Measuring drought sensitivity of Spanish crop yields

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(joint work with Sergio Contreras and Johannes Hunink)

Fondazione Eni Enrico Mattei (Venice, Italy)

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FutureWater
Investigación y consultoría en recursos hídricos para un futuro sostenible

Fondazione Eni Enrico Mattei

Motivation

Drought stress impacts on agriculture

- Droughts in Europe
  - Episodes more frequent in the last two decades
  - Erode the stability of agricultural production
  - Pose threats to homeland's food security
- Crucial to properly measure (economic) impacts on agriculture
- Lobell *et al.* (2014) study the US corn belt
  - Yield data from USDA's Risk Management Agency (1995-2012)
  - Measure drought stress via Vapour Pressure Deficit (VPD)
  - Increased crop yields during last years thanks to agronomic developments
  - Maize shows greater sensitivity to drought
- Policy implications:
  - Foster more drought-resistant varieties
  - R&D on genomic research

Motivation

Drought stress impact on agriculture

- **Challenges**:
  1. Indicators: How to measure drought?
     - Meteorology, Hydrology, Soil moisture, etc
  2. Great spatial resolution: field-level data
  3. Insulate from irrigated crop varieties
- How to overcome these challenges? Features of our paper:
  - We strongly believe in remote sensing (satellite) measures
    - High resolution
    - Distant areas
    - Easy and prompt access
    - No parametric assumptions
    - More sensors: new variables
    - Remote sensing in the literature (Economics): Lobell (2013), Burke *et al.* (2016)
  - Field-level data set on land use, surface and productivity
  - Focus on non-irrigated varieties: cereals

Objective of the paper

The objective of this paper is twofold:

- Determine whether remote sensing vegetation health indicators are good predictors of cereal yields
- Assess the evolution of Spanish cereals' productivity in response to drought stress (as measured by remote sensing indicators)

Data

Yield and surface data

- ESYRCE (Spanish Survey on Surface and Crop Yields)
- Annual survey at field-level data. Stratified conglomerate sampling.
- Input of EC's Farm Accountancy Data Network (FADN) database

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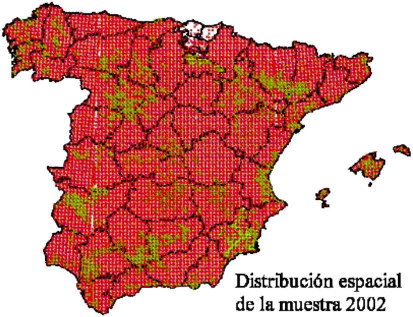

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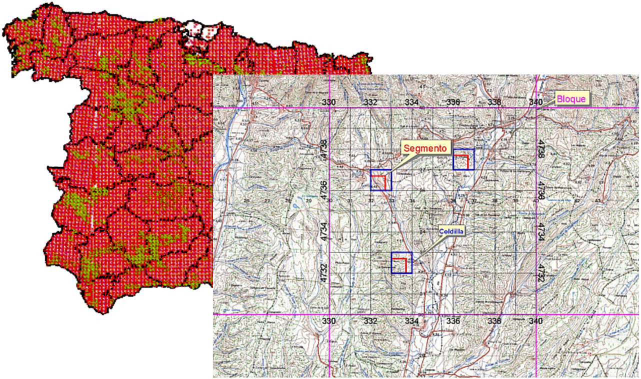

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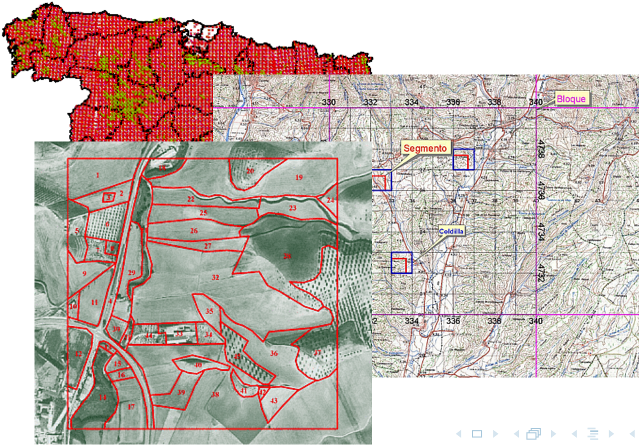


Data

Cereal crops in Spain

- Wheat, barley and maize account for more than 85% of cereal production
- Barley: 5th largest world producer
- Maize: More than 90% irrigated (will act as control)

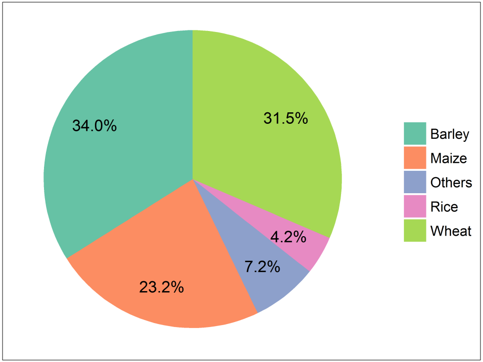
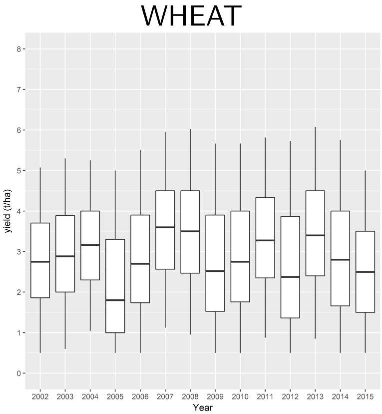


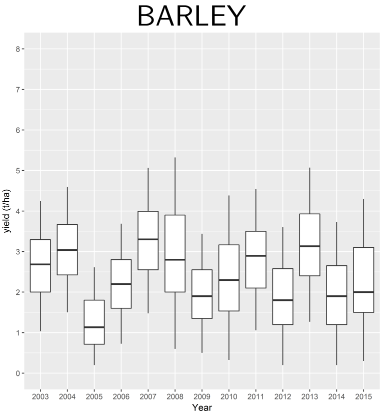
Figure: Spain's Cereal Production. Year 2014. Source: Ministry of Agriculture (Spain)

Data

Cereal crops in Spain

- Yields measured in t/ha
- Predominantly flat yields over the period
- In line with Lobell and Moore (2014, 2015)





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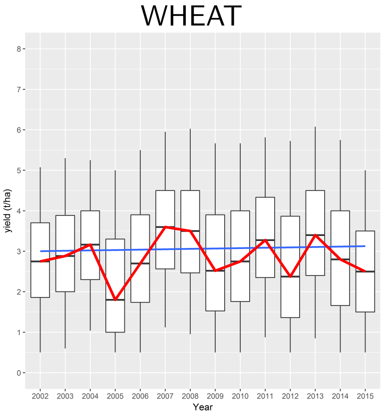

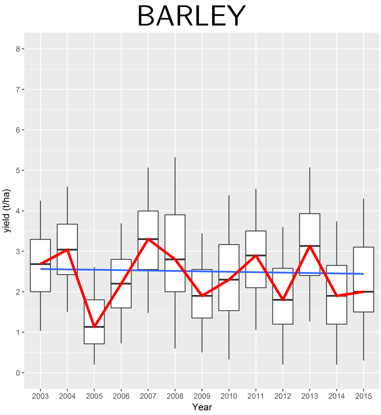

Data

Drought data: the NDVI

- NDVI: Normalised Difference Vegetation Index
- Satellite-based
- Characterises respectively the moisture and thermal condition of vegetation
- Optical spectrometer measures spectral reflectance

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{VIS}}{\mathrm{NIR} + \mathrm{VIS}}$$

where
NIR is acquired in the near-infrared regions
VIS is acquired in the visible regions

Data

Drought data: the NDVI

- Available from 2002.
- Resolution: 1km x 1km
- NDVI shows values $\in (0, 1)$, where 0 (red) indicates higher stress

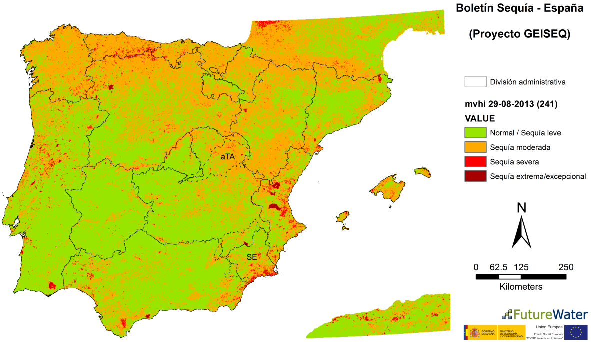

Figure: NDVI. August 2013. Source: Future Water

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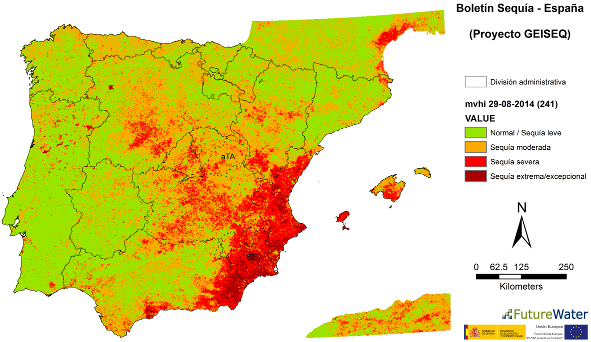

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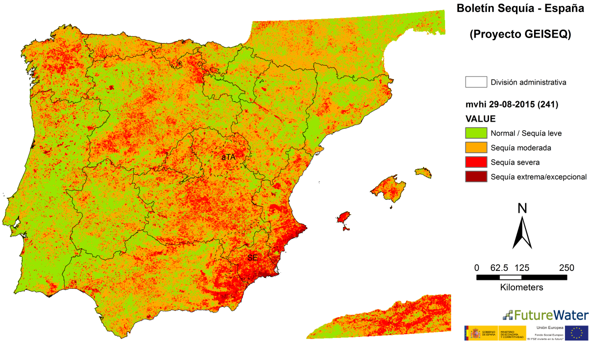


Figure: NDVI. August 2015. Source: Future Water

Data

Matching drought and yield data

- Mismatching resolution between ESYRCE and NDVI
- In ESYRCE each segment is geo-referenced by its SW coordinate
- Average yields per cell (1km x 1km)
- We match yield data with:
  - NDVI
  - Temperature: Land Surface Temperature (LSF)
  - We also control for non-weather year effects
- Number of (cells) observations
  - Wheat $\approx$ 26000
  - Barley $\approx$ 30000
  - Maize $\approx$ 2200

Methods

MARS: Multiple Adaptive Regression Splines

- Great evidence of non-linear effects of temperatures on aggregate production (Burke et al., 2015) and, especially, in agriculture (Deschenes and Greenstone, 2007)
- We don't want to impose any structure
- Multivariate Adaptive Regression Splines (MARS). Friedman (1991), Hastie et al. (2001)
  - Good to model non-linearities and interaction between variables
  - Non-parametric, automatic variable selection technique
  - Implemented in R, embedded in package *earth*

Methods

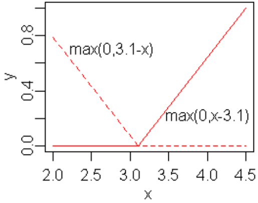
MARS: Multiple Adaptive Regression Splines

- The MARS general model takes the form

$$f(X) = \beta_0 + \sum_{m=1}^{M} \beta_m h_m(X)$$

where the optimum number of elements, m^*, is chosen by the algorithm, given our candidate predictors

- Uses piece-wise linear (hinge) functions as basis functions



- Two step procedure: forward and pruning pass
- Choose specification with less GCV

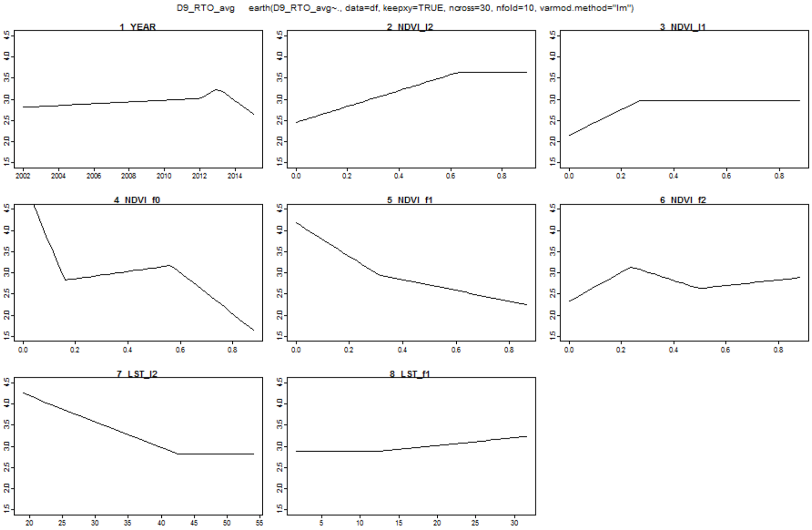
Methods

MARS: Description of the model

- Regress yields on 11 (candidate) predictors
  - NDVI (5): Rolling window around sowing month (+-2 months)
  - LSF (5): Rolling window around sowing month (+-2 months)
  - year-technology (1)
- MARS implemented in R (earth package); degree = 2, which allows for interactions between variables
- Each variety is studied separately: wheat, barley, maize (as control)
- Sample period: 2002-2015
- Non-linear, non-parametric: Graphical output

Results: The role of NDVI as a determinant of yields

Wheat



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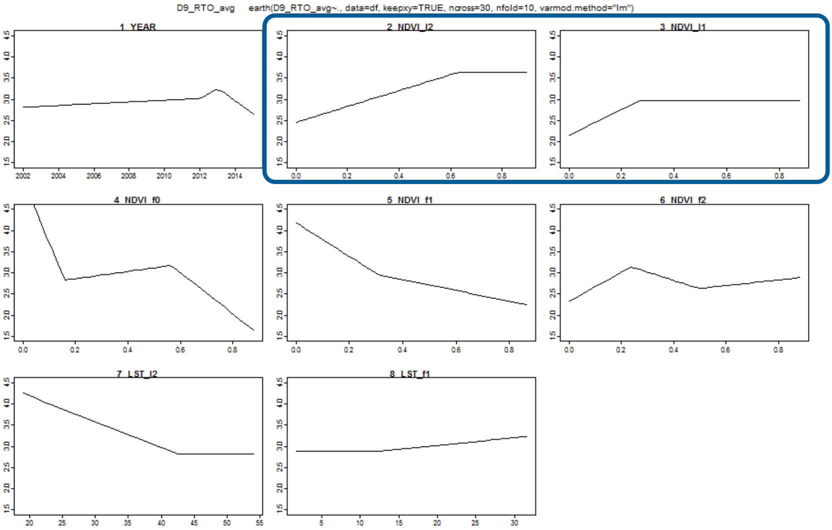

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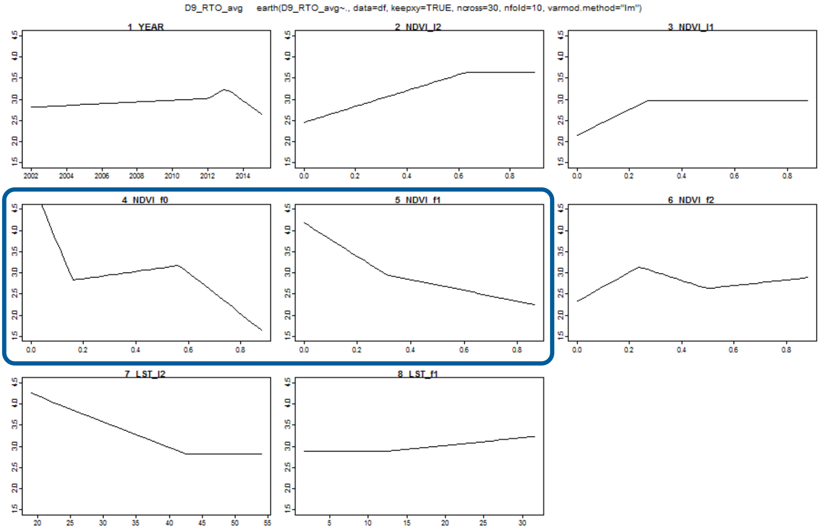

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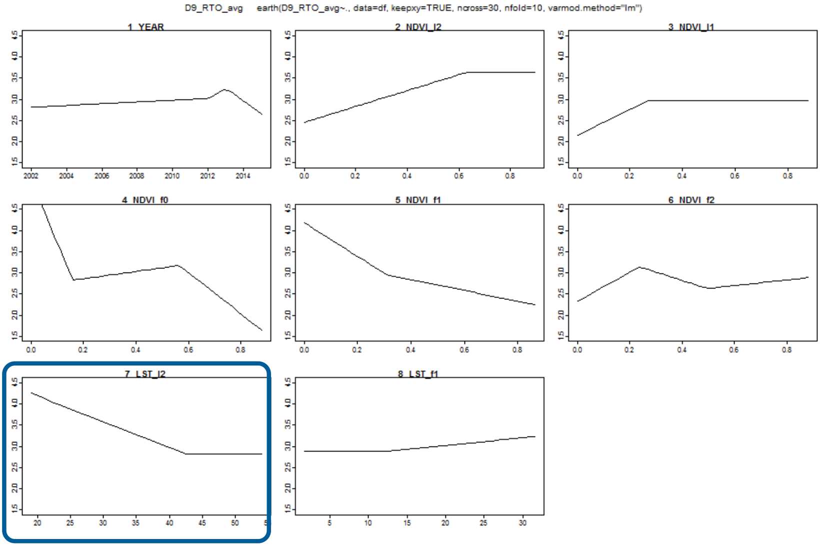

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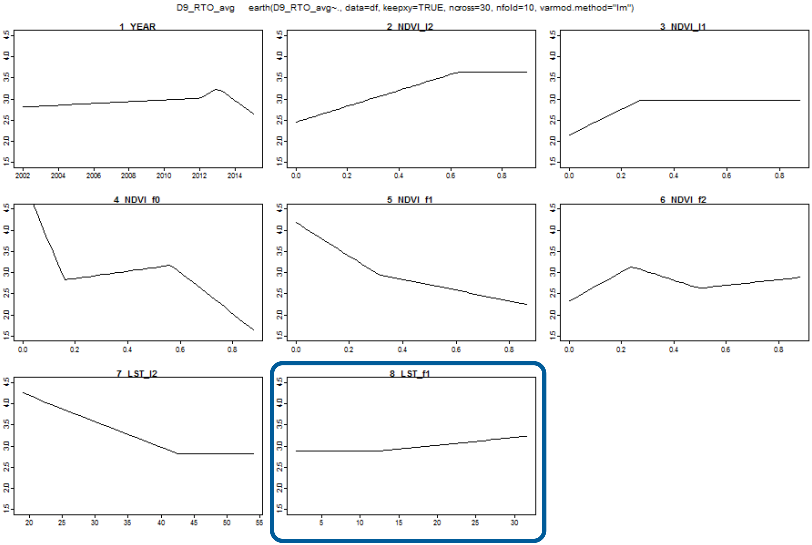
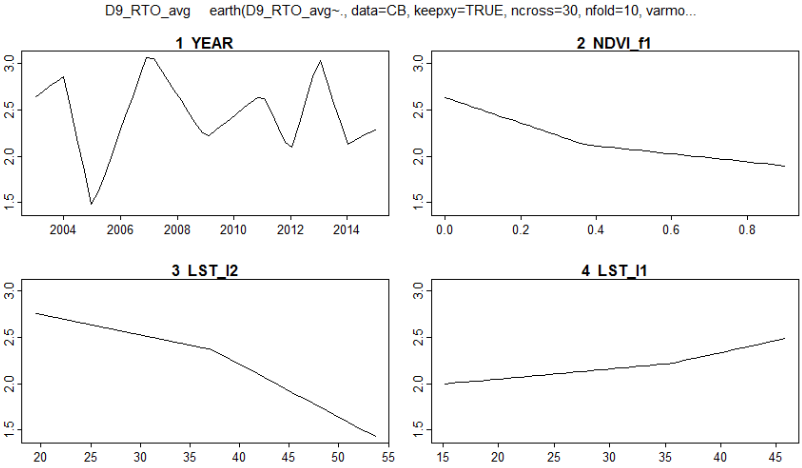


Results: The role of NDVI as a determinant of yields

Barley

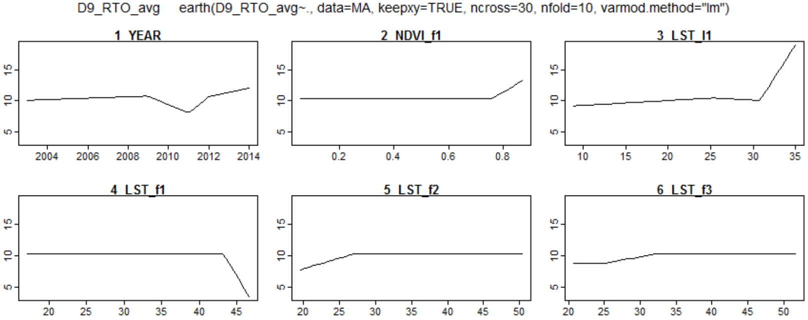
- Similar role of NDVI



Results: The role of NDVI as a determinant of yields

Maize

- Yields do not respond to NDVI variations
- Irrigation copes with drought stress anomalies



Results: Measuring drought sensitivity

the Environment Index

- Stress levels are often quantified as the average yield across all cultivars grown at a given site and season
- This is referred to in the literature as the **Environment Index**

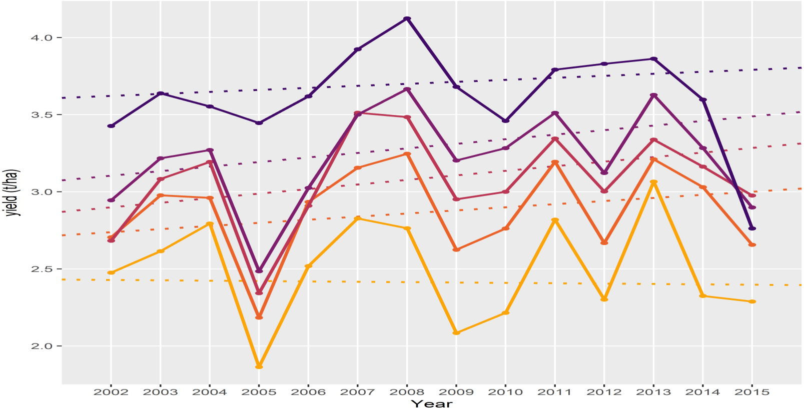
$$\mathrm{EI} = \hat{\beta}_0 + \sum_{\mathrm{m}=1}^{\mathrm{m}*} \hat{\beta_{\mathrm{m}}} \mathrm{h}_{\mathrm{m}}(\mathrm{X})$$

- A plot of yields versus environment index is then used to measure the sensitivity of that cultivar's yield to stress
- We study the response of yields to different stress levels along time to test for changes in sensitivity (technology fixed at year 2005)
- We look in particular at
  - the time trends of yields according to different drought stress (EI quintiles)
  - the contribution of each indicator

Results: Measuring drought sensitivity (Wheat)

the Environment Index: distribution of yields wrt EI quintiles

- Yields over different growing conditions (represented by EI quintiles)
- Slopes significantly greater than 0 for Q2-Q5



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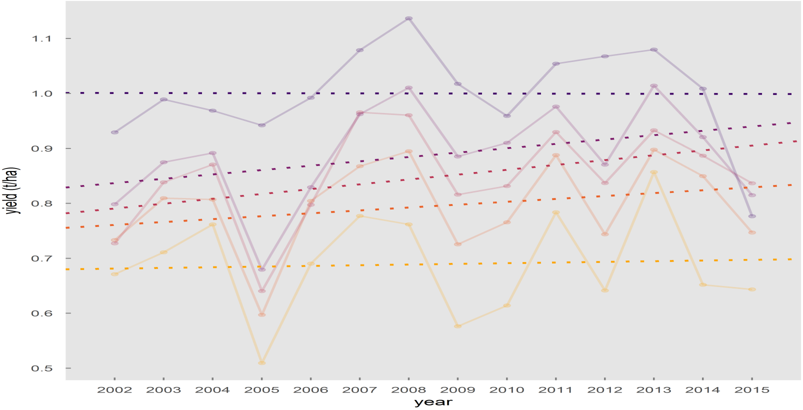
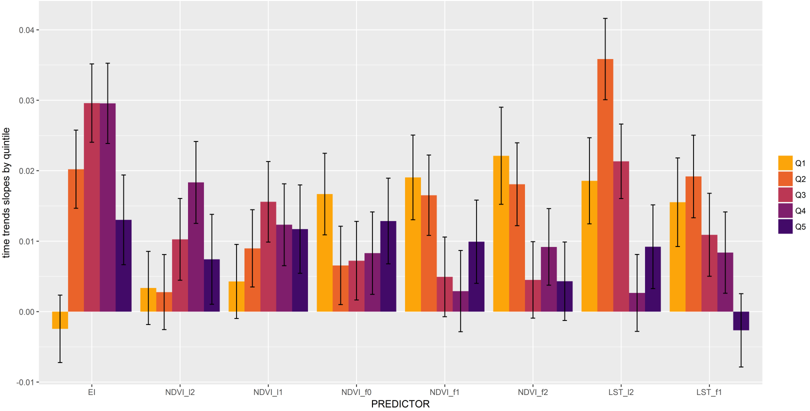


Results: Measuring drought sensitivity (Wheat)

the Environment Index: contribution of indicators by quintiles

- Marked differences of time trend slopes by quintiles
- Lower quintiles growing at lower paces

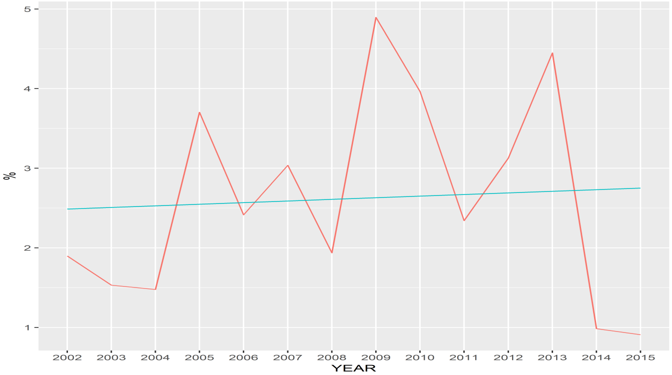


Results: Measuring drought sensitivity (Wheat)

Yields and NDVI: Cross-section analysis

- Complements the previous analysis
- Increased sensitivity of yields wrt NDVI
- % change of yield per additional 0.1xNDVI (p-value=0.15)

$$\log(\mathrm{yield_t}) = \alpha + \beta(\mathrm{NDVI_{f0}}/10) + \epsilon_\mathrm{t}$$



Discussion of our (preliminary) results

- Stagnation of non-irrigated cereal yields in Spain over the last 15 years
- Non-linear increasing relation between NDVI values before sowing and non-irrigated cereal yields
- Non-linear decreasing for NDVI after sowing
- Irrigated crops (maize) use external water resources to cope with drought stress oscillations
- Evidence suggests increased sensitivity of wheat yields under relatively worse growing conditions and convergence under mild growing conditions during 2002-2015

Next steps

...to complete this paper

- Refine temporal window of NDVI
- Control for regional heterogeneity
  - Yield anomaly by region/province
- Alternatives to NDVI: corroborate findings with other remote sensing measures
  - NDWI (Normalised Difference Water Index)
  - TCI (Temperature Condition Index)
  - VCI (Vegetation Condition Index)

Next steps

...of my project

- Drought impacts in agriculture
  - Case study: Po river basin. Compare performance with other indicators/methods
  - Enlarge the scope to Europe mainland (using FADN database)
  - Integration of Northern Africa
  - Study/compare remote sensing measures available
- Combine satellite imagery and machine learning techniques to improve forecasts
- Other sectors: public water supply,...
- Other climate extremes: floods, heat-cold waves,...

Thanks for your attention

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