Learning main drivers of crop dynamics and production in Europe

Anna Mateo-Sanchis, Maria Piles, Julia Amorós-López, Jordi Muñoz-Marí, Álvaro Moreno, Jose E. Adsuara, Adrián Pérez-Suay, Gustau Camps-Valls

Remote Sensing applications in the Biogeosciences

EGU General Assembly 2020

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IPL Image Processing Laboratory

Image Signal Processing - ISP

Intro

- ❑ Accurate crop yield estimation is relevant, many implications [1,4]
- ❑ Climate change poses new scenarios for managing fields [5,6]
- ❑ Crop yield estimation from remote sensing data [1,4]

Climate change has likely already affected global food production

Deepak K. Ray[1]*, Paul C. West[1], Michael Clark[2,3], James S. Gerber[1], Alexander V. Prishchepov[4], Snigdhansu Chatterjee[5]

Global Warming Threatens to Dry Out Europe's Crop Fields

European satellite data and atmospheric models are sending warnings to farmers about climate change.

By Jonathan Tirone

Local food crop production can fulfil demand for less than one-third of the population

Pekka Kinnunen, Joseph H. A. Guillaume, Maija Taka, Paolo D'Odorico, Stefan Siebert, Michael J. Puma, Mika Jalava & Matti Kummu

Nature Food **1**, 229–237(2020) | Cite this article

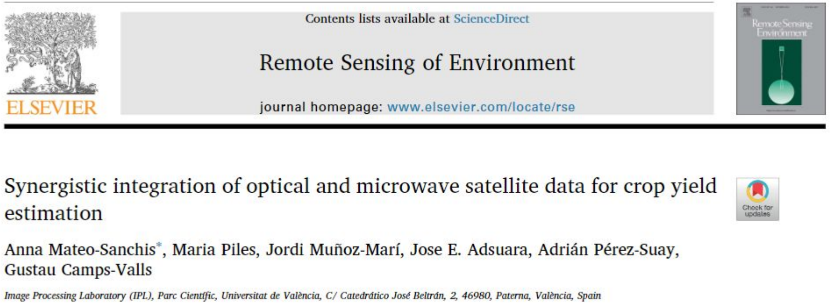
Goals

G1. Study the transportability of machine learning models across regions

G2. Study the relevance of agro-ecological drivers for crop yield estimation

G3. Explore unique capabilities of microwave satellite data: sensing water in soils and vegetation

Previous methodology [4]



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Synergistic integration of optical and microwave satellite data for crop yield estimation

Anna Mateo-Sanchis*, Maria Piles, Jordi Muñoz-Marí, Jose E. Adsuara, Adrián Pérez-Suay, Gustau Camps-Valls

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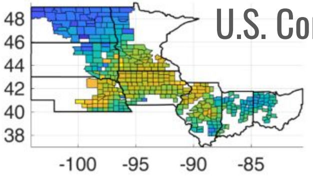
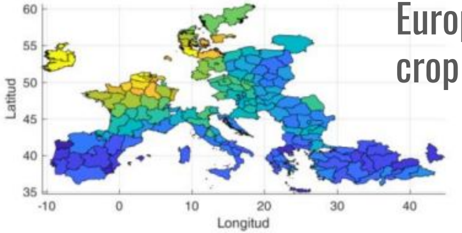


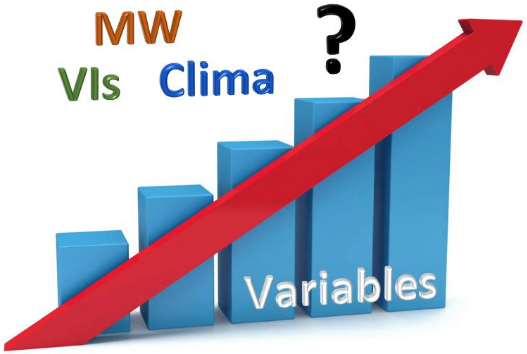
U.S. Corn Belt



European croplands

Agro-ecological drivers:

- ❏ MW: microwave satellites
- ❏ VIs: optical vegetation indices
- ❏ Climatic variables



Data collection & preprocessing

- Survey Data: EUROSTAT (link)
- Products:
  - EVI: MOD13C1, 0.05º, 16 days
  - LAI & FAPAR: CGLS, 1km, 10 days
  - SM: SMOS BEC, 1km, daily
  - SM & VOD: SMAP, 9km, daily [7]
  - TEMP, PRE, RAD, ET: ERA5-LAND, 9km, monthly
- Study Area: NUTS2 regions EU
- Years: 2015-2017
- Main Crops: Corn, Barley, Wheat

- Preprocessing steps:
  a. Daily products temporally composited to 16 days
  b. Two Land covers used to identify purely cropland pixels: ESA CCI @1km, MOD12C1 @0.05º,9km
  c. Satellite and modeled data extracted per NUTS2 at its original spatial resolution

Results (G1)

Methodology successfully evaluated over U.S. [4]:

- ❏ X input = EVI & VOD
- ❏ Y = yield (t/ha)
- ❏ Method: Kernel Ridge Regression [8]

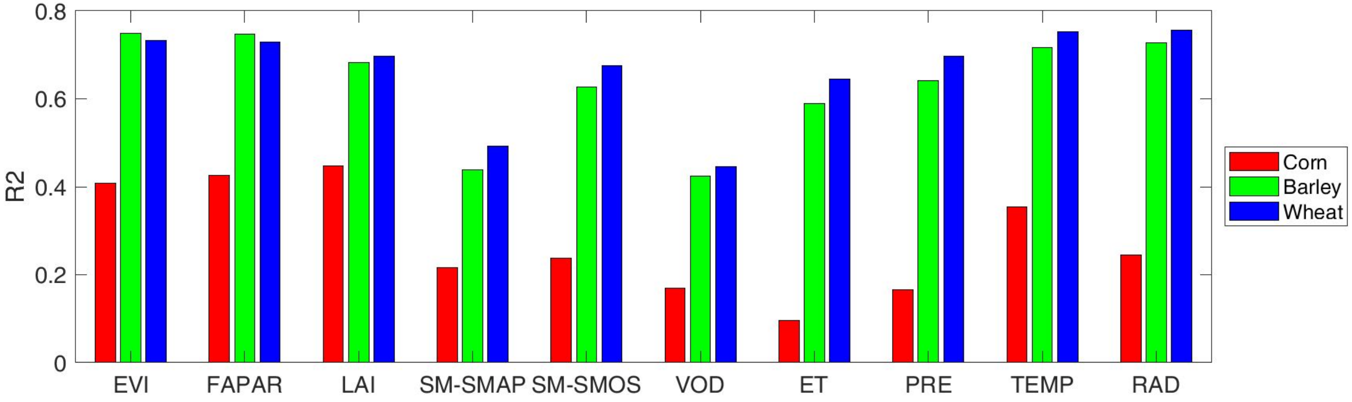
European croplands are fragmented & diverse
→ need of a dedicated approach

US Corn Belt **2015** single-year **<u>Homogeneous</u> landscapes**			Europe **2015** single-year **<u>Heterogeneous</u> landscapes**			Europe **2015-2017** multi-year	
Main Crops	N	R2	Main Crops	N	R2	N	R2
Corn	363	0.9	Corn	155	0.45	403	0.5
Soybean	361	0.9	Barley	163	0.7	423	0.8
Wheat	204	0.72	Wheat	163	0.75	420	0.8

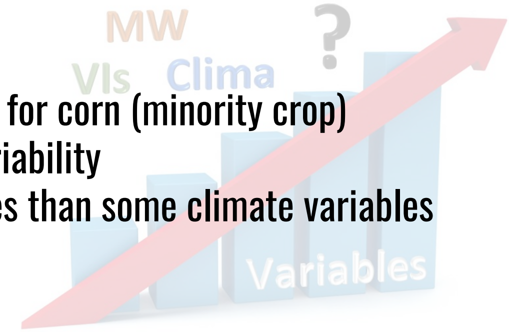
N: number of regions
R2: coefficient of determination

Results (G2)

Single variable ranking in a multi-year setting

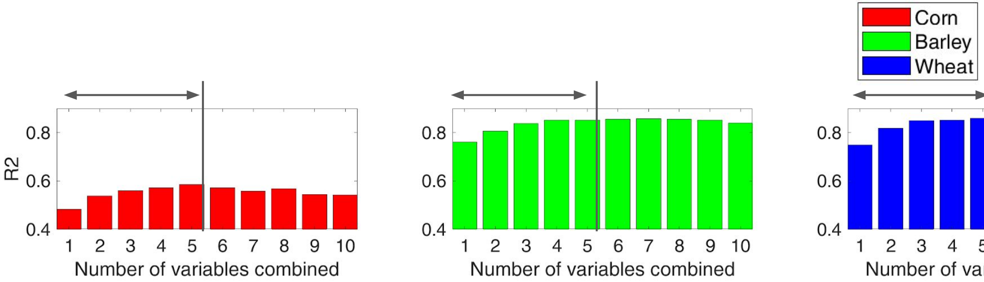


- ❑ Generally good estimates are obtained for barley and wheat, whereas models fail for corn (minority crop)
- ❑ Low spatial resolution products (SM-SMAP and VOD) fail to explain crop yield variability
- ❑ SM-SMOS (1km) improves the SM-SMAP (9km) results, obtaining better estimates than some climate variables



Results (G2)

Best variable combinations

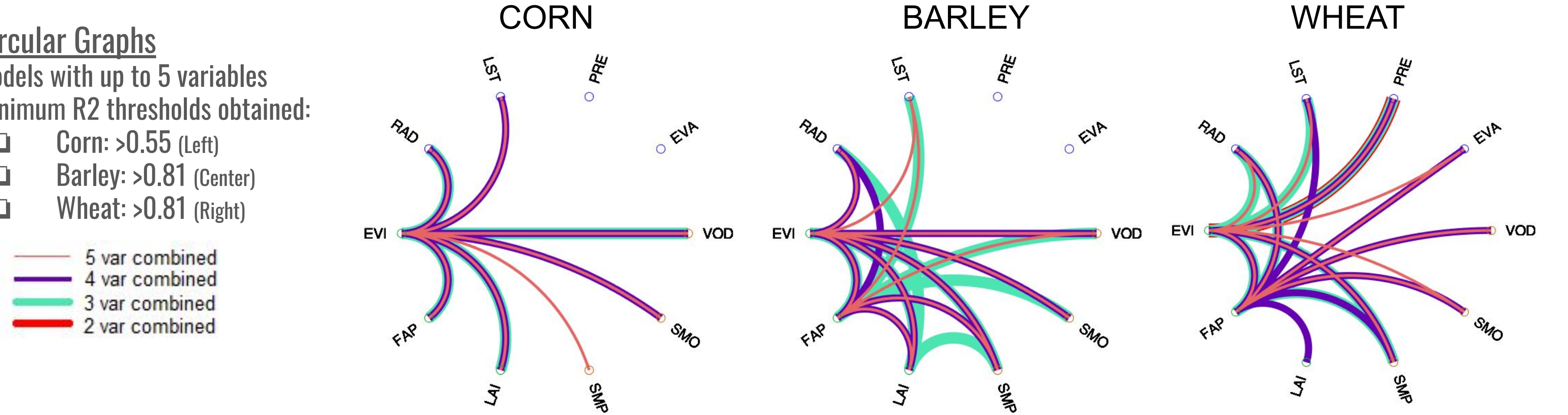


<u>Circular Graphs</u>

Models with up to 5 variables

Minimum R2 thresholds obtained:

- ❑ Corn: >0.55 (Left)
- ❑ Barley: >0.81 (Center)
- ❑ Wheat: >0.81 (Right)



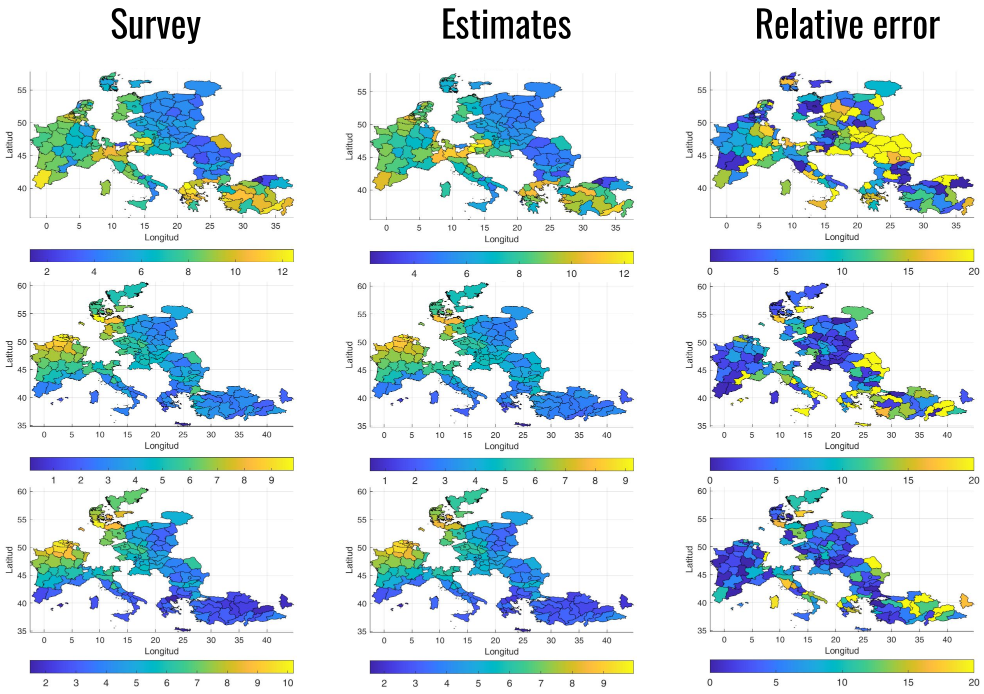
- ❑ Combining a greater number of variables does not imply a better result
- ❑ Precipitation and evaporation are not included in the best models resulting from up to 5 variable combinations
- ❑ Models including **vegetation** (optical data), **soil water** (MW data) and **atmospheric** (climatic data) (G3) information achieve the best results

Results (G2)

Best estimates results/maps

Crop	Variables	Year	N	R2	RMSE (t/ha)
Corn	EVI, LAI TEMP, RAD SM (1km)	2015*	157	**0.86**	0.97
		2016	139	0.85	0.97
		2017	113	0.85	0.97
Barley	EVI, LAI RAD SM (9km)	2015*	145	**0.95**	0.52
		2016	127	0.91	0.46
		2017	101	0.93	0.53
Wheat	EVI, Fapar RAD, ET SM (9km)	2015*	145	**0.97**	0.47
		2016	124	0.92	0.48
		2017	101	0.95	0.47

*Year represented in the maps



Conclusions

- Region-specific crop yield models needed: homogeneous vs heterogeneous croplands
- Europe crop data is limited → A multi-year setting is necessary to ensure good training
- ML approaches allow exploiting optical, microwave and climatic data (vegetation, soil and atmosphere information) for improved crop yield estimates
- Recent microwave data at medium-scale resolution (1-9 km) can add value to present agricultural systems
- A crop type mask could allow improving the estimates, particularly for the minority crop (corn)

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Thanks!!

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