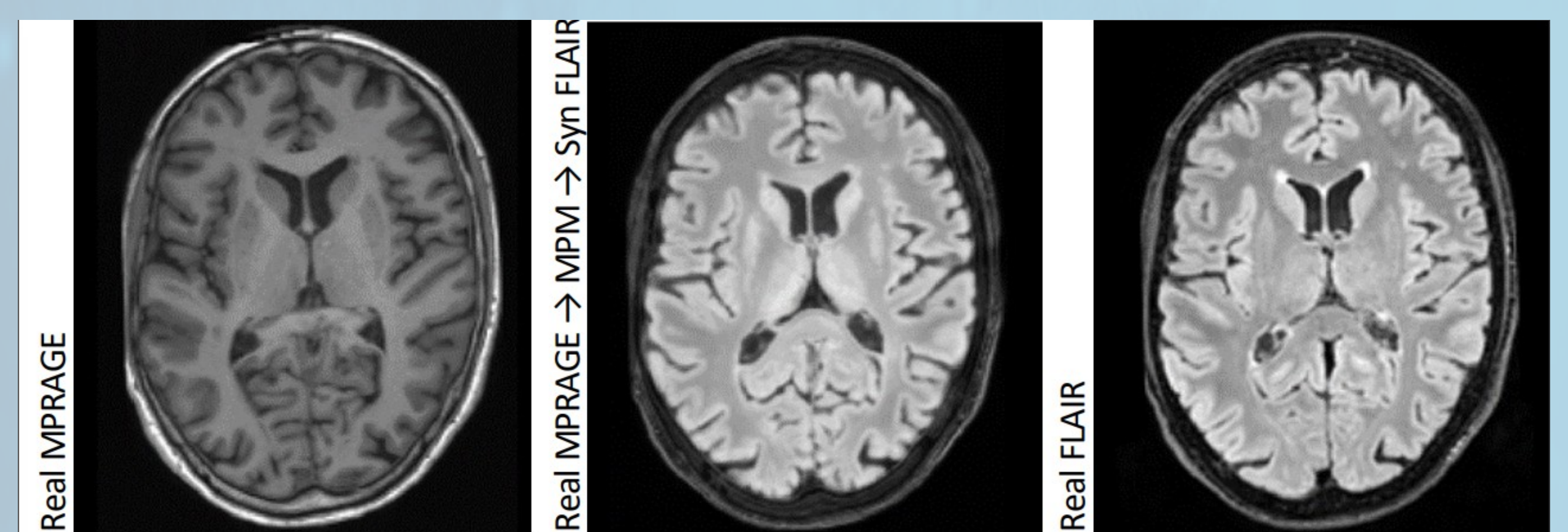
- Outputs are enforced to resemble MPMs because they are used to re-generate the original images using a static-equation-based simulation in conjunction with the sequence parameters

- Fidelity is verified via:

- Consistency: Reconstructing a modality the network has been fed
- Imputation: Reconstructing a modality the network has NOT been fed
- Imputation for segmentation: Applying network to real data to impute modalities for a segmentation network that is familiar with imputed modality



Consistency



Imputation

Inputs		MPMs			Gen.	Real
FLAIR	T2-SE	T1	T2	PD	MPRAGE	MPRAGE

- MPMs are generated from FLAIR and T2SE, used to generate MPRAGE that are fed to segmentation network
- Mean Dice scores:
 - Real 74.08 | Imputed 64.92 | FLAIR 51.71
- While imputed data cannot replace real data, it is far preferable to using network-unfamiliar modalities

Conclusion

- We have shown that **MPMs translated** from a variety of starting image combinations are **high fidelity** via **internal consistency and imputation analyses** and via a **real data imputation task on external data**

- Crucially, we do so in an **unsupervised manner**, and can be applied to **standard datasets retrospectively**

- **Paves the way** for models to be trained with **translated MPM** data, reducing the need for **domain adaptation or post-hoc harmonization**