IBM **Research**

Science and Technology Facilities Council

Hartree National Centre for Digital Innovation

A collaborative partnership between STFC and IBM

Earth Observation Foundation Models For Region-specific Flood Segmentation

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1. Motivation

- AI foundation models for earth observation are an important tool to inform and adapt to extreme weather events brought on by climate change
- We investigate the performance of these models for a region-specific task, using flooding as an example
- We build upon the Prithvi-EO foundation model[1], which uses optical imagery, by incorporating Synthetic Aperture Radar (SAR) imagery
- We carry out flood segmentation for UK and Ireland (UKI) by both additional pretraining and directly fine tuning on the Prithvi-EO model

2. Methods

Prithvi-EO foundation models: a family of remote sensing foundation models created in collaboration between NASA and IBM. They are pretrained using a masked autoencoder approach to reconstruct masked images using an encoder-decoder architecture with a Vision Transformer backbone

We use Prithvi as a starting point and carry out further training to make a regional, task-specific model.

Step 1. Additional pretraining:

- 15,448 unique cloud free 224x224 tiles for 2022-2023 using HLS[2,3] and SAR imagery

Step 2. Fine-tuning:

- 69 image patches of 512 x 512 pixels at 10m resolution
- 50, 10 and 9 images each for train, validation and test
- Curated by matching annotated flood maps in Copernicus EMS[4] to corresponding S2 and SAR imagery occurring within a 2 day window.

Bands used:

HLS/SAR[5, 6]: VV, VH.

S2[5, 7]: blue, green, red, narrow NIR, SWIR, SWIR2, cloud mask derived from scene classification map

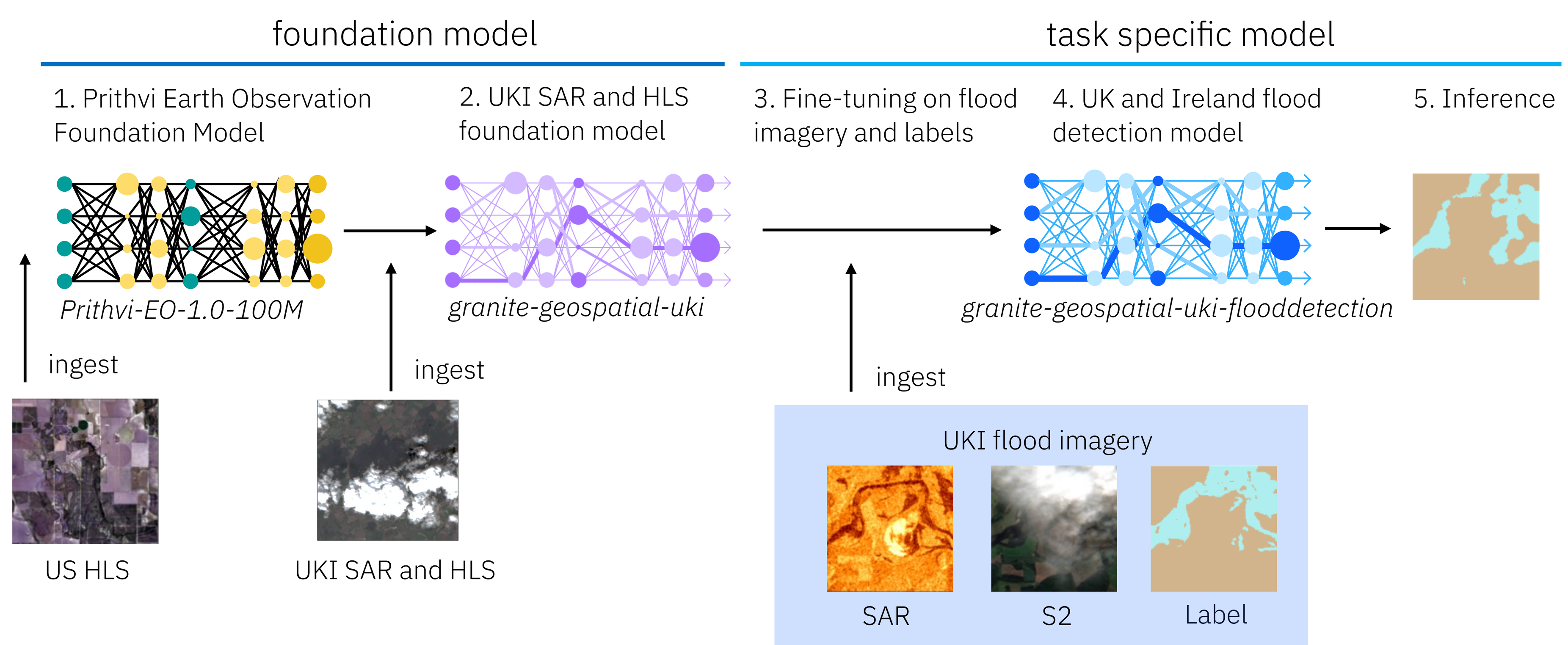

Figure 1: training workflow for building a regional, multimodal flood detection model

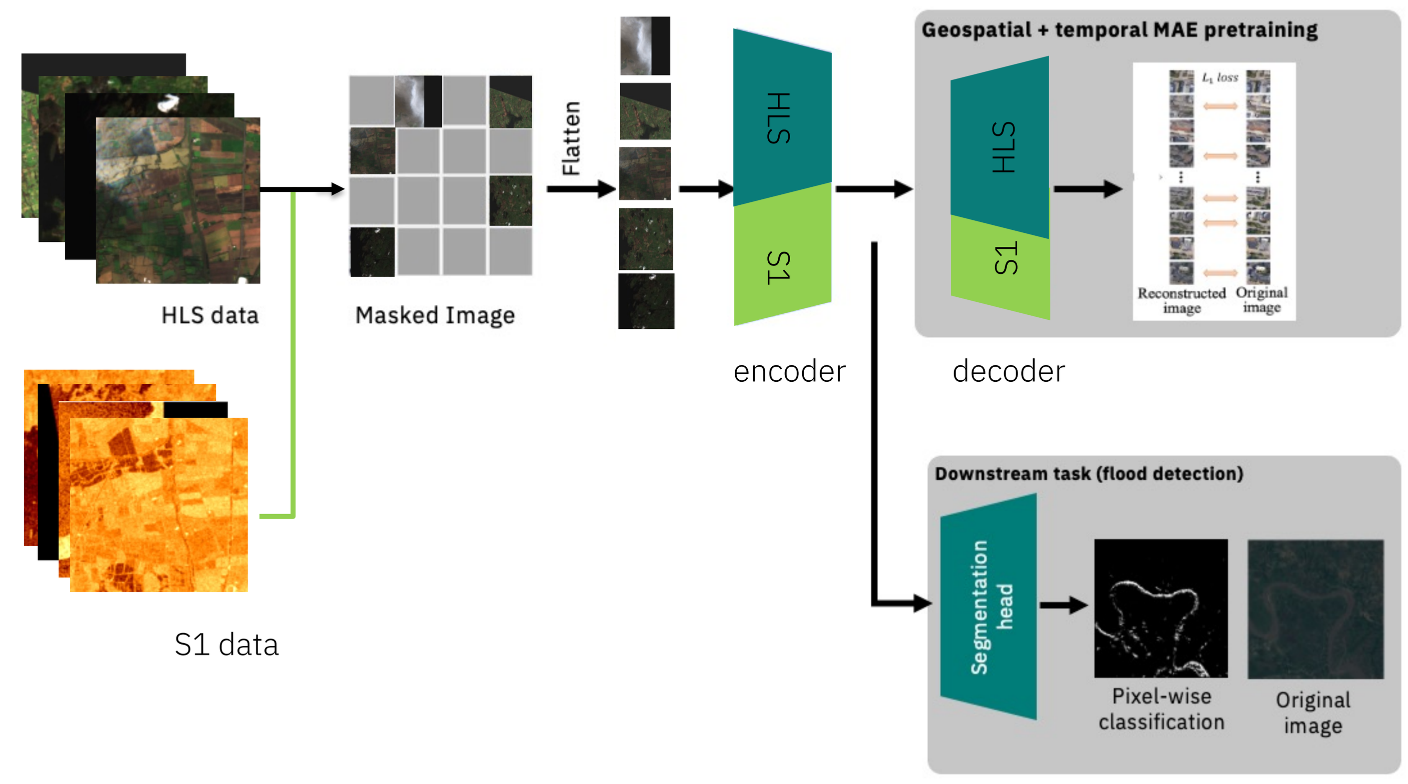

Figure 2: Prithvi approach to training a UKI flood detection model

3. Experiments and Results

- We carry out three experiments, where we incorporate region-specific, multimodal data at different stages in the training process (Table 1)
- We evaluate the model performance for each set-up twice; 1. on the whole test set and 2. only on relatively cloud-free images within the test set

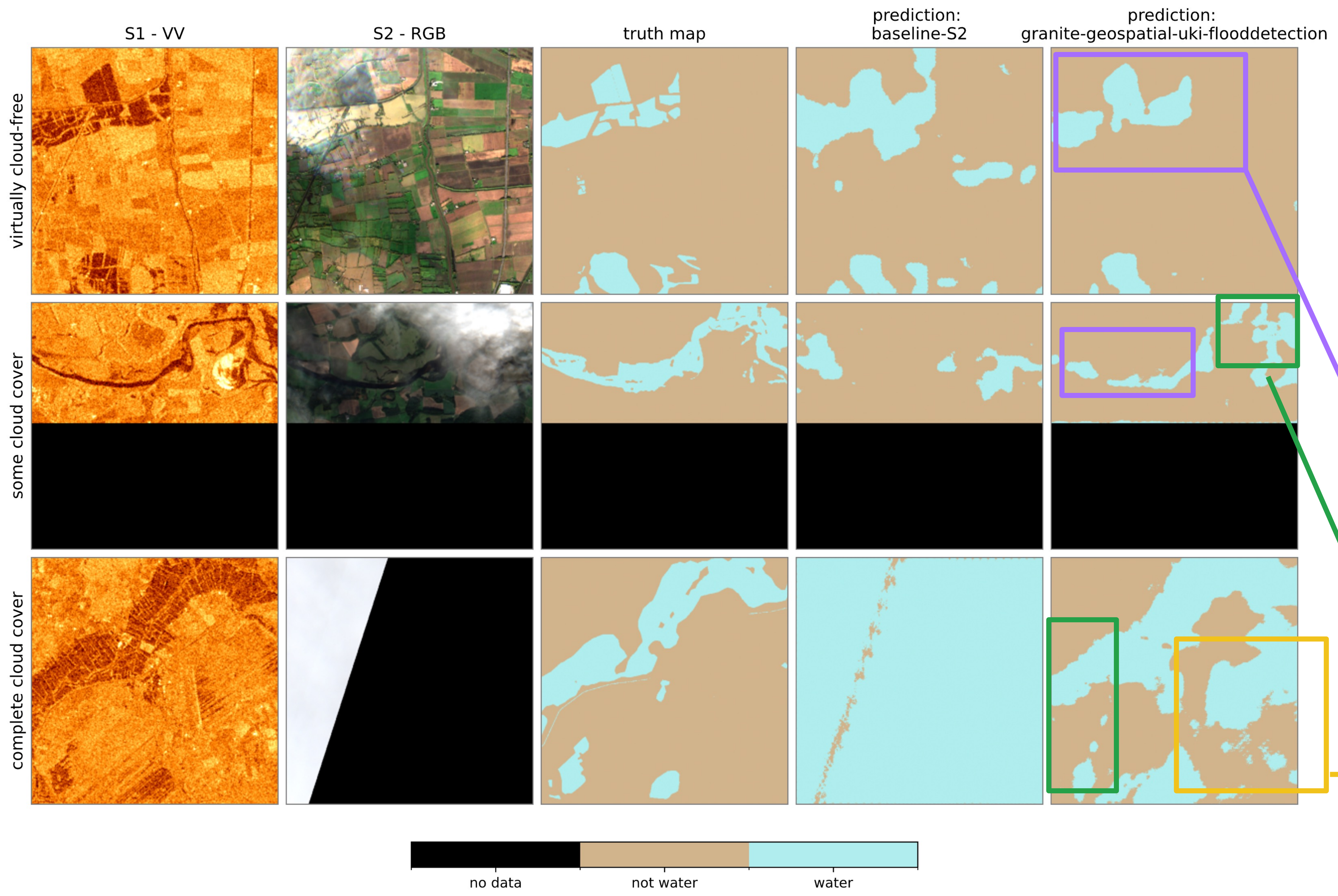

Figure 3: UKI flood detection model inference examples, comparing across experiments.

	baseline-S2				*baseline-S1-S2*				*granite-geospatial -uki-flooddetection*			
	US	UKI	S1	S2	US	UKI	S1	S2	US	UKI	S1	S2
base (Prithvi-EO-1.0-100M)	✓	-	-	✓	✓	-	-	✓	✓	-	-	✓
additional-pretraining	-	-	-	-	-	-	-	-	-	✓	✓	✓
fine-tuning	-	✓	-	✓	-	✓	✓	✓	-	✓	✓	✓
inference	-	✓	-	✓	-	✓	✓	✓	-	✓	✓	✓
mIoU on whole test set	0.575 ± 0.019				0.790 ± 0.015				0.786 ± 0.012			
mIoU on cloud-free test set	0.803 ± 0.017				0.845 ± 0.011				0.845 ± 0.009			
F1 on whole test set	0.828 ± 0.020				0.942 ± 0.006				0.938 ± 0.006			
F1 on cloud-free test set	0.952 ± 0.007				0.966 ± 0.003				0.967 ± 0.004			

Table 1: experiment set-up and model evaluation results. Blue shows difference to *baseline-S2*.

Observation 1: cloud-free regions perform similarly, with slight improvements when incorporating SAR bands

Observation2: areas of cloud cover are significantly improved with the addition of SAR data

Observation 3: mismatched swaths can lead to model artefacts. To safeguard predictions only use images with matched swaths across different satellites

4. Conclusion

- Earth Observation Foundation Models can be tuned to new locations and application-specific satellite bands relatively easily
- We improved flood segmentation tasks in UKI from an mIoU of 0.58 to 0.79 (by approximately 35%) by incorporating SAR band imagery by using a foundation model approach and relatively small amounts of task-specific data

References
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Check out the models on Hugging Face 🤗

Prithvi foundation models

UKI foundation model

UKI flood detection model