Mapping Flood Waters with Satellite Imagery and Topography using Convolutional Neural Networks

Flood Events

Ephemeral Surface Water
Spatio-temporal + Spectral Variance`

Multispectral Imagery

Spectral Signature of object
Reflection across EM bands

Machine Learning

Supervised Learning AI
CNNs

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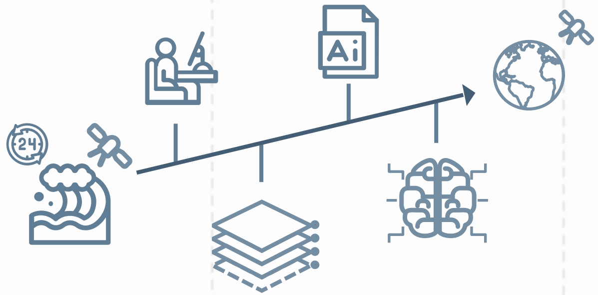
Need and Challenge

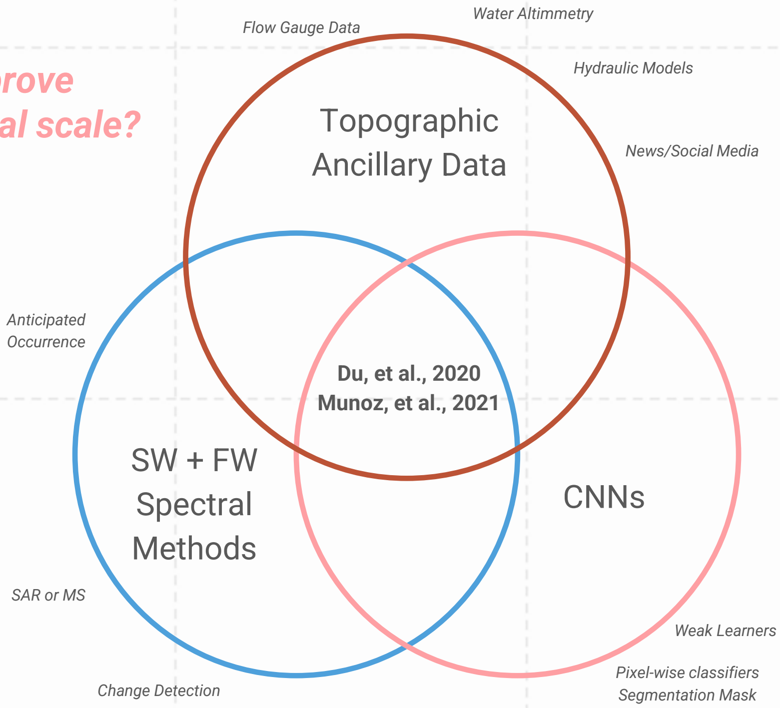


- Flood Risk intensity under a changing climate
- Developments in AI methods and imagery data availability
- “*...advanced transition phase...*” (Hoeser and Kuenzer, 2020) global benchmark datasets
- Effects of topography in the field of flood modelling

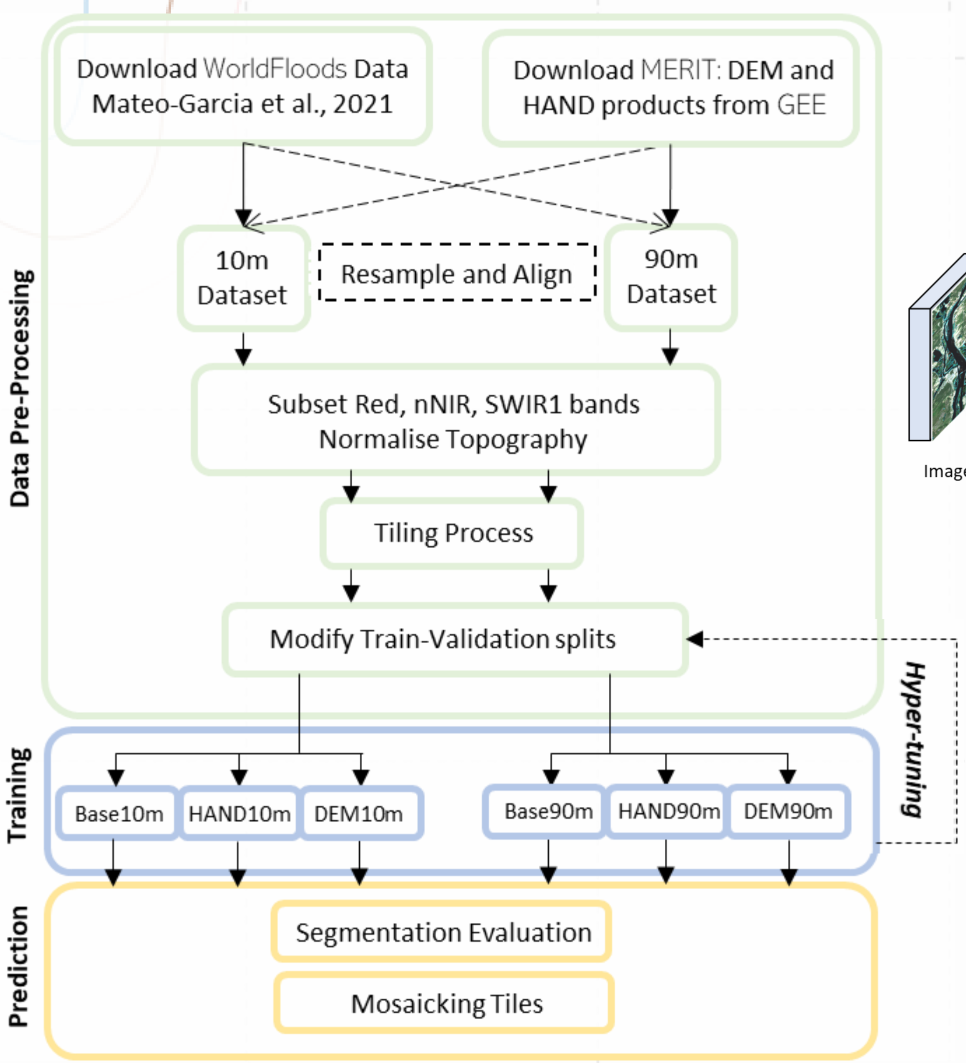
Can topography be used to improve FW mapping in CNNs on a global scale?

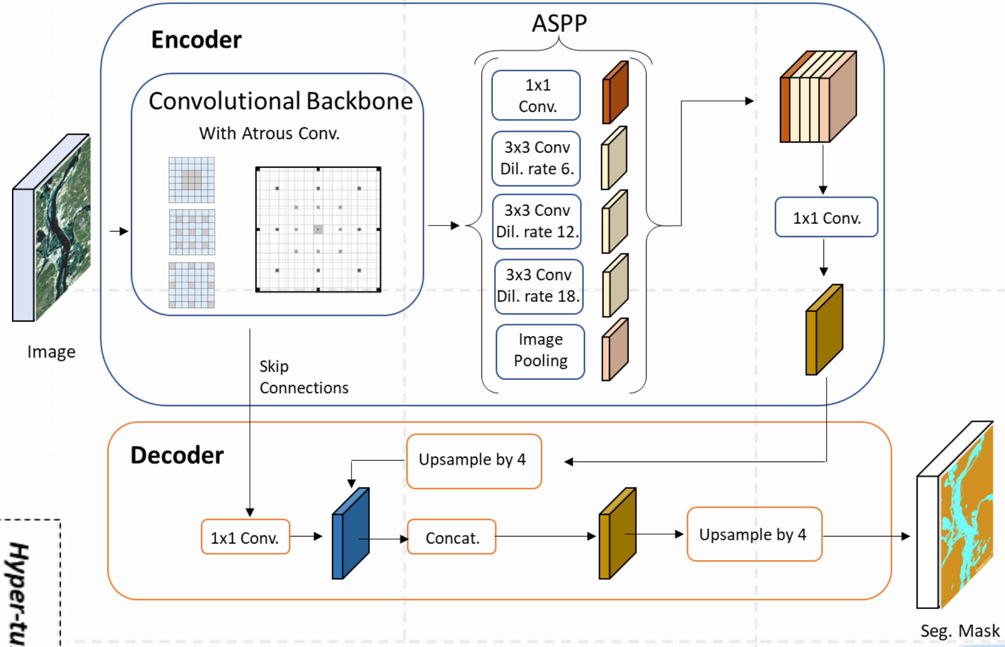
Current Literature

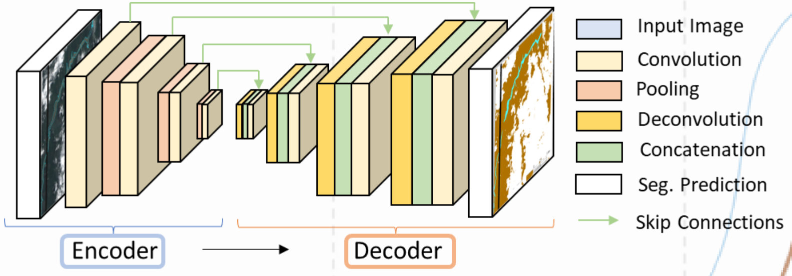
- Fragmented: Data Fusion, ML models, Water Mapping methods
  - Two relevant studies but limited in :
    - Flood event types
    - Study area type
    - Local scale
  - MERIT global terrain dataset
    - Punching above it weight
    - ‘raw’ DEM vs derived HAND TI

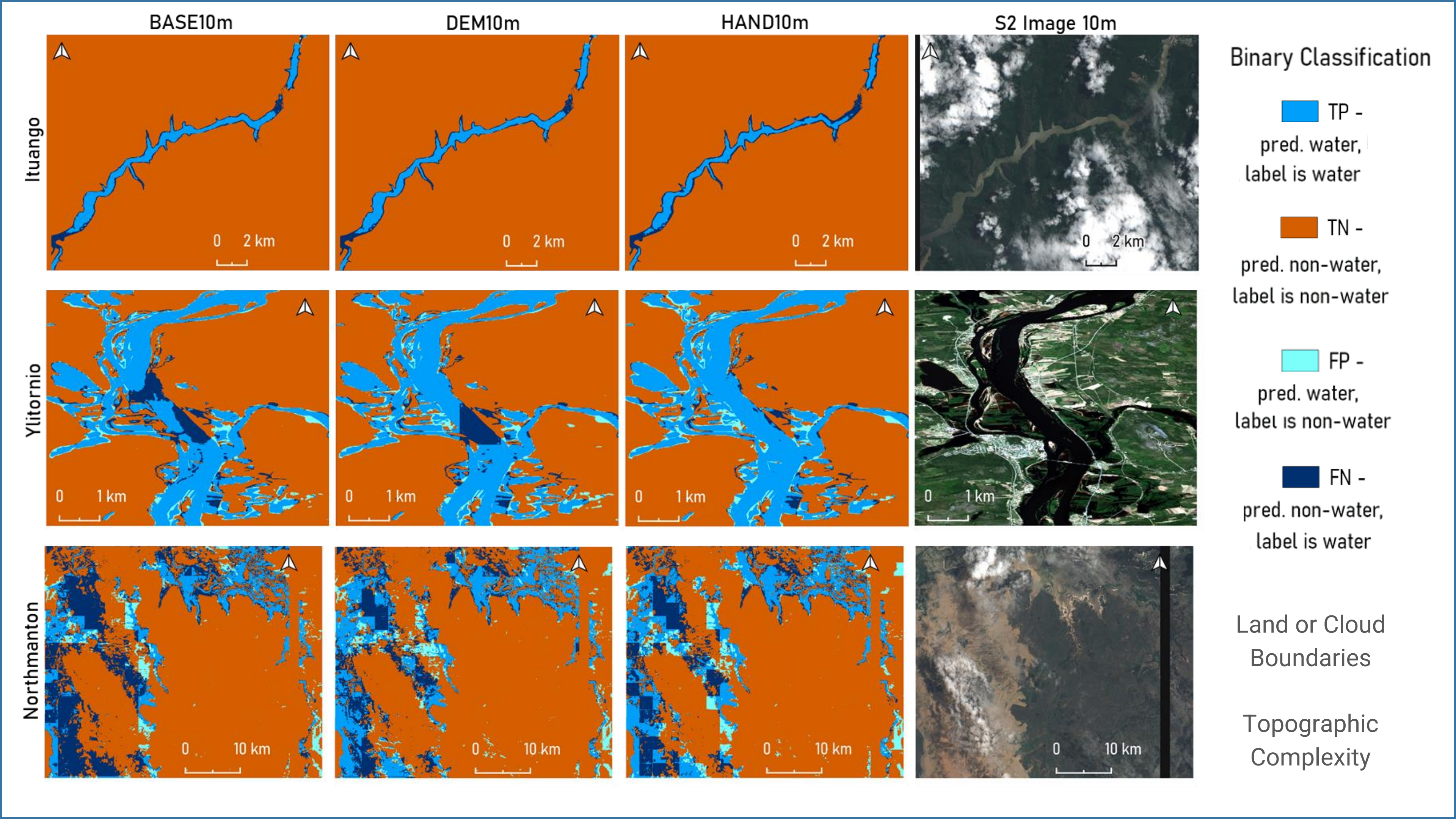


Methodology









BASE10m
DEM10m
HAND10m
S2 Image 10m
Ituango
Ylitornio
Northmanton
0 2 km
0 1 km
0 10 km
Binary Classification
TP - pred. water, label is water
TN - pred. non-water, label is non-water
FP - pred. water, label is non-water
FN - pred. non-water, label is water
Land or Cloud Boundaries
Topographic Complexity

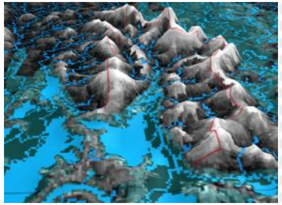
Observed Behaviours

- Topo. **was useful** in 10m models (DEM + HAND)
- DEM10m performance better in complex **multi-catchment** scene

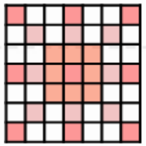
- In models with DEM, target function **harder to learn** than BASE or HAND
- In 90m models Topo., **no additional benefit** or **detrimental**
    - Despite data imbalance
    - DEM90m failed to learn to predict water

Causes:

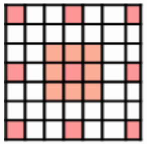
- *HAND / DEM differences*



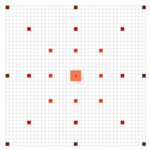
- *Scale-dependent differences*
- *Model architecture*



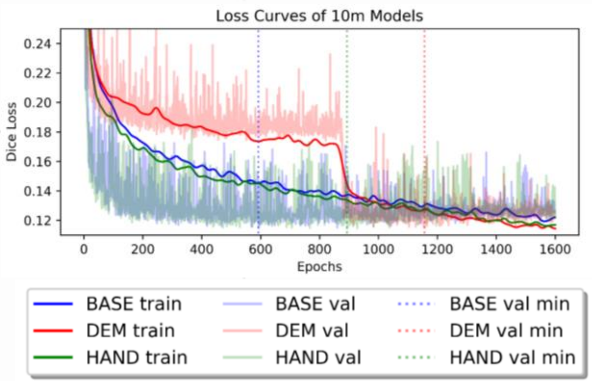
Dilation Rates: 0, 1, 2



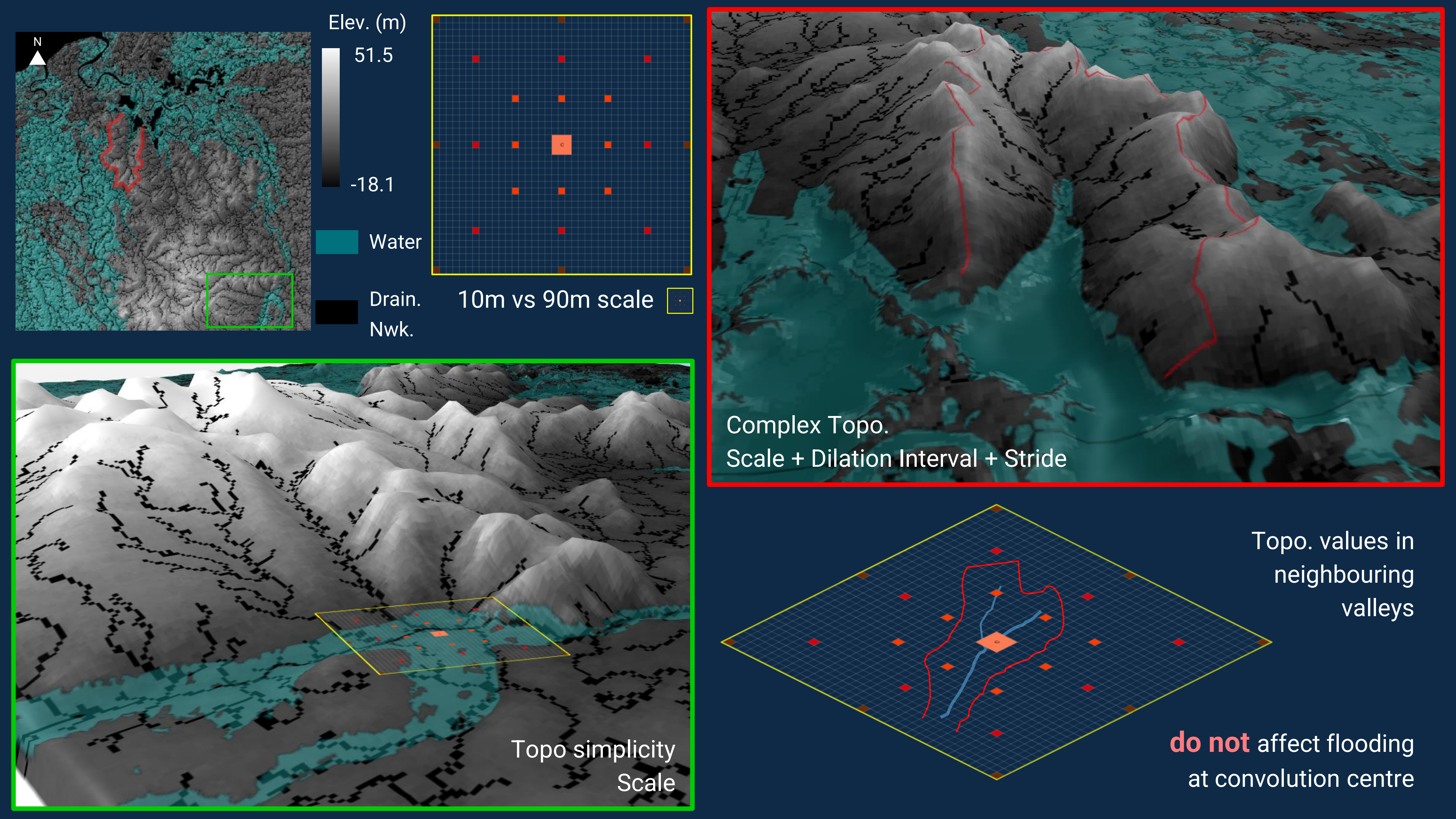
Dilation Rates: 0, 2



Dilation Rates: 6, 12, 18



Model	OA (%)	F1 (%)	mIOU Water (%)	Recall Water (%)	Precision Water (%)	Epochs (n)
BASE10m	79.24	36.86	12.96	13.36	24.69	592
DEM10m	80.53	36.22	14.02	16.06	24.82	1156
HAND10m	**88.03**	**36.72**	**15.94**	**18.28**	**26.99**	**893**
BASE90m	**87.55**	**46.14**	**21.47**	**18.17**	**50.98**	**3907**
DEM90m	81.41	35.91	0.00	0.00	0.00	3840
HAND90m	87.24	45.18	20.77	17.90	52.40	3908



N
Elev. (m)
51.5
-18.1
Water
Drain.
Nwk.
10m vs 90m scale
Complex Topo.
Scale + Dilation Interval + Stride
Topo simplicity
Scale
Topo. values in
neighbouring
valleys
do not affect flooding
at convolution centre

Conclusions and Future Work

- Topo. can improve FW mapping in CNNs on a global scale
- The training data imbalance between 10m and 90m models affected comparability
- Interesting to see model behaviours on full dataset

Future work can:

- Tweak dilation rates in atrous convolutions
- Assess if there is any benefit in using both the DEM and HAND TI
- Assess alternative CNN architectures (backbones/conv. arms)
- Should these results be promising it opens up questions on additional uses the MERIT dataset to “peek under occlusions”.
- Examine other open global ancillary data sources

MERIT data - Yamazaki, et al., 2017, 2019
WorldFloods Sentinel-2 Data – Mateo-Garcia, et al., 2021