Weather Shocks and their Long-Term Impact on Agricultural Yields: Evidence from Italy

by

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Abstract: This paper examines the effects of weather shocks on agricultural yields. Using data on wheat and corn yields from seven Italian provinces over the period 1866-2014. We find that the effects of weather shocks are asymmetric, with much larger impacts on the lower tail of the distribution than the upper tail. The analysis also shows slow dynamic adjustments. This indicates that negative shocks have significant and persistent effects on agricultural productivity.

Keywords: grain yields, quantile autoregression, weather shocks, risk, Italy.

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1. Introduction

A large body of literature has analyzed the impact of climatic factors and shocks in agriculture (e.g., Mendelsohn et al., 1994; Maddison, 2000; Parry et al., 2004; Lobell and Field 2007; Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009; Hertel et al., 2010; Lobell et al., 2011; De Salvo et al., 2013; Bassu et al. 2014; Rosenzweig et al., 2014; Di Falco and Veronesi, 2014; Van Passel et al., 2016). Of special concerns are the effects of heat stress and drought on crop yields (e.g., Lobell et al., 2013, 2014). Related issues are the adverse effects of climate change and its implications for agricultural productivity growth (e.g., Brisson et al., 2010; Ray et al., 2012) and agricultural risk (e.g., Kim et al. 2014; Lunt et al., 2016). The dynamic effects of weather shocks on the probability distribution of agricultural production remain, however, poorly understood. This implies a need to study how weather shocks affect yield distributions and their dynamics. The objective of this paper is to explore such issues, with an application to crop yields in Italy. This paper presents an empirical investigation of how weather shocks, measured as annual differences from the long term rainfall and temperature means, affects the distribution of agricultural production using a dynamic quantile autoregression (QAR) approach (Koenker and Xiao, 2006). A QAR model provides a flexible representation of the distribution of crop yields. It also allows for yield dynamics to vary across quantiles of the distribution (Koenker and Xiao, 2006; Chavas and Di Falco, 2017). Estimating QAR models of crop yields provides the information needed to understand the role of weather shocks and their effects on agricultural productivity both in the short run and in the long run.

We use crop yield data for wheat and corn in seven Italian provinces over the period 1866-2014. This dataset provides a great case study for three reasons. First, Italy exhibits large agroclimatic variations, going from a relatively cool climate in the North to a moderate climate in the center and to a hotter and drier Mediterranean climate in the South. Second, the analysis covers a century. The long data period is important for our analysis as it allows estimating the evolution of yield distributions, with special attention given to estimated patterns in the lower tail of the distributions. Third, the investigation focuses on two major grains that differ in their response to adverse weather shocks. Corn is more productive under favorable weather conditions, while wheat is more drought tolerant.

The key results are as follows. First, we show that the effects of weather shocks are asymmetric, with much larger impacts on the lower tail of the distribution than on the upper tail. Second, we document how these effects vary across provinces and across crops. Third, we find slow dynamic adjustments, indicating that weather shocks have significant long-term effects on agricultural productivity. These novel results contribute to two broad strands of literature in agricultural and resource economics. First, and most obvious, is the expanding literature using cross sectional analysis, structural approaches and panel data to estimate the impact of climatic factors in agriculture (e.g., Mendelsohn et al., 1994; Schlenker et al., 2006; Deschenes and Greenstone, 2007; Lobell et al., 2011; Fisher et al., 2012). This paper is the first to adopt a dynamic approach to understand how weather conditions affect crop yields and their dynamics. The second strand of related literature is the one on risk exposure and climatic shocks. Shocks such as droughts or floods are indeed important contributors to food production risk (e.g., Adams et al., 1990; Mearns et al., 1997; Mendelsohn, 2007; Lobell and Field, 2007; Rozensweig et al., 2014; IPCC, 2014; Nelson et al., 2014). Crop failures correspond to events located in the lower tail of the yield distribution. This paper provides a study of how weather shocks affect the lower tail of the yield distribution and how the effects can differ in the short run versus the longer run. Assessing such issues is also relevant in evaluating the resilience of agro-ecosystems and their ability to recover from adverse shocks (e.g., Chavas and Di Falco, 2017).

The paper is organized as follows. Section 2 presents a general model of yield dynamics and its QAR representation. Sections 3 and 4 report the estimated QAR model applied to wheat yield and corn yield in Italy. The implications of the results are discussed in section 5. Finally, section 6 concludes.

2. The Model

This section presents our conceptual model. Consider an agricultural production system exhibiting productivity $y_t \; \mathbb{R}$ at time t. The crop productivity evolves over time according to the m-th order stochastic difference equation

$$y_t = f(y_{t-1},\ldots,y_{t-m},\ z_t, e_t), \tag{1}$$

where z_t is a vector of exogenous variables and e_t is a vector of random variables with a given distribution function.. Equation (1) can be alternatively written as

$$w_t \equiv y_t\, y_{t-1}\ \ y_{t-m+1} = f\, y_{t-1},\ldots,y_{t-m},z_t,e_t\, y_{t-1}\ \ y_{t-m+1} \equiv g(w_{t-1},\ z_t,e_t), \tag{2}$$

Under the differentiability of $f(\ )$ and evaluated at point (w_{t-1},z_t,e_t), consider the $(m\times m)$ Jacobian matrix $D_{w_{t-1},z_t,e_t} = \partial g(w_{t-1},z_t,e_t)/\partial w_{t-1}$. Let the Eigenvalues of

$D(w_{t-1}, z_t, e_t)$ be $(\lambda_1(w_{t-1}, z_t, e_t), \ldots, \lambda_m(w_{t-1}, z_t, e_t))$, where $\lambda_1(w_{t-1}, z_t, e_t)$ is the dominant root with the largest modulus $|\lambda_1(w_{t-1}, z_t, e_t)|$. The Eigenvalues provide useful information about the dynamics of y_t. Around point (w_{t-1}, z_t, e_t), the local forward trajectory of y_t diverges (converges) if $\lambda_1(w_{t-1}, z_t, e_t) > 1$ (< 1), with $\ln(|\lambda_1(w_{t-1}, z_t, e_t)|)$ measuring the rate of divergence of neighboring forward paths (Wiggins, 2003). When $f(y_{t-1}, \ldots, y_{t-m}, z_t, e_t)$ is linear in $(y_{t-1}, \ldots, y_{t-m})$, the system exhibits linear dynamics and the roots $(\lambda_1, \ldots, \lambda_m)$ are independent of (w_{t-1}, z_t, e_t). In particular, the system is globally stable (unstable) if $\lambda_1 < 1$ (> 1). In situations where (w_{t-1}, z_t, e_t) are held constant over time, global stability means that $\lim_{t\to\infty} y_t \to y_e$, y_e being a unique steady state equilibrium that is eventually reached under any initial condition y_0 (Wiggins, 2003). Alternatively, the system exhibits non-linear dynamics when $f(y_{t-1}, \ldots, y_{t-m}, z_t, e_t)$ is non-linear in $(y_{t-1}, \ldots, y_{t-m})$. Then, the root $\lambda_1(w_{t-1}, z_t, e_t)$ provides information about local system dynamics. If $\lambda_1(w_{t-1}, z_t, e_t) < 1$ for all (w_{t-1}, z_t, e_t), the system would exhibit dynamic stability everywhere. Alternatively, if $\lambda_1(w_{t-1}, z_t, e_t) > 1$ for $(w_{t-1}, z_t, e_t) \in N$, then the dynamic system would tend to escape the neighborhood N over time. When the neighborhood N is undesirable, the dynamic escape from this neighborhood may be good if the system moves toward more desirable states. This would correspond to a resilient system that recovers from adverse shocks (Chavas and Di Falco, 2017).

Let $F(c \mid w_{t-1}, z_t) = Prob\{f(y_{t-1}, \dots, y_{t-m}, z_t, e_t) \le c\}$ be the cumulative distribution function of y_t conditional on (w_{t-1}, z_t). We will be interested in the associated conditional quantile function $Q_q(w_{t-1}, z_t)$ defined as the inverse of the distribution function: $Q_q(w_{t-1}, z_t) = Min_c\{c : F(c \mid w_{t-1}, z_t) \ge q\}$, $q \in (0, 1)$.[2] We will focus our attention on the case where the quantile function takes the form

$$Q_q(w_{t-1}, z_t) = \alpha(q, z_t) + \sum_{i=1}^{m} \beta_i(q, w_{t-1}, z_t)\, y_{t-i}\ , \qquad (3)$$

where $\alpha(q, z_t)$ and $(\beta_1(q, w_{t-1}, z_t), \dots, \beta_m(q, w_{t-1}, z_t))$ involve parameters to be estimated using quantile regression (Koenker, 2005). Allowing $\alpha(q, z_t)$ to vary with (q, z_t) permits the specification (3) to represent any conditional distribution function with arbitrary moments (i.e., mean, variance, skewness and kurtosis). When $\beta_i(q, w_{t-1}, z_t)$ does not dependent on (q, w_{t-1}, z_t) for all $i = 1, \dots, m$, the specification (3) reduces to a standard m-th order autoregression model, AR(m). When $\beta_i(q, w_{t-1}, z_t)$ can change with q but not with (w_{t-1}, z_t) for all $i = 1, \dots, m$, (3) corresponds to the quantile autoregression model, QAR(m), proposed by Koenker and Xiao (2006). The QAR(m) model is more flexible than the AR(m) model in the sense that it allows the autoregression parameters $\beta_i(q)$ to vary across quantiles, thus permitting dynamic adjustments to differ with the type of shock (e.g., favorable shock versus adverse shock). More generally, the

[2] When $q = 0.5$, the quantile $Q_{0.5}(w_{t-1}, z_t)$ is the median of y_t conditional on (w_{t-1}, z_t). More generally, when $q \in (0, 1)$, the conditional quantile function $Q_q(w_{t-1}, z_t)$ provides all the information about the distribution of y_t and its dynamics.

autoregression parameters β_{iq}, w_{t-1}, z_t can vary with both q and (w_{t-1}, z_t), allowing for nonlinear dynamics.

3. Empirical Analysis

The QAR model presented in section 2 is now applied to two major crops (winter wheat and corn) in seven Italian provinces (Milan, Venice, Bologna, Florence, Rome, Naples and Palermo). The data involve annual yield for each crop in each province over the period 1900-2014.The yields are measured in 100 kg per harvest ha. We also use weather data in each province, including annual temperature and annual rainfall over the period 1866-2014.[3] The data were obtained from the Italian Istituto Nazionale di Economia Agraria (INEA). Summary statistics of the data are presented in Table 1. In addition, graphs of the data are presented in the Appendix for selected regions.

Table 1 shows that corn yields are much higher than wheat yields (60% higher on average). Also, compared to Southern Italy (e.g., the Palermo province in Sicily), Northern Italy (e.g., the Milan province in Lombardia) exhibits higher yields and faces lower temperature and higher rainfall. Contrasting the rainier and cooler North with the drier and hotter South makes it an interesting case study of the effects of weather on agricultural productivity. Of special interest will be to investigate how these effects vary between wheat and corn.

[3] Note that we tried to include temperature and rainfall information that is specific to different sub-periods during the growing season. Unfortunately, this information was not available over the sample period 1900-2014. As a result, our analysis focuses on the effects of annual temperature and rainfall. Studying the effects of weather shocks throughout the growing season remains an interesting topic worth further investigations.

Let y_{kjt} be the yield of the k-th crop in the j-th province and the t-th year. From equation (3) applied to the k-th crop in the j-th province, we consider the following QAR(m) specification for the conditional quantiles of y_{kjt}

$$Q_q(w_{t-1}, z_{kjt}) = \alpha_{kj}(q,t) + \sum_{i=1}^{m} \beta_{ki}(q, temp_{jt}, rain_{jt})\, y_{kj,t-i}$$

$$+ \sum_{i'=i}^{m} \sum_{i=1}^{m} \beta_{kii'}(q)\, y_{kj,t-i}\, y_{kj,t-i'} + \alpha_{pk}(q)\, temp_{jt} + \alpha_{ppk}(q)\, temp_{jt}^2 + \alpha_{rk}(q)\, rain_{jt} +$$

$$\alpha_{rrk}(q)\, rain_{jt}^2, \tag{4a}$$

where $z_{kjt} = (k, j, t, temp_{jt}, rain_{jt})$, t denotes the year, $temp_{jt}$ is temperature in province j in year t, and $rain_{jt}$ is rainfall in province j in year t. Note that the intercept $\alpha_{kj}(q,t)$ varies across crops, provinces and quantiles. It also varies over time to reflect the role of technology. The effects of changes in productivity is captured by letting

$$\alpha_{kj}(q,t) = \alpha_{kj0}(q) + \alpha_{kj1}(q)\, t_1 + \sum_{s=2}^{\tau} \alpha_{ks}(q)\, t_s, \tag{4b}$$

where $t_1 = (t - 1900)$, $t_s = \begin{cases} 0 & \text{when } t < T_s \\ t - T_s & \text{when } t \geq T_s \end{cases}$, $s = 2, \ldots, \tau$, $\tau \geq 2$, T_s being a threshold year satisfying $1900 < T_2 < \ldots < T_\tau < 2014$. The variable t_1 in (4b) is an overall time trend, and t_s is a time trend starting in the year T_s, $s = 2, \ldots, \tau$. The intercept $\alpha_{kj}(q)$ in (4a)-(4b) can vary across crops k, across provinces j and across quantiles q, providing a flexible representation of spatial heterogeneities in the distribution of agricultural productivity. Also, the trend parameter $\alpha_{kj1}(q)$ in (4b) allows the effects of productivity growth to vary across crops, across provinces as well as over time.

All parameters in (4a)-(4b) are allowed to vary both across quantiles and across crops. The temperature and rainfall variables are measured as deviations from province means. In this context, the variables and capture weather effects in the neighborhood of their means. And the variables $(temp_{jt})^2$ and $(rain_{jt})^2$ capture nonlinear weather effects reflecting the adverse impact of extreme weather conditions on yield (e.g., Schlenker and Roberts. 2009; Lobell et al., 2013, 2014). When $\beta_{kiq, temp_{jt}, rain_{jt}}$ depends on $(temp_{jt}, rain_{jt})$, equation (4a) allows temperature and rainfall to interact with lagged yields if they affect the dynamics of agricultural productivity. Finally, when $\beta_{kii'q} \neq 0$, equation (4a) allows for nonlinear dynamics. The relevance of these effects will be evaluated below.

Note the quantile specification in (4a)-(4b) represents the distribution of agricultural productivity conditional on three key factors: past productivity (captured by the lagged variables $y_{t-i})$, technology (represented by the trend variables $(t_1, \ldots t_\tau)$), and weather conditions given by temperature and rainfall $(temp, rain)$. As such, the specification (4) is appropriate to investigate the effects of technology and weather shocks (e.g., drought, excessive heat). Combining the assessment of weather shocks with dynamics is relevant to the extent that agro-ecological systems respond slowly to such shocks. In this context, the dynamic response of agricultural productivity to weather shocks is of significant interest.

What is the interpretation of the quantile function given in (4a)-(4b)? The specification (4a)-(4b) is conditional on technology and weather shocks. In this context, the distribution function associated with (4a)-(4b) represents unobservable factors affecting agricultural productivity beyond technology and weather shocks. These unobservable factors include unpredictable pest damages affecting farm production. More generally, they include all factors not observed by the econometrician (e.g., managerial skills that are known to the farmer but not observed by the econometrician). There is interest in investigating the dynamics of these unobservable factors as they affect agricultural productivity. For example, we expect the dynamics of pest populations to have both short term and longer term effects on crop yield. Also, adaptive management can play a role as it allows farmers to react and adjust to unforeseen shocks. This seems particularly important in the presence of adverse shocks (e.g., due to drought or pest damages).

The estimation of the parameters in equation (4a)-(4b) requires first choosing a model specification. In all cases, equation (4a) includes the variables $(temp, rain)$ and $(temp2, rain2)$. But three sets of issues remain: 1/ choosing the number of lags *m*; 2/ choosing the number of time trends τ; and 3/ deciding about the role of interactions effects related to $(temp, rain)$ and lagged yields $yt-i$. We consider four possible values for *m*: m $\{1,2,3,4\}$, and two possible values for τ: $\tau=3$ with $T2=1940$ and $T3=1980$, and $\tau=4$ with $T2=1930$, $T3=1960$ and $T4=1990$. Finally, concerning interaction variables, we consider 4 models: "Model a" includes interactions between lagged yields $yt-i$ and $(temp, rain)$; "Model b" includes lagged yields interacting $yt-i$ with $(temp, rain)$ and with lagged yields $yt-i\,'$; "Model c" includes only lagged yields interactions $(yt-i \times yt-i\,')$; and "Model d" has no interaction effects involving lagged yields. In a preliminary analysis, these alternative AR(m) specifications were estimated and evaluated using the Bayesian Information Criterion (BIC) (Schwarz, 1978). The results are reported in Table 2. For both wheat and corn, the BIC criterion was minimized for m = 3, reflecting the presence of significant dynamics in agricultural productivity. On that basis, the analysis presented below relies on autoregressive models of order 3, AR(3). Also, for both wheat and corn, the BIC criterion selected $\tau=3$ (i.e., with 3 time trends) and "Model c" (with lagged yields interactions $(y_{t-i} \times y_{t-i'})$). The effects of lagged-yield interactions $(y_{t-i} \times y_{t-i'})$ indicate the presence of nonlinear dynamics in agricultural productivity.

The estimates of the model selected by the BIC criterion (i.e., AR(3) applied to "Model c" with $\tau=3$, $T2=1940$ and $T3=1980$) are presented in Table 3 for wheat and corn. Although the AR(3) estimates should be seen as preliminary (given the QAR results presented below), Table 3 provides some insights on the determinants of crop yield. First, the lagged coefficients are highly significant, providing statistical evidence that productivity dynamics is important in agriculture. Second, the trend variables $t2$ are positive and significant for both wheat and corn, documenting the presence of much technological progress after 1940. Yet the effects of $t3$ are negative and significant, reflecting a decline in productivity growth after 1980. Third, Table 3 reports how the weather variables $(temp, rain)$ affect crop yields. It shows that the coefficient of $temp$ and $rain$ are highly significant, $temp$ being negative while $rain$ being positive. It also shows that the coefficient of $rain2$ is negative and highly significant for both wheat and corn, indicating that extreme rainfall patterns have adverse effects on crop productivity. Such effects are further discussed and evaluated below.

4. Econometric results

This section presents the estimation of a quantile autoregression (QAR) model given in (4a)-(4b). Following the preliminary analysis presented in section 3, we focus our attention on a

QAR(3) model where $m = 3$, $\tau=3$ (with $T2=1940$ and $T3=1980$) and including lagged yields interactions $(yt-i \times yt-i')$. Following Koenker (2005) and Koenker and Xiao (2006), under some regularity conditions, the quantile estimation of (4a)-(4b) generates consistent estimate of the parameters. Applied to Italian yield data, the estimated parameters are reported in Table 4 for wheat and in Table 5 for corn for selected quantiles $q=(0.1, 0.3, 0.5, 0.7, 0.9)$. The standard errors of the parameters are evaluated using bootstrapping.

Tables 4 and 5 show that the lagged yields $(yt-1, yt-2, yt-3)$ have coefficients that are statistically significant for all quantiles. This indicates the presence of much dynamics in the distribution of agricultural productivity. Also, the terms $(yt-i \times yt-i')$ have sometimes statistically significant effects, reflecting the presence of nonlinear dynamics (e.g., the case of $(yt-1 \times yt-3)$ for wheat or of $(yt-1 \times yt-2, yt-12, yt-32)$ for corn). As further discussed below, productivity adjustments are slow, indicating that longer term productivity effects can be much larger than corresponding short term effects. The time trend variables $(t1, t2, t3)$ and the weather variables $(temp, rain)$ often exhibit statistical significance, but their effects tend to vary across quantiles. The differences across quantiles presented in Tables 4 and 5 document how weather and technology affect the yield distributions for Italian wheat and corn. Such differences also highlight the usefulness of the quantile approach to yield analysis.

For both wheat and corn, Tables 4 and 5 show that the impact of the overall time trend $t1$ is negative and statistically significant in the lower quantiles but it is positive in the upper quantiles. This identifies an increase in the spread of yield distributions over time, implying a rise in yield variability. The parameter estimates for the variable $t2$ (time trend after 1940) also vary across quantiles. For both wheat and corn, the estimates of $t2$ effects are positive and statistically significant in the lower quantiles. This means that technological progress in Italian agriculture has contributed to a decline in the probability of facing low yields over the last few decades. But the effects of $t2$ differ between wheat and corn in the upper quantiles. At the 0.9 yield quantile, Tables 4 and 5 show that $t2$ has a positive and significant impact for corn but a negative and insignificant impact for wheat. It means that, over the period 1940-1980, the prospects of obtaining high yields have continued to improve for corn but less so for wheat. This provides evidence that the contributions of technological progress to higher yields are stronger for corn than for wheat. Finally, the effects of $t3$ are negative across quantiles for both wheat and corn; and they are statistically significant for all but the 0.9 quantile. This indicates that the rate of productivity growth has declined after 1980. The effects of $t3$ being negative and statistically significant in the lower quantiles mean that, while controlling for weather shocks, the last few decades have seen increasing exposure to the risk of facing lower yields.

The impacts of the weather variables $(temp, rain)$ are also reported in Tables 4 and 5. For both wheat and corn, the coefficients of temperature $temp$ are not statistically significant in the upper quantiles. This indicates that the effects of temperature on Italian agriculture are located in the lower quantiles of the yield distributions. But such effects vary with the crop. For wheat in the 0.1 quantile $temp$ has a negative effect while $temp2$ has a positive effect (both statistically significant). As documented below, this reflects the adverse effects of heat waves on wheat yield.

For corn, the coefficients of $temp2$ are not statistically significant. But $temp$ has negative and statistically effects for the 0.1 and 0.3 quantiles. As discussed below, such effects reflect the strong adverse impacts of heat waves on corn yield.

For both wheat and corn, the coefficients of $rain$ are all positive and most are statistically significant. This reflects that, at least around sample means, rainfall contributes positively to agricultural productivity. However, from Tables 4 and 5, the coefficients of $(rain2)$ are consistently negative for both wheat and corn, and most are statistically significant. This reflects the adverse impacts of extreme rainfall conditions on agricultural productivity. We document below that such adverse effects are associated with low rainfall (droughts).

5. Discussion

The quantile regression estimates reported in tables 4 and 5 provide useful information about the determinants of the distribution of agricultural yields in Italy. In this section, these estimates are used to gain additional insights on the role of weather shocks and the factors affecting farm productivity. Our analysis proceeds in three steps: 1/ we assess the evolving distribution of crop yields in Italy; 2/ we evaluate the effects of weather shocks on yield distribution; and 3/ we investigate the nature of yield dynamics.

First, we use our quantile regression estimates to simulate the distribution of crop yields during our sample period. The simulation results are reported in Figures 1-2 for three selected provinces: Milan, Rome and Palermo. Figure 1 shows the simulated distribution of wheat yield for 5 quantiles $q=(0.1, 0.3, 0.5, .0.7, 0.9)$, $q=0.5$ corresponding to the median yield. Figure 1a displays the evolving distribution of wheat yield in the Milan province. It reveals three interesting results. First, the overall trend is positive, reelecting the impact of technological progress on wheat productivity over the last few decades. Second, the dispersion of the wheat yield distribution around its median has increased over time, reflecting higher variability in agricultural productivity. Third, Figure 1a shows some decline in productivity trends during the 2000's. As illustrated in Figures A3 and A4 in the Appendix, this was a period when Italian agriculture faced significant weather shocks, including heat waves and droughts. In a way consistent with Brisson et al. (2010) and Ray et al. (2012), it means that the recent declines in Italian crop yields are due in part to weather shocks. In other words, Figure 1a illustrates that weather conditions have had adverse impacts on farm productivity during the last 15 years.

Figure 1b and 1c show similar patterns for wheat yields in different provinces: Rome in Figure 1b, and Palermo in Figure 1c. Compared to Milan (in Figure 1a), Figure 1b and 1c indicate that productivity is lower in the Central province (Rome) and even lower in the Southern province (Palermo). This reflects large differences in agro-ecosystem productivity across Italian provinces, with the Northern province having a much more productive agriculture than the Southern province.

Figure 2 reports the simulated distribution of corn yield for three provinces: Milan, Rome and Palermo. The patterns are similar to the ones identified in Figure 1. First, there has been massive productivity gains over time. Second, Figure 2 shows that adverse weather conditions have contributed to some decline in corn yields during the last 15 years. Third, agricultural productivity is higher in the Northern province (Milan reported in Figure 2a) than in the Central province (Rome reported in Figure 2b), which is higher than in the Southern province (Palermo reported in Figure 2c).

Next, we re-estimated the quantile yield model under all quantiles and used the estimates to evaluate the yield distribution under alternative weather scenarios. The weather scenarios involve three temperatures (cold, medium and hot), and three rainfalls (dry, medium and wet). Evaluated for the Rome province in 2000, the results are presented in Figure 3 for both wheat and corn. In Figure 3, the temperature states (cool, medium and hot) are set to the 0.05, 0.5 and 0.95 quantiles of the Rome temperatures; and the rainfall states (dry, medium, wet) are set to the 0.05, 0.5 and 0.95 quantiles of the Rome rainfall. Figure 3 reports how changing weather conditions affect the yield distribution for wheat (Figure 3a) and corn (Figure 3b). Figures 3a and 3b show that hot and dry weather conditions have the most adverse impact on wheat yield as well as corn yield. And among all the scenarios evaluated, the most favorable weather conditions are cool and rainy. Figures 3 also reveals two important results. First, it shows that the effects of weather shocks are asymmetric: while they have small impacts on the upper tail of the yield distribution, they have much larger impacts on the lower tail of the distribution. This illustrates that adverse weather shocks affect crop yields mostly by increasing the prospects for yield reductions. In the face of recent climate change, this can help explain the recent reductions in crop yields observed over the last 15 years. Second, comparing Figures 3a and 3b, the effects of weather shocks are much larger for corn than wheat. Indeed, evaluated at the median quantile ($q = 0.5$), the largest simulated yield difference due to weather shocks is 400 kg for corn (in Figure 3b) compared to 150 kg for wheat (in Figure 3a). This reflects that wheat is a much more weather-tolerant crop than corn. This illustrates that the effects of weather shocks can vary a lot across crops. To the extent that farmers choose the mix of crops they grow, this stresses the important role of farm management in dealing with weather shocks.

Finally, our estimated QAR(3) model captures dynamic adjustments in agricultural productivity. To evaluate the nature of these dynamic adjustments, we evaluated the dominant root associated with of the specification given in equation (2) across all quantiles. The results are presented in Figure 4 (Figure 4a for wheat and Figure 4b for corn.). Figure 4 shows that the dominant root is less than 1 for all quantiles. This means that, conditional on technology and weather conditions, productivity dynamics exhibits local stability everywhere. Figures 4a and 4b also reveals that the dominant root is in the range [0.8, 1] for all quantiles. These high values reflect very slow adjustments over time. They indicate that the dynamic adjustments from one period to the next would account for only 10-20 percent of the adjustments toward long run equilibrium. Thus, besides their short term effects, weather shocks also have significant long term effects on agricultural productivity.

6. Conclusions

This paper has investigated the effects of weather shocks on the evolving distribution of crop yields. The analysis involved wheat and corn yield data in seven Italian provinces over the last 150 years (from 1866 to 2014). The approach relied on a quantile autoregression (QAR) model which provides a flexible representation of how weather shocks affect yield distributions and its dynamics. The econometric analysis documents how weather conditions have had adverse impacts on farm productivity during the last 15 years (Brisson et al., 2010; Ray et al., 2012). It shows large differences in agro-ecosystem productivity across Italian provinces, with the Northern province having a much more productive agriculture than the Southern province. We find that hot and dry weather conditions have adverse impact on both wheat yield and corn yield. One important finding is that weather shocks are asymmetric: they have small impacts on the upper tail of the yield distribution but with much larger impacts on the lower tail of the distribution. In other words, adverse weather shocks affect crop yields mostly by increasing the prospects for yield reductions. Such effects help explain the recent reductions in crop yields observed over the last 15 years. We document how the effects of weather shocks vary across crops and across provinces. For example, we find much larger effects for corn than wheat, reflecting that wheat is a more weather-tolerant crop than corn. Finally, our estimated QAR model captures dynamic adjustments in agricultural productivity. We find very slow adjustments over time, indicating that weather shocks also have significant longer term effects on agricultural productivity.

At this point of the paper it is important to emphasize that our empirical findings are specific to wheat and corn in seven Italian provinces. The analysis could be extended in several directions. First, it would be useful to apply the analysis to different agro-ecosystems. This could involve different crops and different provinces. Second, finding that weather effects vary across crops indicates that farm management decisions can help farmers adapt to weather conditions. Further studies are needed to evaluate the role of management as an adaptive response to climate change issues.

Table 1: Summary statistics: means and standard deviations.

	Provinces						
Variables	Milan	Venice	Bologna	Florence	Rome	Naples	Palermo
Wheat yield (100 kg/ha)	27.80 (15.54)	27.58 (15.33)	27.12 (14.74)	21.09 (10.64)	19.47 (11.07)	15.48 (8.28)	14.01 (7.43)
Corn Yield (100 kg/ha)	44.85 (32.53)	44.39 (32.30)	45.13 (32.96)	34.87 (24.35)	32.64 (24.86)	25.69 (18.66)	23.33 (16.85)
Temperature (degree Celsius)	13.74 (0.85)	13.78 (0.62)	14.21 (0.63)	14.96 (0.70)	15.95 (0.47)	17.15 (0.78)	18.07 (0.78)
Rainfall (mm per year)	937.24 (274.10)	737.07 (216.50)	653.03 (174.77)	811.99 (194.61)	767.78 (198.84)	875.04 (233.76)	618.98 (245.90)

Note: Based data over the period 1900-2014. Standard deviations are in parenthesis.

Table 2: Model Evaluations using the Bayesian Information Criterion (BIC)

Number of lags	m=1	m=2	m=3	m=4
Wheat				
Model a	3425	3347	3311	3342
	3413	3360	3334	3364
Model b	3420	3362	3325	3340
	3407	3369	3345	3363
Model c	3439	3350	**3301**	3320
	3419	3358	3318	3337
Model d	3436	3363	3315	3319
	3469	3397	3327	3333
Corn				
Model a	4276	4151	4087	4124
	4228	4155	4105	4138
Model b	4269	4199	4123	4143
	4222	4189	4138	4156
Model c	4282	4155	**4082**	4105
	4229	4155	4095	4114
Model d	4275	4200	4115	4122
	4297	4231	4125	4130

Note: The Bayesian Information Criterion (BIC) is evaluated based on data over the period 1900-2014. In the model specifications, τ is the number of time trends: τ $\{3,4\}$ and m is the number of lags: m $\{1,2,3,4\}$. All models include the variables $(temp, rain)$ and $(temp2, rain2)$. In addition, "Model a" includes interactions between lagged yields $yt-i$ and $(temp, rain)$; "Model b" includes lagged yields $yt-i$ interacting with $(temp, rain)$ and with lagged yields $yt-i'$; "Model c" includes only lagged yields interactions $(yt-i \times yt-i')$; and "Model d" has no interaction effects involving lagged yields.

Table 3: Autoregressive Model for Crop Yield, AR(3).

Variable	Wheat yield, *yt*	Corn yield, *yt*
Intercept	2.436***	2.908***
$yt-1$	0.292***	0.251***
$yt-2$	0.525***	0.515***
$yt-3$	-0.092	0.104
$yt-12$	0.027***	0.025***
$yt-22$	0.016*	0.012**
$yt-32$	0.025***	0.014***
$yt-1 \times yt-2$	-0.030**	-0.027***
$yt-1 \times yt-3$	-0.022	-0.021***
$yt-2 \times yt-3$	-0.014	-0.002
$t1$	0.006	-0.019
$t2$	0.107***	0.195***
$t3$	-0.119***	-0.224***
temp	-0.275**	-0.520***
temp2	0.008	-0.017
rain	2.226***	3.262***
rain2	-1.859***	-3.156***
R-square	0.981	0.988

Note: Based on data over the period 1900-2014. The estimated model also includes province dummies (not reported in the Table). Asterisks represent the significance level: *** at the 1% level, ** at the 10% level, and * at the 10% level. The statistical significance was evaluated based on bootstrapped standard errors.

Table 4: Quantile Autoregressive Model for Wheat Yield, QAR(3).

Variables	Quantile q				
	0.1	0.3	0.5	0.7	0.9
$Intercept$	1.752***	2.558***	2.308***	1.604***	1.176*
$yt-1$	0.444***	0.300***	0.343***	0.291**	0.411**
$yt-2$	0.631***	0.560***	0.454***	0.560***	0.597***
$yt-3$	-0.280*	-0.193	-0.125	-0.053	-0.059
$yt-12$	-0.037	0.031	0.018	0.023*	0.011
$yt-22$	0.017	0.010	0.011	-0.021	0.004
$yt-32$	-0.035	0.027*	0.025*	0.028**	0.016
$yt-1 \times yt-2$	-0.025	-0.027	-0.016	0.012	-0.014
$yt-1 \times yt-3$	0.106**	-0.034	-0.020	-0.056**	-0.009
$yt-2 \times yt-3$	-0.025	-0.006	-0.016	0.015	-0.009
$t1$	-0.033**	-0.007	0.014	0.045***	0.041***
$t2$	0.119***	0.137***	0.103***	0.029	-0.006
$t3$	-0.106***	-0.136***	-0.129***	-0.092***	-0.046
$temp$	-0.372**	-0.243**	-0.070	-0.115	-0.096
$temp2$	0.068*	0.004	-0.041	-0.042	0.008
$rain$	1.970***	2.065***	1.845***	1.946***	1.053*

rain2	-2.104	-2.882***	-1.676*	-1.910**	-0.618

Note: Based on data over the period 1900-2014. The estimated model (4) also includes province dummies (not reported in the Table). Asterisks represent the significance level: *** at the 1% level, ** at the 10% level, and * at the 10% level. The statistical significance was evaluated based on bootstrapped standard errors.

Table 5: Quantile Autoregressive Model for Corn Yield, QAR(3).

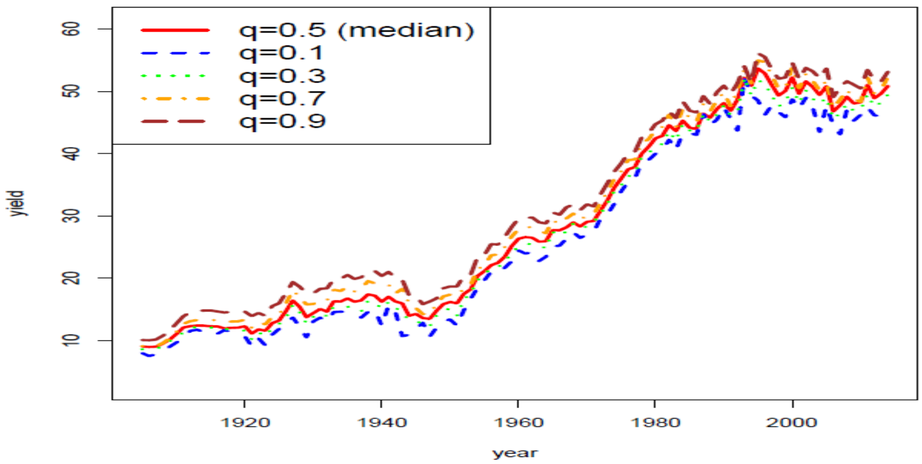
Variables	Quantile q				
	0.1	0.3	0.5	0.7	0.9
Intercept	2.882***	2.457***	2.408***	1.593**	1.795**
$yt-1$	0.358**	0.255***	0.245***	0.242*	0.308**
$yt-2$	0.396***	0.480***	0.488***	0.625***	0.495***
$yt-3$	0.010	0.121	0.134	0.046	0.158
$yt-12$	0.011	0.032***	0.028***	0.017***	0.017
$yt-22$	0.013	0.015	0.015	0.023	0.000
$yt-32$	0.008	0.012*	0.018***	0.017**	0.013
$yt-1 \times yt-2$	-0.018	-0.037**	-0.029**	-0.030**	-0.009
$yt-1 \times yt-3$	-0.001	-0.023	-0.024	-0.003	-0.025
$yt-2 \times yt-3$	-0.012	0.001	-0.008	-0.025	0.002
$t1$	-0.052**	-0.043***	-0.019	0.011	0.031
$t2$	0.230***	0.217***	0.197***	0.128**	0.084*
$t3$	-0.214***	-0.248***	-0.223***	-0.230***	-0.050
$temp$	-0.885***	-0.431**	-0.231	0.069	0.106
$temp2$	0.068	0.001	-0.072	-0.070	-0.076
$rain$	2.177**	2.810***	3.004***	3.085***	0.802

rain2	-1.112	-3.730***	-3.641***	-3.129**	-0.614

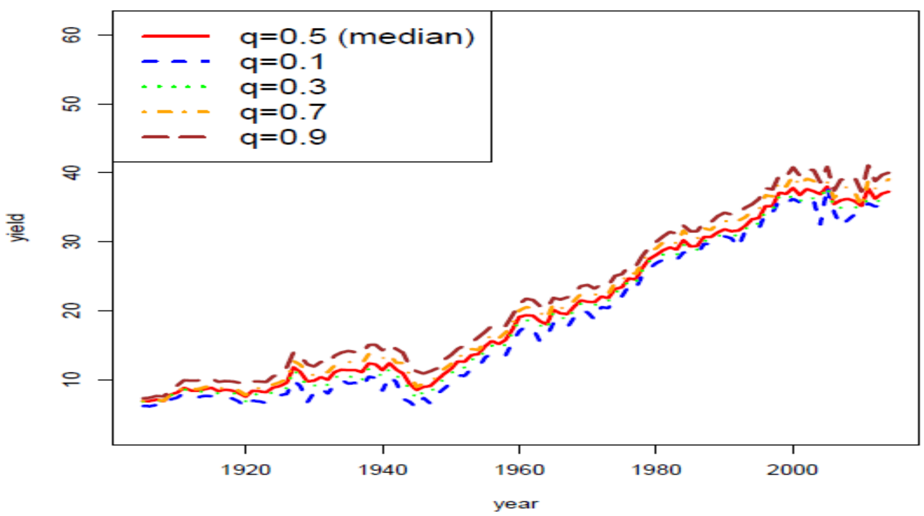
Note: Based on data over the period 1900-2014. The estimated pooled model also includes province dummies (not reported in the Table). Asterisks represent the significance level: *** at the 1% level, ** at the 10% level, and * at the 10% level. The statistical significance was evaluated based on bootstrapped standard errors.

Figure 1: Estimated Evolution of Quantile Yields for Wheat in Selected Provinces.

1a. Milan Province



1b. Rome Province



1c. Palermo Province

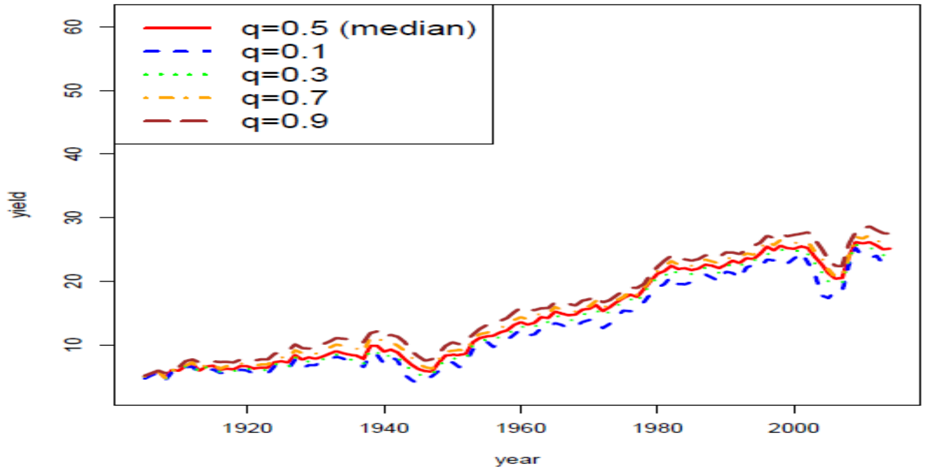
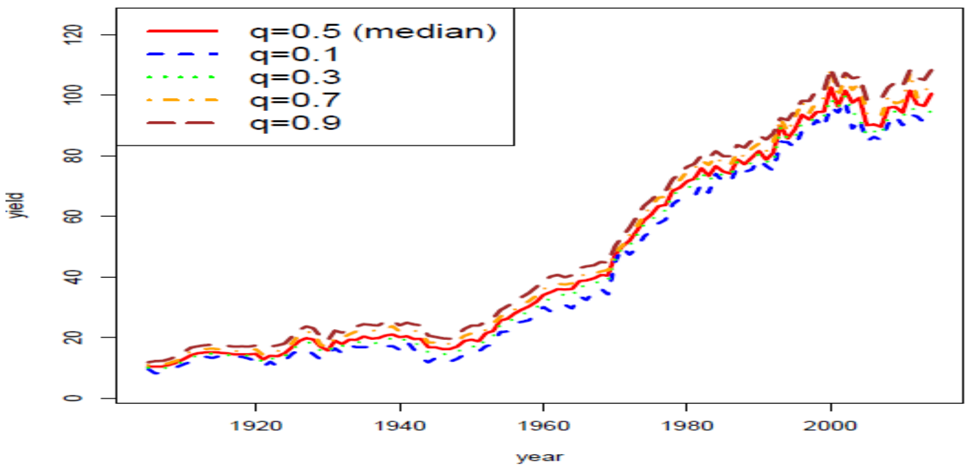
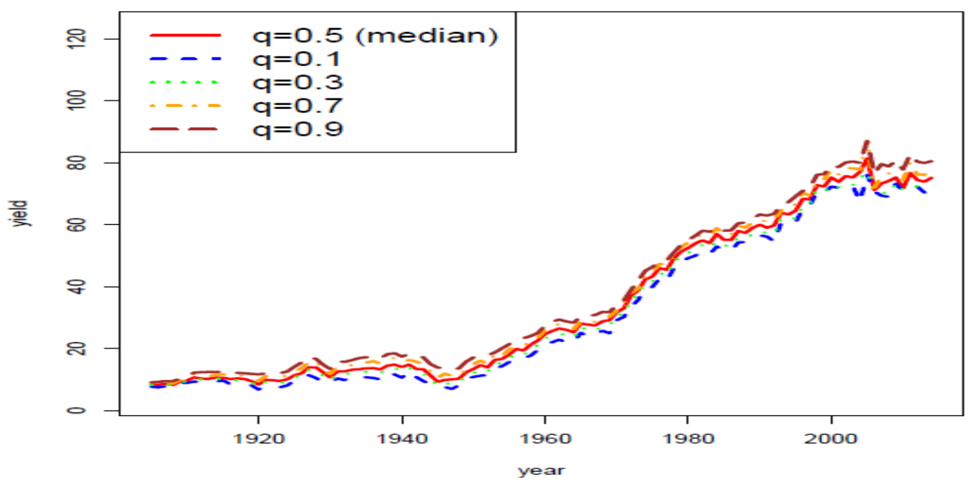


Figure 2: Estimated Evolution of Quantile Yields for Corn in Selected Provinces.

2a. Milan Province



2b. Rome Province



2c. Palermo Province

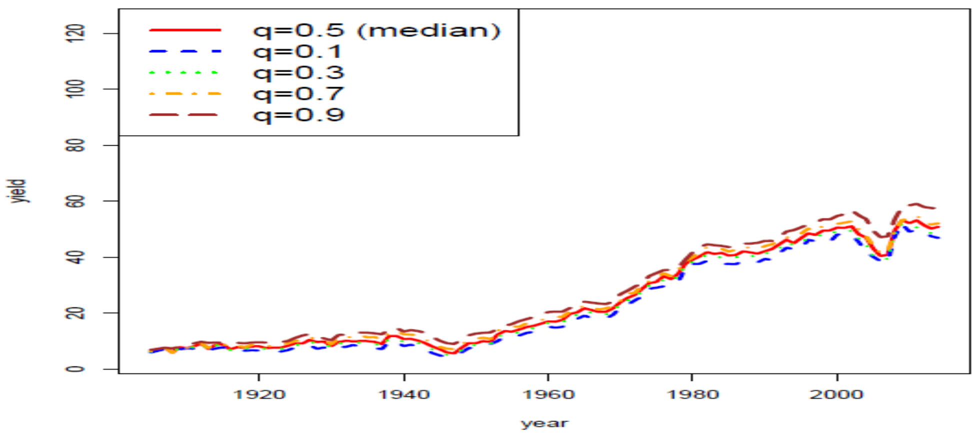
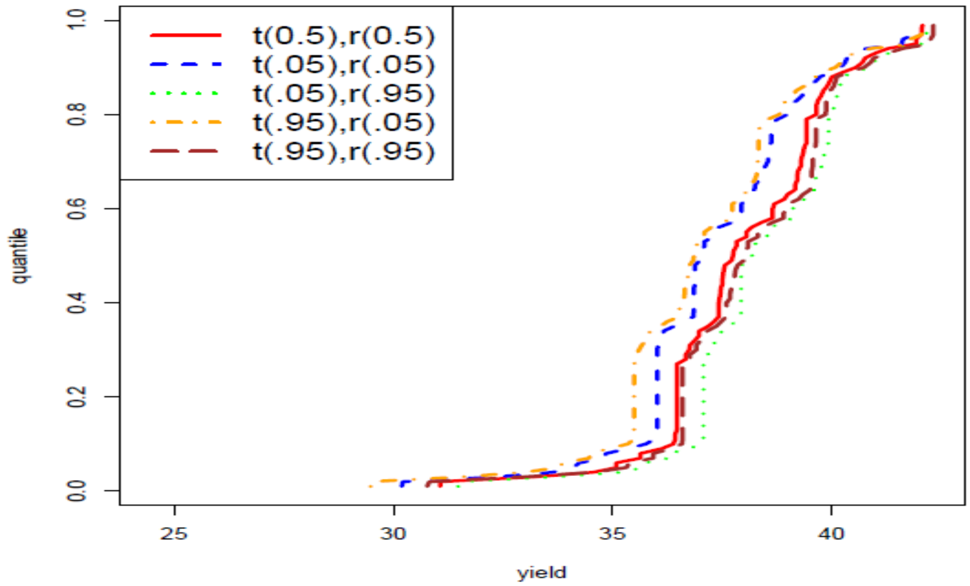
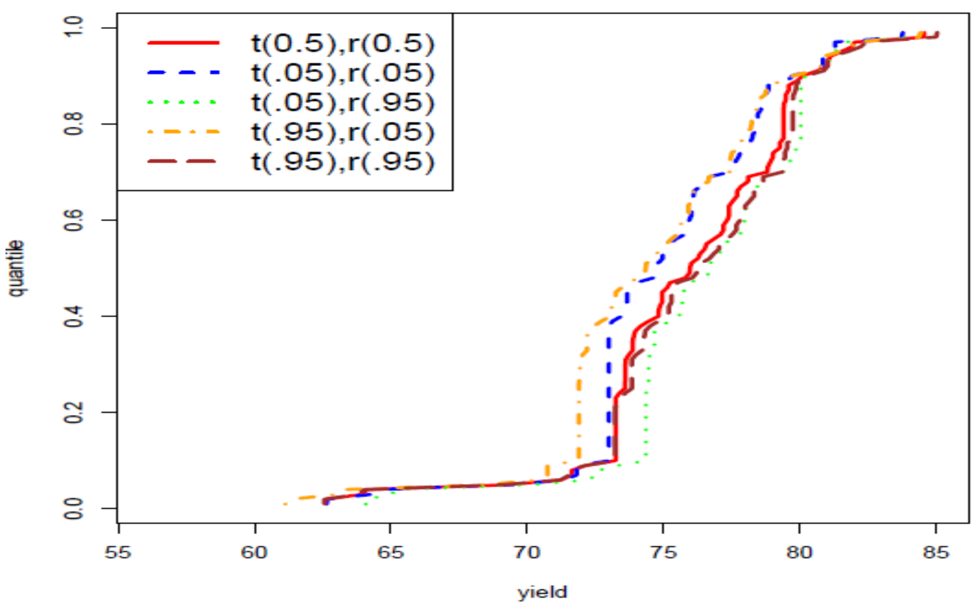

q=0.5 (median)
q=0.1
q=0.3
q=0.7
q=0.9
yield
0
20
40
60
80
100
120
1920
1940
1960
1980
2000
year

Figure 3: Simulated Distributions of Yield under Alternative Weather Scenarios.

3a. Wheat



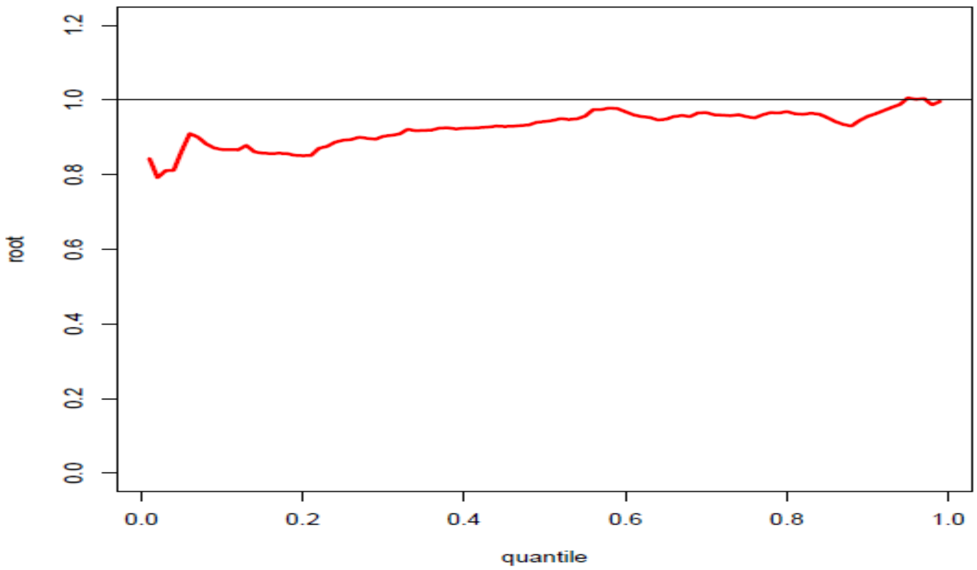
3b: Corn



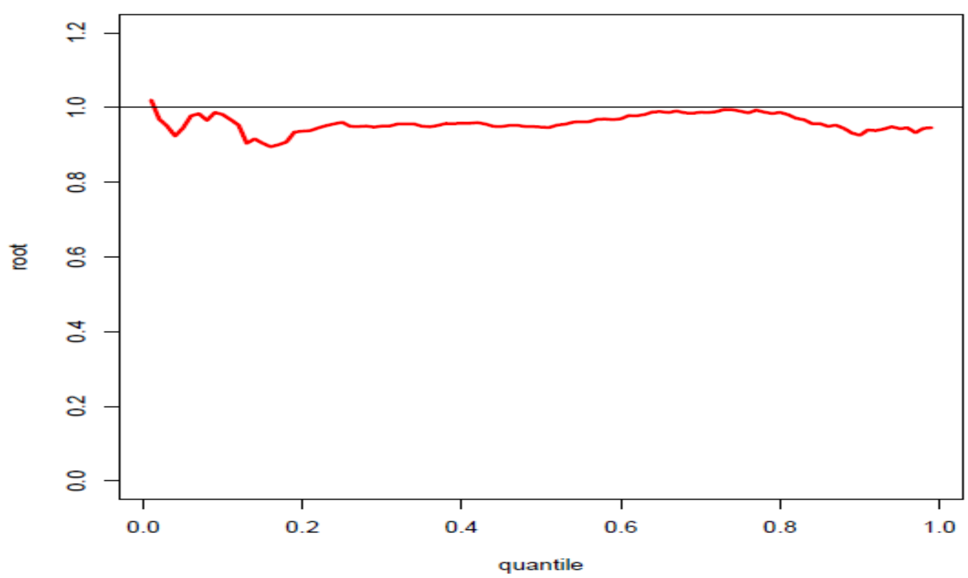
<u>Note</u>: The simulated yield distributions are evaluated for the Rome province in 2000. Weather scenario [$t(q)$, $r(q')$] stands for the q-th quantile for *temp* and the q'-th quantile for *rain*, with q,q' *(0.05, 0.5, 0.95)*.

Figure 4: Dominant Eigenvalue for the Dynamics of Crop Yield across Quantiles under Alternative Weather Scenarios

4a. Wheat



4b: Corn



Note: The Eigenvalues are evaluated for the Rome province in 2000.

Appendix

Figure A1: Historical wheat yields in selected regions

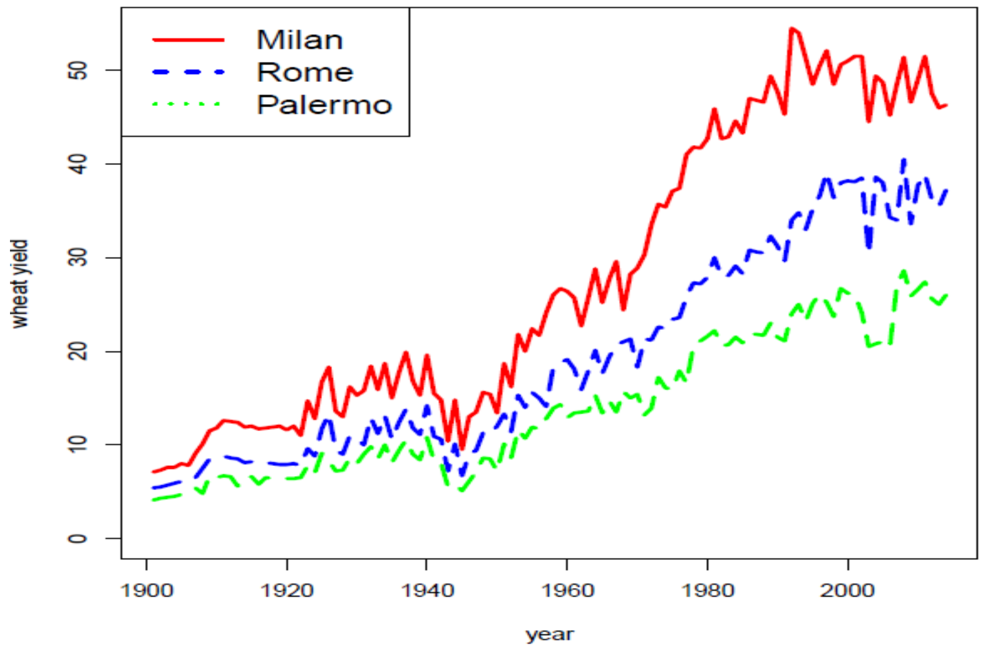


Figure A2: Historical corn yields in selected regions

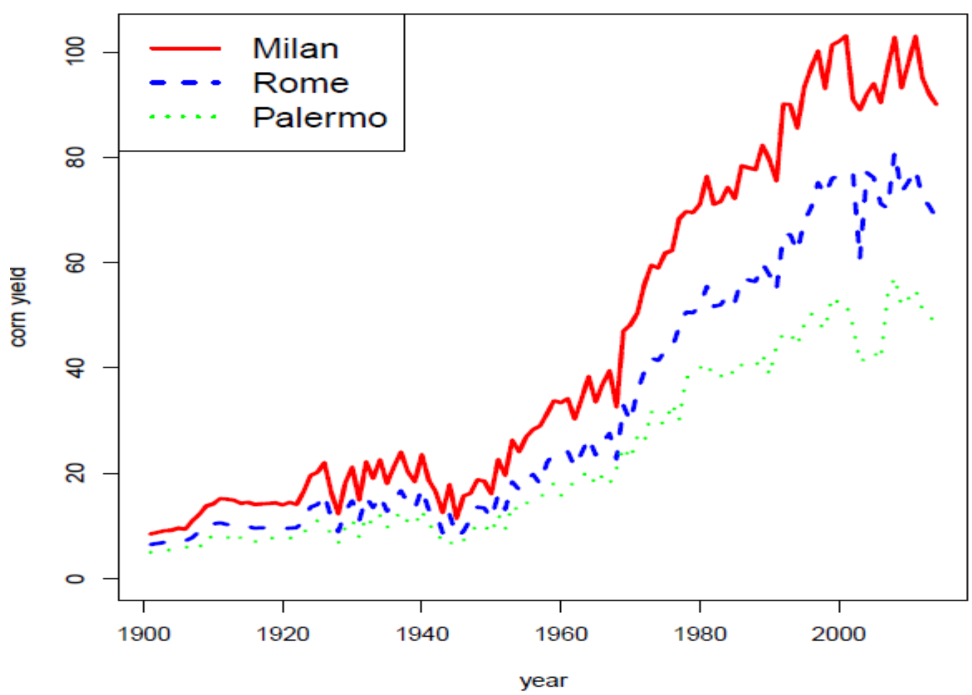


Figure A3: Historical temperatures in selected regions

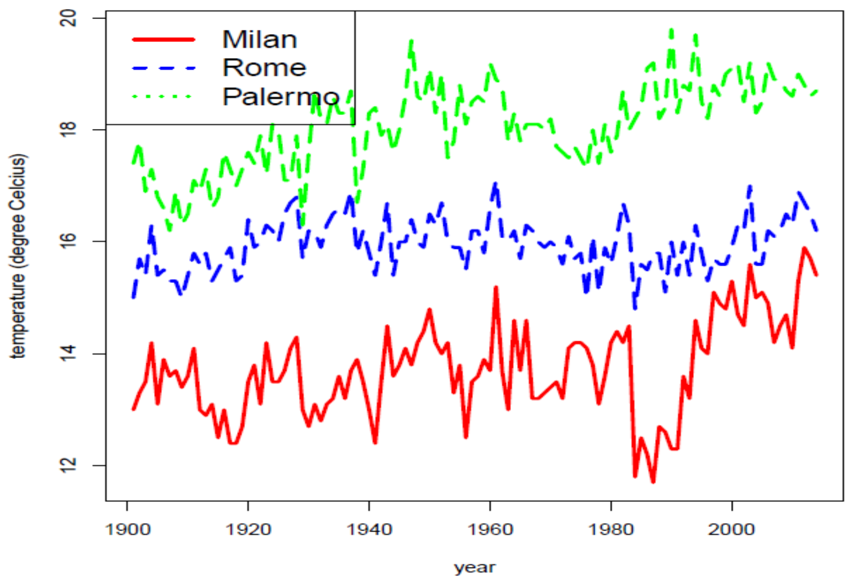
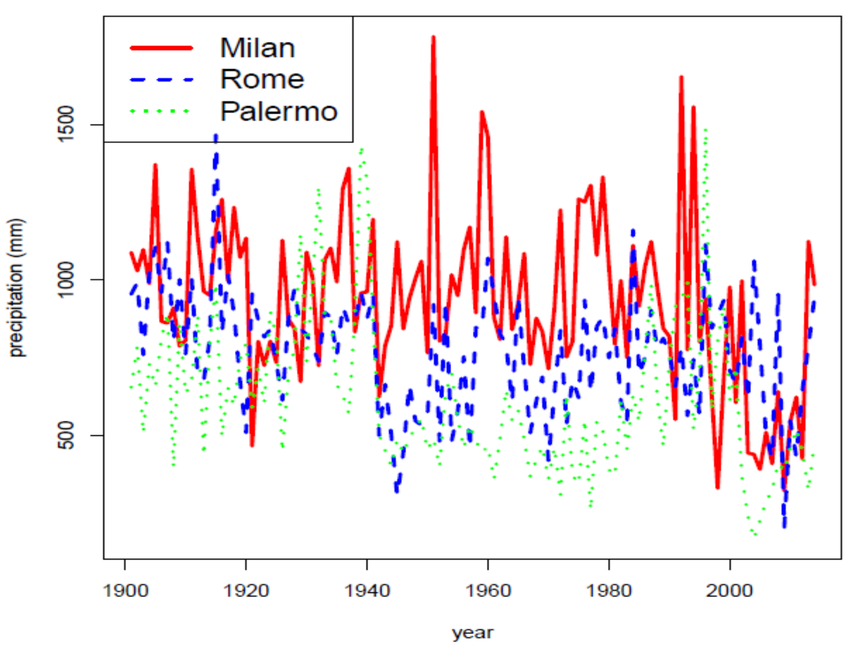


Figure A4: Historical rainfalls in selected regions



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