Research in Geomatics at ULiege

François Jonard and Andrea Nascetti

SGLg Conference

April 2023

PhD in Remote Sensing (2009-2012)
Faculty of Bioscience Engineering at UCLouvain

- Passive and active microwave remote sensing for soil moisture
- Radiative transfer modelling in microwave radiometry
- Soil roughness and vegetation effects on radar signal
- Vegetation water content retrieval

Research Scientist (2012-2020)
Institute of Bio- and Geosciences at Research Center Jülich (Germany)

- Microwave, multispectral and hyperspectral data analysis
- Land surface modelling and climate change
- Drought monitoring using SIF remote sensing
- UAS for mapping and monitoring of agro and forest ecosystems (multispectral, thermal, and LiDAR)

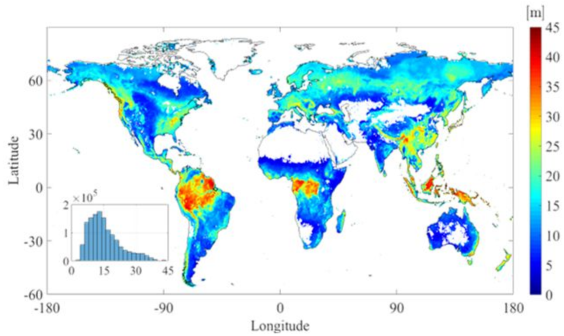
Ass. Professor (2015-2020)
Earth and Life Institute and Faculty of Bioscience Engineering at UCLouvain

- Remote Sensing for Hydrology
- Integrated Water Resources Management
- Photogrammetry and GNSS
- Smart Technologies in Environmental Engineering

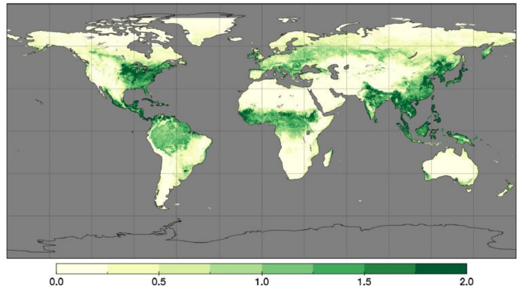
François Jonard – About my experience

Research activities in Remote Sensing

- Earth system parameter retrieval by muti-scale and multi-sensor data integration
- Remote sensing of water in soils and vegetation
- Monitoring of extreme events (forest fires, floods, heat waves, drought)
- Ecosystem health monitoring (photosynthetic activity and GPP mapping, water/carbon fluxes estimation)
- Forest biomass and structure mapping
- Permafrost and peatland monitoring
- UAV and SmallSat remote sensing



Global Vegetation heights
ICESAT LiDAR



Global map of photosynthetic activity
TROPOMI SIF

UAV remote sensing for smart farming and forest monitoring

Multi-sensor data integration

My Research Interest

Observed Water- and Light-Limitation across Global Ecosystems

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Biogeosciences Open Access EGU

Research article

Observed water and light limitation across global ecosystems

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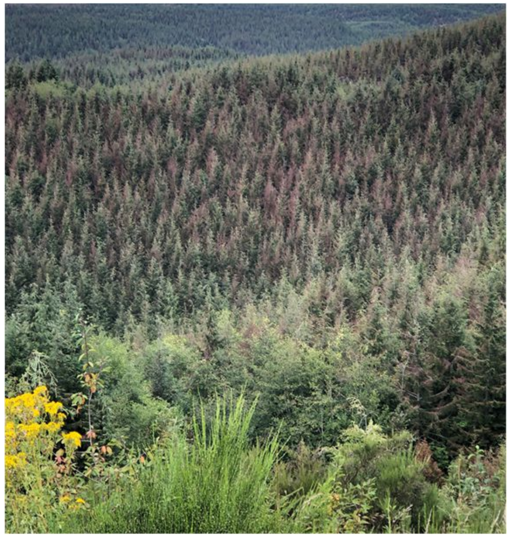
Abstract. With a changing climate, it is becoming increasingly critical to understand vegetation responses to limiting environmental factors. Here, we investigate the spatial and temporal patterns of light and water limitation on photosynthesis using an observational framework. Our study is unique in characterizing the nonlinear relationships between photosynthesis and water and light, acknowledging approximately two regime behaviours (no limitation and varying degrees of limitation). It is also unique in using an observational framework instead of using model-derived photosynthesis properties. We combine data from three different satellite sensors, i.e., sun-induced chlorophyll fluorescence (SIF) from the TROPOspheric Monitoring Instrument (TROPOMI), surface

the two regimes is connected to soil type and mean annual precipitation for the SIF–soil moisture relationship and for the SIF–PAR relationship. These thresholds therefore have an explicit relation to properties of the landscape, although they may also be related to finer details of the vegetation and soil interactions not resolved by the spatial scales here. The simple functions and thresholds are emergent behaviours capturing the interaction of many processes. The observational thresholds and strength of coupling can be used as benchmark information for Earth system models, especially those that characterize gross primary production mechanisms and vegetation dynamics.

Observed Water- and Light-Limitation across Global Ecosystems

- Vegetation plays a large role in the Earth's system, modulating land-atmosphere exchanges of water, carbon, and energy.
- With a changing climate, it is becoming increasingly critical to understand vegetation responses to limiting environmental factors.
- These change-induced factors that affect vegetation productivity have impacts on global carbon budgets and food security.
- Understanding how climatic factors create limitations is essential for predicting and validating terrestrial ecosystem productivity responses in Earth system models.

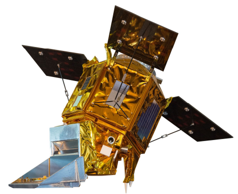


Observed Water- and Light-Limitation across Global Ecosystems

The objective is to look at environmental factors -> water and light availability
that limit surface water and carbon exchanges over vegetated areas -> photosynthetic activity

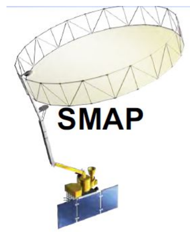
Observations-Driven Approach to Diagnose Water- and Light limitation

- ○ Photosynthetic activity - TROPOMI Sun-Induced chlorophyll Fluorescence (SIF)



Sentinel 5P

- ○ Soil water availability - SMAP Soil Moisture (SM)



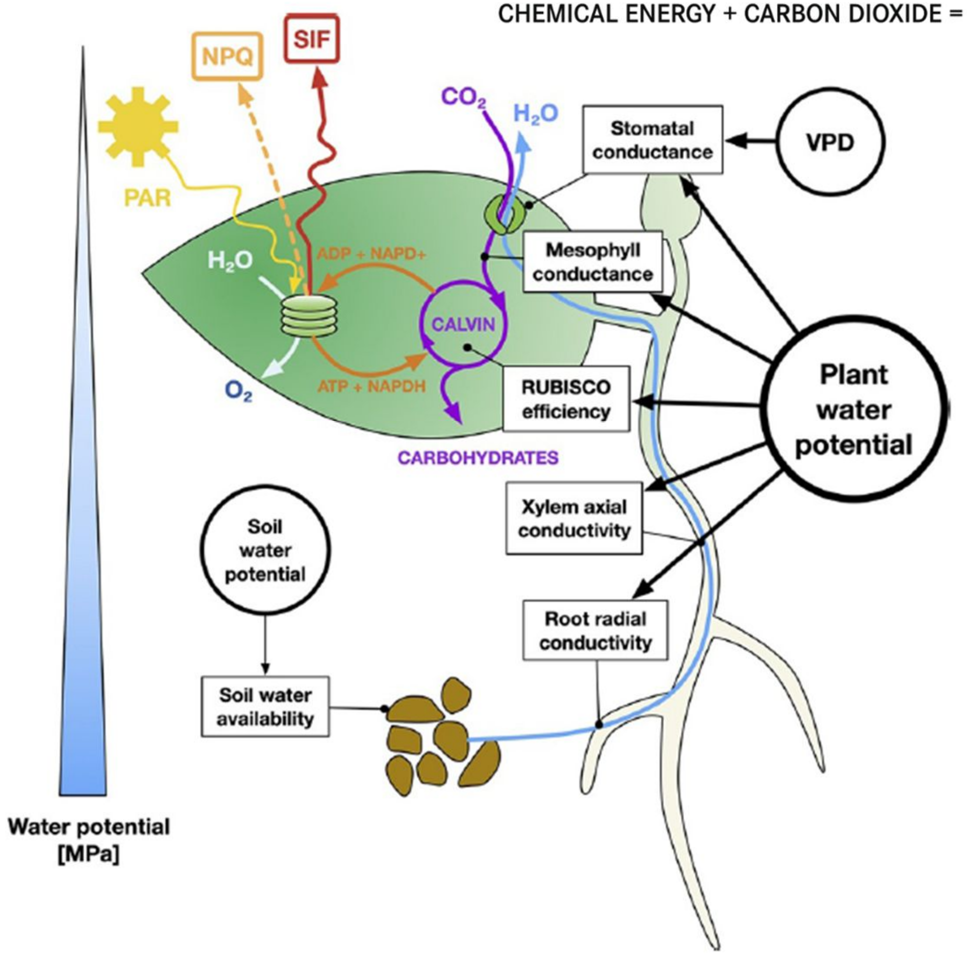
- ○ Light availability - MERRA-2 Photosynthetic Active Radiation (PAR)

Photosynthesis is at the intersection of water and carbon cycles

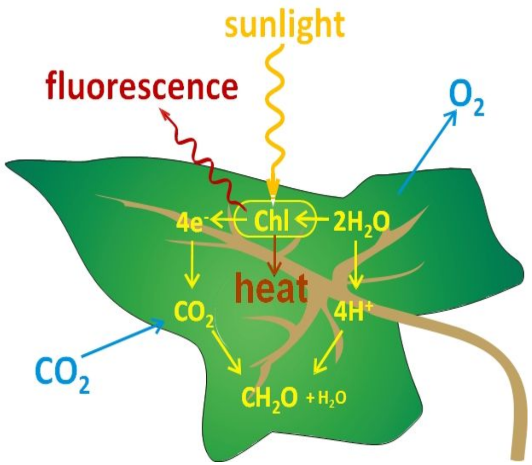
- Plants pump up water from soil to do photosynthesis
- Drought stress increases leaf resistance, slowing down photosynthesis
- Subsequent change in the light reactions of photosynthesis

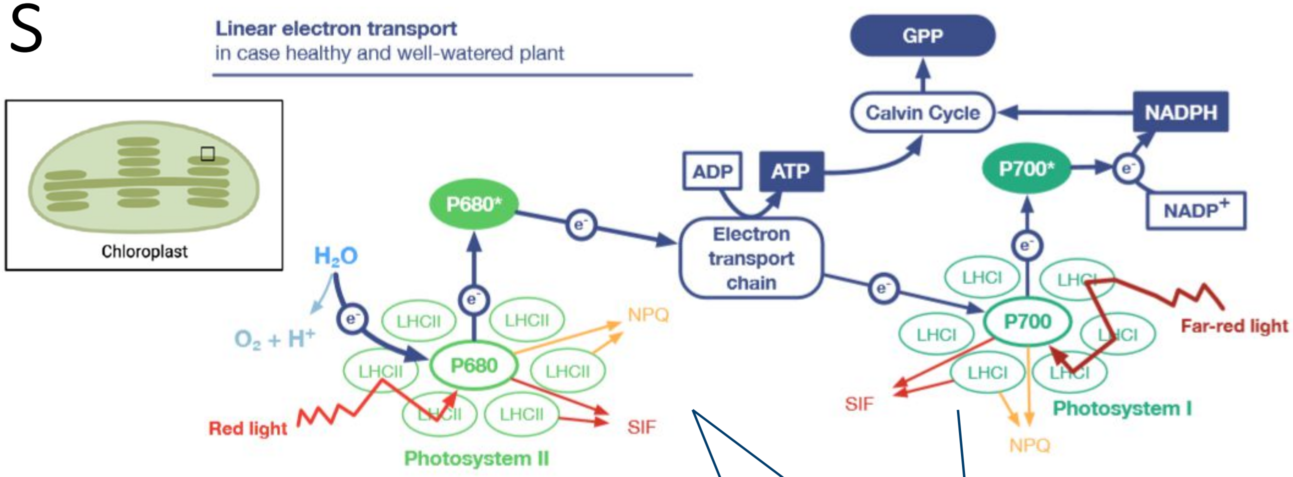
"PHOTOSYNTHESIS"
WATER + LIGHT = CHEMICAL ENERGY

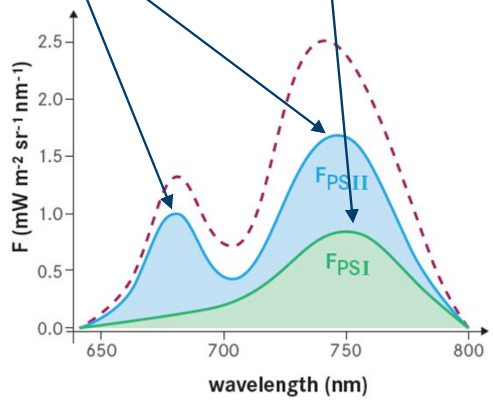
CHEMICAL ENERGY + CARBON DIOXIDE = SUGAR



Chlorophyll fluorescence, a signal from the heart of photosynthesis



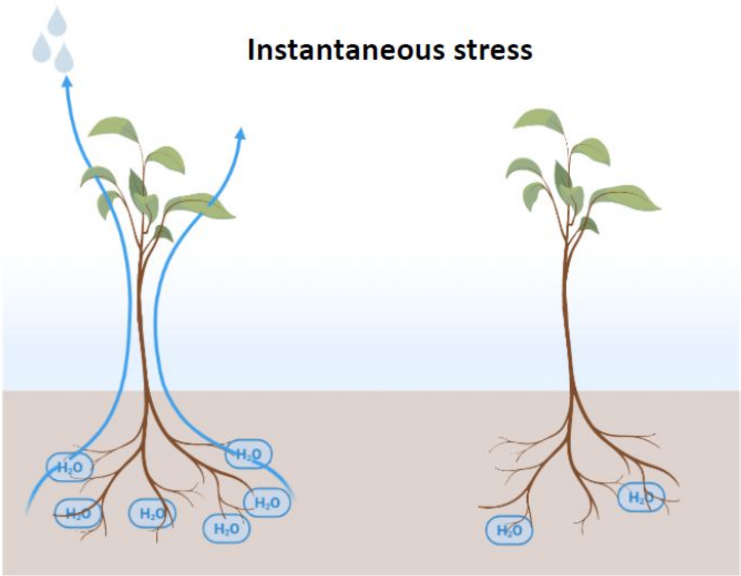




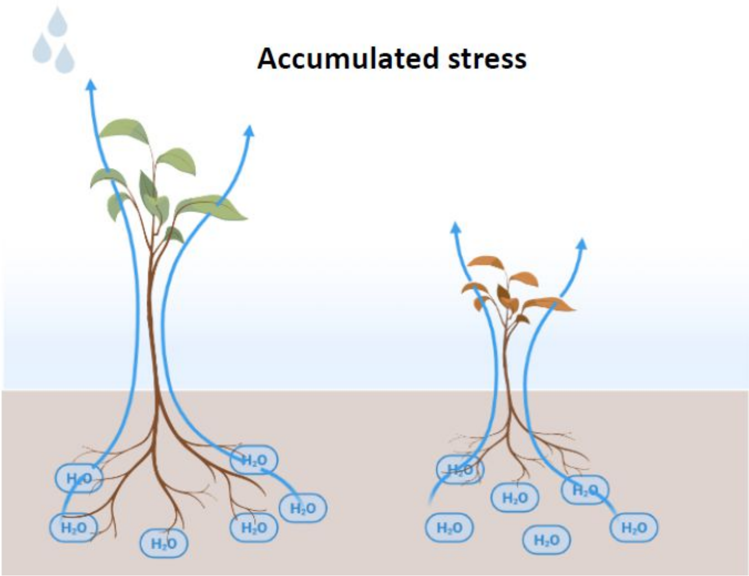
- Photosynthesis is a highly regulated process that involves a cascade of electron transfers (*Light reaction*) to fuel carbon fixation (*Calvin cycle*)
- Sun-Induced Chlorophyll Fluorescence (SIF) is emitted from the cores of the photosynthetic machinery: Photosystems I and II

A good proxy of photosynthetic activity and gross primary production (GPP)

Chlorophyll fluorescence, a signal from the heart of photosynthesis



SIF can detect early/instantaneous stress



Classic methods (like NDVI) observe the damage caused by the stress

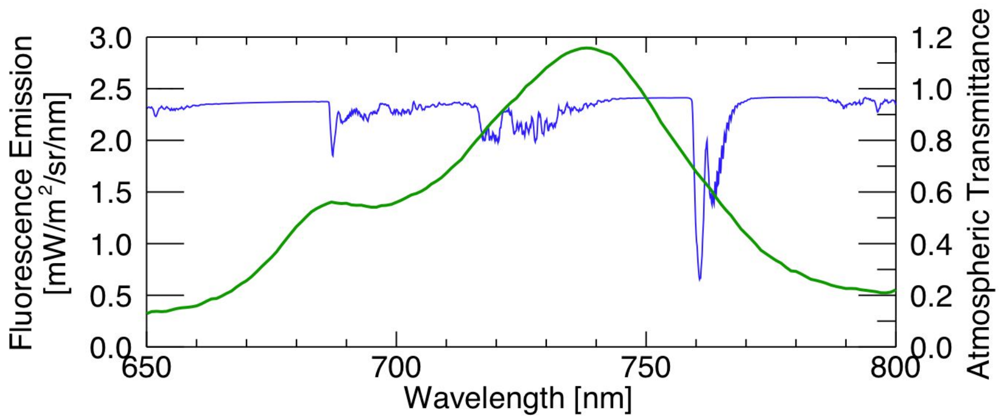
- Early detection of plant water stress not detected using reflectance methods
- Better understanding of the links between the water and carbon cycle

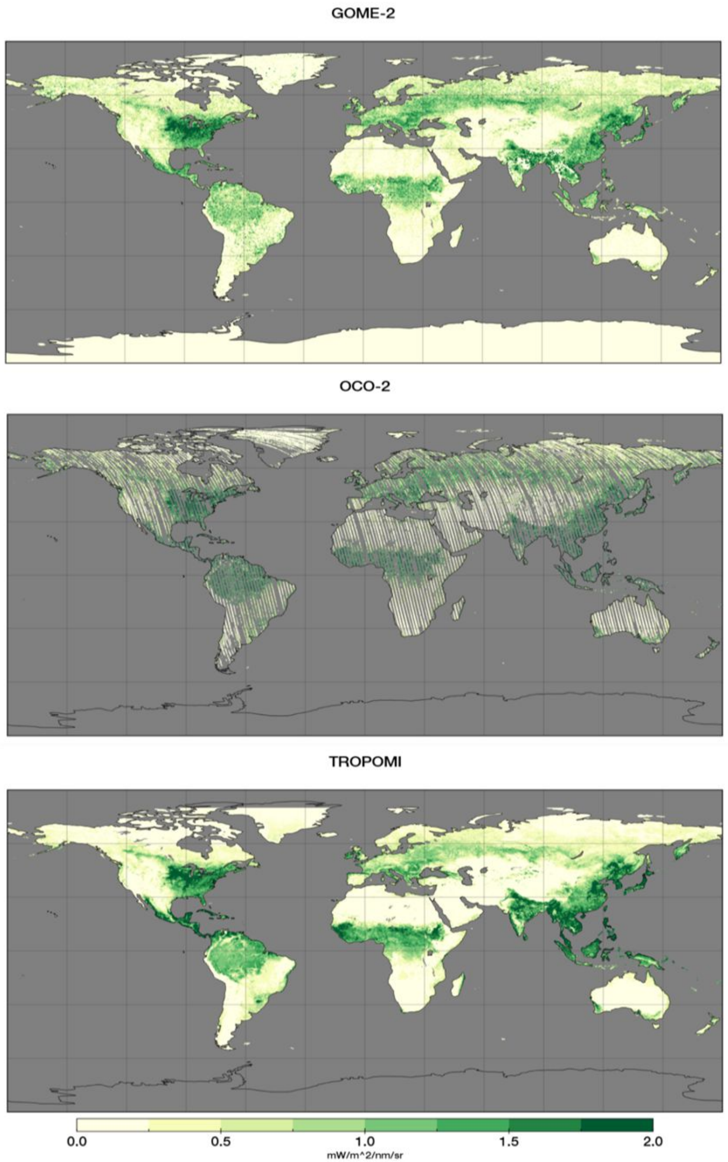
Spaceborne remote sensing of SIF

- Fluorescence can be measured with remote sensing in the solar and Earth's atmospheric absorption lines (Fraunhofer lines)

- Atmospheric oxygen and solar absorption lines facilitate the retrieval of the weak fluorescence signal from the surface reflectance

- Very-high spectral resolution (< 0.1nm) in the red/far-red part of the visible spectrum (680 and 760 nm)





Jonard F. et al. Agric. For. Meteorol. 2020

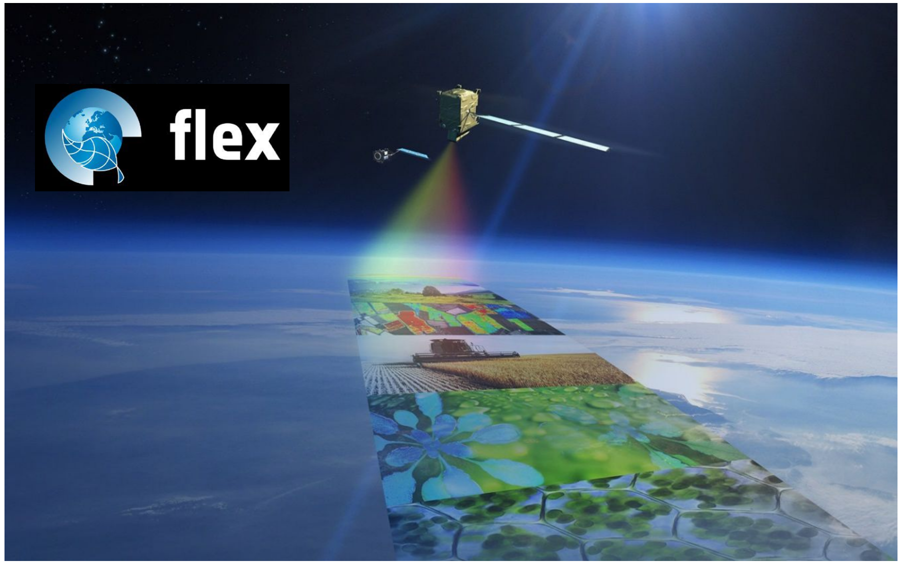
Spaceborne remote sensing of SIF

Fluorescence at global scale

- Average instantaneous passive chlorophyll fluorescence observations at 740 nm for August 2018
- Up to now, global retrievals of fluorescence from space have only been achieved from spaceborne spectrometers designed to monitor atmospheric trace gases
- Sentinel 5P-TROPOMI:
    - Observation period: Oct. 2017 – present
    - Repeat cycle: 16d (1d for global mapping)
    - Spatial resolution: 7×7 km
    - Overpass time: 13:30
    - Spectral resolution: 0.5 nm
    - SIF spectral range: 675–775 nm

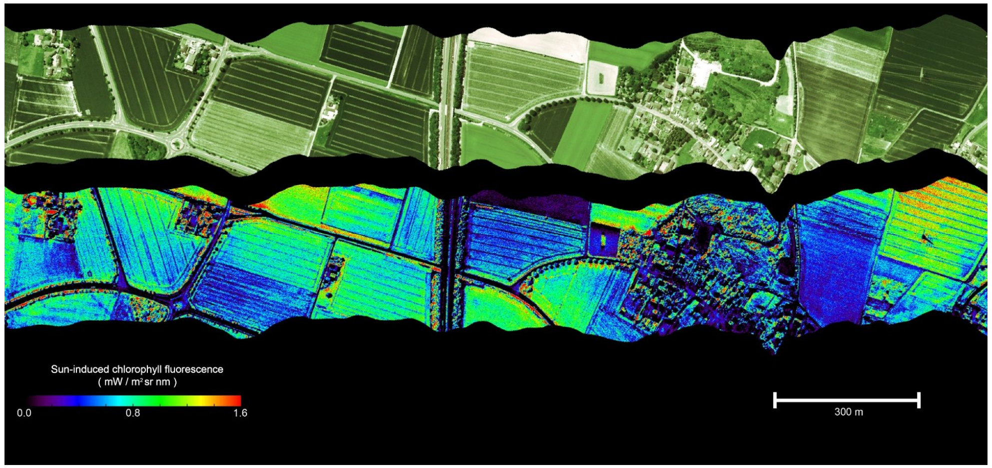
Spaceborne remote sensing of SIF

Fluorescence at global scale



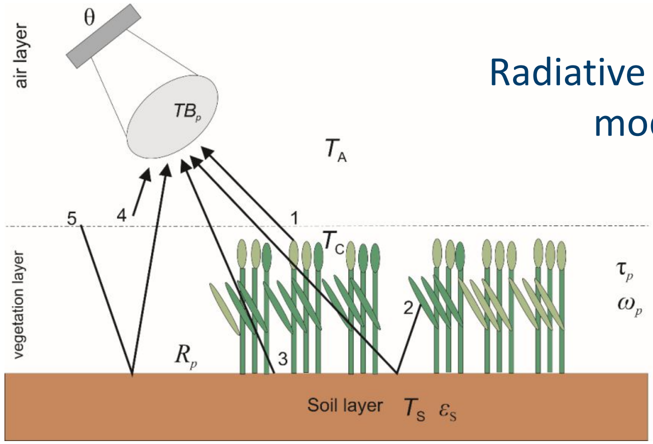
ESA FLuorescence EXplorer (FLEX) satellite mission

- The 8th Earth Explorer of ESA
- Planned launch date: 2025
- Direct measurements of vegetation fluorescence at 300 x 300 meters every 10-25 days

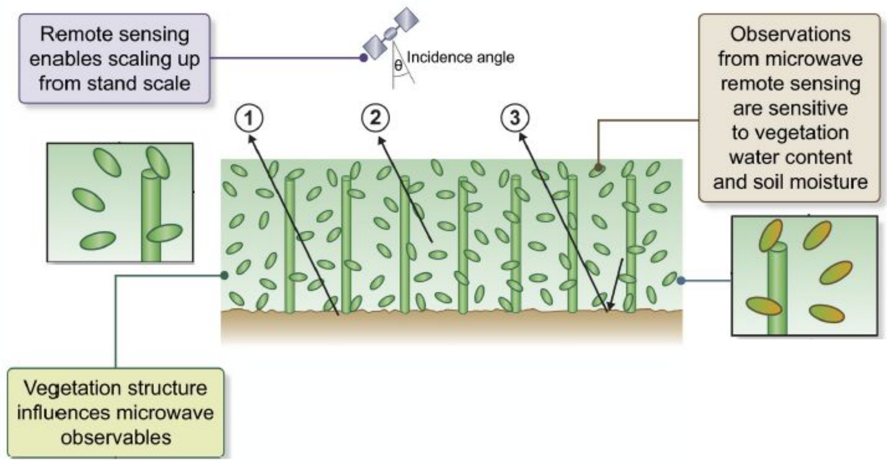


Sensing water in soils and vegetation

- Soil and vegetation water content can be retrieved from passive L-band microwave radiations
- Soil roughness, vegetation structure, and soil organic content influence microwave radiations

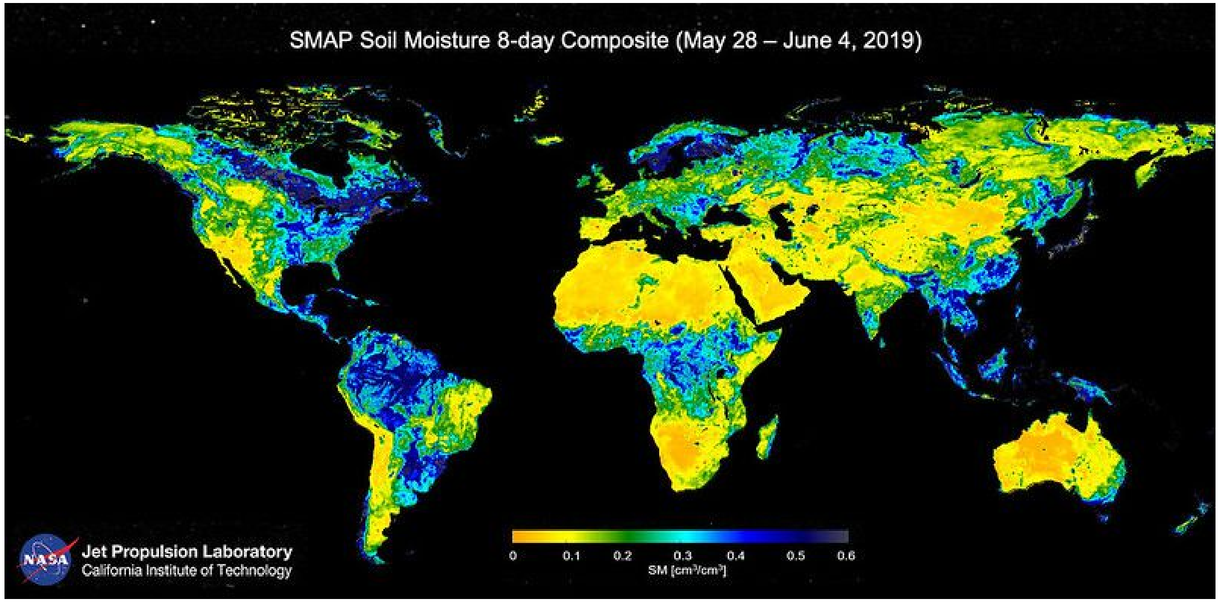


Radiative transfer (RT) modelling

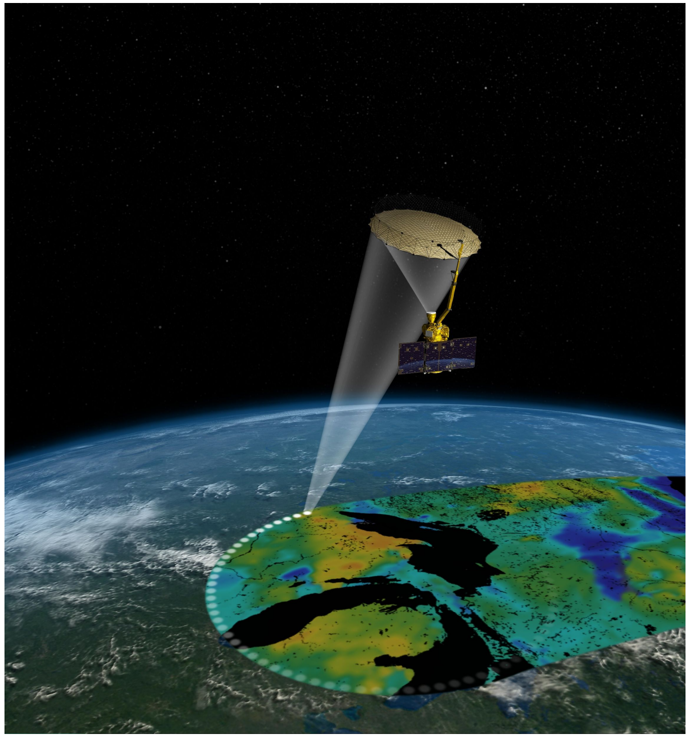


Passive microwave remote sensing of Soil Moisture

Frequent-revisit global mapping of soil moisture

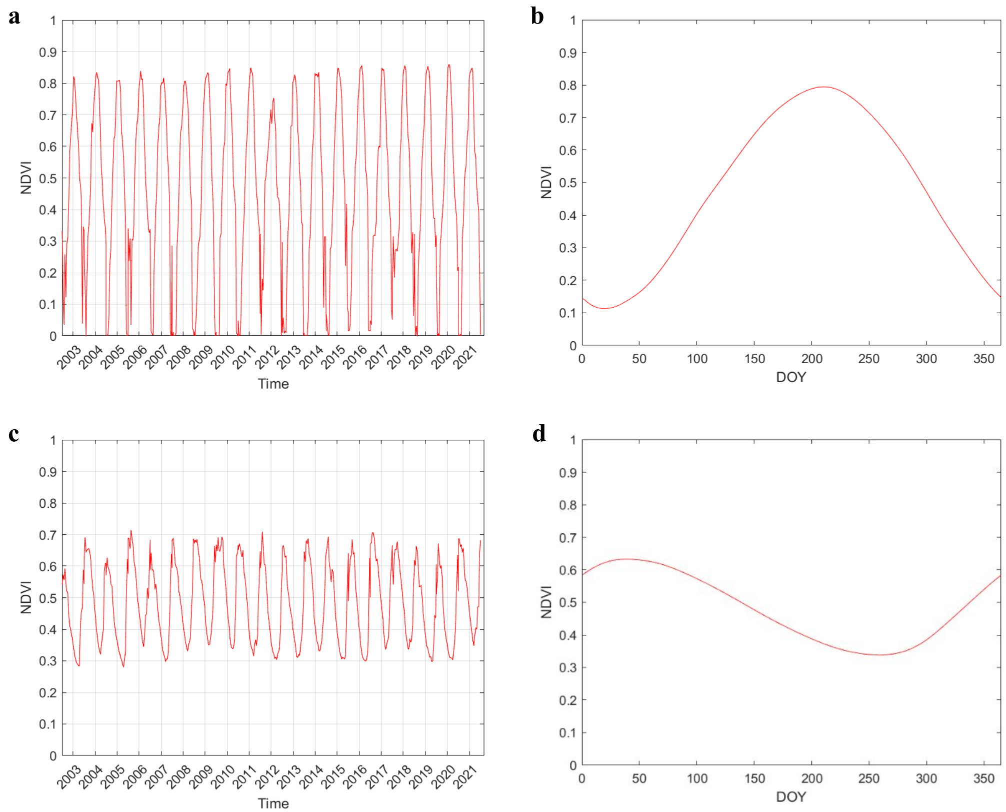


- Estimate global water and energy fluxes at the land surface
- Enhance weather and climate forecast skill
- Improve drought/flood prediction



NASA Soil Moisture Active and Passive (SMAP) satellite

Growing season determination

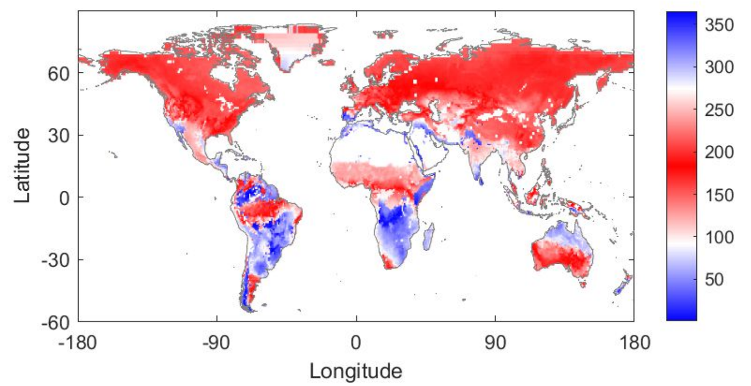


Terra/Aqua MODIS NDVI time series and mean climatology

(a,b) Pixel in the US Corn Belt region; (c,d) Pixel in southern Africa (Zimbabwe)

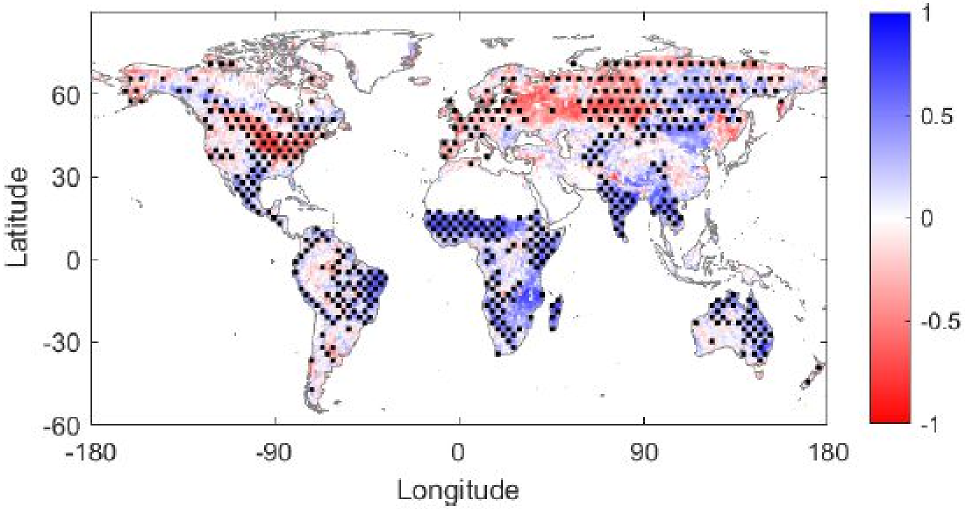
How to define the active growing season (primary water and energy interactions with the carbon cycle)?

Estimation of the peak of the NDVI climatology and the green up and brown down times, i.e., when NDVI reaches 50% before and after the peak.

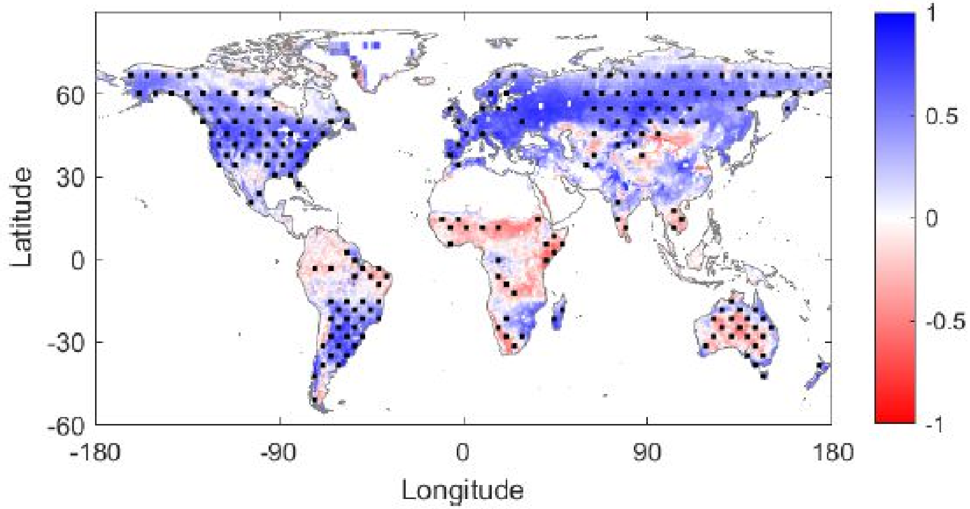


Day of the year for the phenological peak

Correlation maps



TROPOMI SIF and SMAP SM correlation



TROPOMI SIF and MERRA-2 PAR correlation

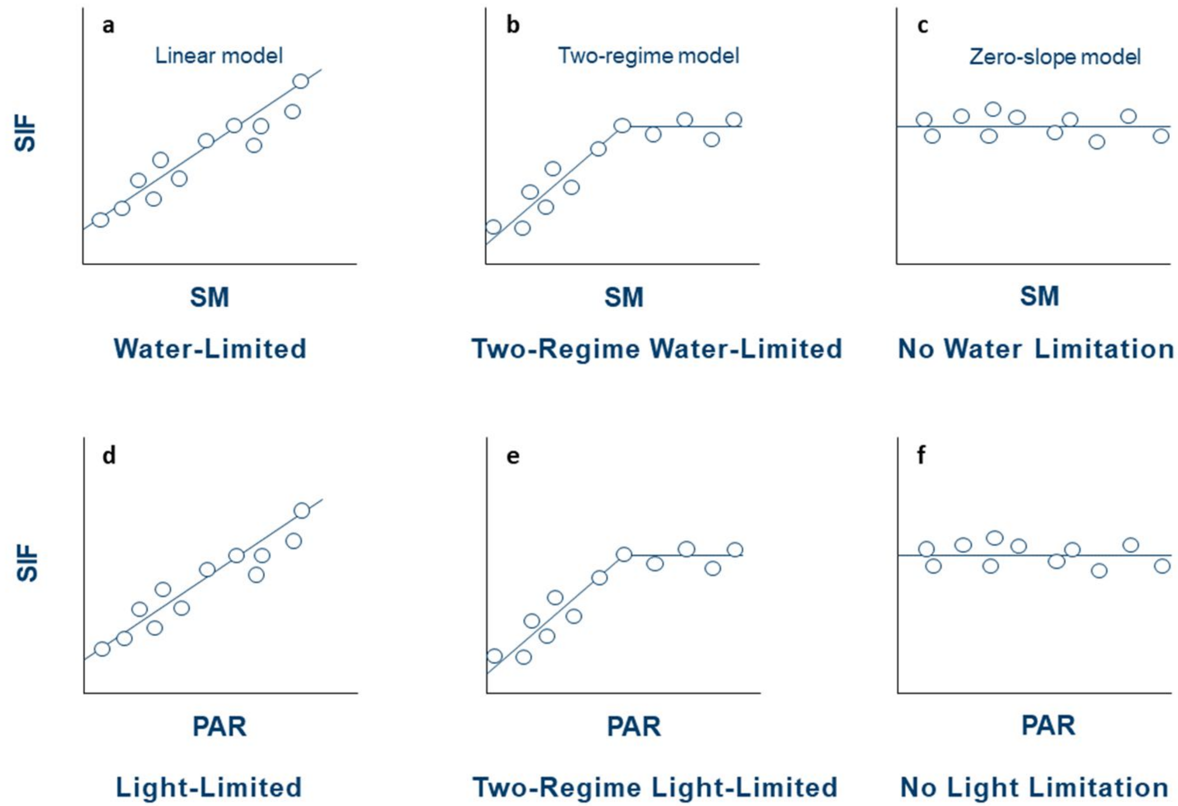
Factors that limit SIF would appear as positively correlated with SIF

Only looking at the blue regions → SIF-SM shows large regions of water limitation
SIF-PAR shows large regions of light limitation

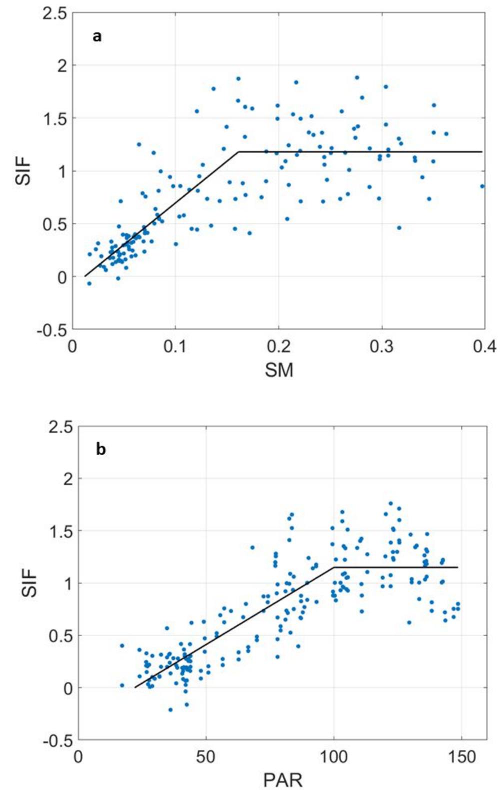
Regime classification

So far, we looked at rate limitation by looking at linear correlations

Are there regimes where the rate limitation stops?

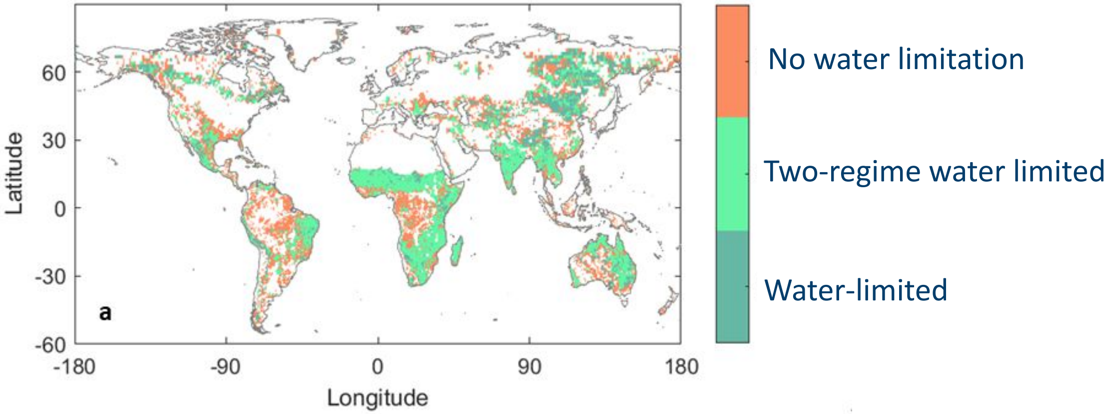


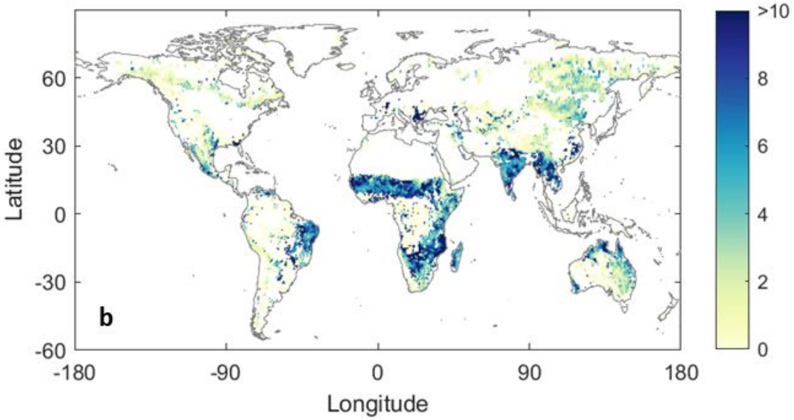
Example pixels located in the Sahel region (top) and Spain (bottom)



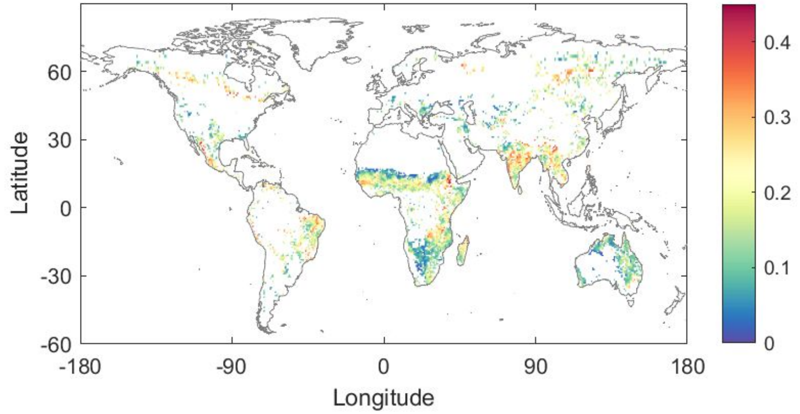
Model selection based on the Bayesian Information Criterion (BIC)

Where are the water-limited regimes?





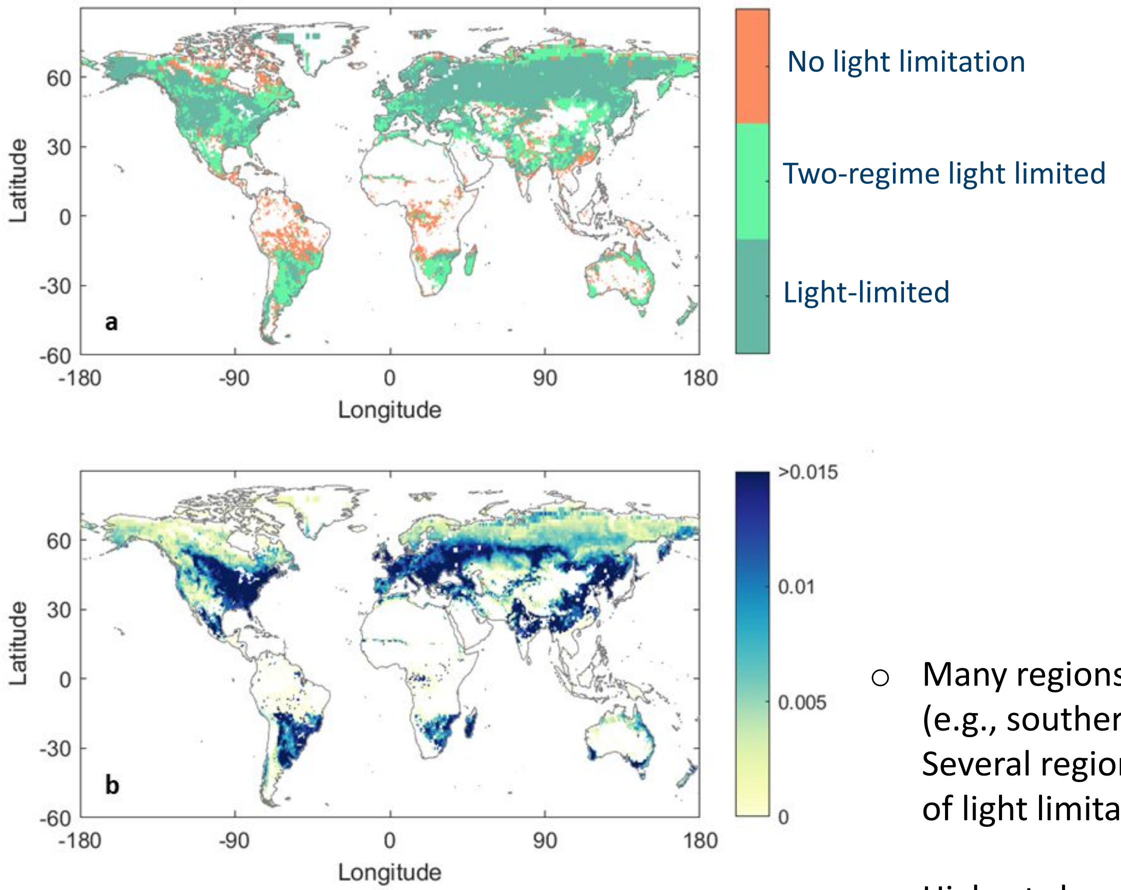
Spatial distribution of the model type and model slope ($mW\ m^{-2}\ nm^{-1}\ sr^{-1}$) in the water-limited regime



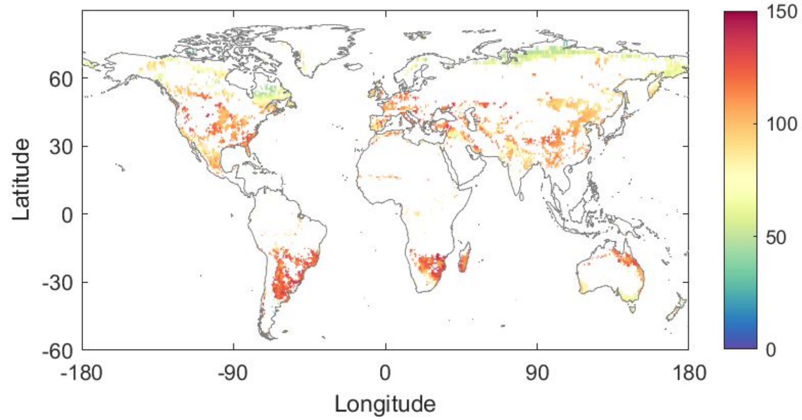
Spatial distribution of the model threshold ($m^3\ m^{-3}$)

- Many regions with a two-regime water limitation identified (e.g., sub-Saharan Africa, southern Asia, eastern Australia, eastern Brazil) suggesting widespread nonlinearity of the soil moisture controls on vegetation.
- Highest slope values in the Sahel region, India, the Mekong basin, eastern Brazil, … where a small incremental increase in soil moisture corresponds to a large increase in vegetation productivity.

Where are the light-limited regimes?



Spatial distribution of the model type and model slope (10^{-3} nm^{-1} sr^{-1}) in the light-limited regime

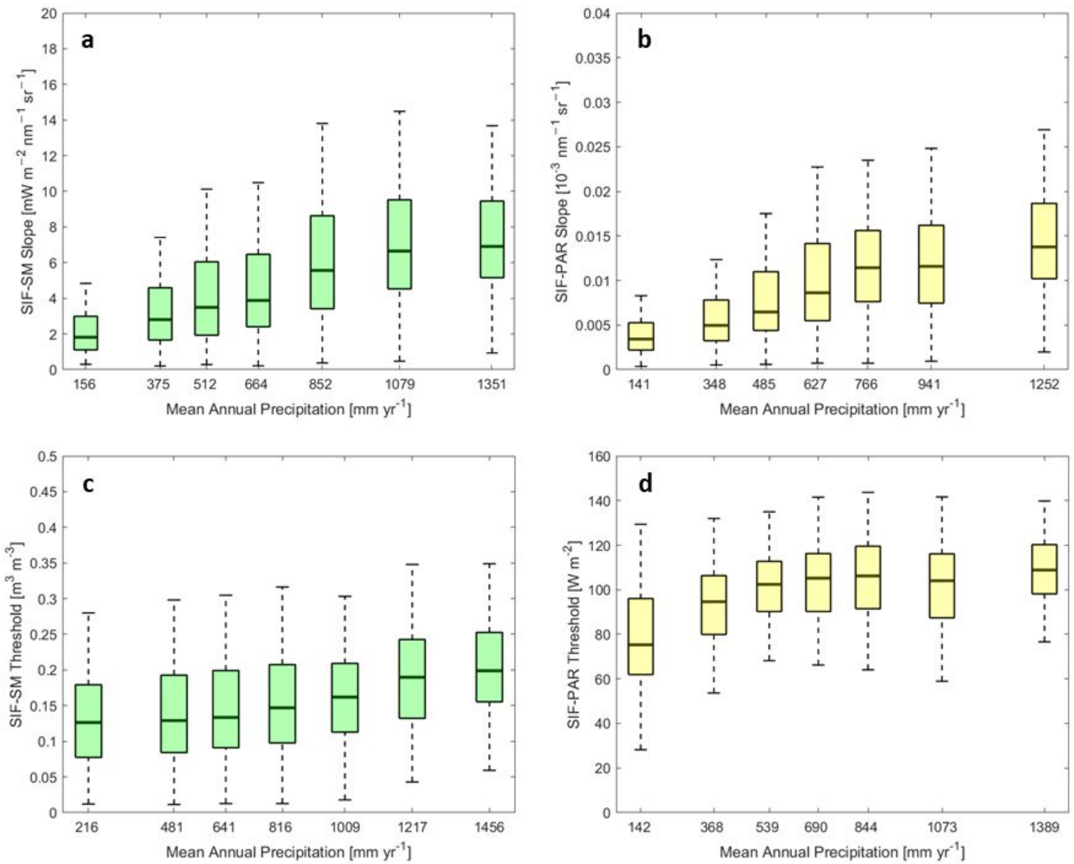


Spatial distribution of the model threshold (W m^{-2})

- Many regions of the Northern Hemisphere with a light limitation regime (e.g., southern Canada, the western US, western and central Russia). Several regions identified as having a break point between two regimes of light limitation (e.g., western Europe)

- Highest slope values in the midlatitudes (Great Lakes regions of North America, most of Europe, southern Russia, …). A large proportion of these regions is used for annual crops.

SIF sensitivity vs Mean annual precipitation



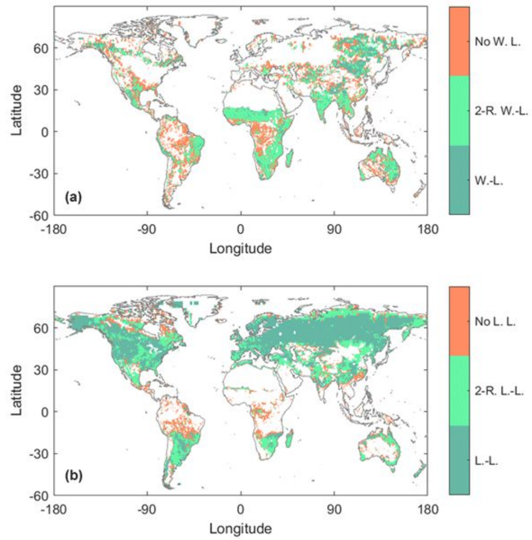
Mean annual precipitation obtained between 2010 and 2020 from the Global Precipitation Measurement (GPM) satellite constellation

SIF sensitivity to soil moisture/PAR increases with mean annual precipitation

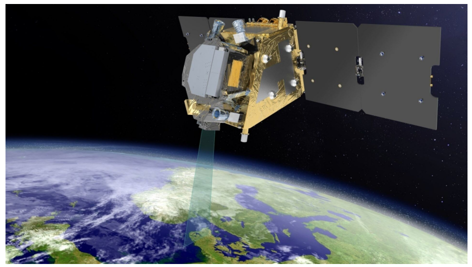
- The increasing sensitivities may be an adaptation of the vegetation to utilize light or water availability, given that moisture is typically less limited in these regions.
- It also indicates that wetter regions may have a stronger plant–water stress response when the land surface becomes drier below the soil moisture/PAR threshold.

Water- and Light-Limitation – Summary

- ○ To detect where nonlinear controls of water and light on photosynthesis occur, three distinct models were tested.
- ○ Observations-driven approach only (different satellites data streams) instead of using model-derived parameters.
- ○ Large regional variations in ecosystem productivity strongly influenced by water and light related controls.
- ○ Nonlinear relationships between plant function and water and light widely observed across the globe.
- ○ Many locations with saturation for water. Two-regime light influence on photosynthesis observed at large scales for the first time.



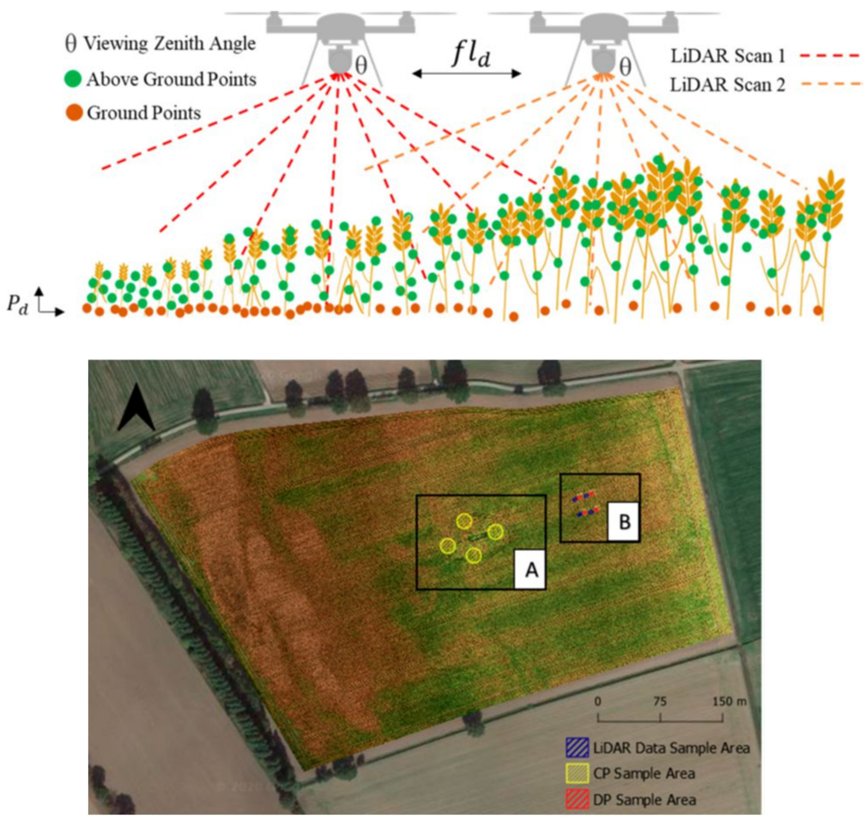
- ▪ FLEX (+Sentinel 2-3), the first mission dedicated to fluorescence, should significantly improve the monitoring of ecosystem functioning and health.
- ▪ The observational thresholds and strength of coupling can be used as benchmark information for Earth system models.
- ▪ SIF can also be assimilated in mechanistic vegetation models to improve estimates of carbon and water fluxes (- > De Cannière and Jonard, RSE 2021)



UAV-based LiDAR, thermal and multispectral remote sensing for ecosystem monitoring

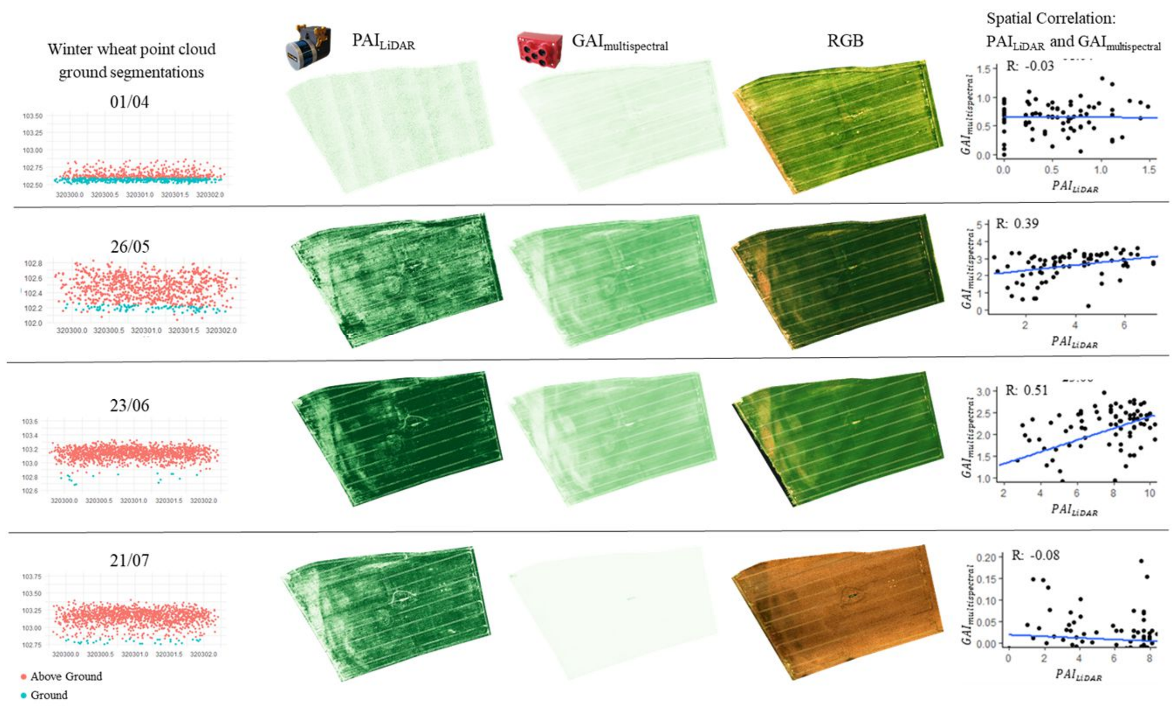
UAS Research Activities

1. Estimating crop canopy density parameters time-series using UAV-mounted LiDAR



Bates and Jonard, *Remote Sensing*, 2021

- LiDAR method based on gap fraction analysis and light extinction theory



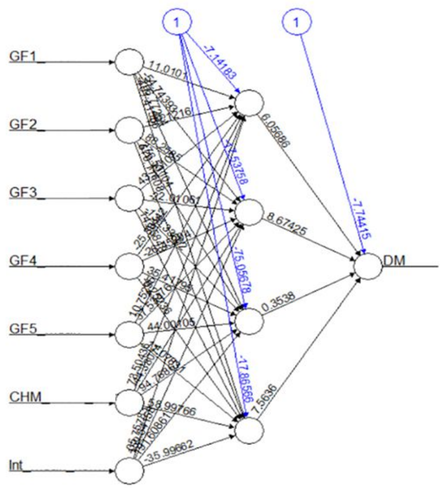
PhD of Jordan Bates (2020-2024)

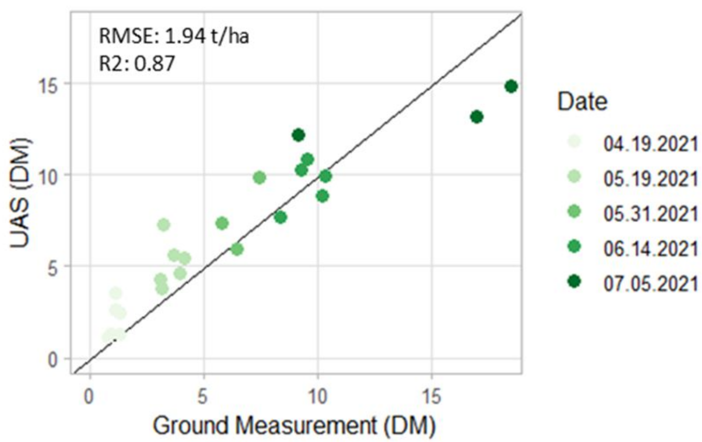
UAS Research Activities

2. Vegetation biomass estimation with UAV-based LiDAR data

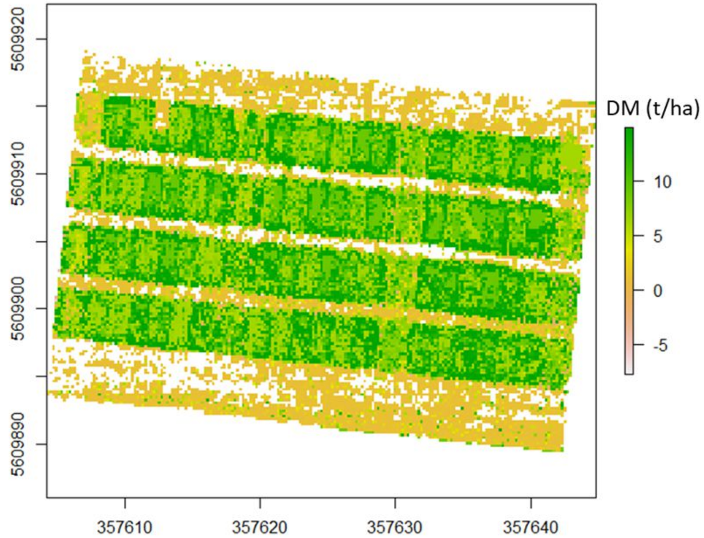
Artificial Neural Network (ANN)

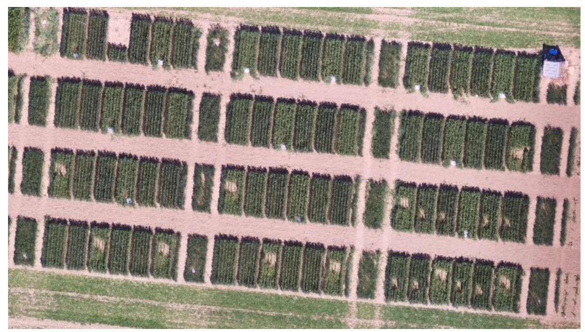
- **Crop height** (vertical information), **gap fraction** (lateral density), **intensity** (chlorophyll content) are being used as predictors in the model.
- A combination of hidden layers and nodes were tested until the best results were found.
- Neuralnet package in Rstudio used.





Bates and Jonard, *AGILE-GISS*, 2022

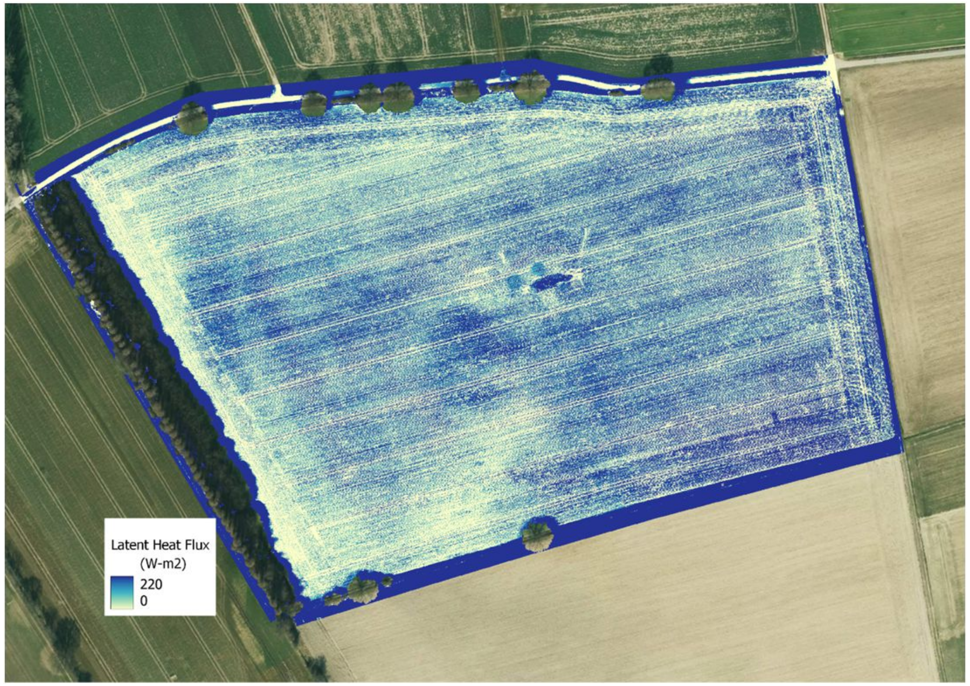


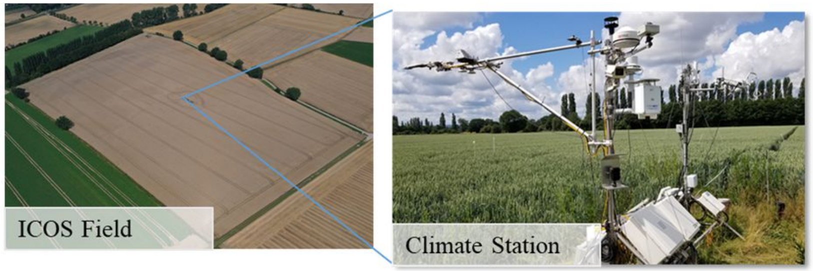


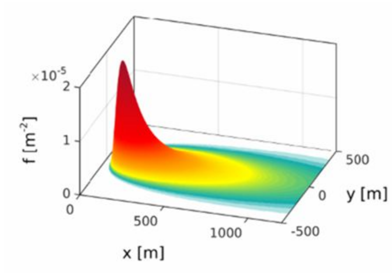
UAS Research Activities

3. Evapotranspiration estimation with UAV-based thermal data

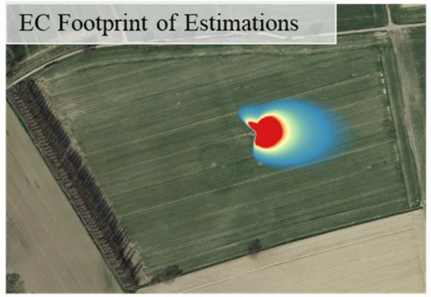
- Thermal IR used to estimate evapotranspiration using the two-source energy balance (TSEB) model
- Estimates were compared against traditional eddy covariance estimations







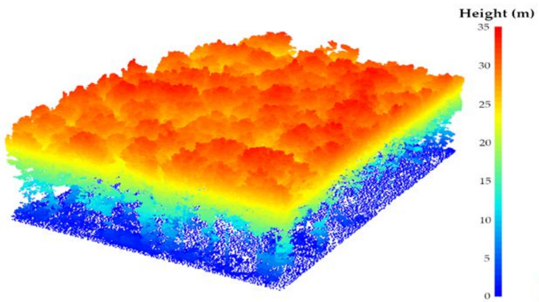
Flux Footprint Prediction (FFP)
(Kljun et al. 2015)

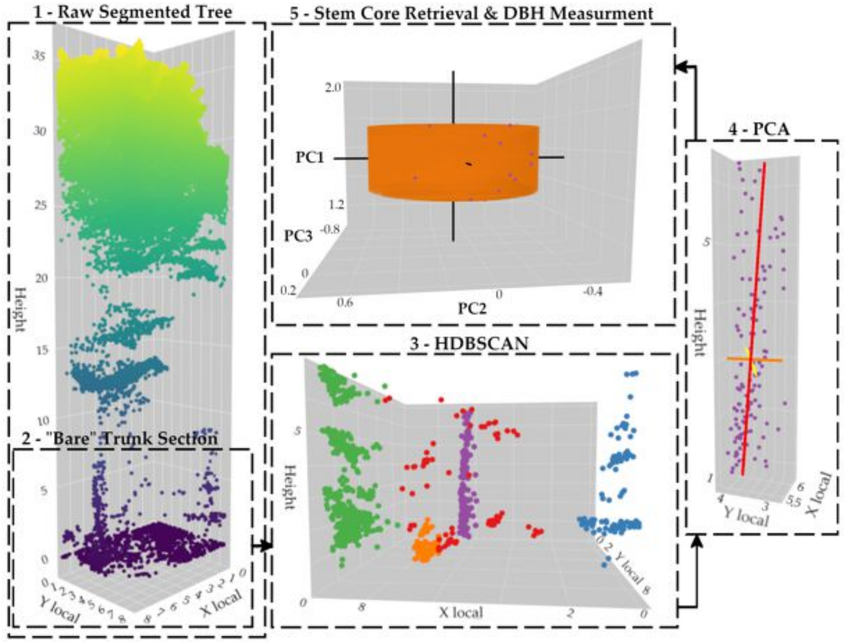


Bates and Jonard, *Remote Sens. Env.*, prep.

UAS Research Activities

4. Assessment of forest structure from UAV-mounted LiDAR point cloud and machine learning





Neuville and Jonard, *Remote Sensing*, 2021

- Diameter at breast height (DBH):
  - 1 – Raw segmented tree
  - 2 – Bole trunk section
  - 3 - Trunk detection & segmentation
  - 4 - Trunk orientation
  - 5 - DBH measurement

UAS Research Activities

5. Monitoring of intra-plot variability of vine water status

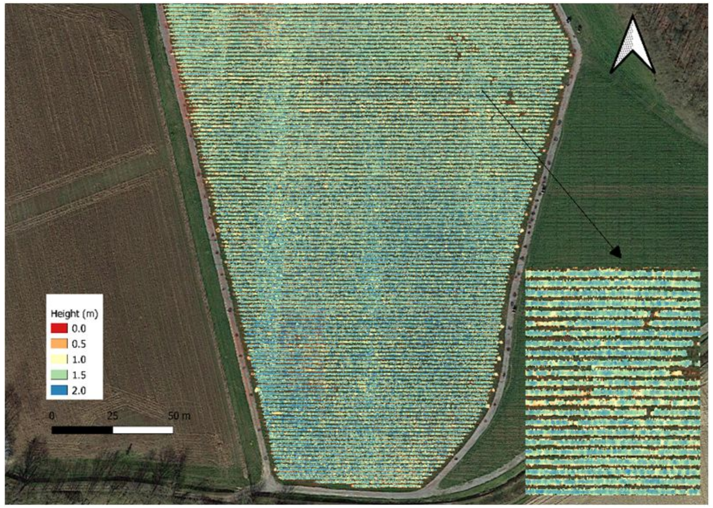
'Château de Bousval' vineyard

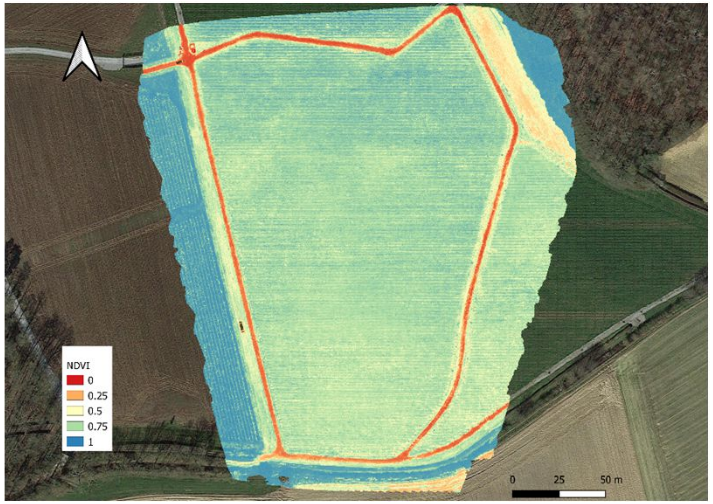
- Correlation between spectral indices or thermal data and in situ leaf water potential measurements

PhD of Louis Delval (2020-2024)

UAS Research Activities

5. Monitoring of intra-plot variability of vine water status

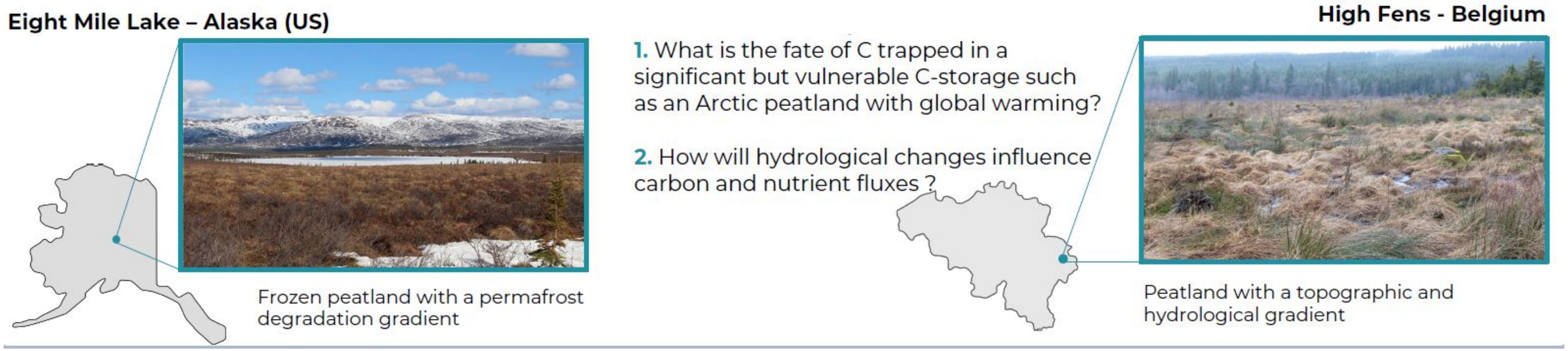




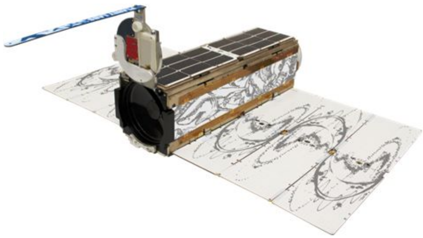
UAS Research Activities

With the degradation of permafrost due to the increase in air temperature in high latitudes, soil organic carbon is becoming more and more vulnerable to mineralization resulting in the reinforcement of the global warming

- UAV-borne remote sensing to characterize a peatland landscape of the Belgian High Fens
  PhD of Yanfei Li (2021-2025)
- Tracking the impact of permafrost thaw on soil hydrology using UAV remote sensing (Alaska)
  PhD of Eléonore du Bois d'Aische (2022-2026)

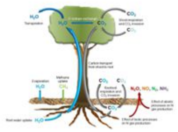


Multi-scale observations to predict carbon, energy and water fluxes

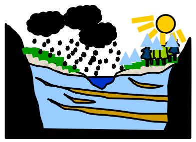


Data fusion

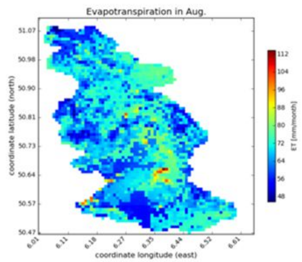
Process understanding



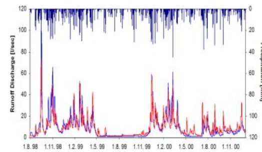
Modelling



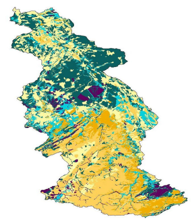
Evapotranspiration



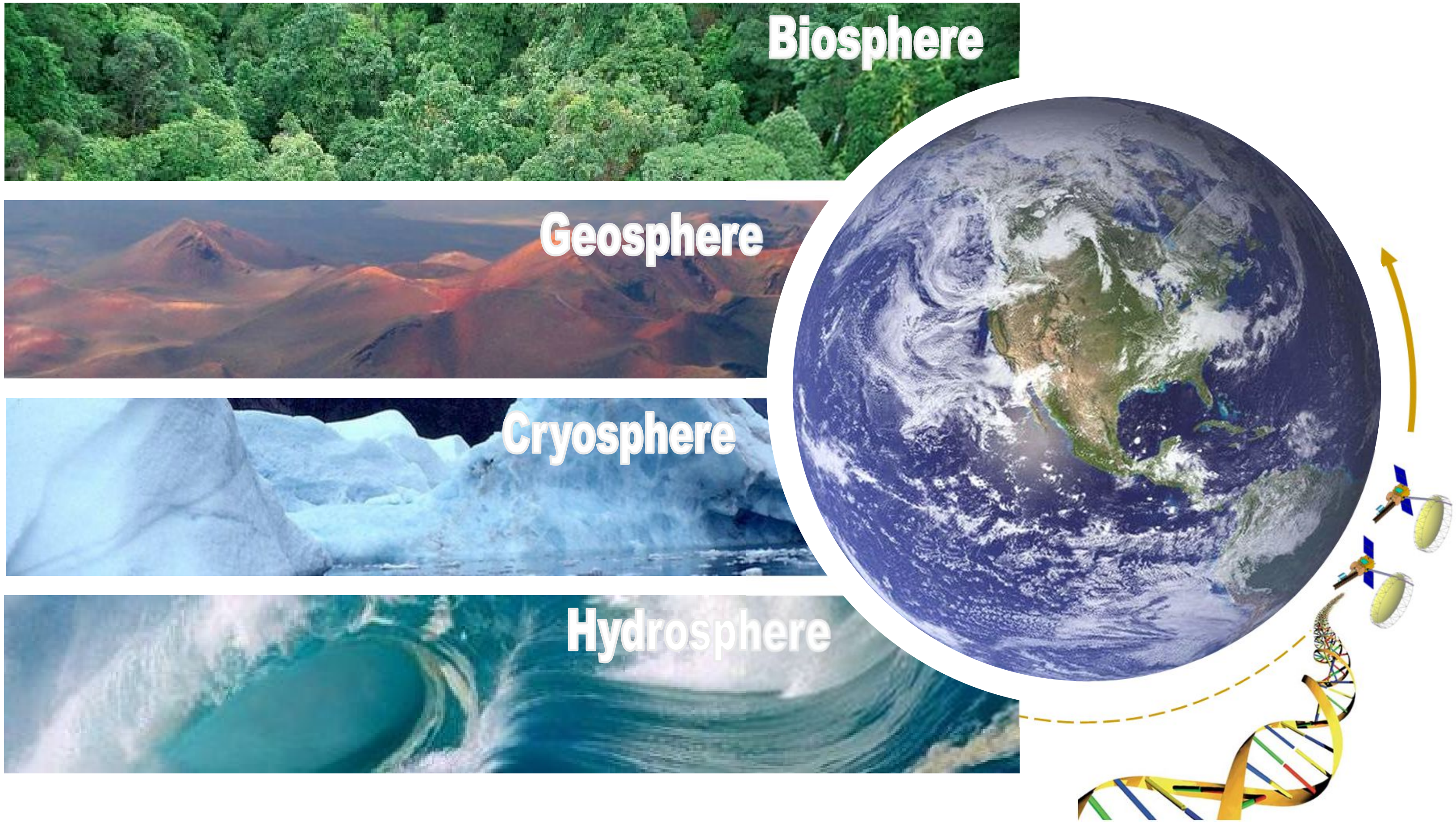
Runoff



GPP / NEE



Predictions



Thank you

PhD in Geomatics (2009-2013)
University of Rome “La Sapienza”

- Satellite Photogrammetry and Radargrammetry for DSM generation
- SAR data processing (i.e. InSAR, orbit correction)
- FOSS (Free and Open Source Software) programming
- Geomatics fundamentals (GNSS; Surveying)

Post-Doc Fellowship (2013-2017)
Geodesy and Geomatics Division at University of Rome “La Sapienza”

- Close range remote sensing (UAV; ToF camera)
- Computer Vision (i.e. SLAM, SfM, DIC)
- Earth Observation big data processing (Google Earth Engine)
- Several geomatics application projects
- Project proposal writing and management

Faculty Researcher (2017-2021)
Geoinformatics division at
KTH Royal Institute of Technology

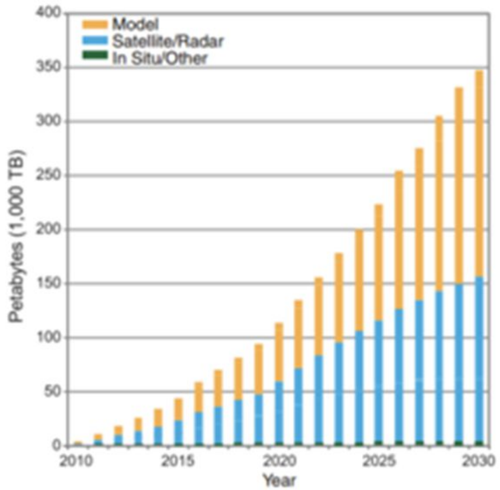
- Multi-spectral satellite image analysis
- Urban & Forest Remote Sensing
- Machine Learning and Deep Learning techniques
- Cloud computing and big data handling (i.e. GCP and AWS)

Andrea Nascetti

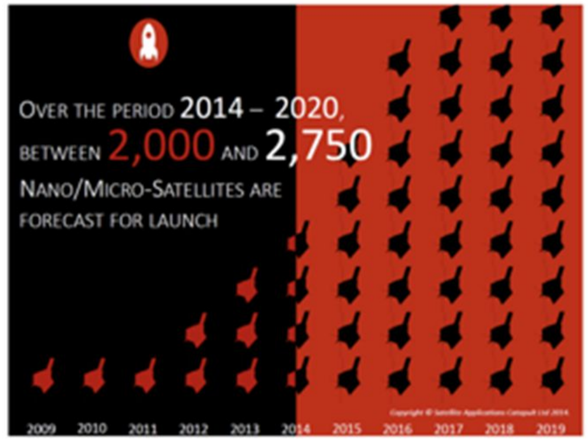
Earth Observation Big Data

Where do we stand on Earth Observation?
Thanks to the fast growth of satellite technology, we are moving forward into a new era of Earth Observation

Both National and International space agencies and innovative companies are supporting various EO programs acquiring huge amounts of data every day



Jonathan T. Overpeck et al, Science 2011



#GeoForGood19

Earth Observation Big Data: Opportunities & Challenges

Opportunities

- Near-real time monitoring of phenomena affecting built and natural environment
- Dense time series for analysis of global environmental changes
- New possibility to deploy operational and reliable services

Challenges

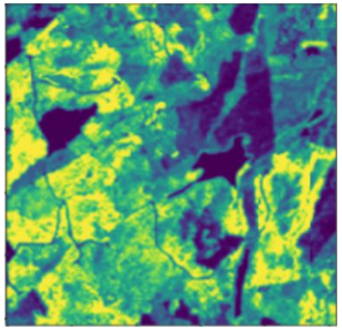
- Deploy innovative computing infrastructure to handle, store and process the data
- Develop new methods and algorithms to extract valuable information
- Integrate the analysis of the EO imagery with other geospatial big data (i.e. social media, ground sensors, crowdsourced data)

Earth Observation Big Data research activities:

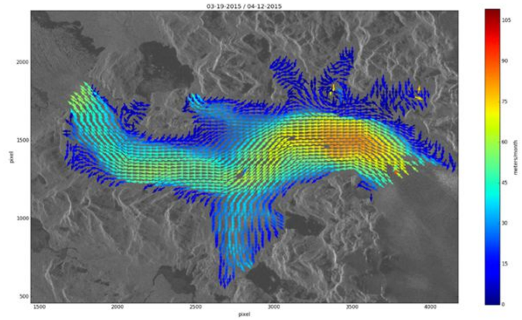
- Develop new methods to exploit both optical and radar dense time series to monitoring global and large-scale phenomena
- 3D information reconstruction using several techniques (photogrammetry, radargrammetry, interferometry)
- Image segmentation and classification using Machine learning and Deep Learning techniques

Applications:

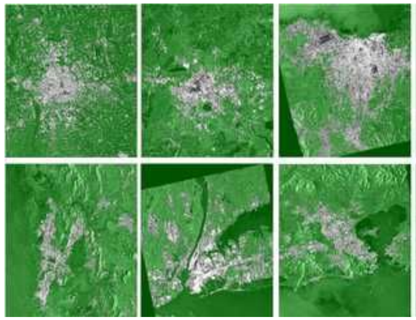
- Land cover mapping
- Urban analysis
- Glacier monitoring
- Emergency Mapping
- Biomass Mapping



Above Ground Biomass Estimation



San Quintin glacier surface velocity map



Urban footprint extraction

Urban Land Cover Classification and Change Detection

My Research Interest

Why Urban Mapping?

-Today, 54% of the world's population lives in urban areas. By 2050, the world is expected to add an additional 2.5 billion urban dwellers.

-SDG Target 11: By 2030, Make cities and human settlements inclusive, safe, resilient and sustainable in all countries:

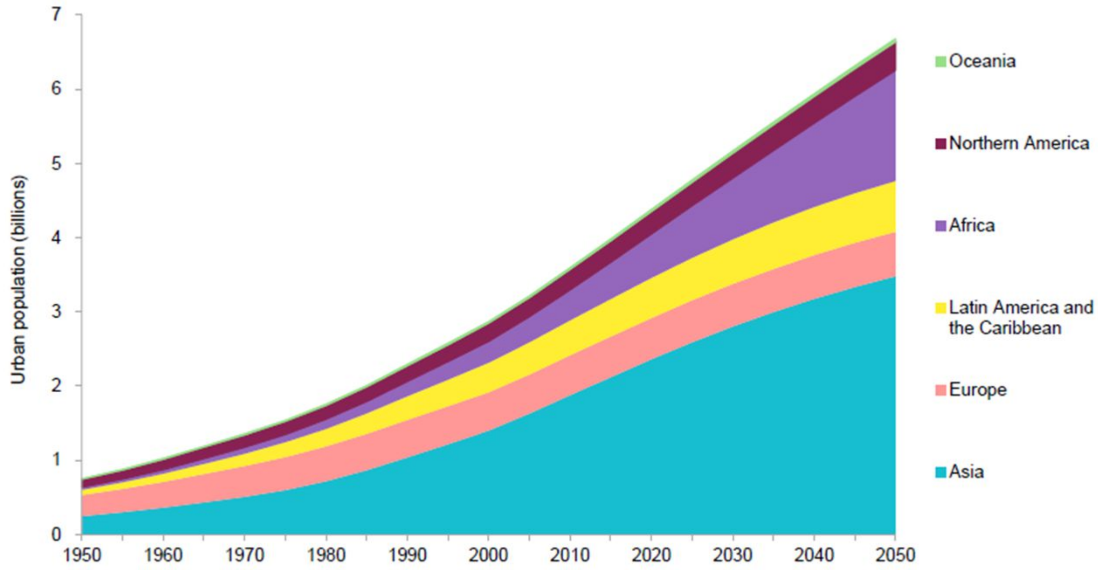
-11.3.1 Ratio of land consumption rate to population growth rate

-11.2.1 Proportion of population that has convenient access to public transport

-11.3.1 Ratio of land consumption rate to population growth rate

-11.6.2 Annual mean levels of fine particulate matter (e.g. PM2.5 and PM10) in cities

-11.7.1 Average share of the built-up area of cities that is open space for public use for all



United Nations, Department of Economic and Social Affairs, Population Division (2019). *World Urbanization Prospects 2018: Highlights* (ST/ESA/SER.A/421).

Urban footprint: products vs global method?

- **DLR Global Urban Footprints (GUF):**
  - global coverage derived from TerraSAR-X data (90% of the data acquired in 2011-2012)
- **DLR World Settlement Footprint (WSF)**
  - Evolution is a 30m resolution dataset outlining the global settlement extent on a yearly basis from 1985 to 2015
- **JRC Global Human Settlement Layer (GHSL):**
  - Global coverage derived from Landsat data (1975,1990,2000,2015)
- **JRC GHS Built-Up:**
  - Global coverage derived from Sentinel-1 data (2019)
- **Urban Layer in GlobeLand30:**
  - Global coverage derived from Landsat data
- **Atlas of Urban Expansion (NYU):**
  - 200 cities global, derived from Landsat data

GROUP ON EARTH OBSERVATIONS

Research Gaps

- Current deep learning frameworks in urban mapping are predominately based on supervised learning
- Lack of investigation on across-region generalization ability of CNNs
- Novel CNN architectures for effective SAR-optical data fusion are required

Research Objective

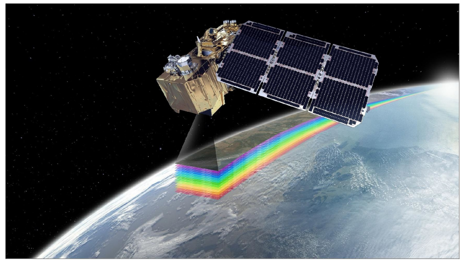
Develop novel and globally applicable methods for urban mapping and urban change detection using Sentinel-1 and Sentinel-2 data fusion.

- Every 6 days
- SAR
- 20 m resolution

ESA
Sentinel-1

- Every 5 days
- Multispectral
- 10-60 m

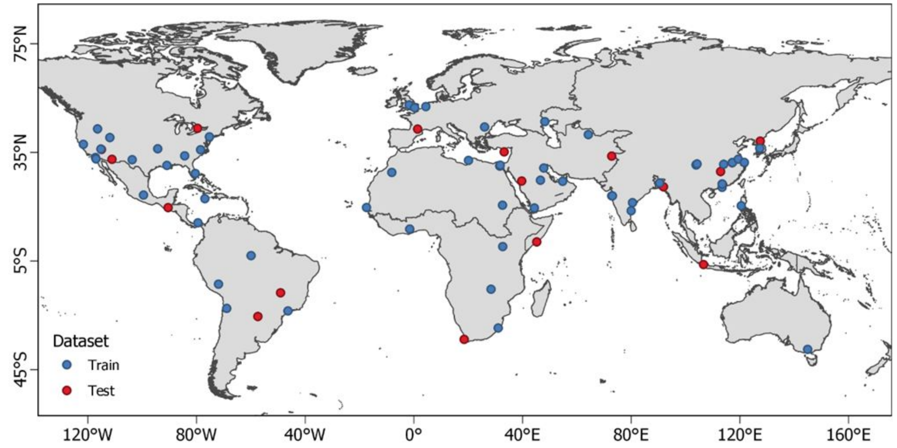
ESA
Sentinel-2



Reference Dataset

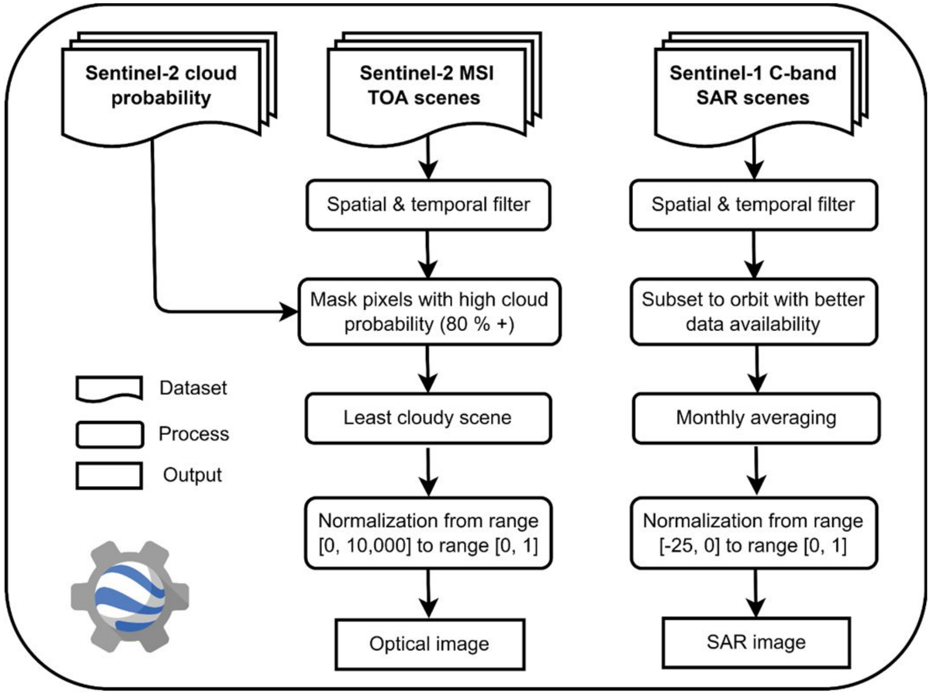
- Time series of monthly Planet images
- Covering ~ 100 unique sites
- Approximately 24 images per site
- Over 10 million individual annotated building footprints

Locations of the SpaceNet 7 training and test sites

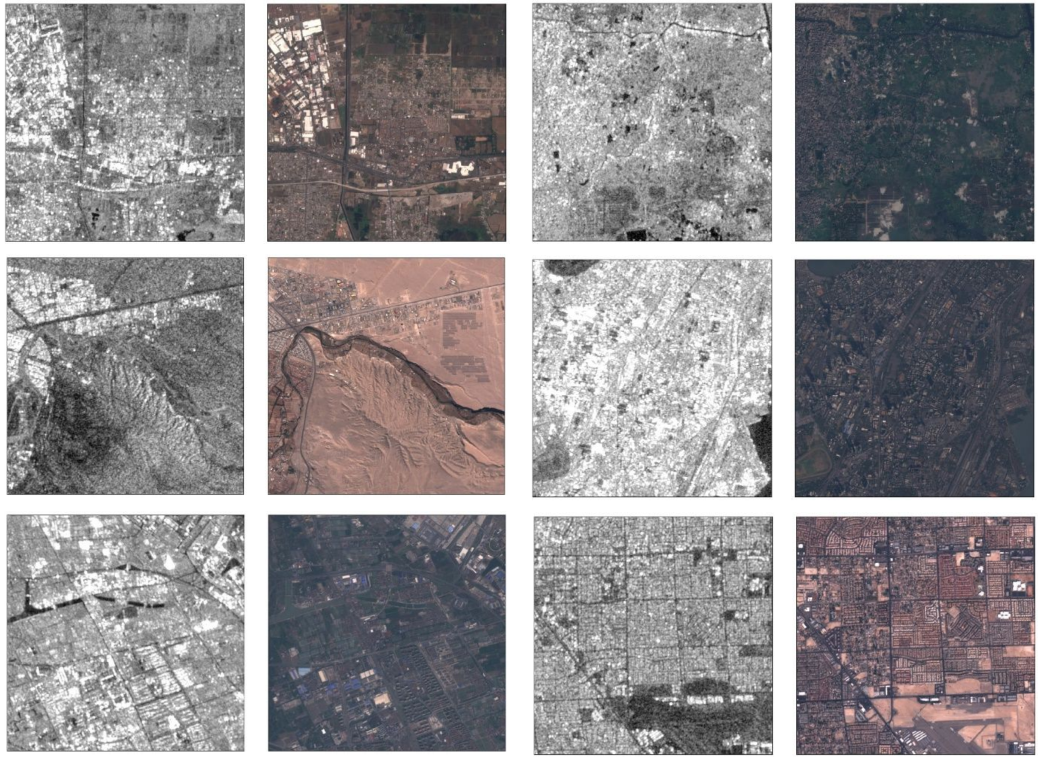


Van Etten, A., Hogan, D., Manso, J.M., Shermeyer, J., Weir, N. and Lewis, R., 2021. The multi-temporal urban development spacenet dataset. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 6398-6407).

Satellite Data Preprocessing

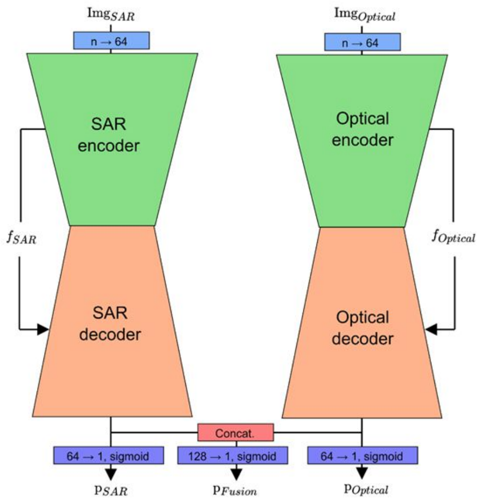


Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D. and Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote sensing of Environment*, *202*, pp.18-27.

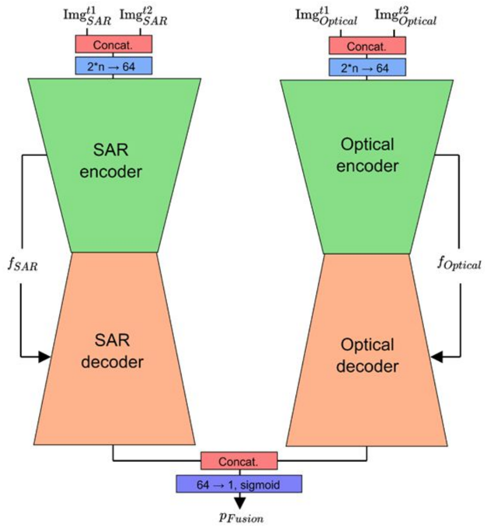


SAR (VV) | Optical (True color) | SAR (VV) | Optical (True color)

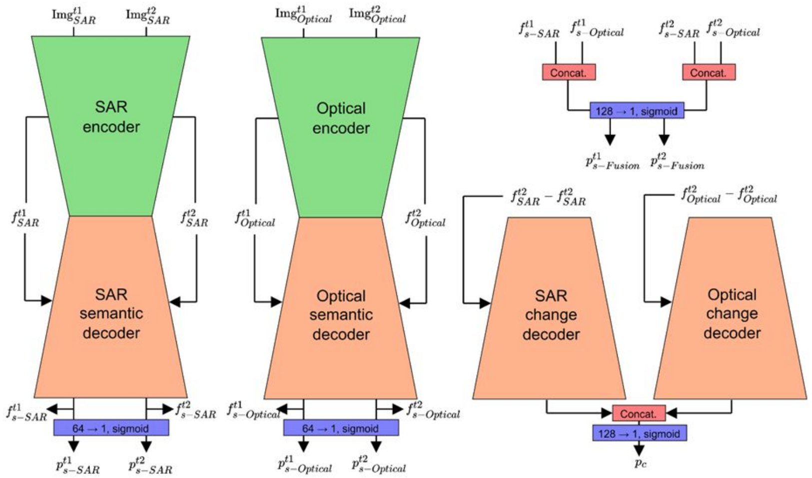
Dual Stream Architectures



Urban mapping



Urban change detection



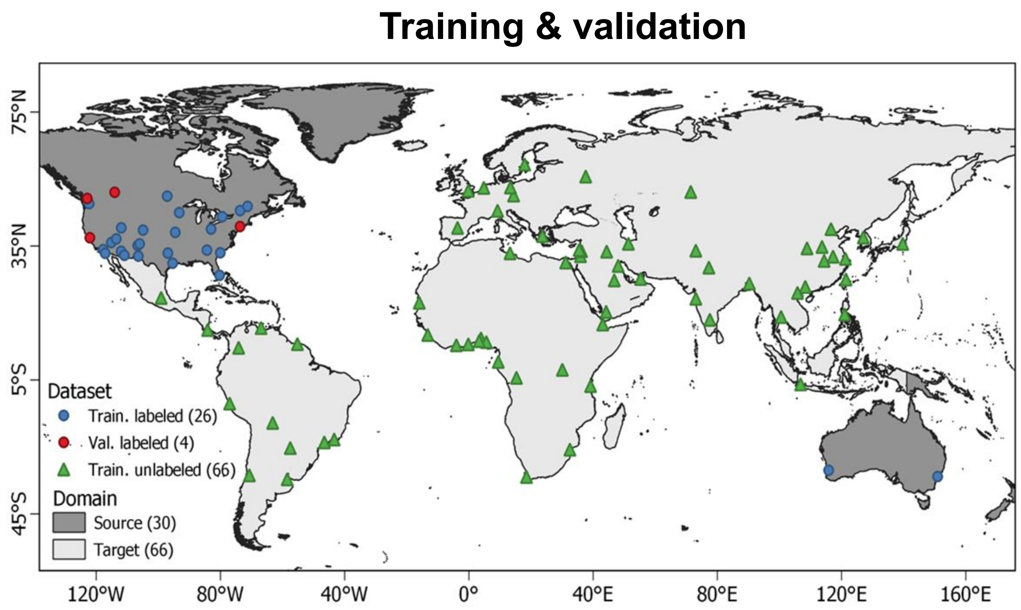
Urban mapping + urban change detection

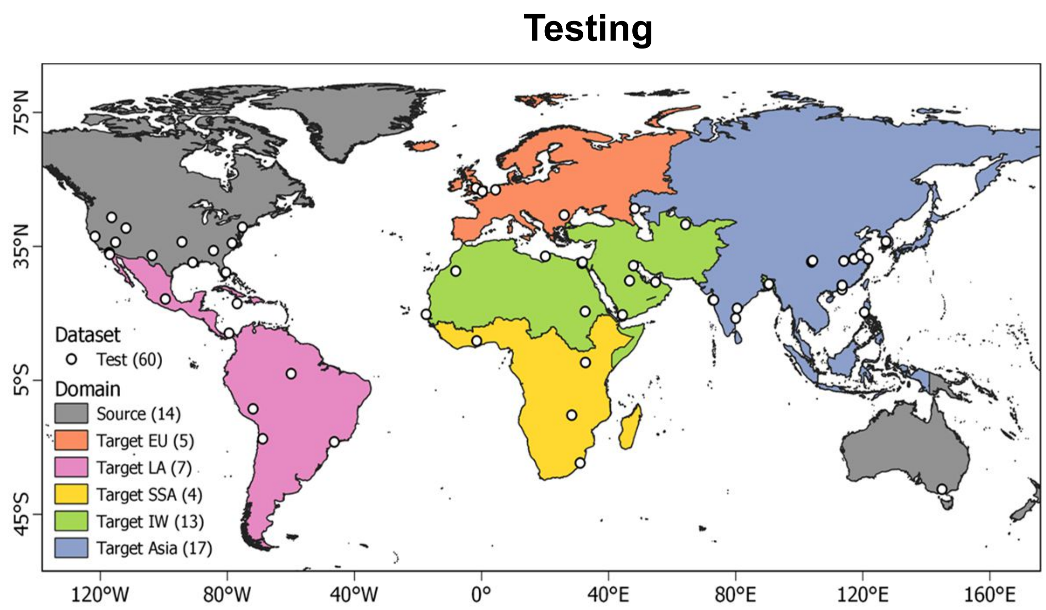
Global Urban Extraction - Dataset

Prepare satellite data and labels

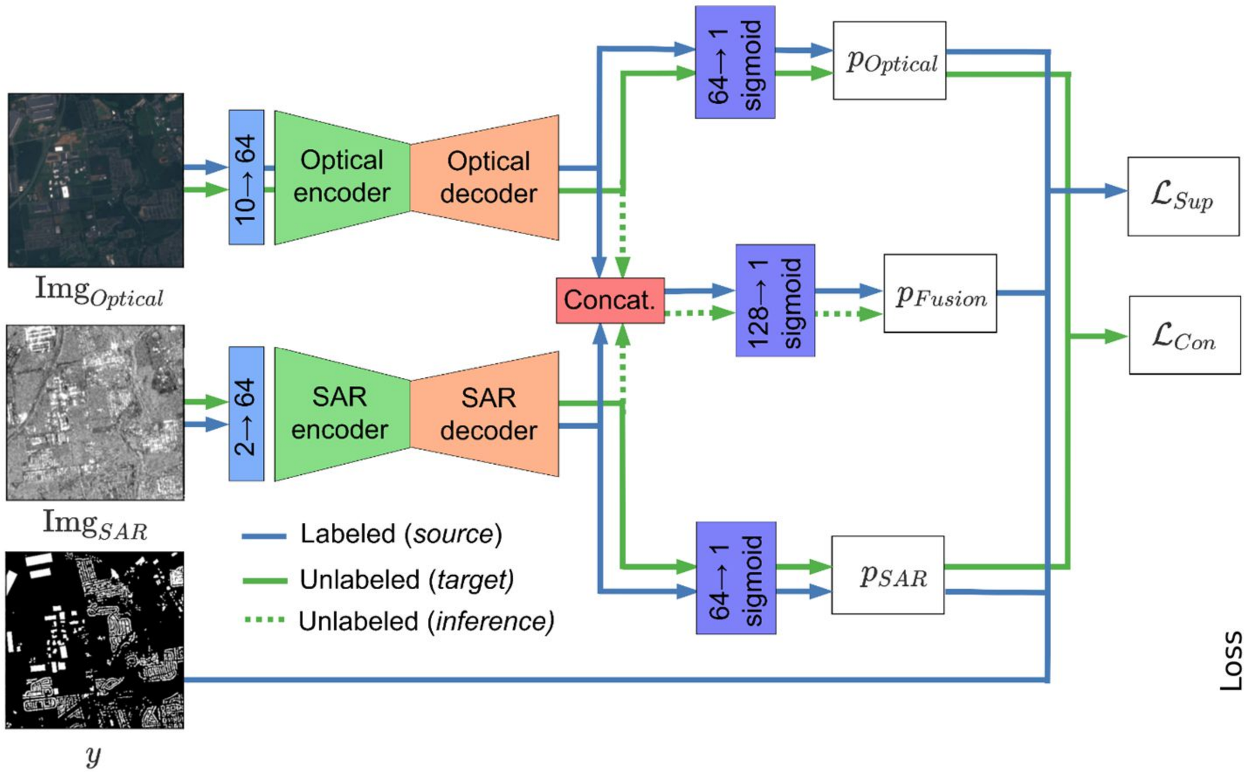
Geographical label availability is limited

-> Domain gap





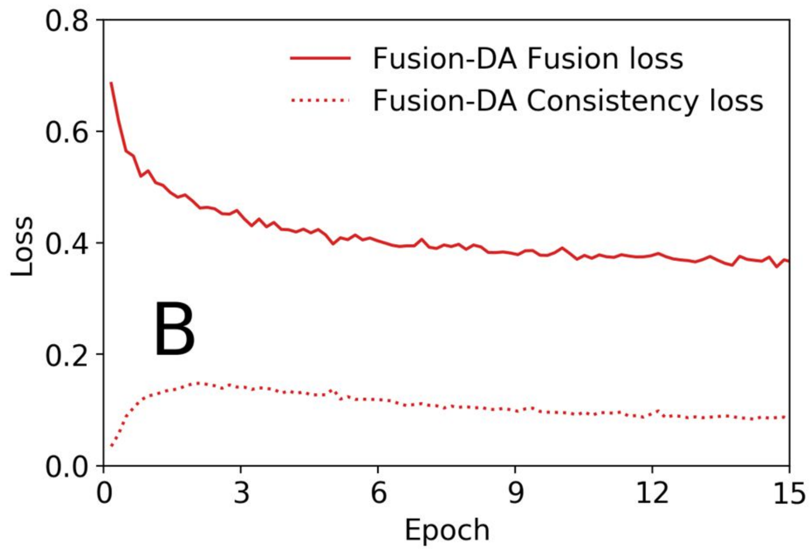
Semi-Supervised Learning



$$\mathcal{L}_{Sup} = \mathcal{L}_{pJacc}(p_{SAR}, y) + \mathcal{L}_{pJacc}(p_{Optical}, y) + \mathcal{L}_{pJacc}(p_{Fusion}, y)$$

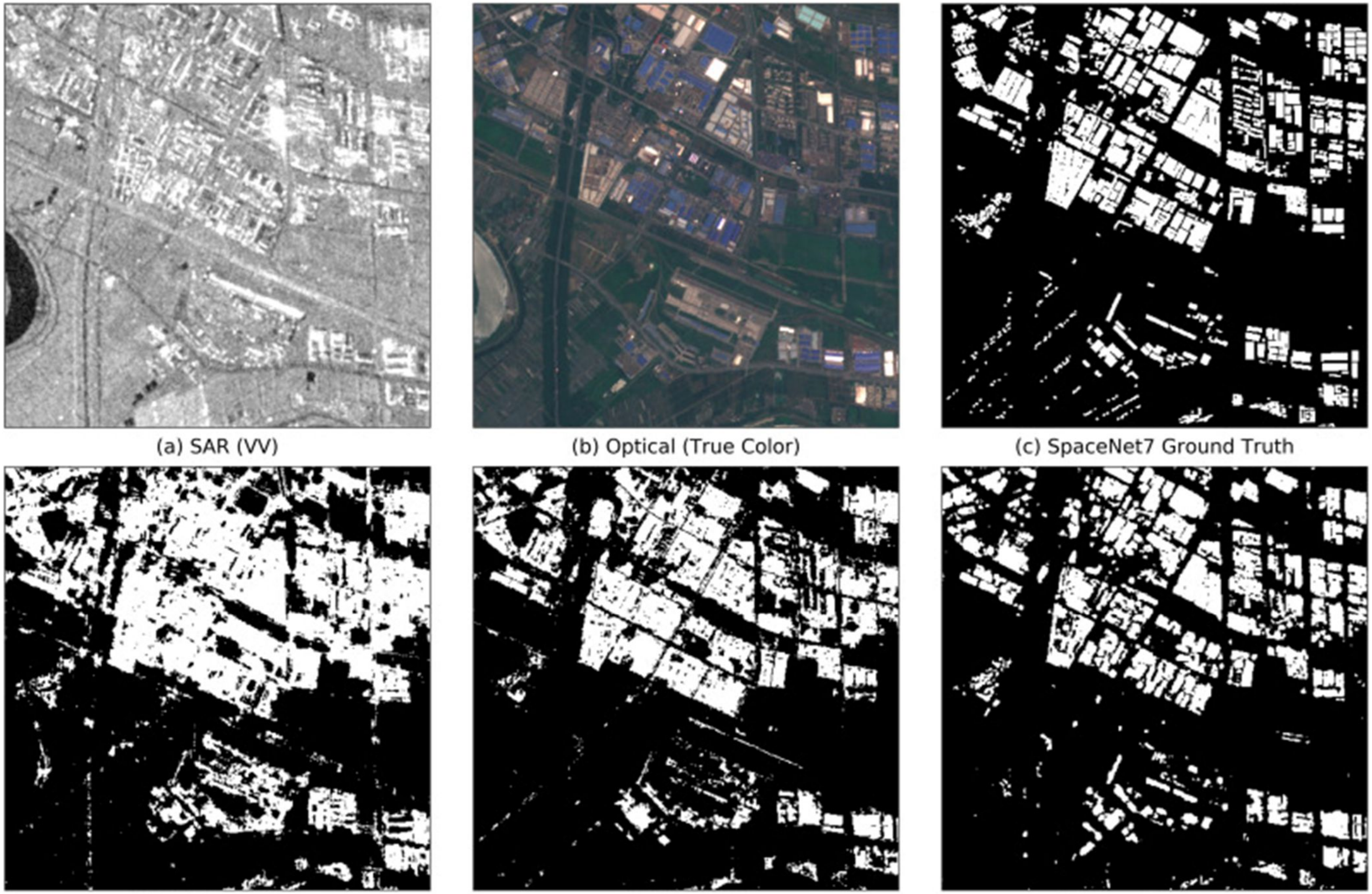
$$\mathcal{L}_{Con} = \mathcal{L}_{pJacc}(p_{Optical}, p_{SAR})$$

$$\mathcal{L}_{sample} = \begin{cases} L_{Sup}, & \text{if } y \text{ exists} \\ \varphi \cdot L_{Con}, & \text{otherwise} \end{cases}$$



Remote Sensing of Environment
Volume 280, October 2022, 113192

Unsupervised domain adaptation for global urban extraction using Sentinel-1 SAR and Sentinel-2 MSI data



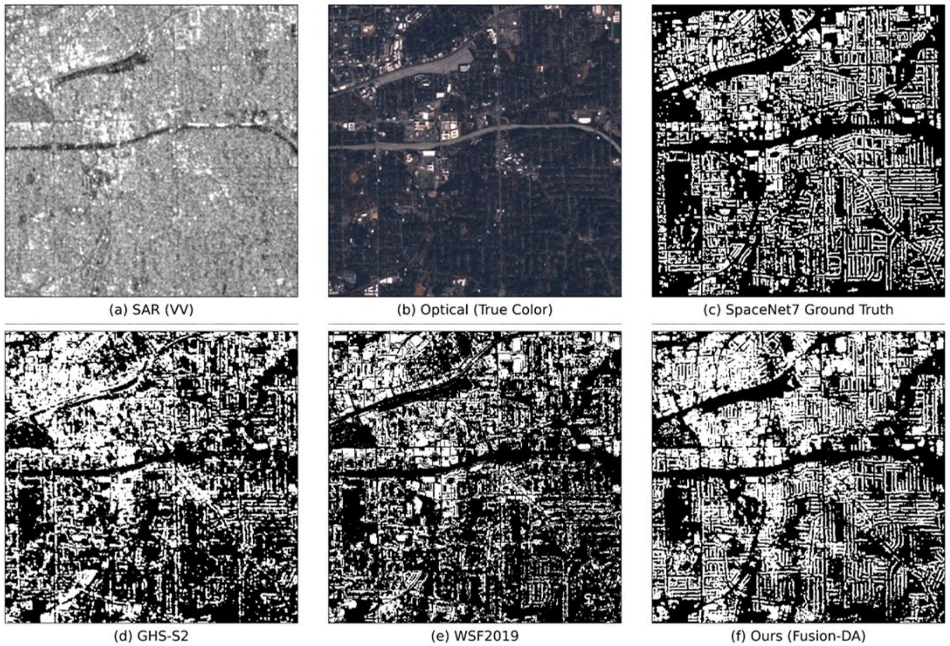
(a) SAR (VV) (b) Optical (True Color) (c) SpaceNet7 Ground Truth

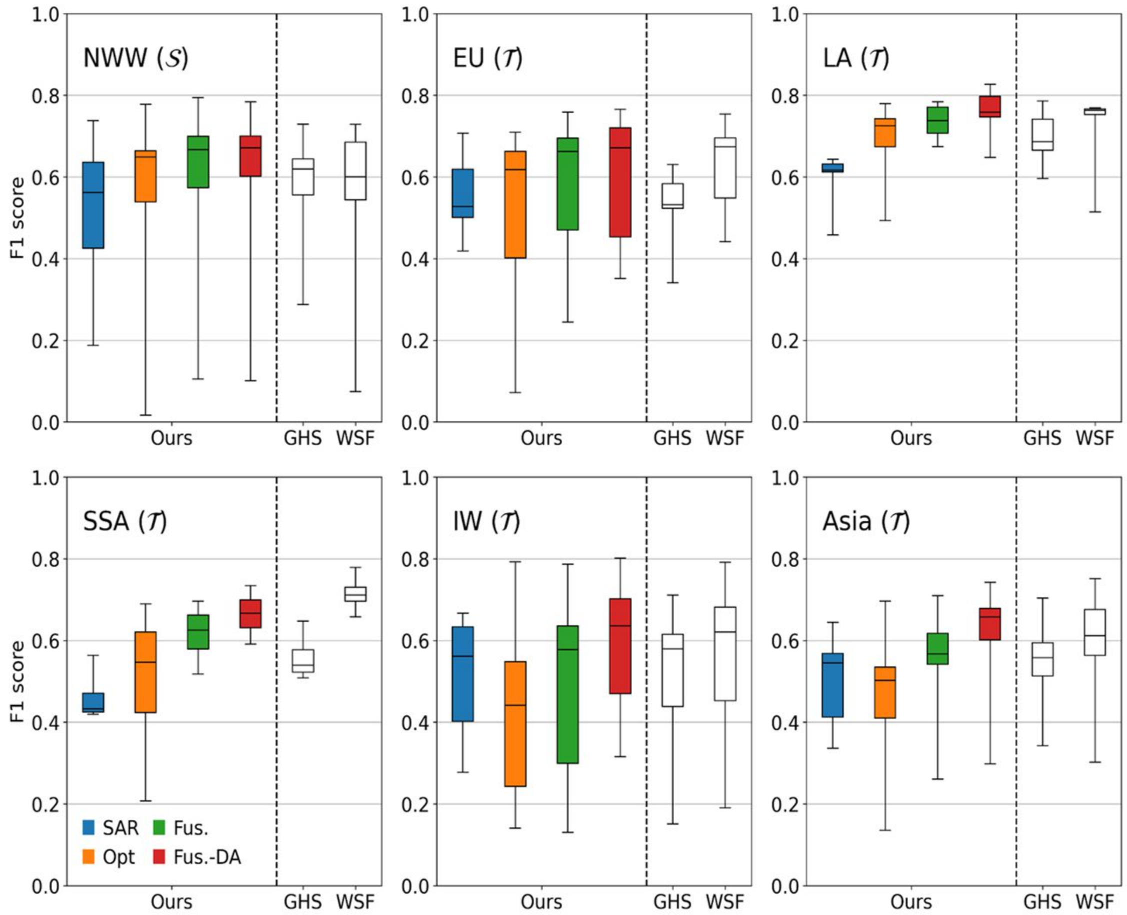
(d) GHS-BUILT-S2 (e) WSF 2019 (f) Ours (Fusion-DA)

Global Urban Extraction - Results

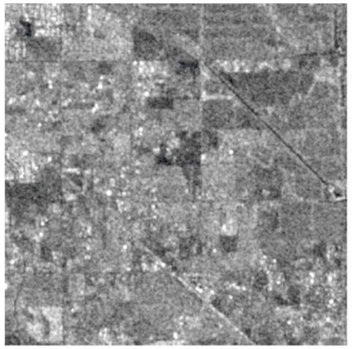
Improved urban mapping compared to fully supervised approaches

Better results than two state-of-the-art global urban products, while using a much simpler methodology



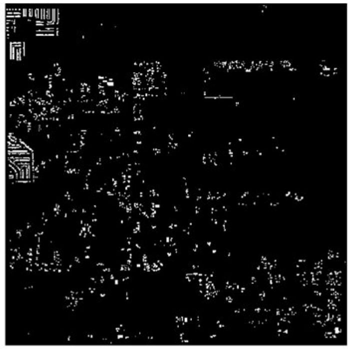


Urban Mapping Results

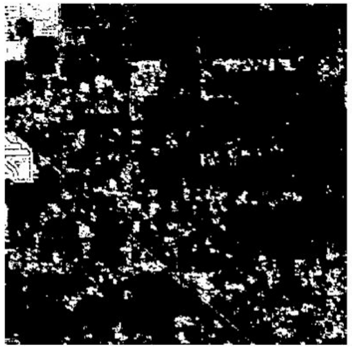


SAR (VV)

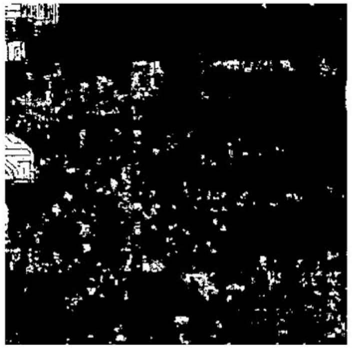
Optical (True Color)



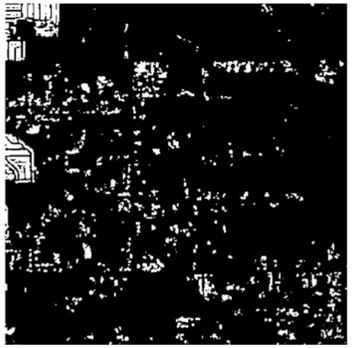
Ground Truth



GHS-S2



WSF2019



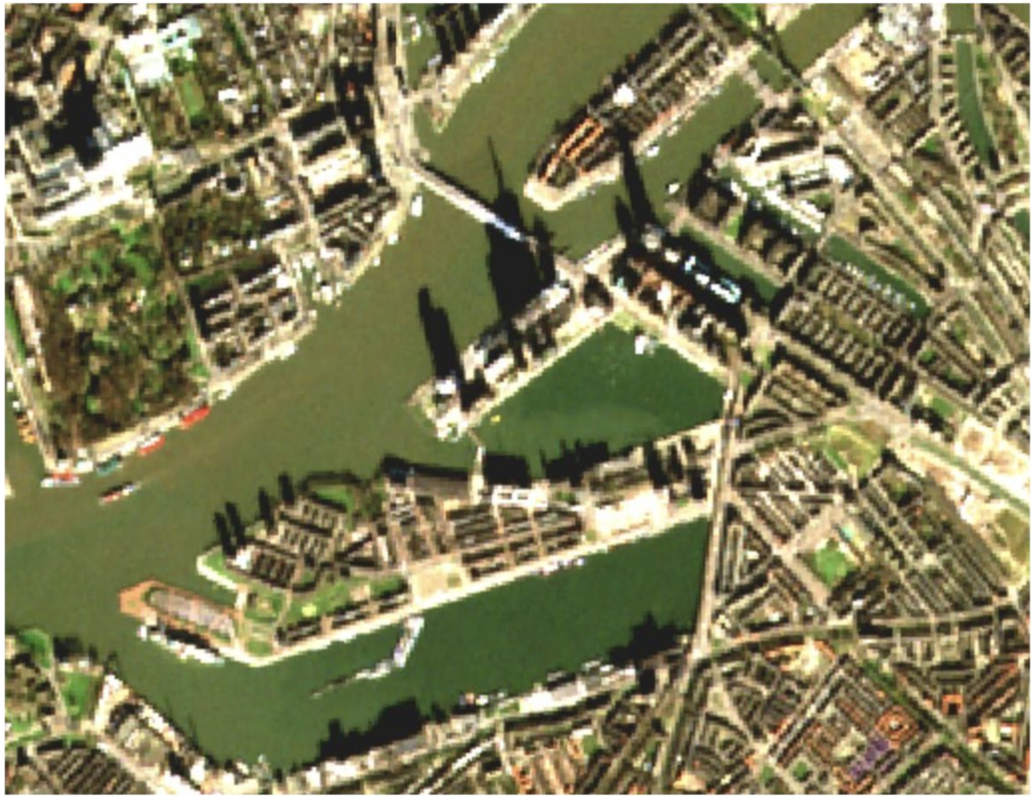
Ours

	F1 score	Precision	Recall
SAR	0.570 ± 0.041	0.576 ± 0.048	0.571 ± 0.064
Optical	0.587 ± 0.077	0.697 ± 0.044	0.520 ± 0.115
Fusion	0.654 ± 0.052	$\mathbf{0.707 \pm 0.036}$	0.613 ± 0.082
Fusion-DA	$\mathbf{0.692 \pm 0.039}$	0.661 ± 0.043	0.728 ± 0.043
GHS-S2	0.591 ± 0.068	0.485 ± 0.083	$\mathbf{0.767 \pm 0.033}$
WFS2019	0.680 ± 0.042	0.652 ± 0.063	0.718 ± 0.059

- Semi-supervised learning (domain adaptation) performs better than supervised learning
- Our method achieves results with comparable or even better quality than the state-of-the-art

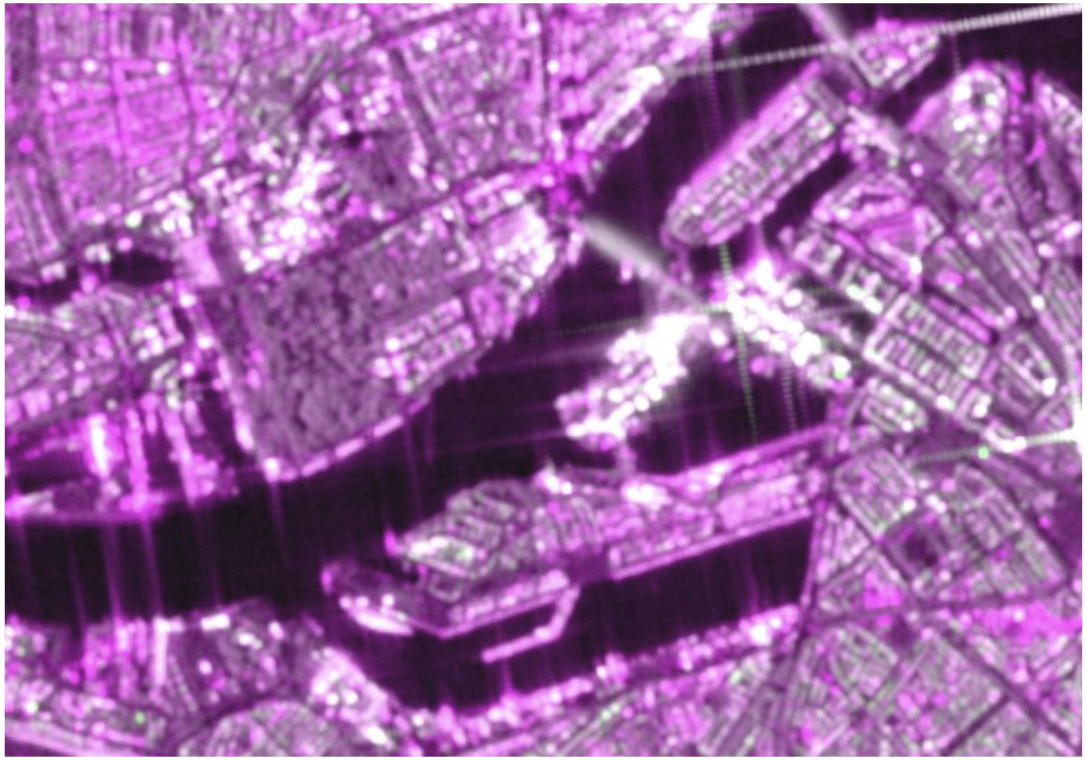
Rotterdam S2 Summer image (B4,B3,B2)

Rotterdam S2 Winter image (B4,B3,B2)

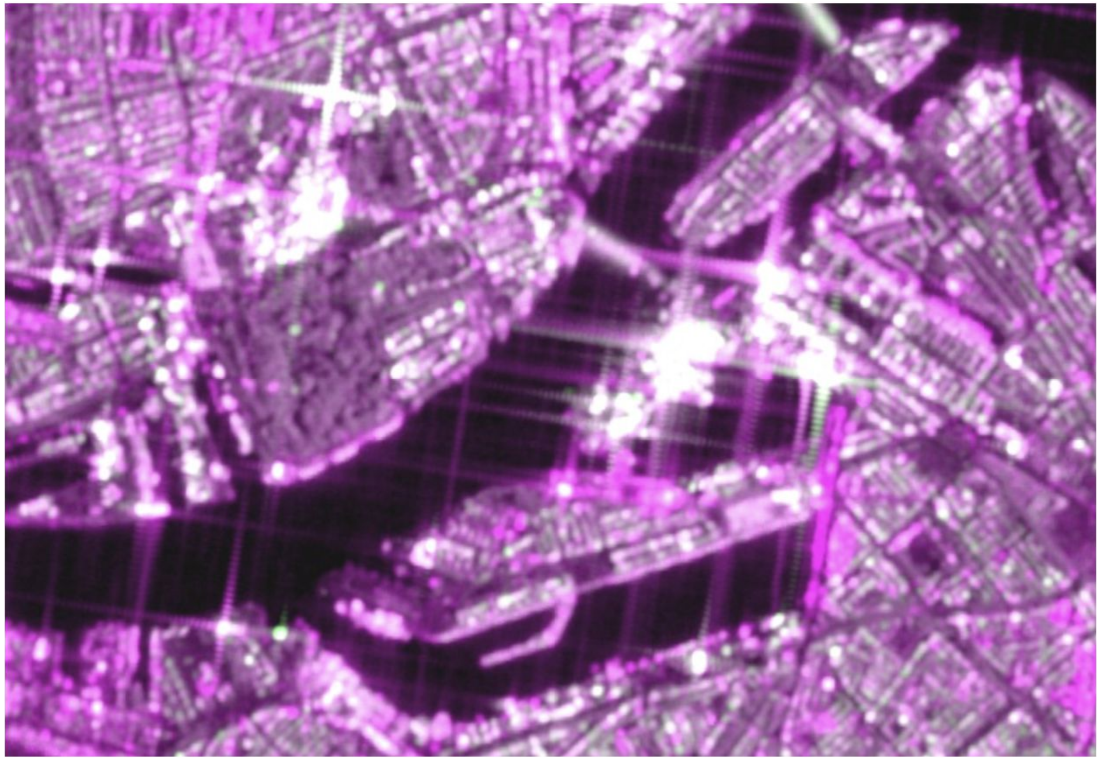


How can we measure building height?

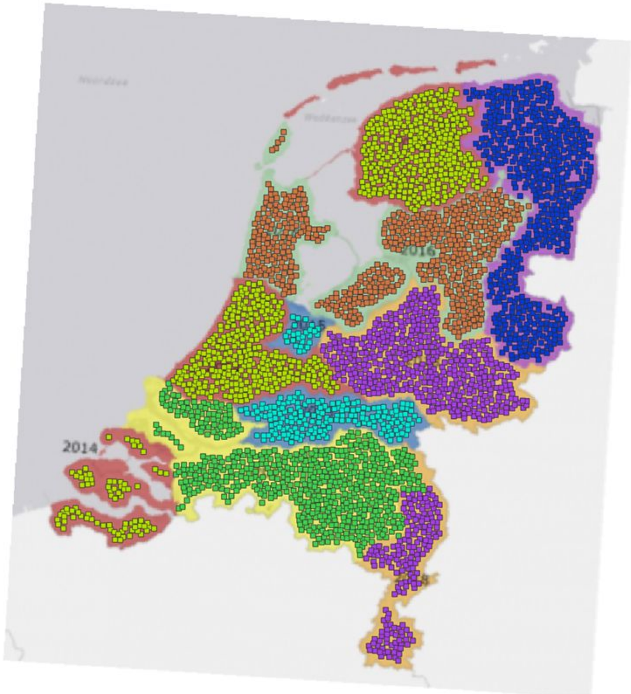
Rotterdam S1 Ascending image (VV,VH,VV)



Rotterdam S1 Descending image (VV,VH,VV)

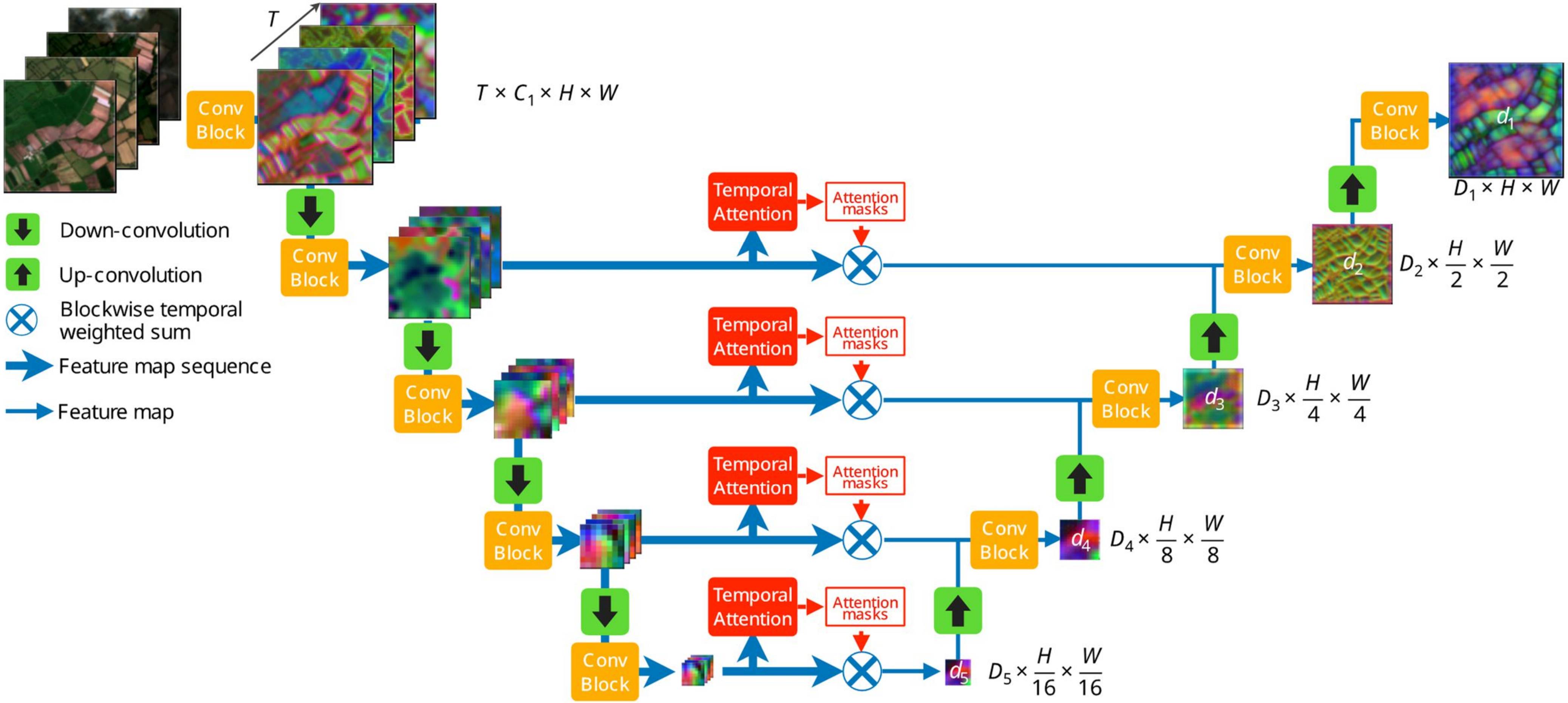


How can we measure building height?

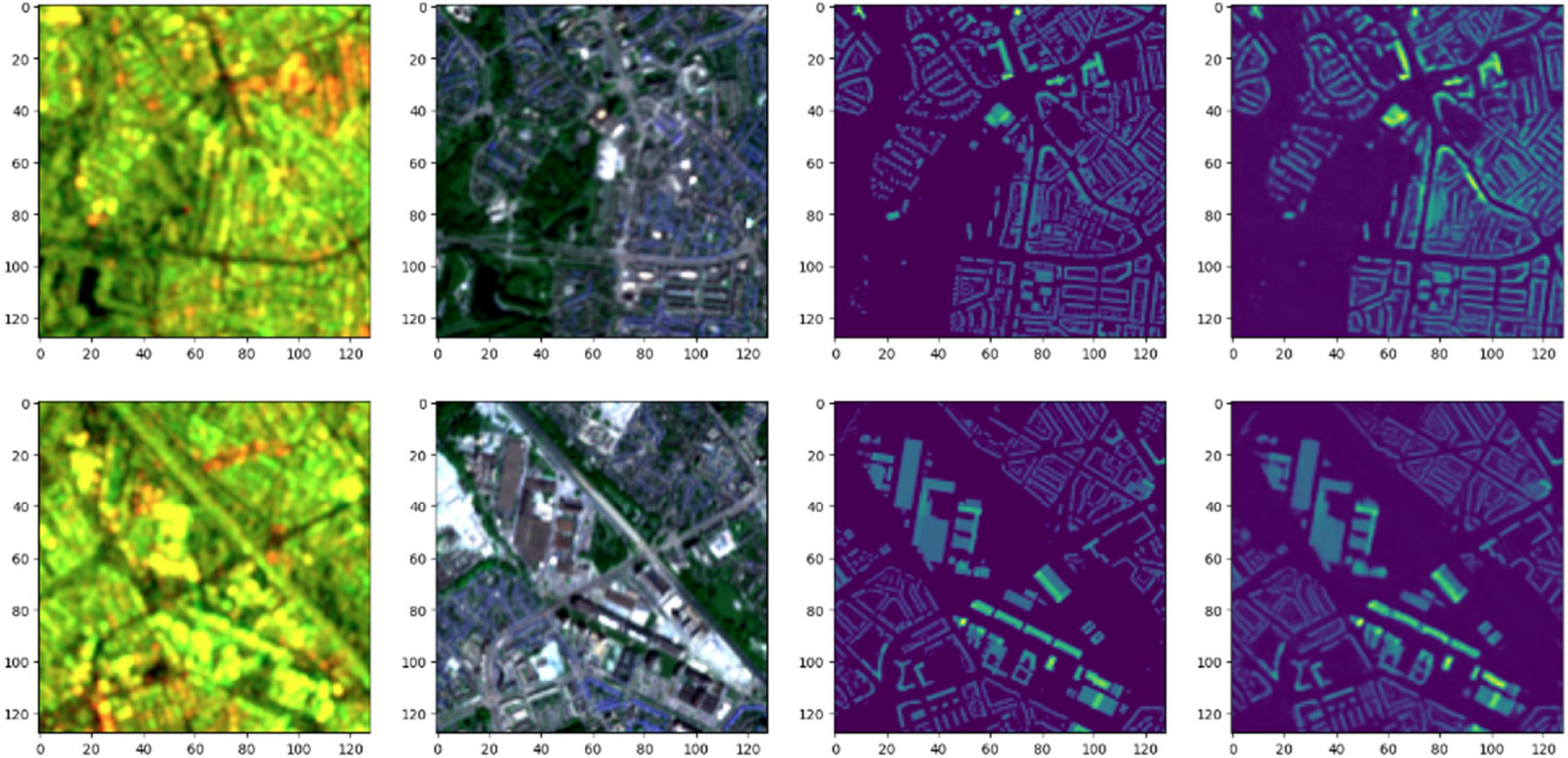


- AHN Lidar reference data available in Netherland
- 5000 buildings heights reference patches

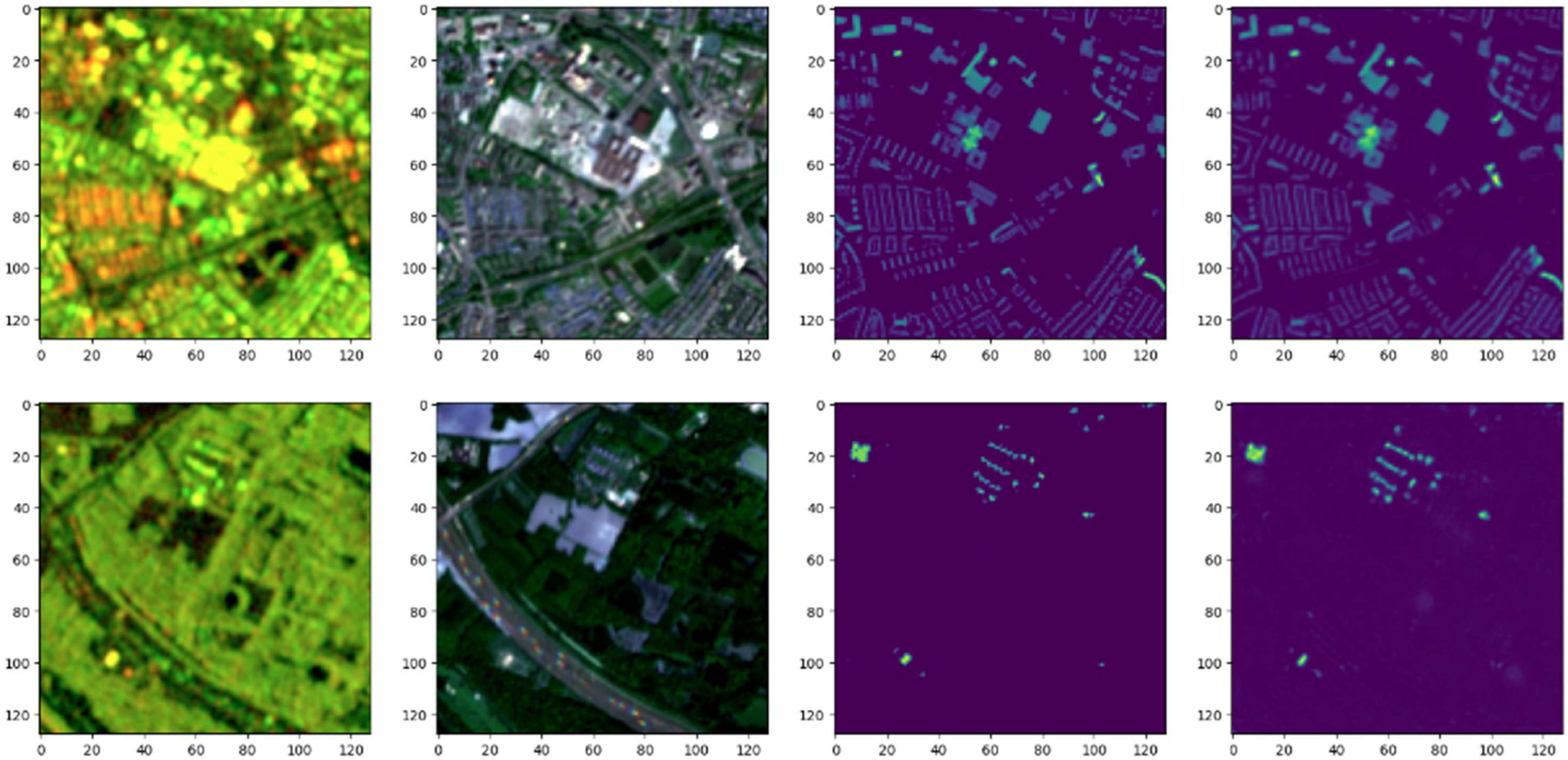
Reference Data



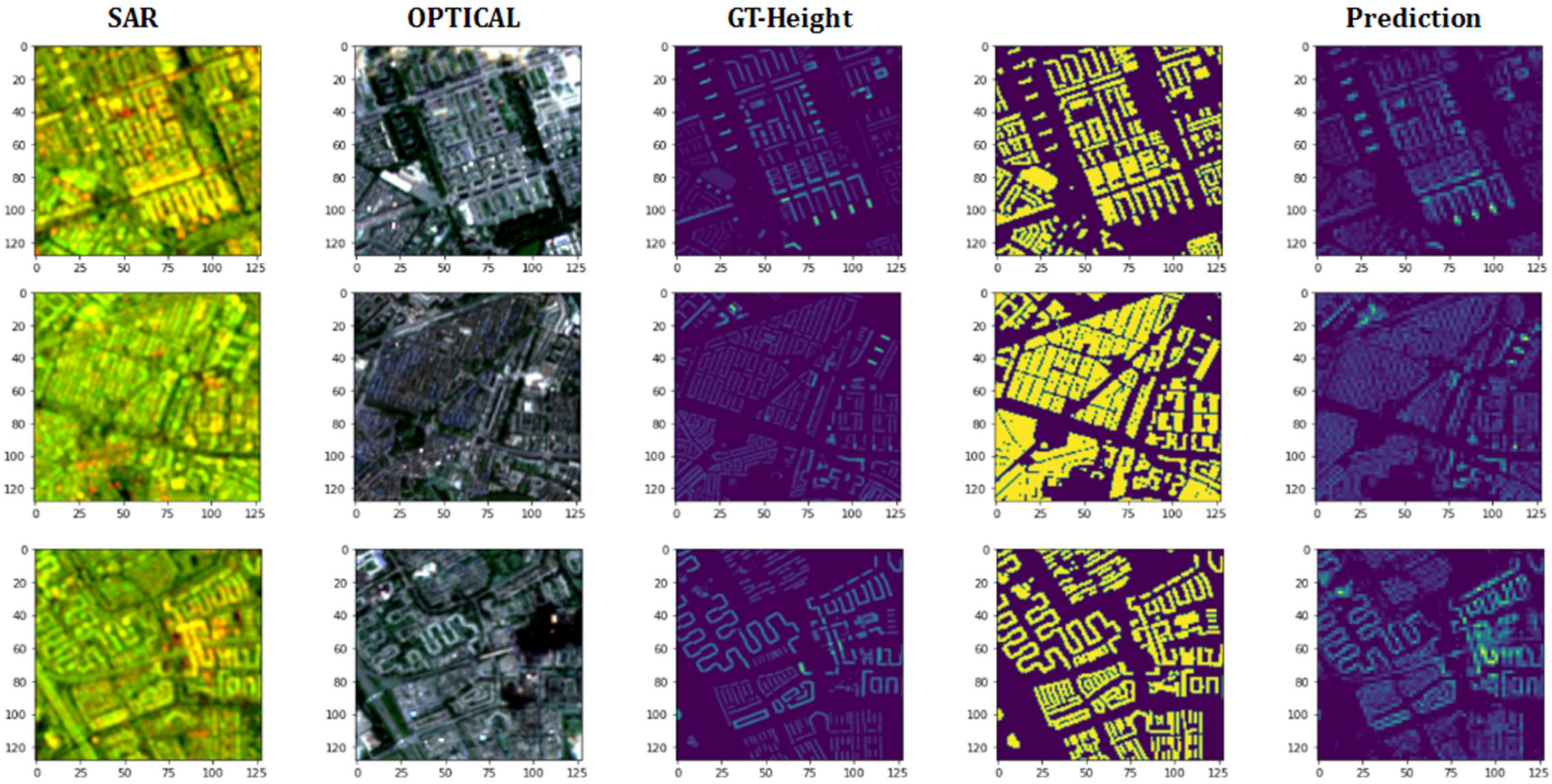
The first model...



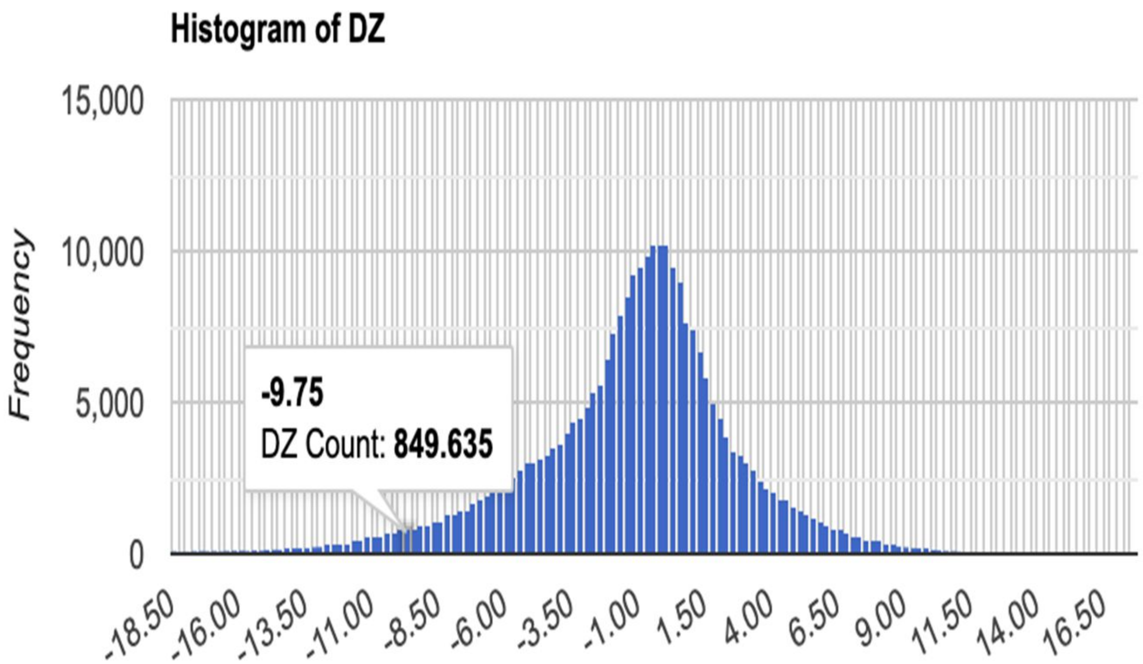
Results



Results



Results



Mean (m):
-1.1801954914714592

Std (m):
4.105660205200064

Median (m):
-0.6248469635226531

LE 68 range (m):
-4.8727666020740985
2.1236163447576804

F1:
0.9259512091595514

Precision:
0.9217748597712357

Recall:
0.9301655749439619

Change Detection Results

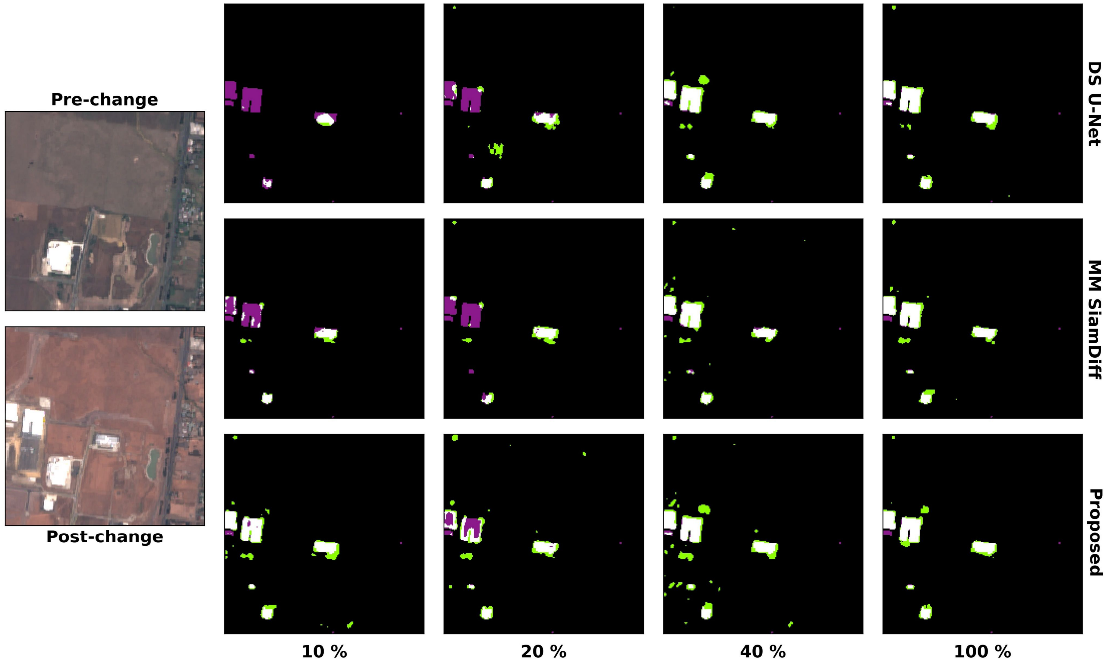


Table 1: Quantitative CD results under different label fraction conditions. Values were obtained on the test set. The best and second-best performance is highlighted in red and blue, respectively.

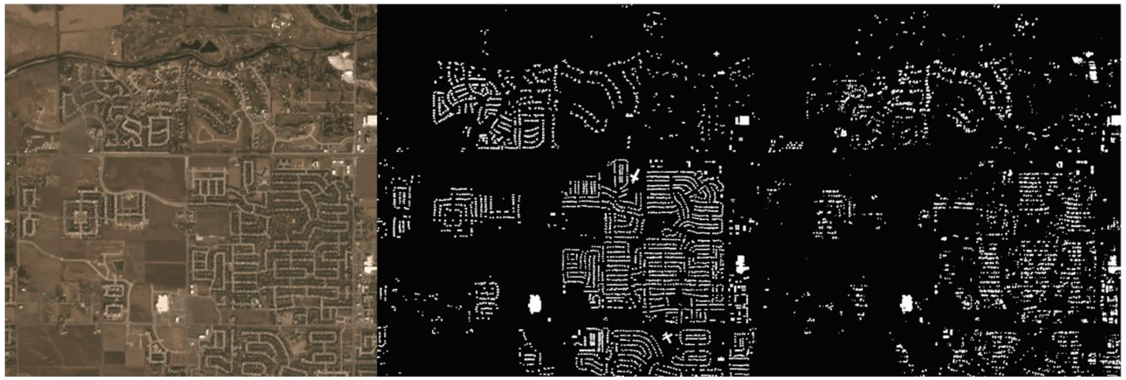
Input	Network	Fraction of the labeled training set used							
		10 %		20 %		40 %		100 %	
		F1	IoU	F1	IoU	F1	IoU	F1	IoU
S1	U-Net EF	0.291	0.170	0.339	0.204	0.357	0.217	0.363	0.222
	Siam-Diff	0.182	0.100	0.368	0.226	0.359	0.219	0.410	0.25
	Siam-Diff DT	0.267	0.154	0.341	0.206	0.363	0.222	0.414	0.261
S2	U-Net EF	0.266	0.153	0.429	0.273	0.466	0.303	0.520	0.351
	Siam-Diff	0.347	0.210	0.447	0.288	0.522	0.353	0.522	0.353
	Siam-Diff DT	0.350	0.212	0.459	0.298	0.484	0.319	0.551	0.380
S1S2	DS U-Net	0.309	0.183	0.397	0.248	0.522	0.354	0.559	0.388
	MM Siam-Diff	0.383	0.237	0.458	0.297	0.500	0.333	0.554	0.383
	Proposed	0.491	0.325	0.501	0.335	0.537	0.367	0.555	0.384

- Good urban change detection results, even when labeled training data is scarce

Future Work

Multi-temporal urban mapping with temporal consistency:

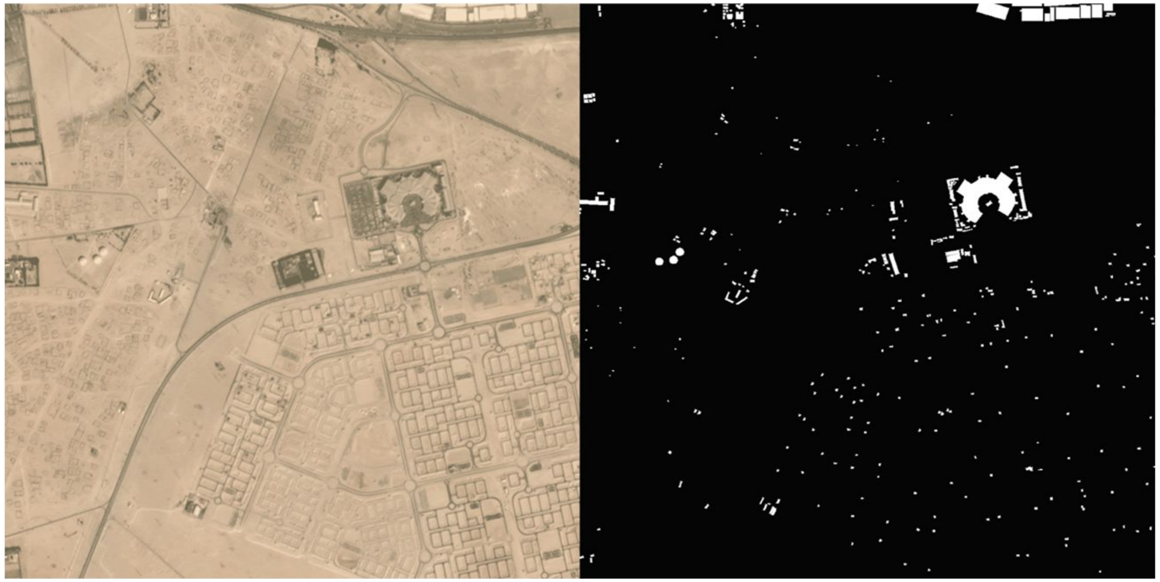
- Transfomer-based model
- Temporal consistency loss



Satellite image | Buildings (Ground Truth) | Model output

Change Detection

- **Identify** and **quantify differences** between two or more images collected at different timepoints or under different conditions



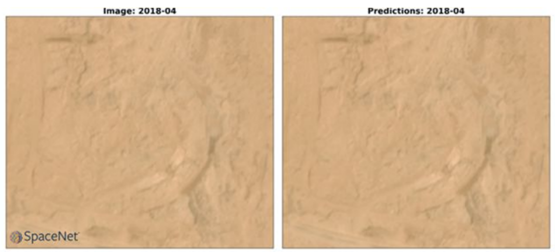
Change Detection

Bi-temporal Change Detection

- Pre and post images (2)
- Detect (abrupt) changes between two dates over matter of days to months to years
- Image differencing, thresholding, segmentation algorithms
- Disaster damage assessment, landcover changes, deforestation

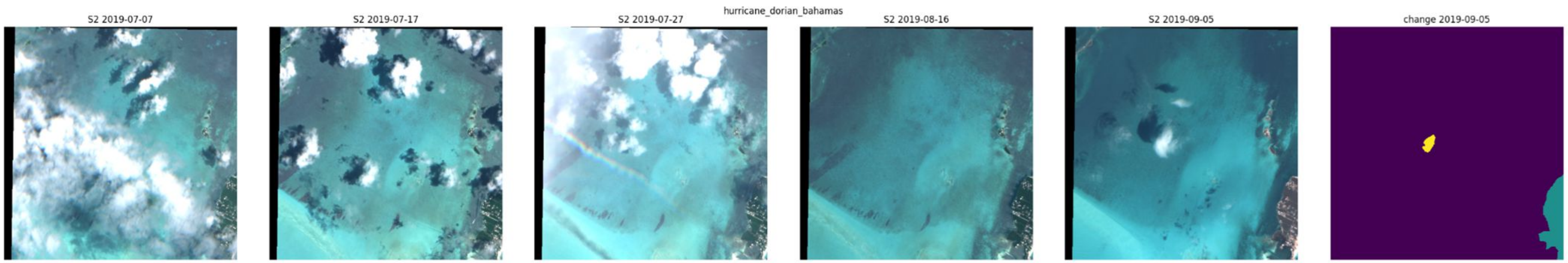
Multi-temporal Change Detection

- Multiple images (> 2)
- Identify long-term trends and (gradual) patterns over several years to decades
- Time-series analysis, probabilistic modeling, PCA algorithms
- Disaster response, urban expansion, vegetation changes, climate change



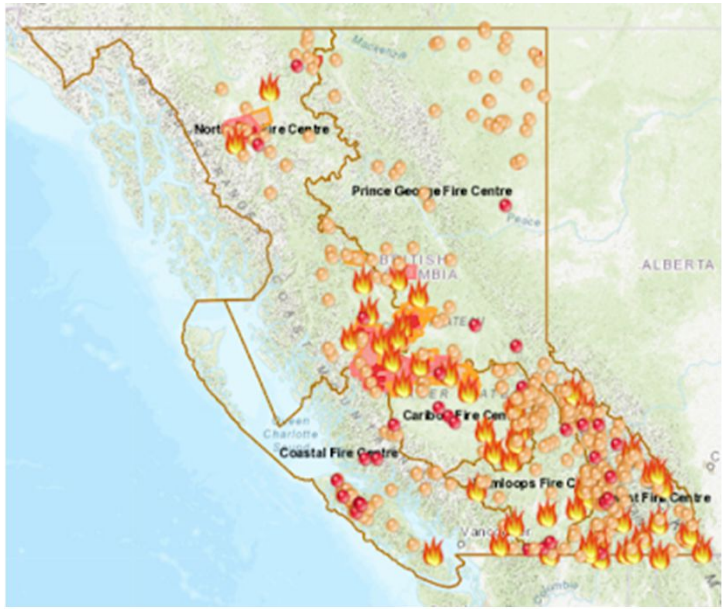
Irrelevant and Relevant Changes

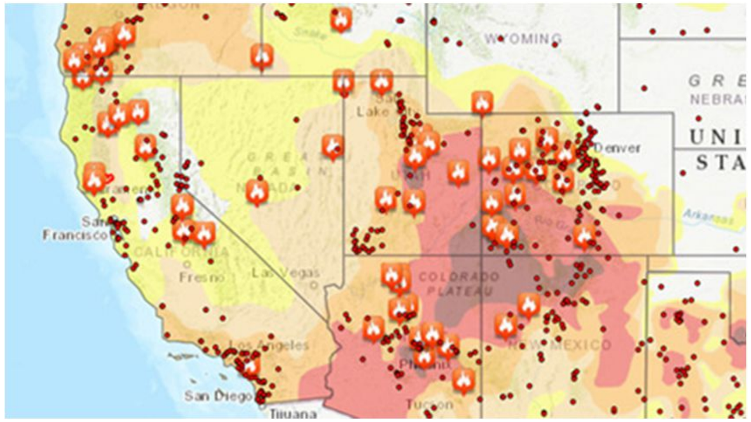
- Irrelevant Changes
  - Any natural/recurring/anticipated changes that we are not interested in
  - Seasonal changes, cloud obstruction, viewpoint shift, …
- Relevant Changes
  - Any known or unknown events that we are potentially interested in detecting
  - Disaster response, urban expansion, …



Wildfires...

- Cost millions or billions of dollars to fight
- Can cause damage to infrastructure and environment
- Lack of information to predict and monitor fire progression





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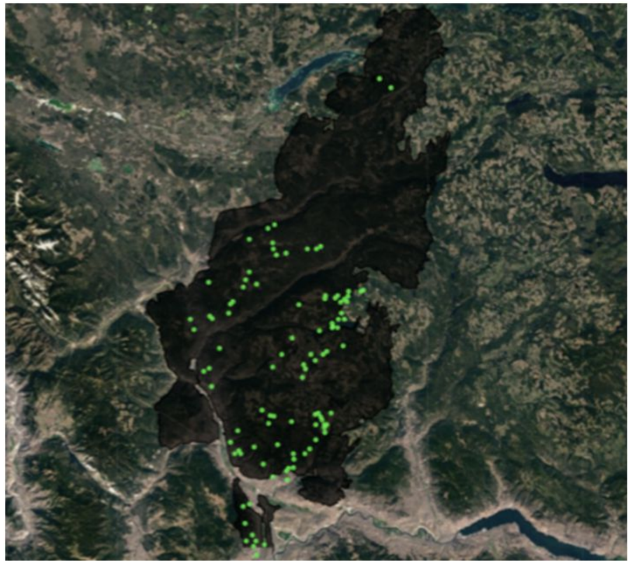
Remote Sensing for wildfire monitoring

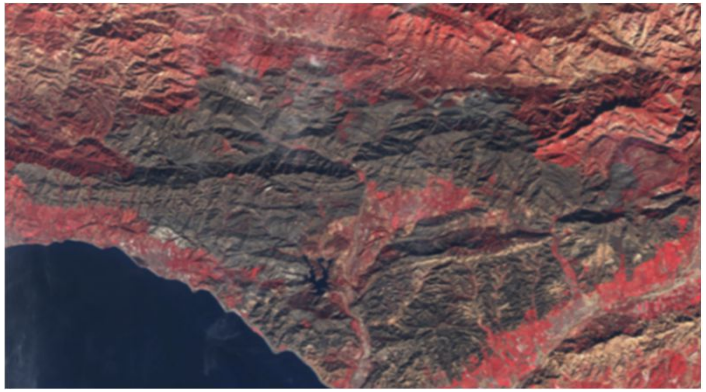
Active wildfire monitoring

- Moderate Resolution Imaging Spectroradiometer (MODIS) Active Fire maps are often used for contextual awareness



Fire scar & burn severity mapping

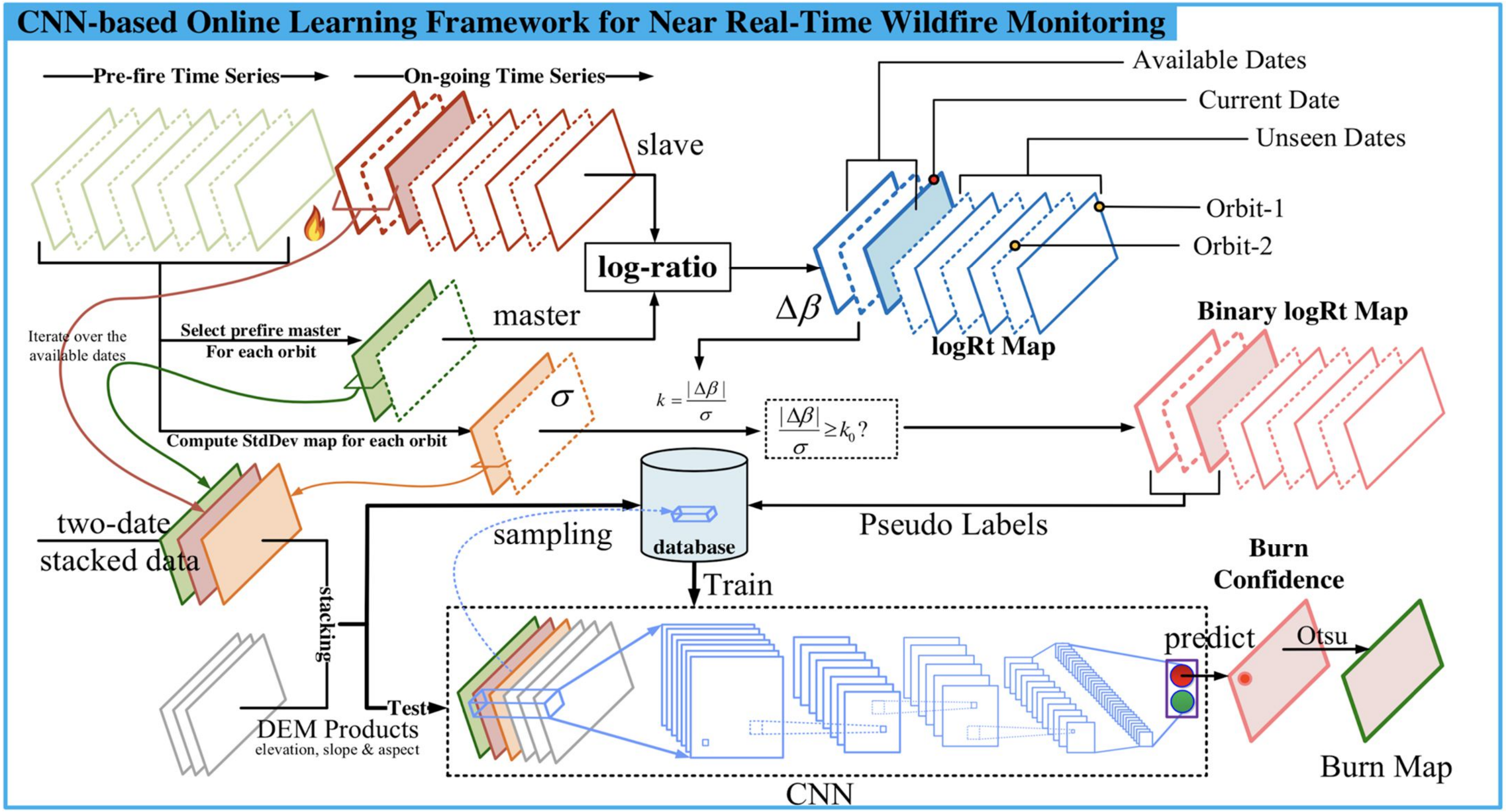
- Landsat data are often deployed for post-wildfire boundary determination and burn severity mapping



Research Objective

The overall objective of this research is to investigate Sentinel-1 SAR dense time series for fire perimeter and fire progression mapping:

- using a fully automatic procedure based on CNN
- considering the operational requirements of producing reliable and frequently updated progression maps



Yifang Ban, Puzhao Zhang, Andrea Nascetti, Alexandre R. Bevington, and Michael A. Wulder
"*Near Real-Time Wildfire Progression Monitoring with Sentinel-1 SAR Time Series and Deep Learning*",
submitted to Nature Scientific Reports

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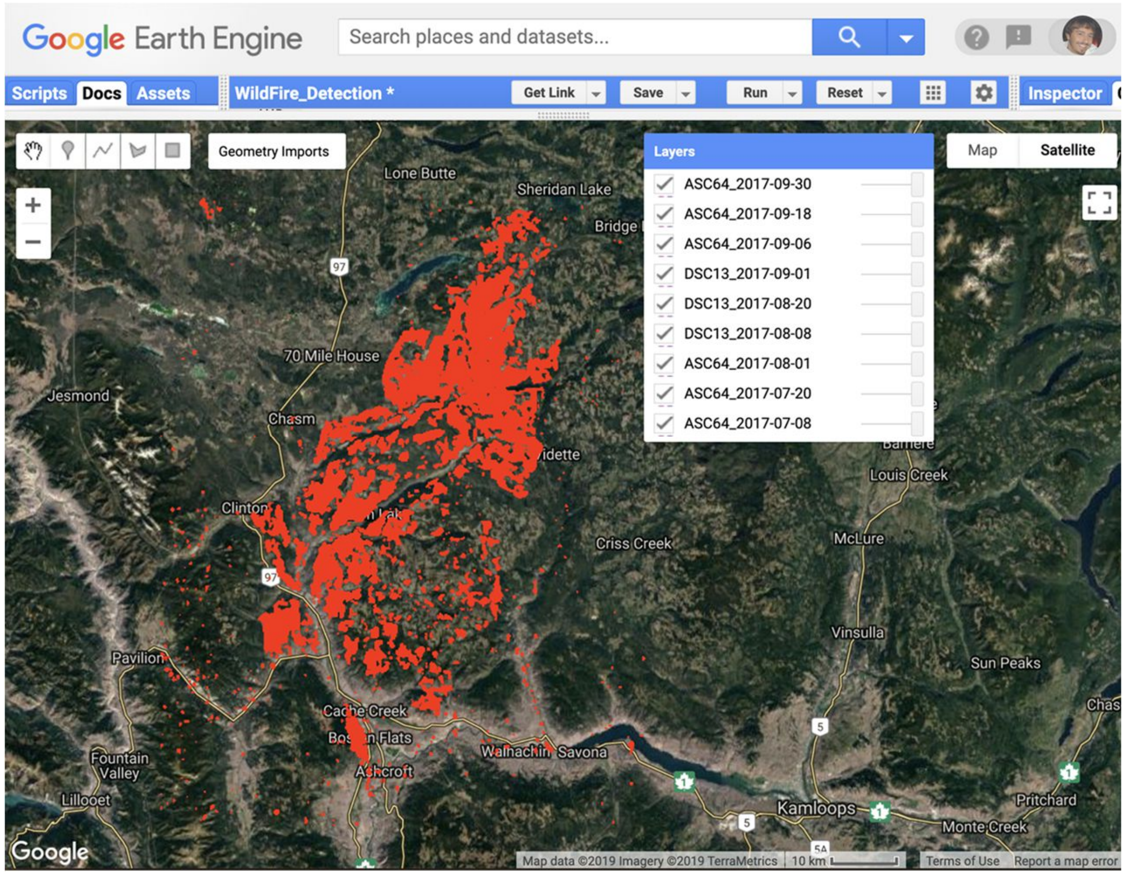
Processing steps

GEE processing:

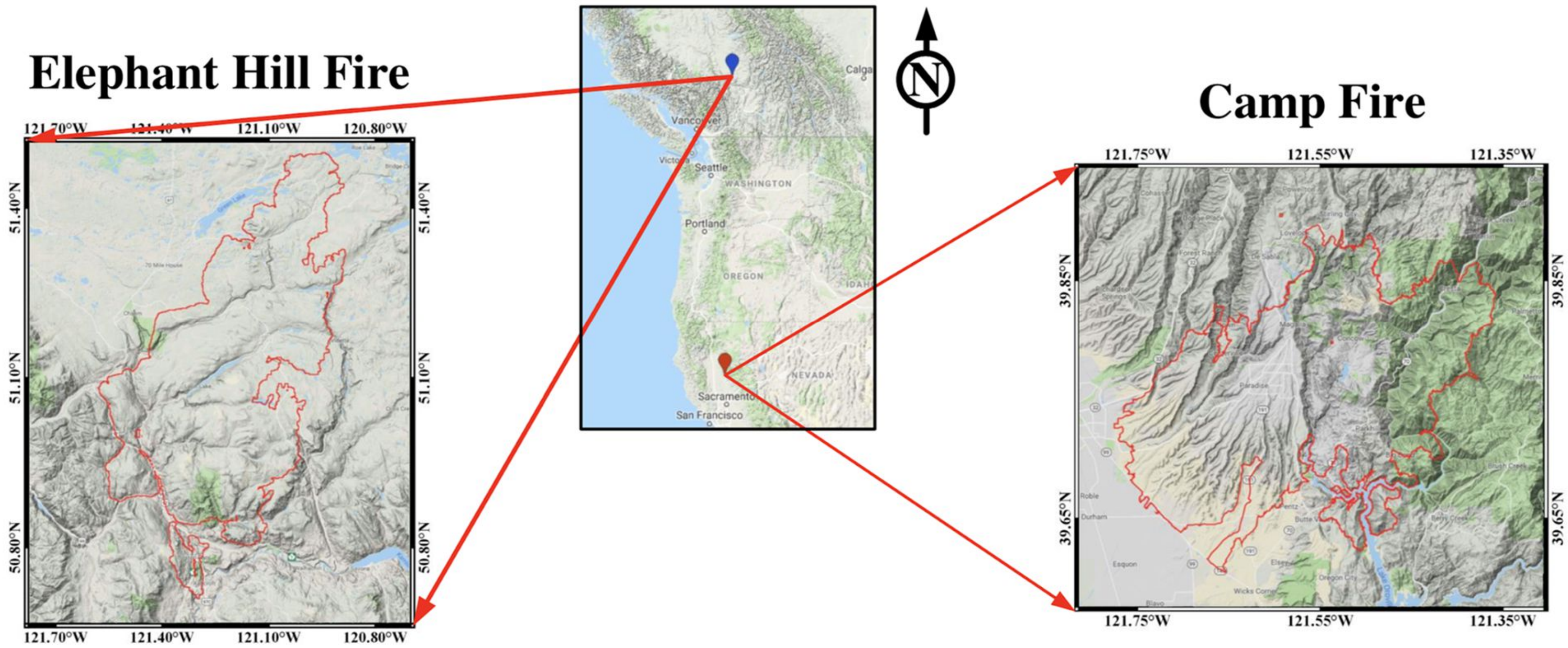
- S1 dense time series statistical analysis to characterize the backscatter in the area
- logRT maps generation
- raw binary mask generation for automatic training sample generation
- Export analysis ready image stacks

Local Machine processing:

- CNN train & prediction
- Burn confidence maps generation
- Final burned area maps generation



Test Sites



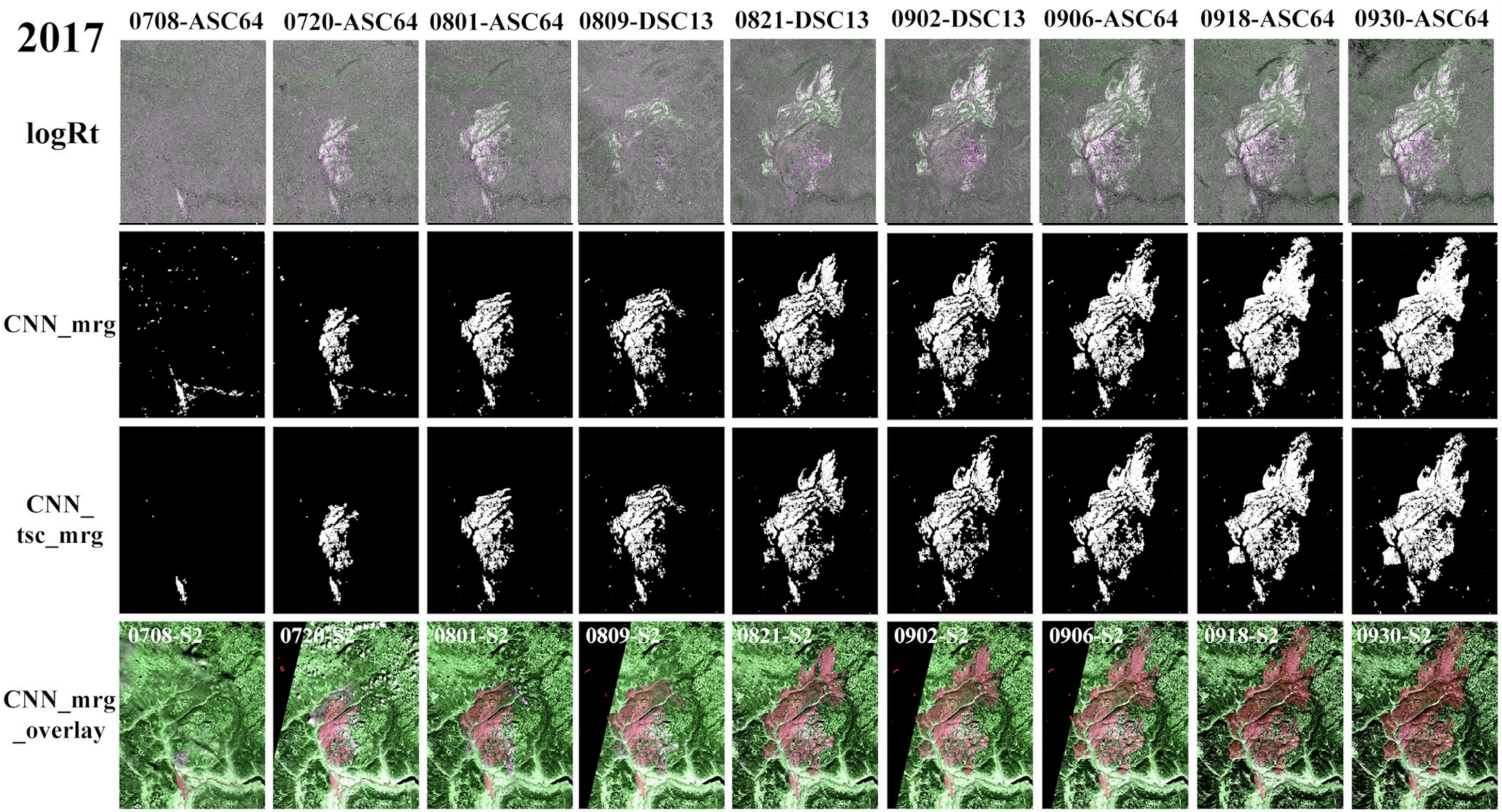
Elephant Hill wildfire (Canada, 2017) was British Columbia's largest wildfire in 2017:

- Started on July 6 along the Thompson River near Ashcroft Ended mid-September, 2017
- destroyed over 300 buildings
- prompted mass evacuations
- burnt an estimated 192,000 hectares of forest

Camp Fire was the deadliest and most destructive wildfire in California history:

- Started on November 8 near Camp Creek Road
- contained on November 25, 2018,
- the fire caused at least 85 civilian fatalities
- evacuation of 52000 people
- destroyed 18804 structures
- burnt about 62000 hectares

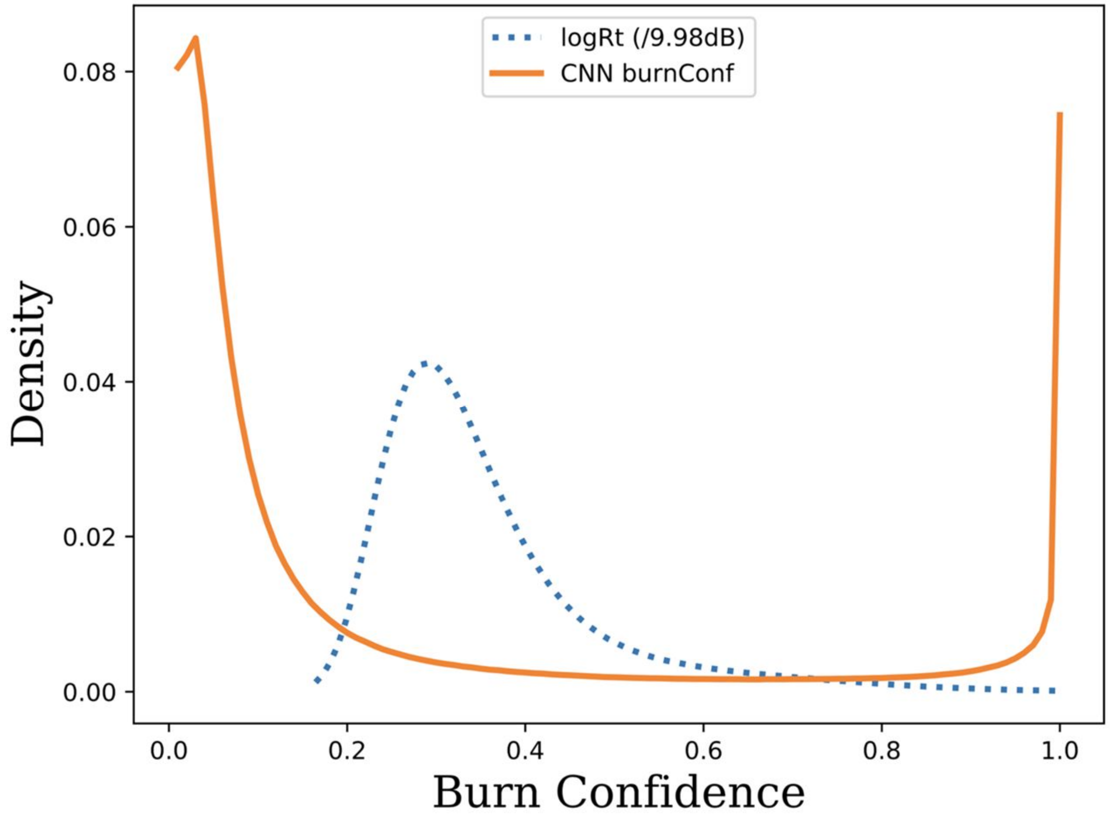
Elephant Hill: fire progression results



Elephant Hill: CNN performance analysis

CNN Confidence maps:

- pixel values are ranging from 0 to 1
- probability that each pixel represents a burnt area (0: unburn, 1: burnt)
- clear bi-modal distribution respect to unimodal distribution of the log-ratio based results



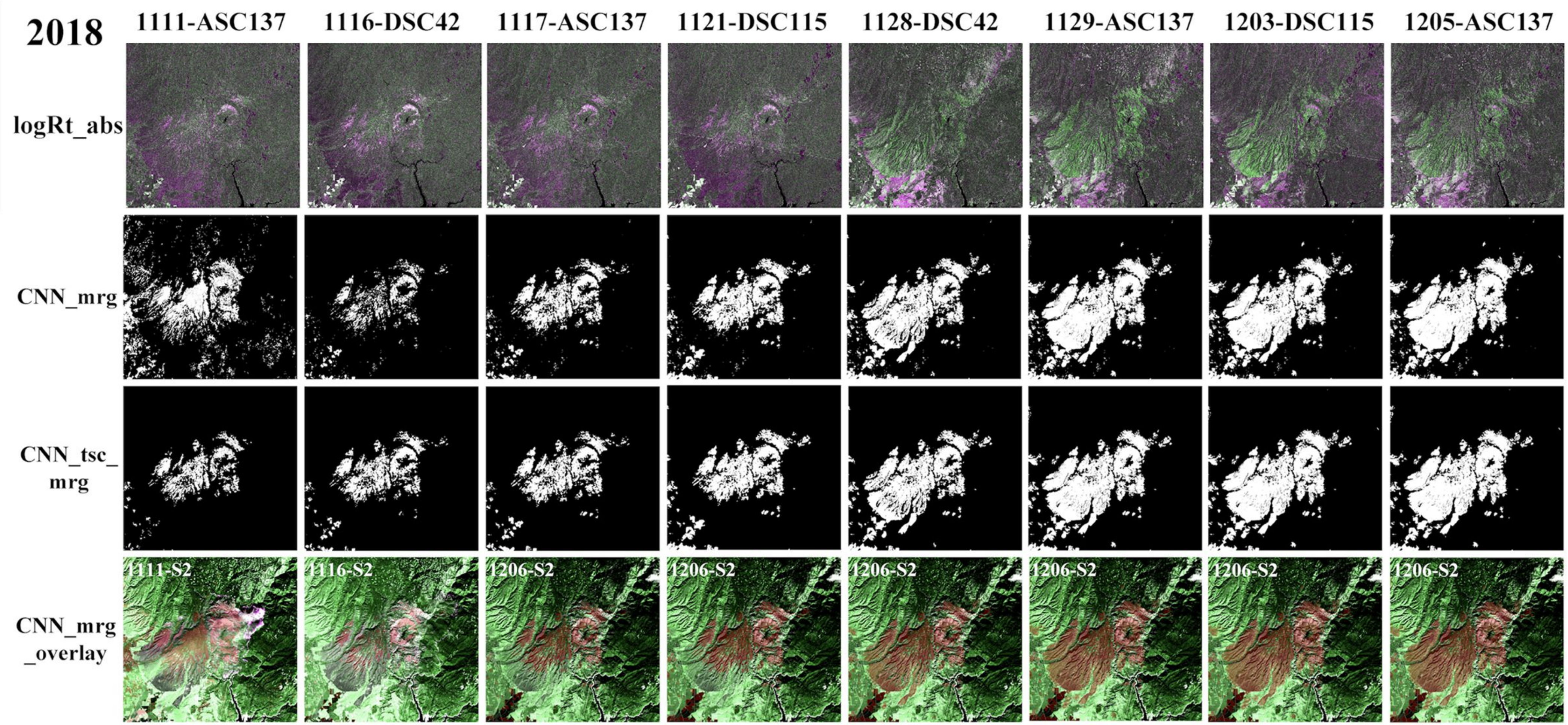
Elephant Hill: Accuracy Assessment

To quantitatively assess SAR-based burnt area results:

- Sentinel-2 dNBR is segmented into a binary map of burnt and unburnt areas and used as the reference maps together field data and WorldView-3 imagery
- 10000 validation points are randomly selected from burnt and unburnt areas respectively

Sat.	Bands	Method	Seg.	Precision	Recall	OA	Kappa	F_1
S1	VH	**logRt**	Otsu	0.6334	0.9712	0.8073	0.6146	0.7667
	VV			0.5942	0.9386	0.7778	0.5553	0.7277
	VH	**kmap**		0.6092	0.9853	0.7970	0.5939	0.7480
	VV			0.5798	0.9723	0.7817	0.5633	0.7264
	VH, VV	**kmap**	>2	0.8366	0.9471	0.8950	0.7899	0.8884
	VH,VV	***CNN_mrg***	Otsu	**0.9041**	0.9336	**0.9492**	**0.8983**	**0.9467**
		CNN_tsc_mrg		0.8589	**0.9952**	0.9274	0.8548	0.9221

Camp fire: progression results



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Camp fire: Accuracy Assessment

To quantitatively assess SAR-based burnt area results:

- Sentinel-2 dNBR is segmented into a binary map of burnt and unburnt areas and used as the reference maps together field data
- 10000 validation points are randomly selected from burnt and unburnt areas respectively

Sat.	**Bands**	**Method**	**Seg.**	**Precision**	**Recall**	**OA**	**Kappa**	**F_1**
S1	VH	**kmap**	>2	0.2182	0.6513	0.5507	0.1014	0.3269
	VV			0.4521	0.8019	0.6702	0.3404	0.5782
	VH,VV	**kmap**	>2	0.5117	0.8211	0.7001	0.4002	0.6305
	VH, VV	***CNN_mrg***	Otsu	**0.7182**	0.9391	**0.8358**	**0.6716**	**0.8139**
		CNN_tsc_mrg		0.7060	**0.9507**	0.8347	0.6694	0.8103

NORTHERN TERRITORY
Coral Sea
Vanuatu
QUEENSLAND
Australia
New Caledonia
WESTERN AUSTRALIA
SOUTH AUSTRALIA
NEW SOUTH WALES
Great Australian Bight
ACT
VICTORIA
Google Earth
TASMANIA
Tasman Sea

Conclusions & Future Prospects

- We developed and tested a CNN based framework to extract near-real-time fire progression maps using SAR data:
  - Sentinel-1 SAR dense time-series data are promising for wildfire progression monitoring
  - fire perimeter and progression maps can be produced automatically with high accuracy (F1 score > 0.8)
- Test the same framework with different satellite SAR data (i.e. ICEYE, COSMO-SkyMed) to produce daily progression maps
- Create an online processing platform based on GEE and GCP to provide the solution as a service