Drought and extreme heat effects on crop yields: statistical crop modelling at the farm scale in Puglia and the Po river basin

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Motivation

- Timely crop yield forecasts are crucial: support EU's CAP
- The JRC's MARS Crop Yield Forecasting System (MCYFS) monitors crop vegetation growth since 1990s
- Proliferation of more frequent and spatially detailed data
  - satellite and weather data
- Climate change: increased frequency and intensity drought episodes (especially in Mediterranean countries)
- A research empirical question is how to optimally combine this amount of data and apply it to near real time crop models

Motivation

Statistical crop modelling and drought remote sensing in the literature

- Countless examples of the use of remote sensing related to agriculture
- Using satellite data to identify drought impacts and document yield gap variability successful work in India (*Jain et al, 2017*)
- Some studies tackle this issue at the global scale (*Zampieri et al, 2017*)
- In Italy, a few studies studies evidence the vulnerability to droughts of the Po valley but lack quantitative results (*Carrera et al, 2013*)
- Some exercises analyse the impact of climate change on Italian agriculture analysing farmland values (*Bozzola et al, 2018*)
- while others address explicitly the role of droughts on yields but a low resolution level (*Mysiak et al, 2013*)
- Ours is, up to our knowledge, the first attempt to look at the impact of heat and droughts on yields in Italy at a "*high resolution*" level

Objective of the paper

The objective of this paper is twofold:

- Advancing through empirical crop modelling in describing the role of remote sensing drought indicators as explanatory factors of crop yields
- Constructing empirical models to predict crop yields using weather and remote sensing near real-time indicators

Data

Agricultural data: RICA

- **RICA: Rete di Informazione Contabile Agricola**
  - INEA: Istituto Nazionale di Economia Agraria
  - Annual survey
  - Surface and production data at the farm level
  - 11k farms represented (95% surface, 97% production)
  - Goes beyond EC's requirements: water use, fertilisers,...
  - Available period: 2001-2015
- Serves as the Italian input to the EC's (DG-AGRI) Farm Accountancy Data Network (FADN)
  - Designed to evaluate CAP
  - Optimised to NUTS-1 level

Data

Agricultural data: RICA

- Farms are geo-referenced from 2011-2012
- Prior to that year, *Comune* ascription is available

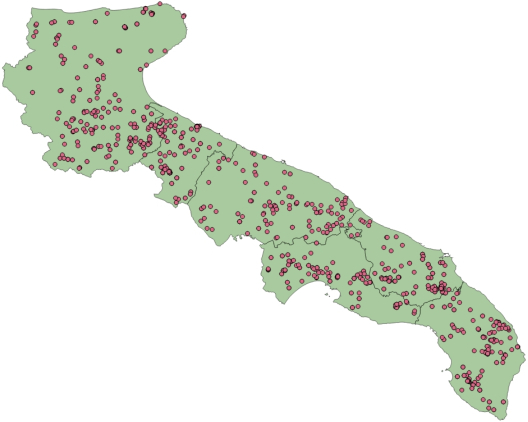

Figure: RICA. Year 2012. Farm geo-locations

Data

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Figure: RICA. Year 2012. Farm geo-locations around Foggia

Data

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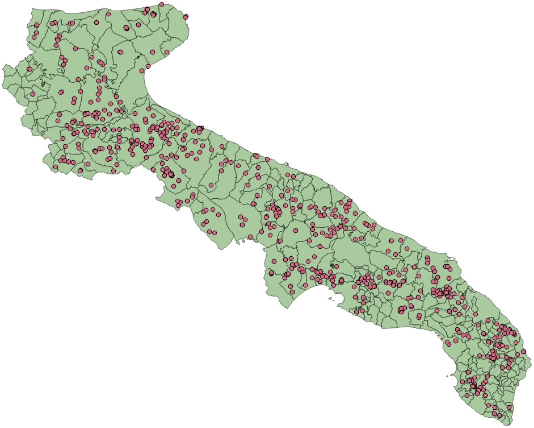
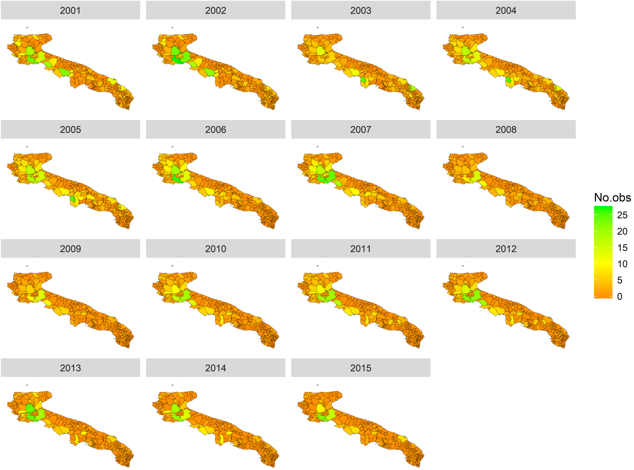


Figure: RICA. Year 2012. *Comune* aggregation

Data

Agricultural data: RICA

RICA: Wheat sampling intensity at the *Comune* level



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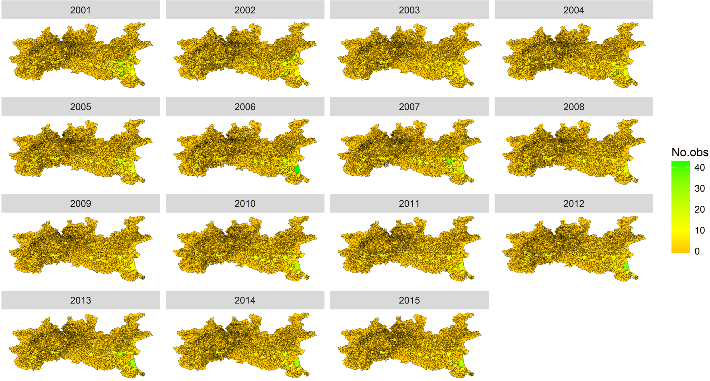

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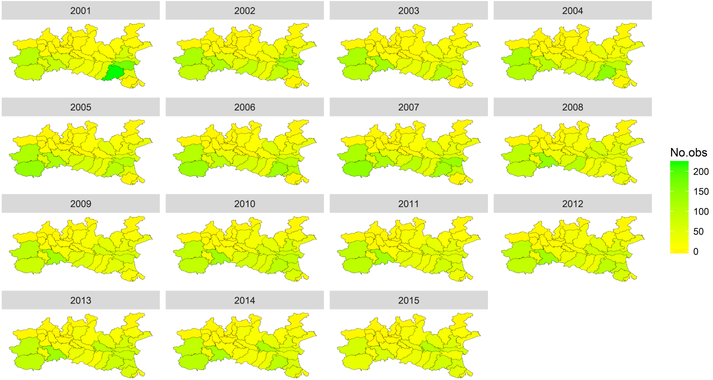


Data

Agricultural data: RICA

WHEAT

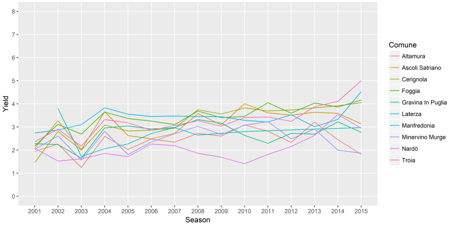


Figure: Puglia

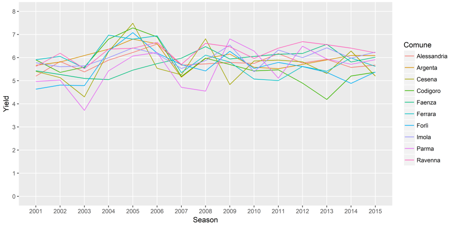


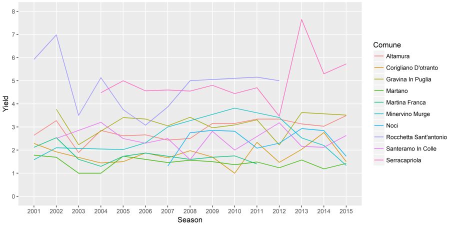
Figure: Po Valley

- Time series of wheat and barley yields in 10 most sampled Comuni
- On average, greater cereal crops productivity in Po valley

Data

Agricultural data: RICA

BARLEY



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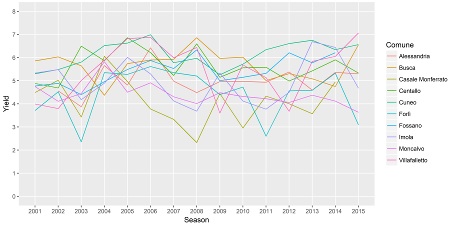

Figure: Po Valley

- Time series of wheat and barley yields in 10 most sampled Comuni
- On average, greater cereal crops productivity in Po valley

Data

Remote sensing: Vegetation and health status indicators

Remote sensing indicators to capture crop performance under water scarcity and drought scenarios

- Land Surface Temperature (MOD11A2)
    - Sensor: Terra
    - Version: 6
    - Coverage: Global
    - Spatial resolution: 1km
    - Temporal resolution: 8-Day
    - Availability: 2000-present
    - Data format: HDF

Data

Remote sensing: Vegetation and health status indicators

Remote sensing indicators to capture crop performance under water scarcity and drought scenarios

- Land Surface Temperature (MOD11A2)
- Evapotranspiration (MOD16A2)
    - Sensor: Terra
    - Version: 6
    - Coverage: Global
    - Spatial resolution: 500m
    - Temporal resolution: 8-Day
    - Availability: 2001-present
    - Data format: HDF

Data

Remote sensing: Vegetation and health status indicators

Remote sensing indicators to capture crop performance under water scarcity and drought scenarios

- Land Surface Temperature (MOD11A2)
- Evapotranspiration (MOD16A2)
- fraction of Absorbed Photosynthetically Active Radiation (fAPAR)
  - Sensor: ESA VGT/PROBA
  - Coverage: Europe
  - Spatial resolution: 1km
  - Temporal resolution: 10-Day
  - Availability: 2000-present
  - Data format: TIFF

Data

Remote sensing: Vegetation and health status indicators

Remote sensing indicators to capture crop performance under water scarcity and drought scenarios

- Land Surface Temperature (MOD11A2)
- Evapotranspiration (MOD16A2)
- fraction of Absorbed Photosynthetically Active Radiation (fAPAR)
- Soil Moisture (ESA CCI SM)
  - Sensor: ESA VGT/PROBA
  - Coverage: Global
  - Spatial resolution: 0.5° (approx. 50km)
  - Temporal resolution: 1-Day
  - Availability: 1978-2016
  - Data format: NetCDF-4

Data

Matching agricultural and remote sensing data

Remote sensing data is extracted at the *Comune* level filtering by Corine Land Cover crop masks

Figure: Regione Puglia

Data

Matching agricultural and remote sensing data

Remote sensing data is extracted at the *Comune* level filtering by Corine Land Cover crop masks

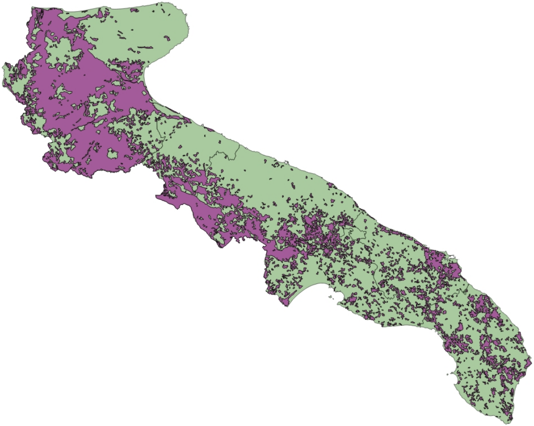

Figure: Regione Puglia + Corine Land Cover 2012 (arable mask)

Data

Matching agricultural and remote sensing data

Remote sensing data is extracted at the *Comune* level filtering by Corine Land Cover crop masks

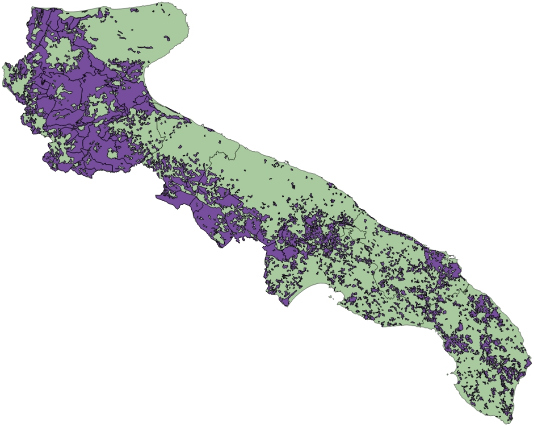

Figure: Regione Puglia + Corine Land Cover 2012 (arable mask) + *Comune* filtered

Data

Matching agricultural and remote sensing data

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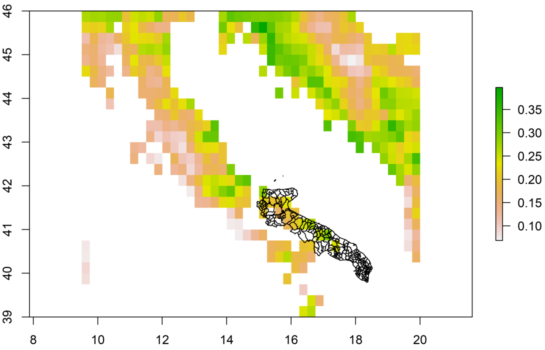

Figure: Soil Moisture

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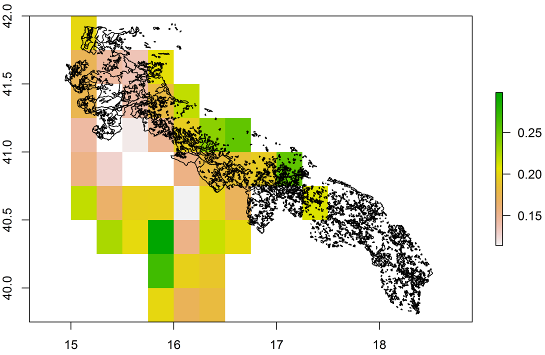

Figure: Soil Moisture + Corine + *Comune*

Data

Remote Sensing data. Regione Puglia

Lower latitudes are hotter (LST) and potentially drier (ET) over the growing cycle

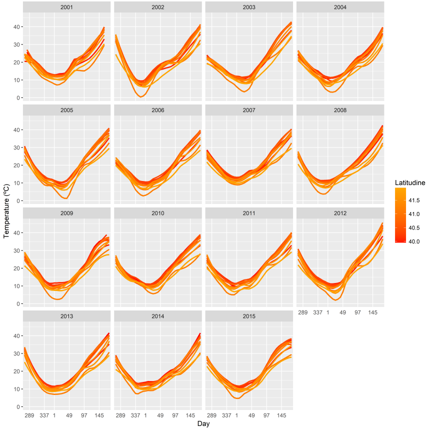

Figure: Land Surface Temperature

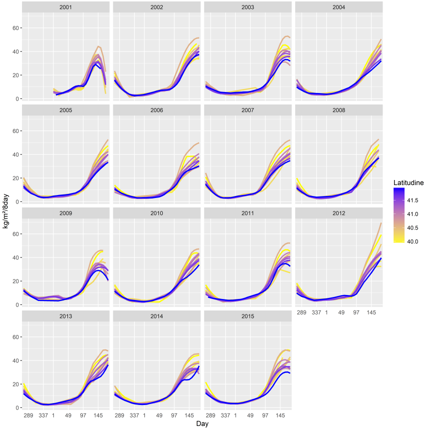

Figure: Evapotranspiration

Data

Meteorological: Temperature and Precipitation

- UERRA-HARMONIE reanalysis
- A ECMWF-led consortium
- Temperature and precipitation grid
- Data assimilation from actual weather stations
- Run for period 1961-2015
- Daily dataset
- Horizontal resolution of 11 km

UERRA
Uncertainties in Ensembles of Regional ReAnalyses

Data

RICA and Remote Sensing data. Wheat yields. Regione Puglia

Optimisation of Remote sensing temporal aggregation according to phenology

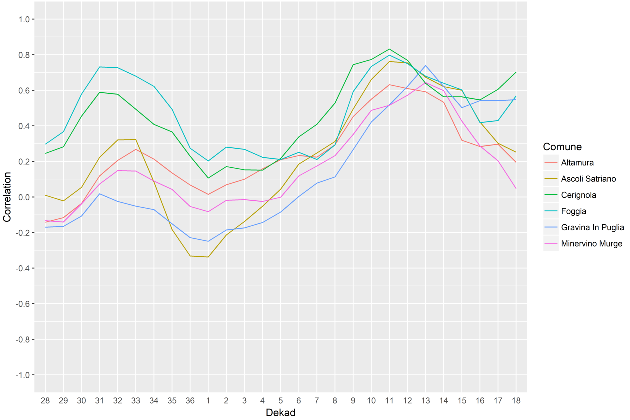

Figure: Correlation (wheat yield, fAPAR)

Data

RICA and Remote Sensing data. Wheat yields. Regione Puglia

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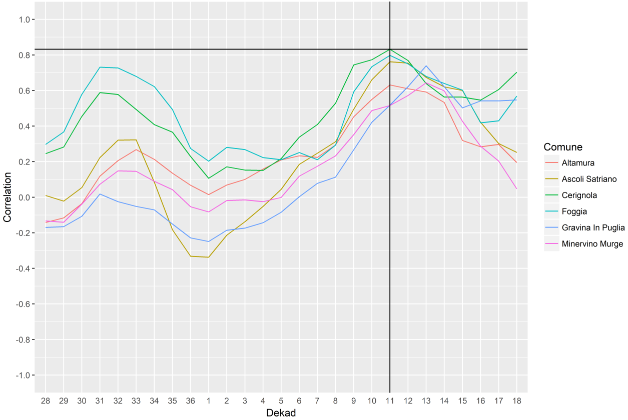

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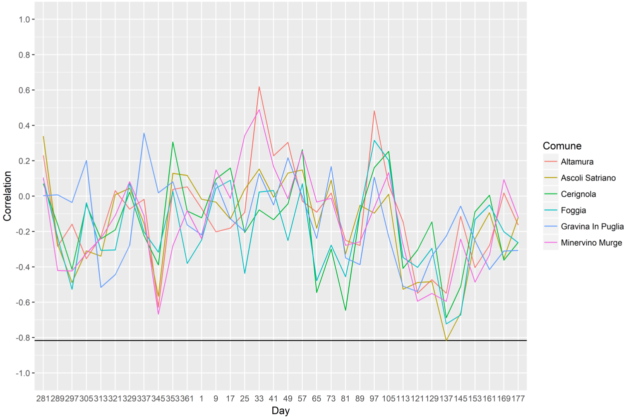

Figure: Correlation (wheat yield, LST)

Data

RICA and Remote Sensing data. Wheat yields. Regione Puglia

Optimisation of Remote sensing temporal aggregation according to phenology

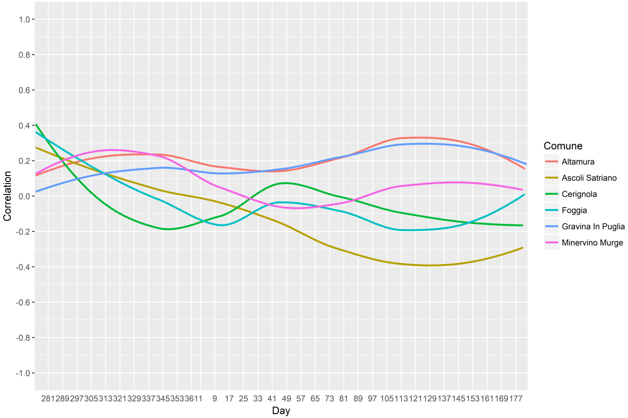

Figure: Correlation (wheat yield, daily SM)

Data

RICA and Remote Sensing data. Wheat yields. Regione Puglia

Optimisation of Remote sensing temporal aggregation according to phenology

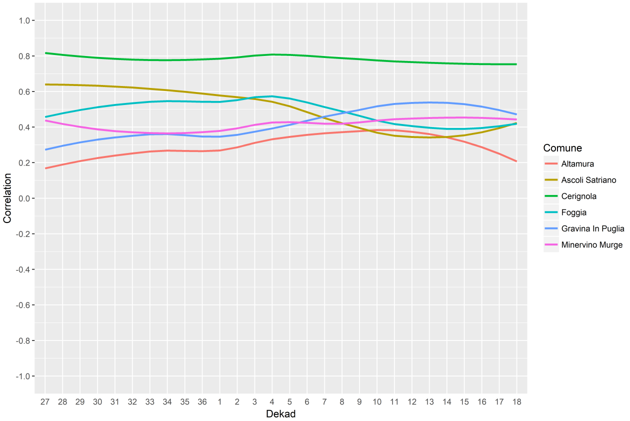

Figure: Correlation (wheat yield, dekad SM)

Methods

A. Optimisation of indicators

- The correlation analysis will be complemented with the use of other statistical techniques
- In particular, Partial Least Squares (PCA) will helps us to select optimal indicators

$$Y = XB + \mathcal{E}$$

$$B = (X'X)^{-1}X'Y$$

$$X = TP$$

decomposing X into T orthogonal scores, from which the first t will be selected

Methods

B. Combined Stress Indicator

- After optimal selection of indicators, weights will be estimated optimally

$$yield_{detr} = a \cdot RS_{detr,std} + b \cdot METEO_{detr,std}$$

  using ridge linear equations (*Zampieri et al., 2017*) accounting for the potential co-linearities between remote sensed and weather indicators
- Methodology applied to Region Puglia and Po valley
- (Near-) Real-Time yield forecasts will be obtained at the *Comune* level

Future steps

- This exercise is part of a more ambitious project
- Current crops: wheat, barley, maize, rice
- Extend our analysis to yet unexplored crops: olive, vineyard
- Mediterranean agriculture: Combine it with Spain's ESYRCE
  - Drought sensitivity analysis
  - Yield spatial heterogeneity
- Process-based crop model improvements: phenology parameters calibration in WOFOST model (in progress)

Thanks for your attention

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