



AI for Good

ITU AI for Good Discovery
Climate Change and GeoAI Session
26 April 2022



Multi-sensor Fusion for Continuous Environmental Change Monitoring



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+ Outline

- Multi-Sensor Fusion
 - Taking a Pulse of the Planet Every Day
- Three AI Applications:
 - High Cadence Land Cover Mapping
 - Sustainable Agriculture
 - Dynamic Hydrology Maps





Earth Explorers

Multi dimensionality, multi-level nature of EO (satellites, HAPs, UAVs) presents connectivity, integration and interoperability challenges.

Credits: ESA

Planet Dove Satellite

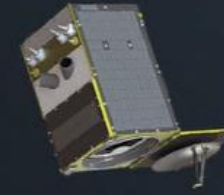


- Always-on, broad-area monitoring
- 3 meter resolution
- RGB and NIR bands

Planet Dove Constellation

~98° Sun-Synchronous Orbit

Planet SkySat Satellite



- Custom, targeted monitoring
- 50 centimeter resolution
- RGB, NIR, and Pan bands

Planet SkySat Constellation

SkySats 1-15

~98° Sun-Synchronous Orbit

SkySats 16-21

~53° Inclined Orbit





Next Generation Monitoring via Sensor Fusion

INPUTS

Analytic Ready OUTPUT

PS TOAR



HLS (L8 and S2)



+ Land Cover Mapping

- Used in many applications
- **Key for measuring sustainability**



- **CORINE Land Cover = Europe's key dataset**
 - Launched in 1985 (reference year 1990)
 - Update frequency 6 years
 - Labor intensive, involving many actors across Europe





The RapidAI4EO Project

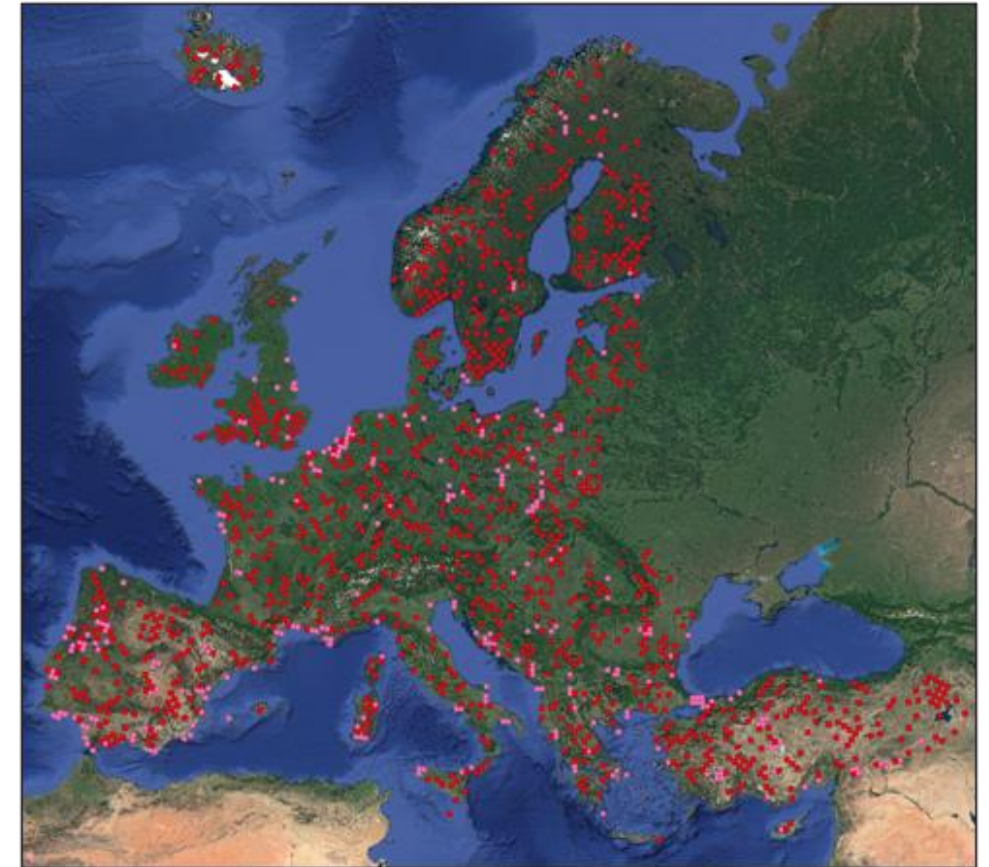
<https://rapidai4eo.eu/>

GOAL

- Establish the foundations for the next generation of rapid cadence land monitoring applications leveraging advances in Deep Learning

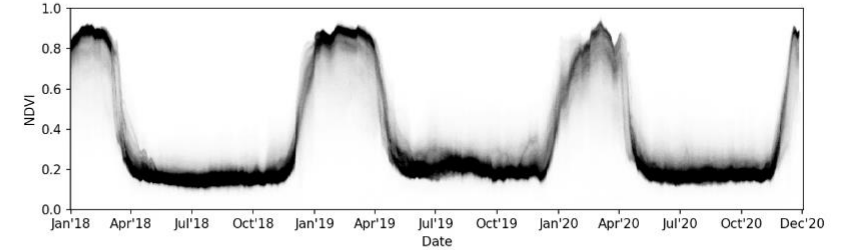
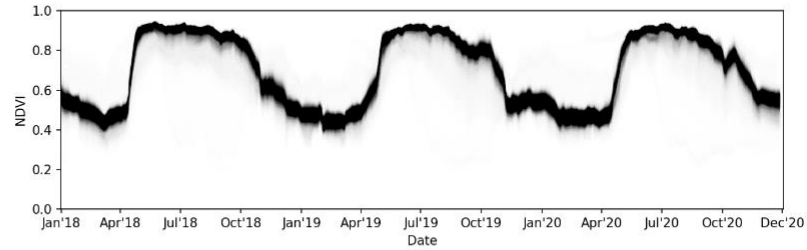
STRATEGY

- Create the largest spatiotemporal ML training dataset for land monitoring applications:
 - Daily time series datacubes (2 full years: 2018-2019)
 - Sampled at 500,000 locations, accounting for
 - CORINE class distribution (44 land cover classes)
 - Spatial distribution & Country representation
- ❖ Open sourcing in July 2022



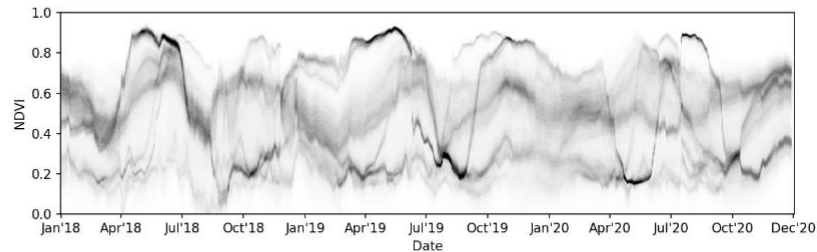


Examples of Stable Land Cover Behavior

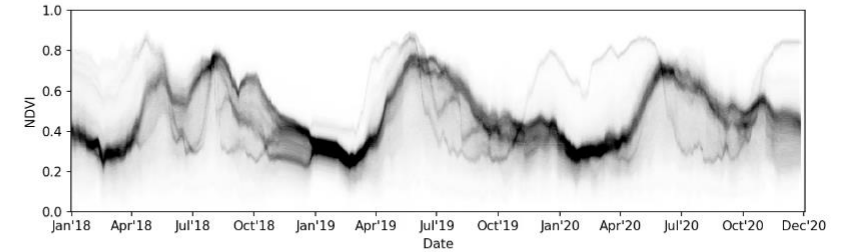


20

Examples of Change



← 3 years →



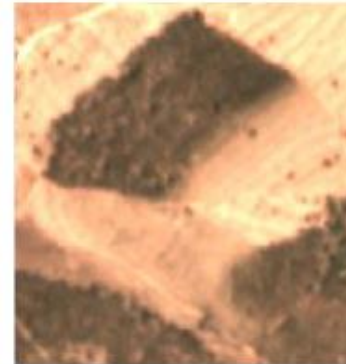
← 3 years →



ML Models Learn to Recognize Land Cover Mixes



Artificial surfaces: 0.36
Agricultural areas: 0.56
Forest: 0.06
Shrubs: 0.00
Bare Areas: 0.00
Wetlands: 0.00
Waterbodies: 0.00



Artificial surfaces: 0.00
Agricultural areas: 0.09
Forest: 0.37
Shrubs: 0.50
Bare Areas: 0.01
Wetlands: 0.00
Waterbodies: 0.00



Artificial surfaces: 0.32
Agricultural areas: 0.64
Forest: 0.02
Shrubs: 0.00
Bare Areas: 0.00
Wetlands: 0.00
Waterbodies: 0.00



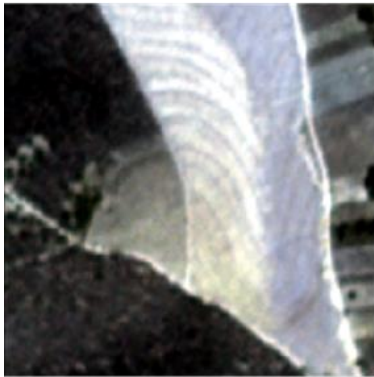
Artificial surfaces: 0.00
Agricultural areas: 0.00
Forest: 0.99
Shrubs: 0.00
Bare Areas: 0.00
Wetlands: 0.00
Waterbodies: 0.00

Class	Class Name	F1-Score (Micro)
1	Artificial Surfaces	80.89
2	Agriculture	92.82
3	Forests	88.85
4	Shrubs	61.94
5	Bare Areas	72.87
6	Wetlands	69.01
7	Water bodies	83.68



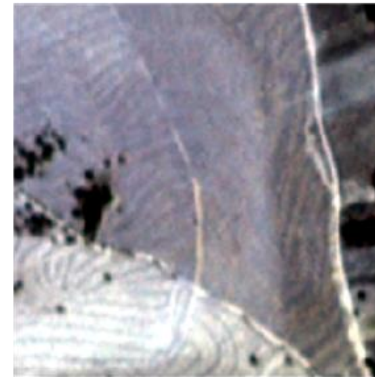
Convolutional Neural Network Activation Map

TILE-ID: 29N-26E-183N/33_17



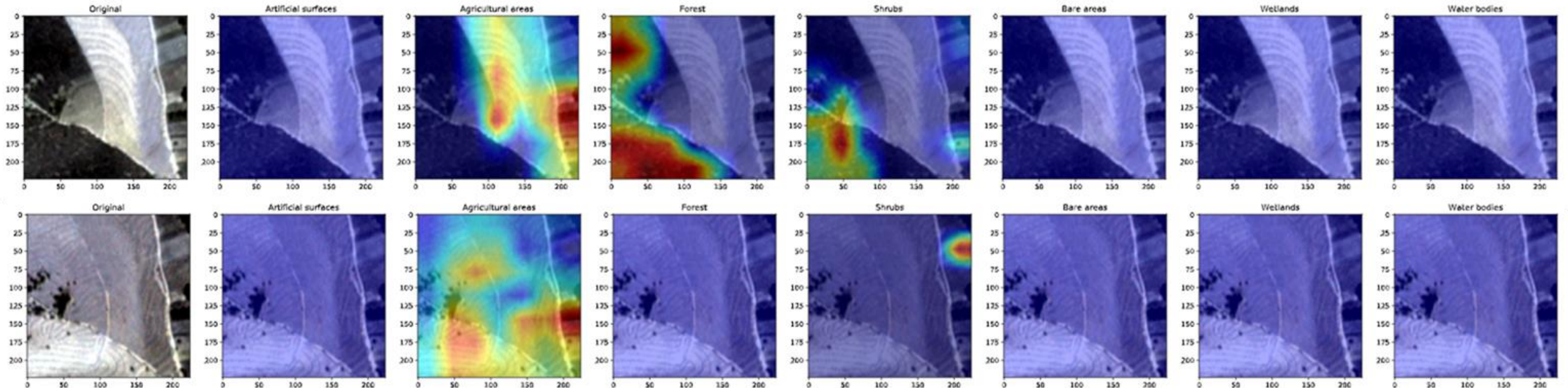
July, 2018

Artificial surfaces: 0.00
Agricultural areas: 0.45
Forest: 0.27
Shrubs: 0.25
Bare Areas: 0.00
Wetlands: 0.00
Waterbodies: 0.00



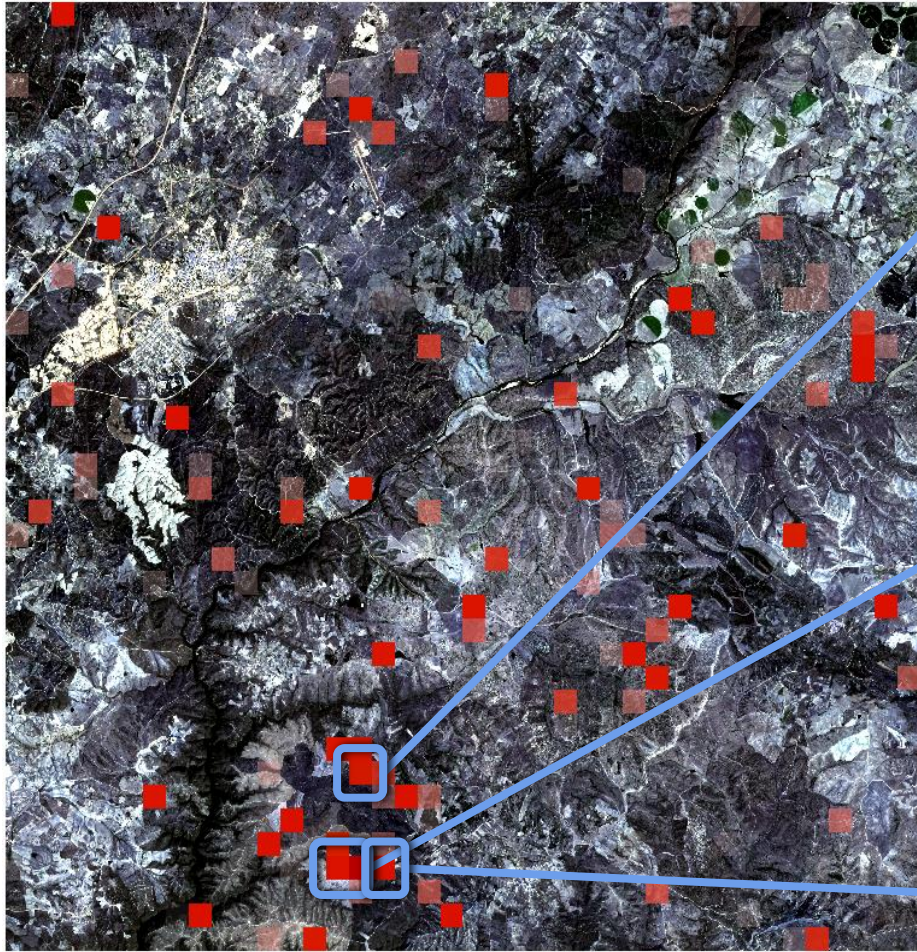
September, 2018

Artificial surfaces: 0.00
Agricultural areas: 0.97
Forest: 0.00
Shrubs: 0.01
Bare Areas: 0.00
Wetlands: 0.00
Waterbodies: 0.00



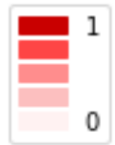


Detected Change (26E-183N)

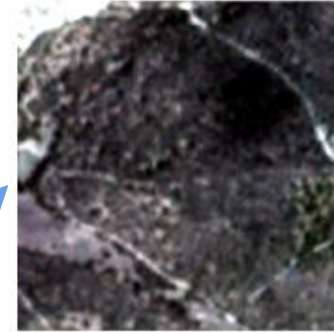


Tile_id: 33_17

3rd Quarter, 2018

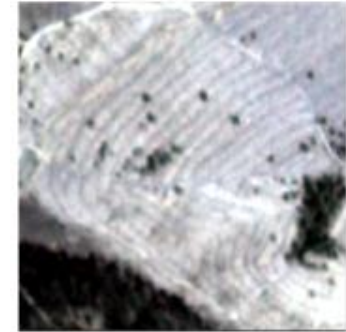


RapidAI4EO



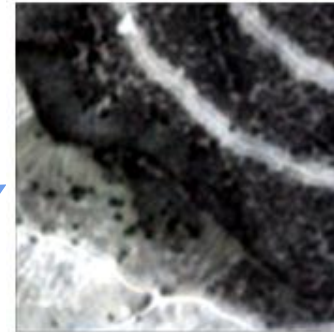
July, 2018

Artificial surfaces:	0.00
Agricultural areas:	0.02
Forest:	0.91
Shrubs:	0.05
Bare Areas:	0.00
Wetlands:	0.00
Waterbodies:	0.00



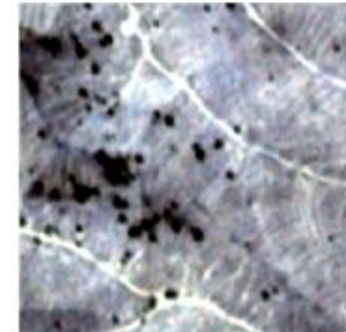
September, 2018

Artificial surfaces:	0.00
Agricultural areas:	0.74
Forest:	0.12
Shrubs:	0.11
Bare Areas:	0.00
Wetlands:	0.00
Waterbodies:	0.00



July, 2018

Artificial surfaces:	0.00
Agricultural areas:	0.15
Forest:	0.10
Shrubs:	0.72
Bare Areas:	0.01
Wetlands:	0.00
Waterbodies:	0.00



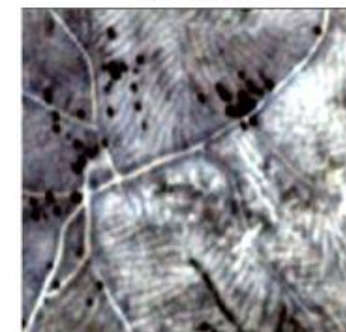
September, 2018

Artificial surfaces:	0.00
Agricultural areas:	0.97
Forest:	0.00
Shrubs:	0.01
Bare Areas:	0.00
Wetlands:	0.00
Waterbodies:	0.00



July, 2018

Artificial surfaces:	0.00
Agricultural areas:	0.02
Forest:	0.95
Shrubs:	0.01
Bare Areas:	0.00
Wetlands:	0.00
Waterbodies:	0.00

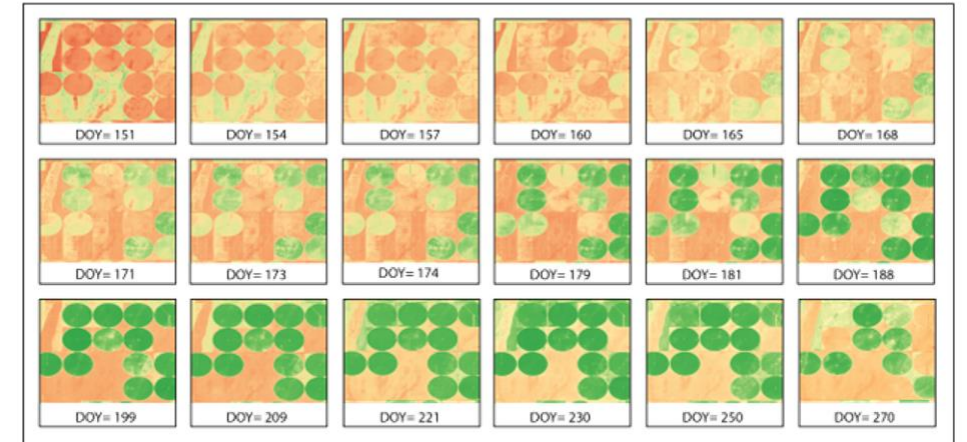
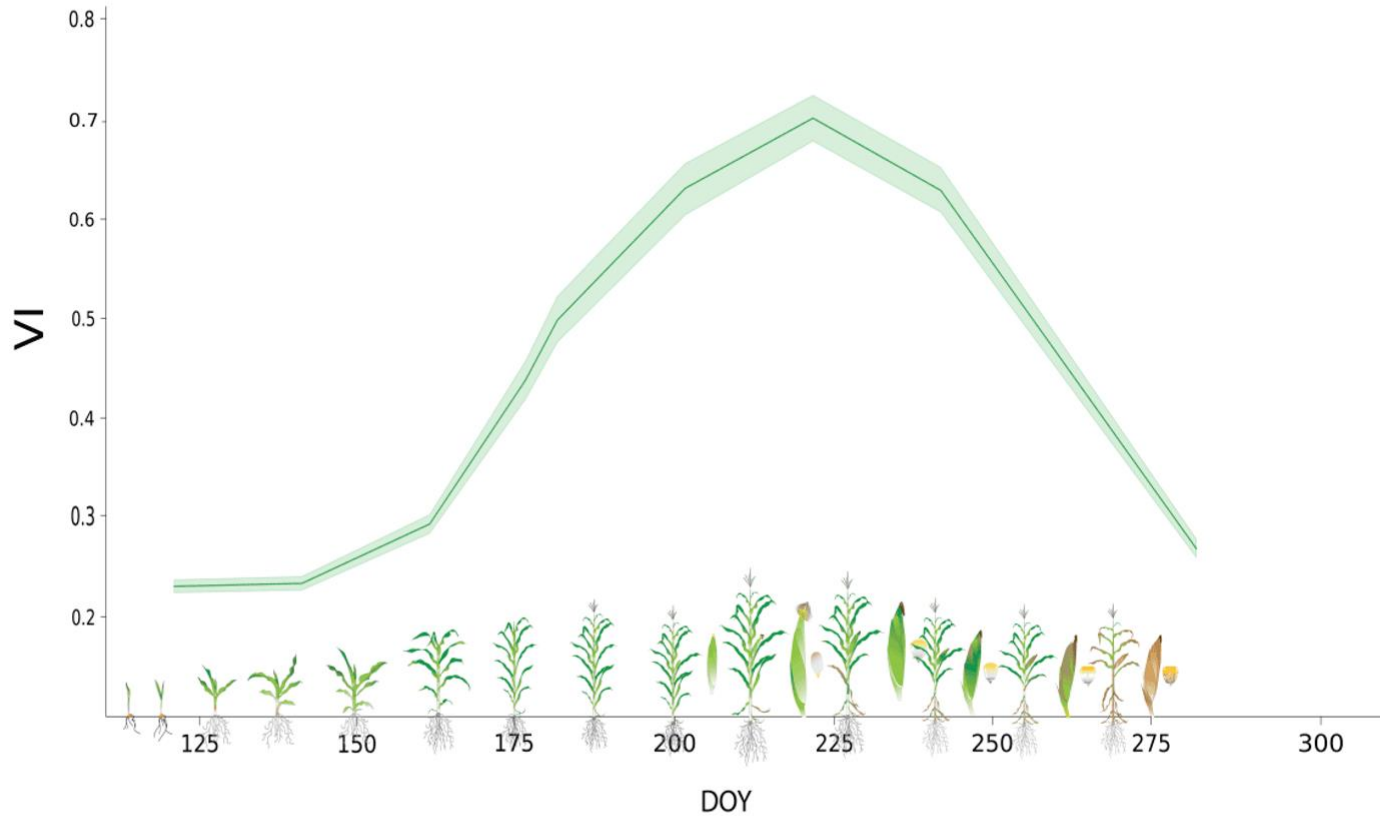


September, 2018

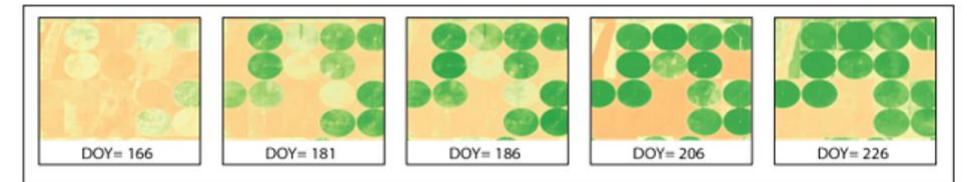
Artificial surfaces:	0.00
Agricultural areas:	0.99
Forest:	0.00
Shrubs:	0.00
Bare Areas:	0.00
Wetlands:	0.00
Waterbodies:	0.00



Sustainable Ag - Detection of Phenology Stages



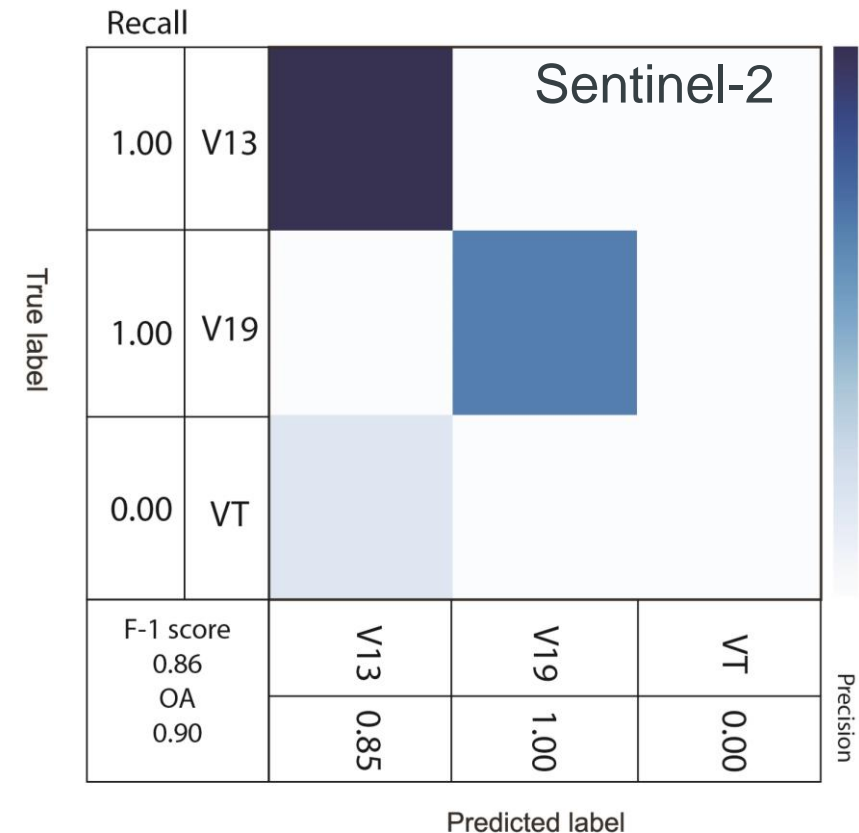
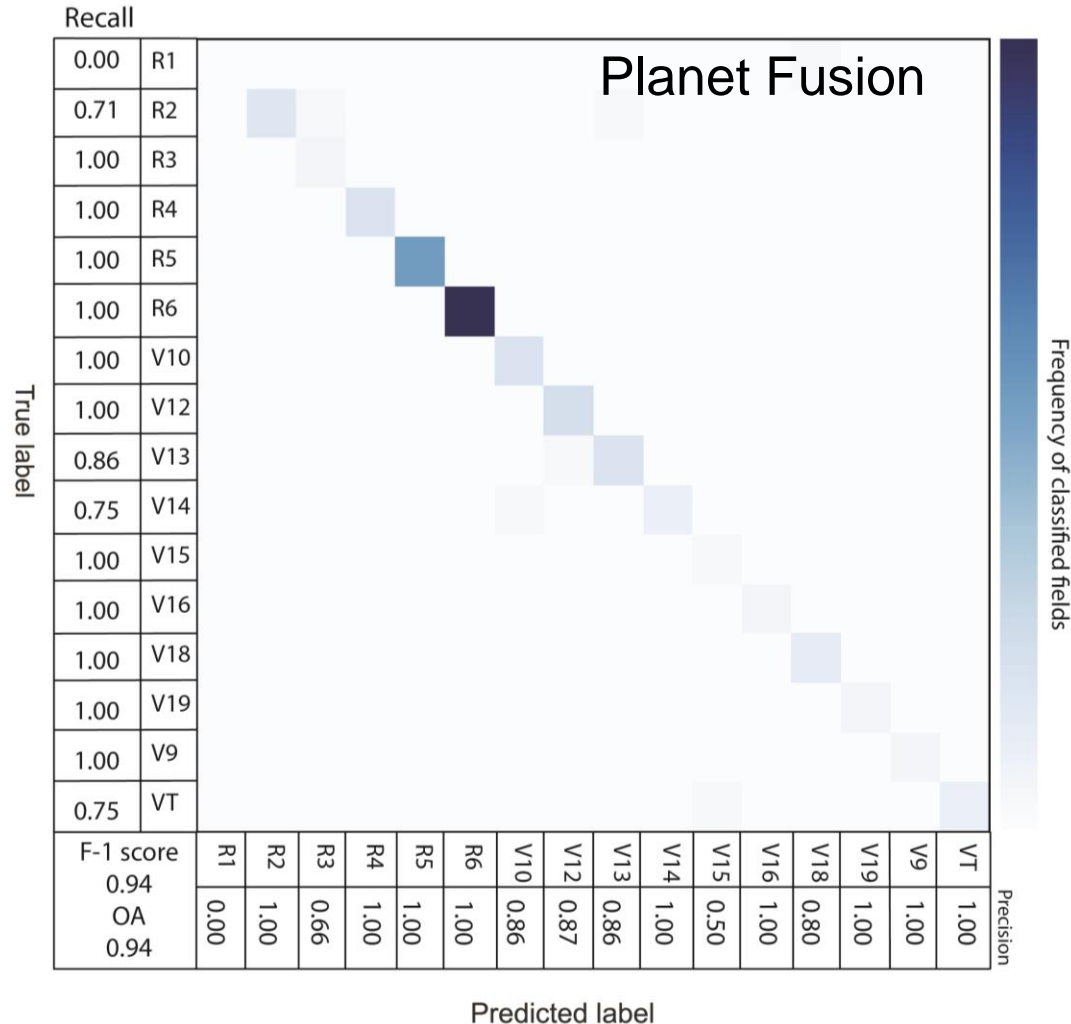
Example L3H, season 2017. 91 dates were present among the phenology datasets. From L3H dataset the same day was retrieved. The present figure only shows a few images to illustrate the differences present in the vegetation signal even during two consecutive days.



Example Sentinel 2, season 2017. Only 5 images were obtained matching the exact same day as the phenology measure.



Sustainable Ag - Detection of Phenology Stages





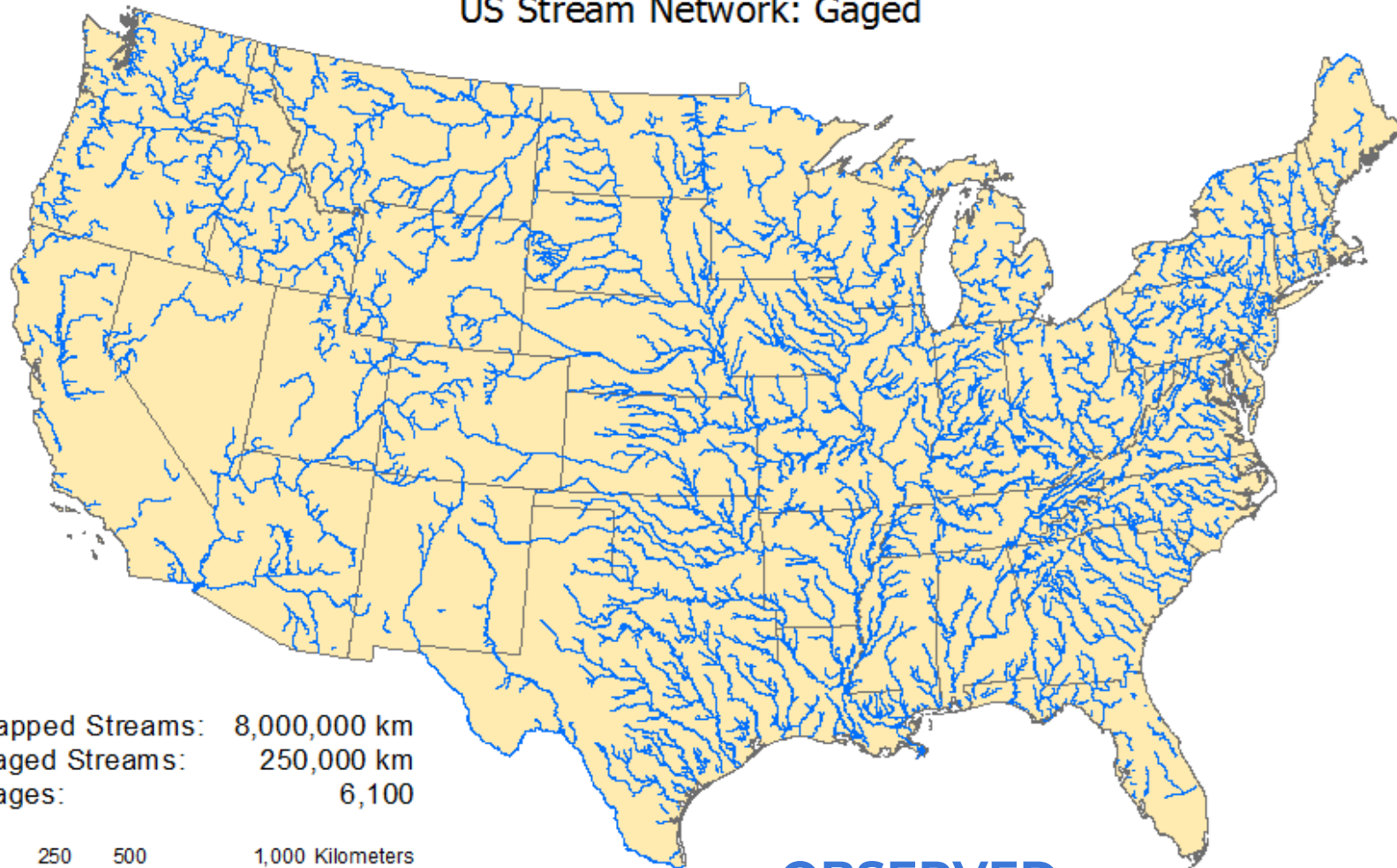
Otterworks: Dynamic Hydrology Maps



A complete map of our daily waters can give us an early warning for where droughts and floods are born.

Current satellite approaches are limited to monthly observations that map only the widest streams.

US Stream Network: Gaged



OBSERVED



Garcia et al, "Pix2Streams: Dynamic Hydrology Maps from Satellite-LiDAR Fusion", 2021:<https://arxiv.org/abs/2011.07584>





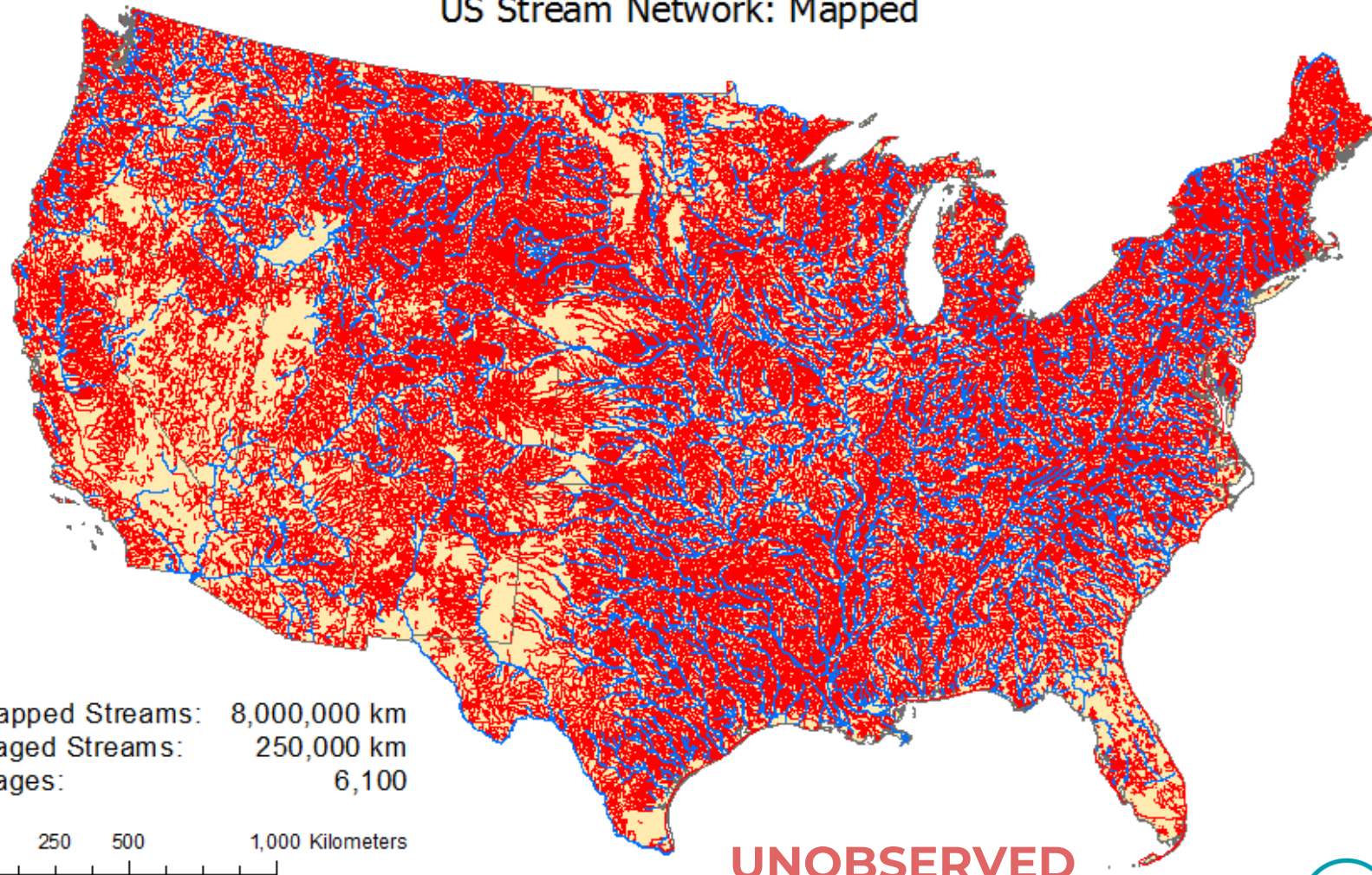
Otterworks: Dynamic Hydrology Maps



The wider streams are fed by smaller tributaries that make up much of the dendritic surface network but whose flow is unobserved.

Mapping them over time can give us a map of impermanence of our waters, showing where to expect water, and where not to.

US Stream Network: Mapped



Mapped Streams: 8,000,000 km
Gaged Streams: 250,000 km
Gages: 6,100



UNOBSERVED

Garcia et al, "Pix2Streams: Dynamic Hydrology Maps from Satellite-LiDAR Fusion", 2021: <https://arxiv.org/abs/2011.07584>



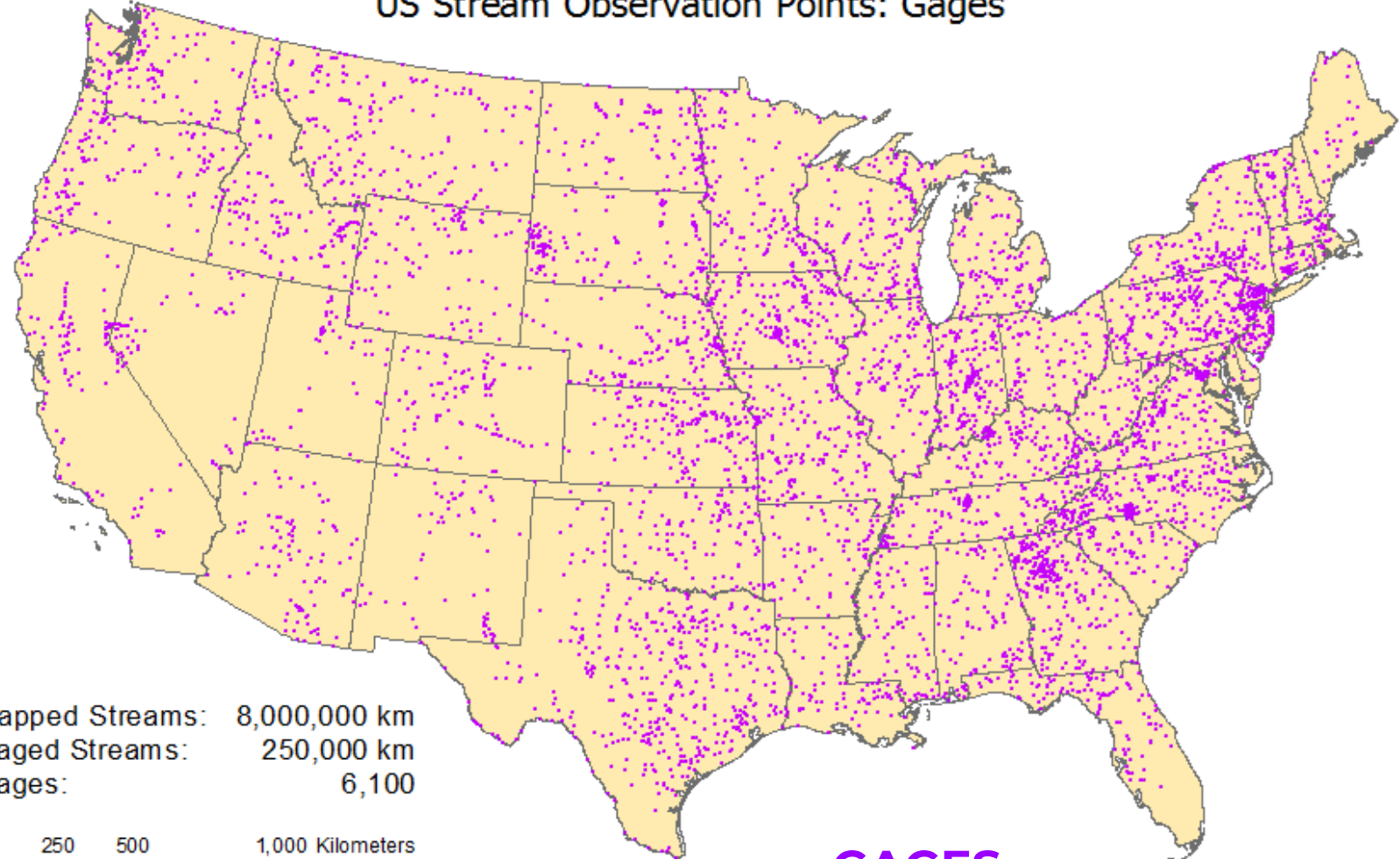


Otterworks: Dynamic Hydrology Maps



These measurements can be linked to 11,000 gage stations downstream and enable development of predictive models that leverage daily observations.

US Stream Observation Points: Gages



Mapped Streams: 8,000,000 km
Gaged Streams: 250,000 km
Gages: 6,100

0 250 500 1,000 Kilometers

GAGES



Garcia et al, "Pix2Streams: Dynamic Hydrology Maps from Satellite-LiDAR Fusion", 2021: <https://arxiv.org/abs/2011.07584>



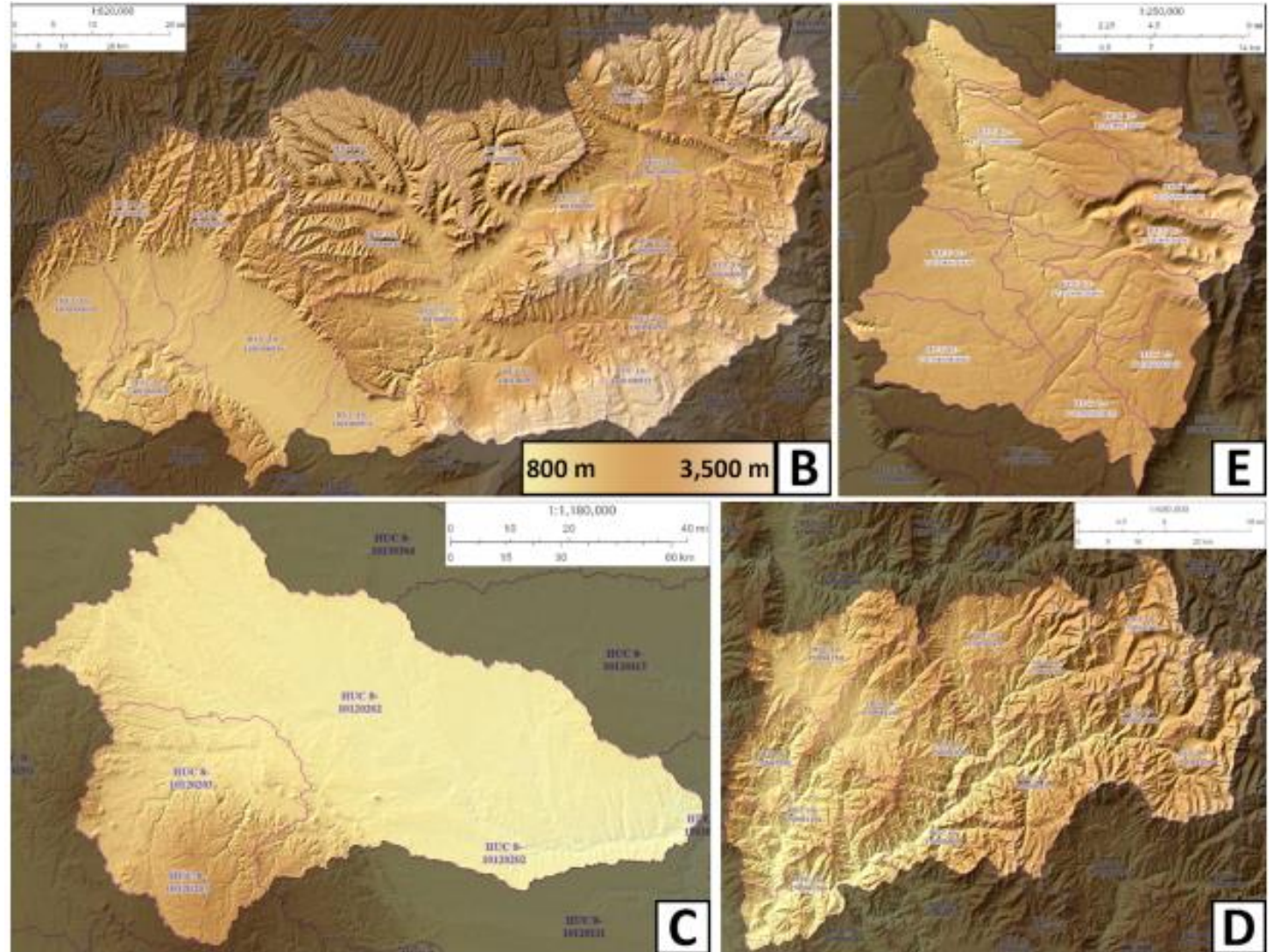


4 Upper River Basins: 2 Year Daily Coverage



Using a Multi-headed U-net, the Otterworks team was able to categorize the temporal behavior of all tributaries and produce the first high-fidelity dynamic map of stream flow frequency.

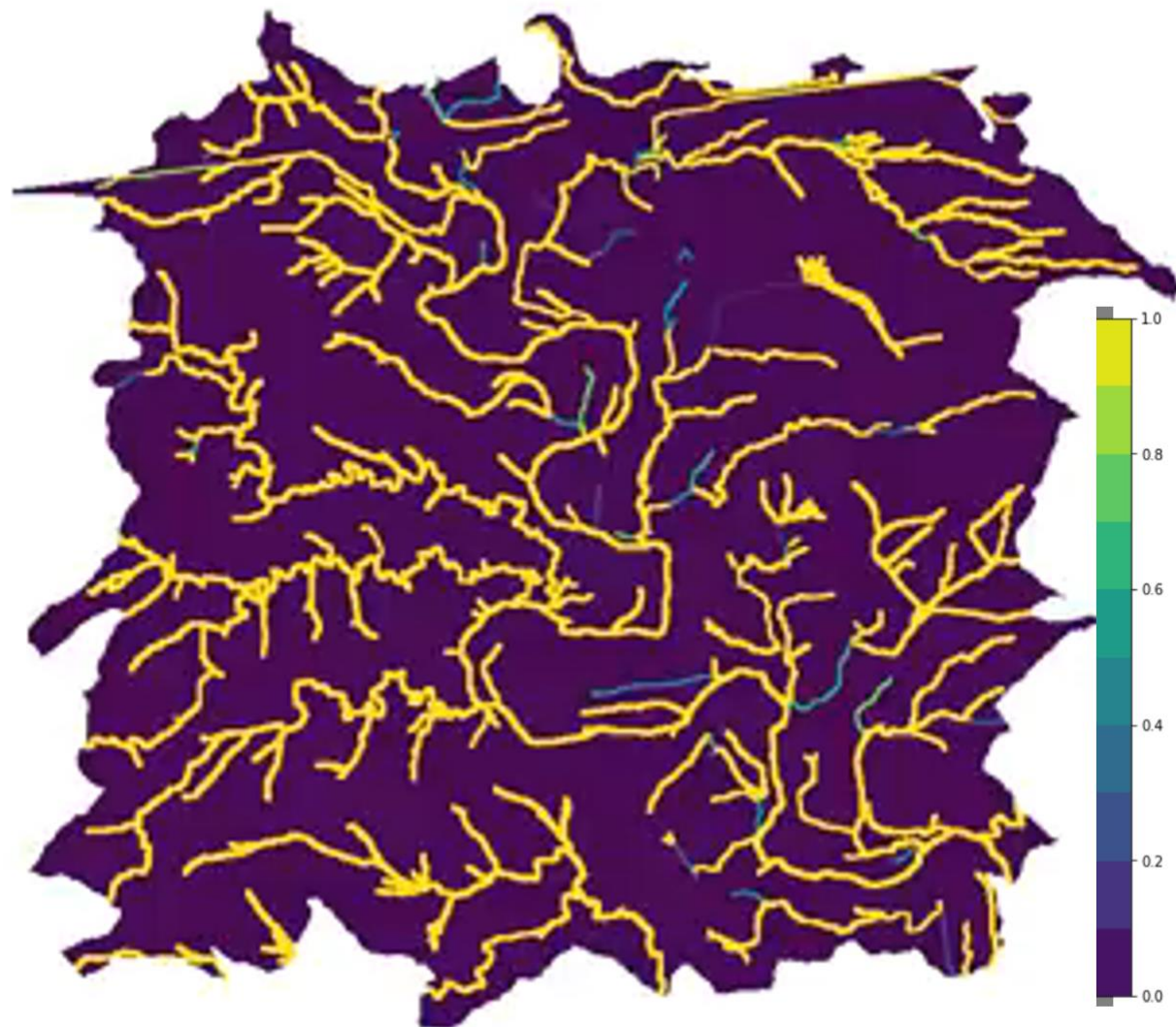
Applied at the national scale, this could fundamentally improve how we manage our water resources around the world.



Garcia et al, "Pix2Streams: Dynamic Hydrology Maps from Satellite-LiDAR Fusion", 2021: <https://arxiv.org/abs/2011.07584>



2018-01-10



+ Outlook

- Recent advances in Remote Sensing make it possible to take a pulse of our planet every day
- Artificial Intelligence + the new daily EO data streams can:
 - take us one step closer to measuring progress towards the SDGs
 - improve our understanding of land use and our food systems
 - help us predict, adapt to and mitigate the effects of climate change
 - and, more generally, help solve some of society's grand challenges with respect to sustainability: can we support growing populations and quality of life without exceeding the resource budget of the planet?
- ***And don't forget:*** *the RapidAI4EO corpus is the largest spatiotemporal training corpus ever produced for remote sensing studies: ARD high cadence time series at 500,000 locations for 2018-2019. Open sourcing in July 2022!*



<https://rapidai4eo.eu/>



THANK YOU!

QUESTIONS?



Reach out to giovanni@planet.com, annett@planet.com

Kure Atoll, Hawaii, USA – May 12, 2016