The impact of high temperatures on Italian maize yield

A functional regression approach

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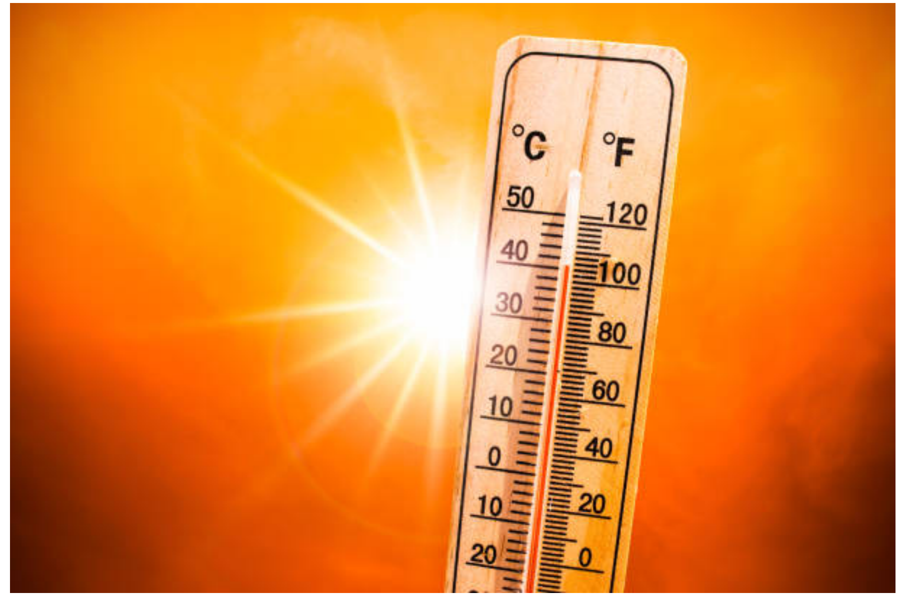
Motivation

Motivation

The impact of climate change on agricultural production is a critical area of investigation. The timing of weather conditions is crucial for agriculture, especially crop production. Understanding within-season changes allows for better adaptation.



Previous studies

Previous studies [1], [2] have demonstrated a negative effect of high temperatures on the productivity of Italy's agricultural sector and food industry. Over the years, numerous efforts have been made to account for time-varying effects within the season including monthly variables [3] and sub-season crop stages [4].

Data

Dataset

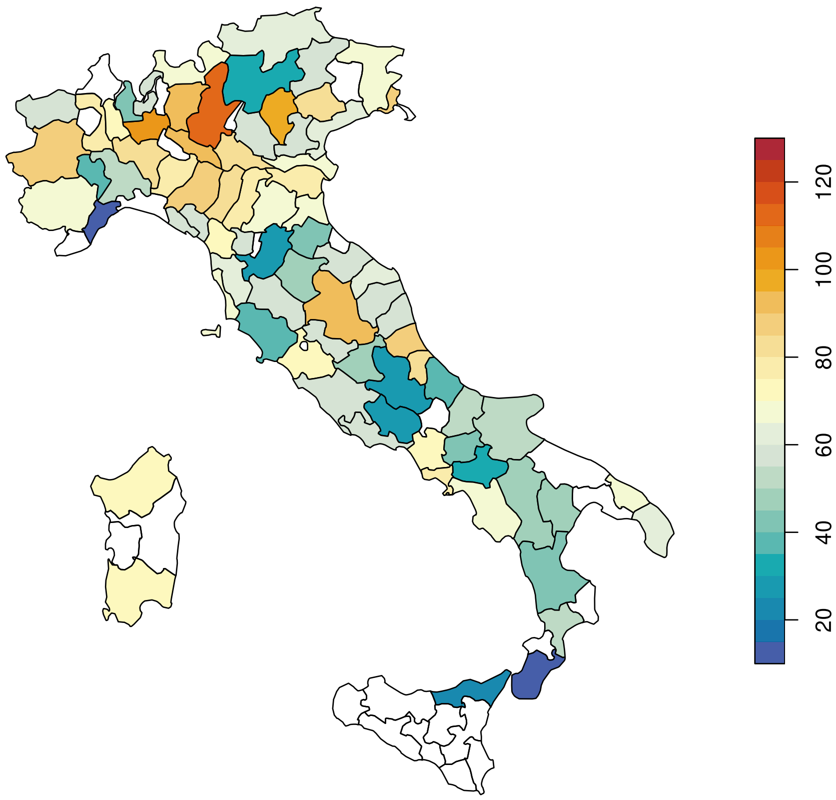
We considered maize yields and temperature data collected from various Italian provinces over an extended period of time.

- Maize yields: (production / area) of 79 Italian provinces measured from 1952 to 2023.
- Hourly temperatures: measured during the maize growing season (April to October).

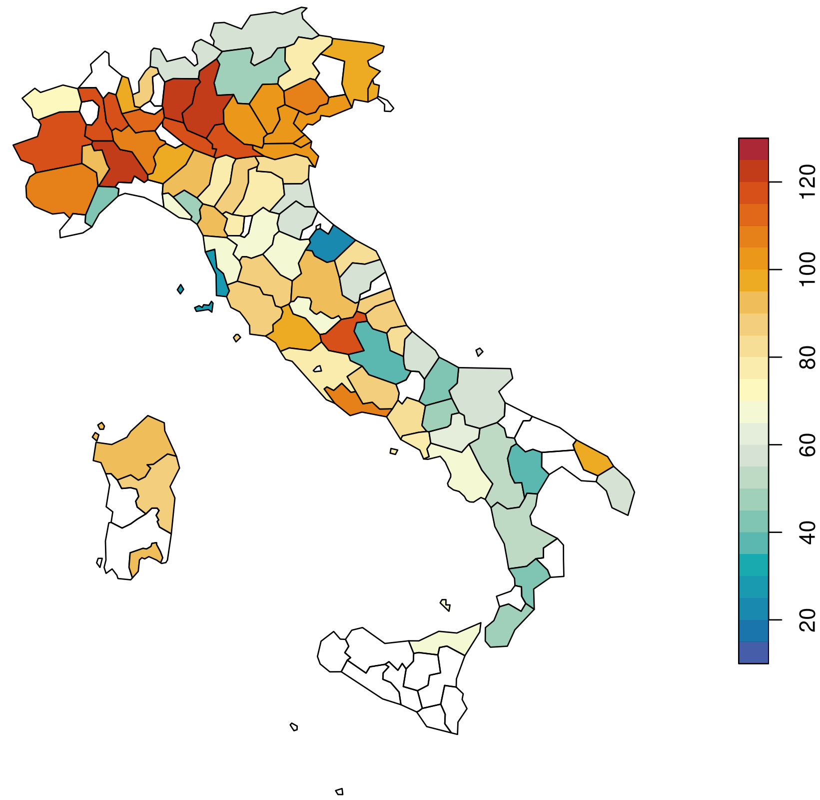
The data were retrieved from the Copernicus Climate Data Store, temperatures series were computed as a weighted mean, using maize production area (in 2018) as weights, for each province.

Spatial distribution of yield

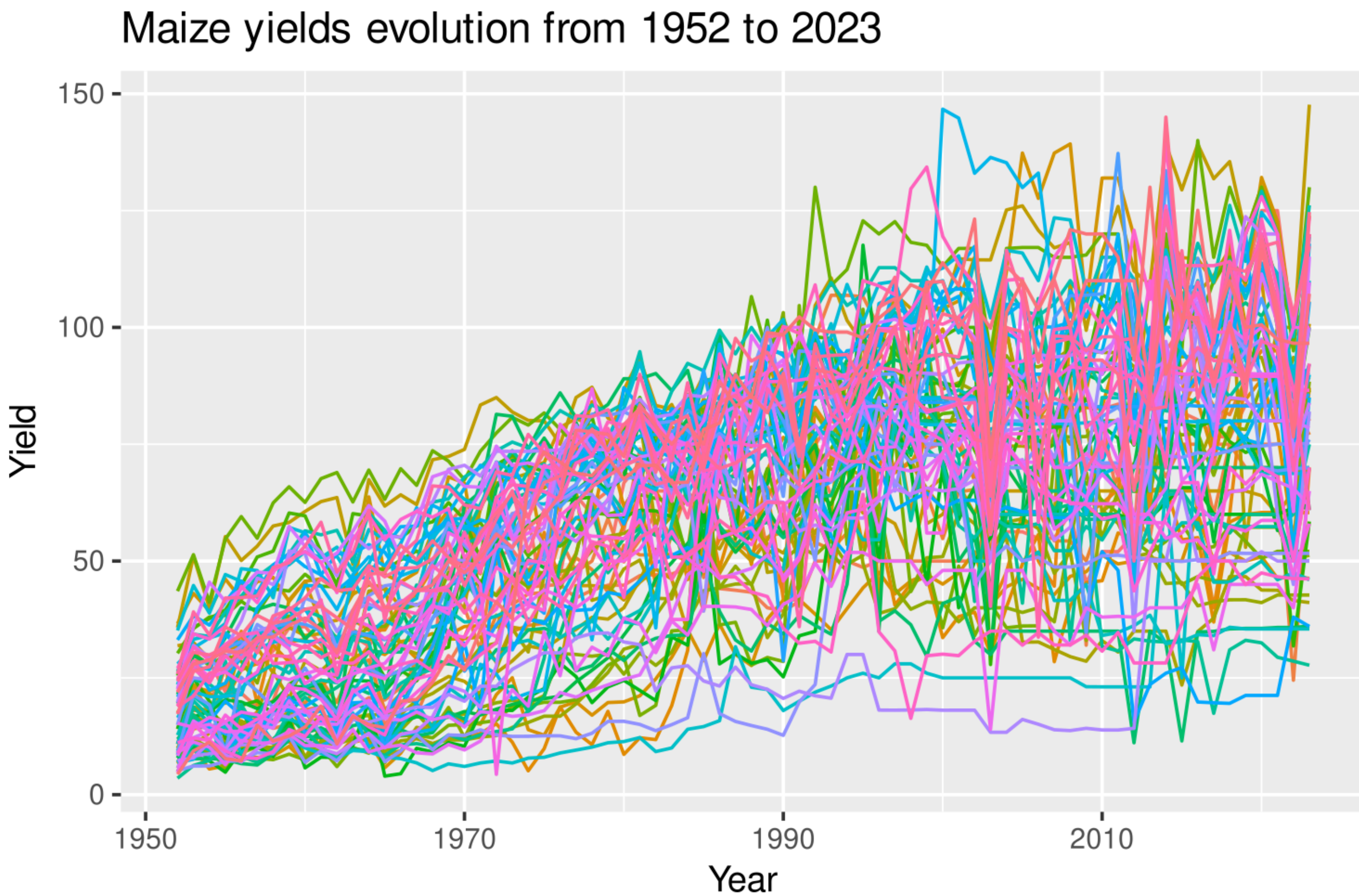
Italy NUTS 3 regions (2003)



Italy NUTS 3 regions (2021)



Temporal evolution of yield



Statistical model

Functional data

We chose to represent temperatures data as a functional data `Temp`. Due to the intrinsic periodicity of temperatures a Fourier basis with `nbasis = 50` was used.

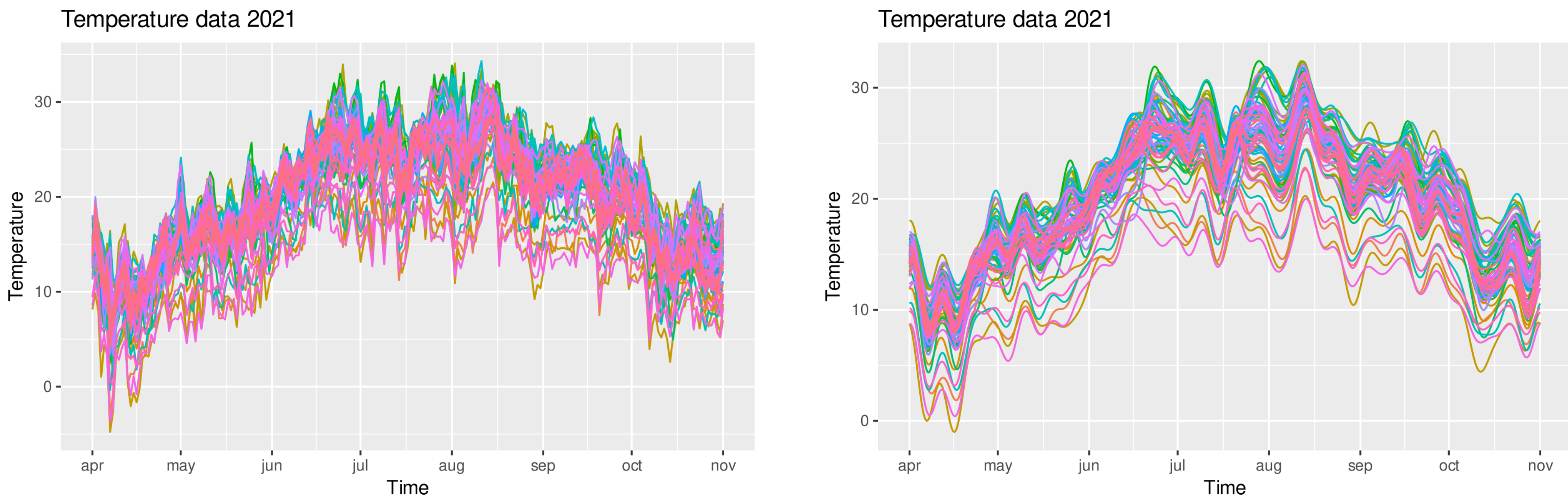


Figure 1: Temperatures 2021

Functional regression ingredients

We considered a functional regression model with scalar response variable where:

- $i = 1, \ldots, 72$ is the year index.
- $j = 1, \ldots, 79$ is the province index.
- $t \in [0, T]$ is the time interval (expressed in hours) for each year, where $T = 5136$.
- $Y_{i,j} = \log(\texttt{Yield}_{i,j})$ is the natural logarithm of $\texttt{Yield}_{i,j}$.
- $\texttt{Temp}_{i,j}(t)$ is the temperature measured in province j during year i at time t.
- $\texttt{Temp}_{\bullet,\bullet}(t)$ is the mean temperature at time t over provinces and years.

Functional regression model

$$Y_{i,j} = \alpha_j + \beta_1 i + \beta_2 i^2 + \\ + \int_0^T \gamma(t)(\mathtt{Temp}_{i,j} - \mathtt{Temp}_{\bullet,\bullet})(t)dt + \varepsilon_{i,j}$$

- A fixed effect α_j for each province j.
- A quadratic dependence (β_1, β_2) from the year i.
- The functional coefficient $\gamma(t)$ accounting for the effect of the temperatures (centered).

Estimate 1

In order to estimate the functional coefficient $\gamma(t)$ we considered the well known Karhunen-Loève transform (functional PCA).

$$\texttt{Temp}_{i,j}(t) - \texttt{Temp}_{\bullet,\bullet}(t) = \sum_{k=1}^{\infty} \xi_k^{i,j} \phi_k(t)$$

where $\{\phi_k\}_k$ is the basis given by the functional principal components.

Estimate 2

Using the fPCs the model simplifies to:

$$Y_{i,j} = \alpha_j + \beta_1 i + \beta_2 i^2 + \sum_{k=1}^{\infty} \gamma_k \xi_k^{i,j} + \varepsilon_{i,j}$$

where $\gamma_k = \int_0^T \gamma(t)\phi_k(t)dt$ are the functional coefficient's scores expanded on the fPCs basis.

Estimate 3

By truncating the series to a finite number M of fPCs the problem turns into the estimate of a classical multiple regression model.

$$Y_{i,j} = \alpha_j + \beta_1 i + \beta_2 i^2 + \sum_{k=1}^{M} \gamma_k \xi_k^{i,j} + \varepsilon_{i,j}$$

At this point we can estimate the coefficients to address both:

- $\mathbb{E}[Y|X]$ the conditional expected value (classical regression).
- $Q_{Y|X}(\tau)$ the conditional quantile function (quantile regression).

Bootstrap

In order to estimate the uncertainty of $\gamma(t)$ as well, we employed a Bootstrap procedure considering:

- $n_b = 25$ Bootstrap replicas (resampling provinces while considering all years).
- The OLS estimator.
- The quantile regression (QR) estimator for a given $\tau \in [0.1, 0.9]$.
- The quantile average estimator (QAE) for a given $\tau \in [0.1, 0.9]$.

Results

OLS Coefficients

```
                          Estimate Std. Error t value Pr(>|t|)    
PC1                     -9.993e-04  9.242e-05 -10.813  < 2e-16 ***
PC2                      7.890e-04  1.054e-04   7.485 8.24e-14 ***
PC3                      1.412e-04  1.071e-04   1.318    0.187    
PC4                      5.861e-04  1.221e-04   4.802 1.62e-06 ***
PC5                     -2.025e-04  1.243e-04  -1.629    0.103    
provinceAlessandria      2.772e+00  3.667e-02  75.599  < 2e-16 ***
...
provinceViterbo          2.780e+00  3.657e-02  76.026  < 2e-16 ***
year                     5.668e-02  7.811e-04  72.565  < 2e-16 ***
I(year^2)               -4.530e-04  1.137e-05 -39.828  < 2e-16 ***
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.292 on 5602 degrees of freedom
```
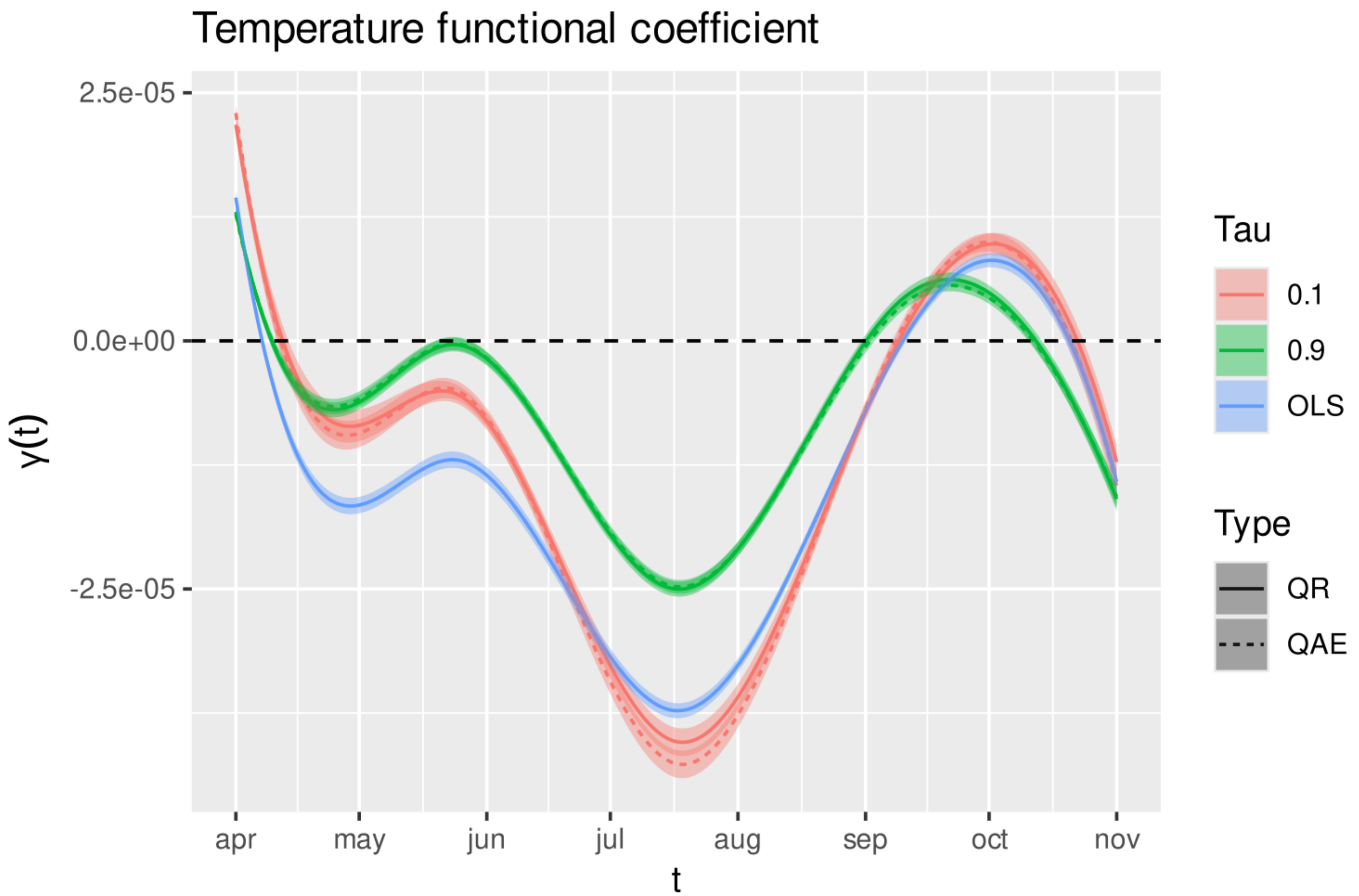

Functional coefficient



Conclusions

Interpretation

Considering the estimate of the functional coefficient $\gamma(t)$ we can draw the following conclusions:

- The impact of above-average temperatures is
  - Clearly negative between June and August i.e. the maize flowering phase.
  - Mildly positive at the beginning of April and between September and October.
- During the summer the impact is more negative on the 0.1 quantile rather than the 0.9.

Future work

In this work we considered the impact of high temperatures on the Italian maize production.

We were able to consider only temperatures as a covariate because maize is an irrigated crop; if this had not been the case, it would have made sense to take precipitations into account. In a subsequent work we are using such approach to study the impact on wheat yields.

Thank you for the attention!

Main references

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