

Rainfall Shocks, Resilience and the Dynamic Effects of Crop Biodiversity on the Productivity of Agroecosystems

by

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Abstract: This paper investigates the dynamic effects of rainfall shocks on agro-ecosystems productivity. The analysis estimates a panel data model of cereal production in southern Italy. It documents the adverse effects of a reduction in rainfall on the agroecosystem productivity both in the short run and the long run. It investigates how increasing the level of spatial crop diversity can mitigate this negative impact. The empirical evidence shows how higher diversity supports resilience and maintains the system productivity under challenging climatic conditions.

Keywords: Agroecosystems, rainfall, productivity, crop biodiversity, Holling-resilience

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1. Introduction

Earth's climate has changed over time. Recent trends have seen an increase in average temperature as well as more volatile rainfall patterns (National Academy of Science, 2001). Over the last century, some areas of the planet have become drier. Annual precipitation trends in southern Europe showed a reduction in annual rainfall up to 20%, and recent projections forecast a further decrease between 5% and 15% over the next decade (EEA Report No 2/2004; IPCC WGII report, 2003; UK; Hulme et al., 1999; Parry, 2000). The reduction of rainfall can have implications of paramount importance for managed ecosystems such as agroecosystems. Agroecosystems¹ are ecological systems transformed and simplified for the purpose of

¹ Agroecosystems are defined as ecological and socioeconomic system comprising domesticated plants and/or animals and the people who husband them, intended for the purpose of producing food, fiber, or other agricultural products (Conway, 1985, 1986, 1987; Conway and Barbier, 1990).

agriculture. Lower rainfall increases the level of environmental stress affecting the capability of the system to maintain productivity (Tisdell, 1996). However, given the complexity of agroecosystems dynamics, the nature and magnitude of productivity decline remain poorly understood. This may involve a regular decline in soil fertility because of nutrient mining. This may also involve the stability and resilience of the agroecosystems (Holling, 1973).

Holling-resilience is defined as the propensity of a system to retain its organizational structure and productivity following a perturbation (Holling, 1973). This definition is rooted in the concept of system stability and how the system responds under stress (Perrings and Stern, 2000). In the case of agroecosystems productivity, these systems have Holling resilience if, in some state, they are able to maintain productivity and withstand stress or external shocks (e.g., due to lower rainfall and droughts). In many situations, biodiversity provides the link between stress and loss of resilience in a system (Perrings et al. 1995). Genetic variation within species and within population increases the ability to respond to the challenges of environmental stress (Mainwaring, 2001).

The objective of this paper is to study the dynamic effects of changing rainfall patterns on the productivity of an agroecosystem. A special focus of the research is to explore the role of crop biodiversity² in reducing some of the possible negative impact of climate change. In other

² Biodiversity is the sum of genetic information that is contained in the genes of individuals, plants, animals and micro organisms. Crop biodiversity, a component of agricultural biodiversity, refers to all diversity within and among wild and domesticated crop species (Qualset et al., 1995; Lenne and Wood, 1999). Crop biodiversity has crucial effects on food production, health and life-support systems. In managed systems, such as agro-ecosystems, crop genetic resources are the raw materials for crop breeding, pest resistance, productivity, stability and future agronomic improvements.

words, we investigate how crop biodiversity supports the system resilience and helps mitigate the adverse effects of lower rainfall and droughts associated with changing climates.

Much research has studied the relation between diversity and resilience. For example, it has been argued that Holling resilience improves with the complexity of the ecosystem. Heal (2000) wrote that the “diversity of organisms in an ecosystem is required for that system to function and to provide services to human societies, and the removal or addition of even a single type of organism can have far reaching consequences.” In a series of plot experiments, plant biomass has been found to be an increasing function of diversity (Tilman and Downing, 1994; Tilman et al., 1996), with higher diversity contributing to increases in the productivity of ecosystems (Tilman et al., 2005). This is because “multiple species coexistence occurs if there is an interspecific tradeoff such that each species is a superior competitor for a limited range of values of the physical factor, and if the physical factor is heterogeneous” (Tilman et al., 2005). Also, genetic variability within and between species confers the potential to resist biotic and abiotic stresses, both in the short and the long term (Giller et al., 1997). Growing more crop species enhance the possibility of producing in years where rainfall regimes or environmental conditions are more challenging. Thus, having functionally similar plants that respond differently to weather and temperature randomness contributes to resilience (Hollings, 1973) and ensures that "whatever the environmental conditions there will be plants of given functional types that thrive under those conditions" (Heal, 2000). Maintaining in situ crop biodiversity tends to provide the agroecosystem a wider range of productive responses to weather shocks. And, this is particularly important in systems such as agroecosystems whose complexity has been simplified and the number of crop species reduced for the purpose of agriculture (Conway, 1993). In such a system crop biodiversity is the most important component of the overall agrobiodiversity.

While the resilience benefit of crop biodiversity seems to be important and plausible, the empirical economics literature on this issue remains unsatisfactory from at least three different viewpoints. First, to date empirical evidence on the beneficial effect of a higher crop biodiversity regime on production is rather scant and inconclusive,³ and it does not consider the implications for resilience. Smale et al. (1998) studied the relationships between crop biodiversity and wheat production in the Punjab of Pakistan. They found that genealogical distance and number of varieties are associated with higher mean yield. Widawsky and Rozelle (1998) using data from regions of China found, instead, that the number of planted varieties reduces both the mean and the variance of rice yield. Di Falco and Perrings (2005), found a positive relationship between inter-specific crop biodiversity and agricultural production in a case study on cereal production in southern Italy. Second, all these studies model crop biodiversity as an input in a static production process. To the extent that biodiversity benefits are dynamic, this neglects the dynamic implications of crop biodiversity. Third, crop biodiversity's role is captured in these studies by using a spatial diversity index (i.e., Shannon index). However, this raises the possibility that these indices are endogenous. The potential for endogeneity bias can have adverse effects on the validity of the econometric analysis and results.

The contributions of this paper to this strand of literature are as follows. First, we provide an analysis of the contribution of inter-specific crop biodiversity to the productivity of cereal agro-ecosystems by investigating the dynamic effects of biodiversity using panel data. The

³ Some applied economists have focused on the empirical assessment of the determinant of in situ crop biodiversity (e.g., Evenson, and Gollin, 1997; Heisey et al., 1997; Smale et al., 2001; Smale et al., 2003; Di Falco and Perrings, 2005). Other authors have addressed the issue of the measurement of biodiversity (Solow et al., 1993; Weitzman, 1992) and its role on potential commercial profits and its social value (e.g., Goeschl and Swanson, 2002; Simpson et al., 1996).

analysis is applied to data for the period 1970-1993 from one of the most important areas for cereals production in Europe: southern Italy. This area is a Vavilonian mega diversity spot for cereals that is considered under threat from desertification. Production environment is rainfed. Therefore, the impact of rainfall reduction on the system productivity cannot be mitigated otherwise (i.e., with irrigation). Both environmental and market conditions restrict potential economic substitution among different crops or activities (e.g. more than 70% of wheat for pasta and bakery products produced in Italy are from southern Italy). The area is characterized by typical Mediterranean dry weather that restricts the production possibilities for agriculture. Thus, the economic substitutions to changes in weather conditions are very limited. The econometric analysis relies on a dynamic GMM estimator, which provides efficient parameter estimates while correcting for potential endogeneity bias associated with the diversity index. Second, we investigate the role of biodiversity and its interaction effects with rainfall in the dynamic analysis of productivity. This provides a basis to test whether crop biodiversity can help mitigate the adverse effects of reductions in rainfall. Reflecting the importance of agroecosystem dynamics, it is found that the effects of diversity are much stronger in the long term than in the short term. Third, the implications of the econometric estimates are illustrated by a set of simulations. The results show how crop biodiversity interacts with rainfall effects so as to buffer against the adverse effects of drier cropping seasons. Especially in the longer term, we find that higher diversity supports resilience and can maintain the system productivity under challenging climatic conditions.

The paper proceeds as follows. Next section presents the framework. A brief description of the agroecosystem is provided in section three. Section four gives background information on the data and the variables used into the econometric analysis. The econometric results are

discussed in section five. Section six provides the simulation exercise. Section seven offers concluding remarks.

2. Framework

In agricultural productivity analysis, a range of mathematical representations of the production technology has been invoked (Mundlak, 2001). Let $y_{it} = f_{it}(x_{it}, \cdot)$ denote the production function, where y_{it} is quantity of durum wheat produced in the i -th region at time t , x_{it} is the vector of inputs used in the i -th region at time t , and “ \cdot ” denotes other factors. The vector x_{it} includes conventional inputs (i.e., land, labour, capital, and fertilizer) along with rainfall and crop biodiversity. To introduce dynamics into the analysis, consider that $f_{it}(x_{it}, \cdot)$ takes the form $f_{it}(x_{it}; y_{i,t-1}, \dots, y_{i,t-p}, x_{i,t-1}, \dots, x_{i,t-q})$ for some $p \geq 0$ and $q \geq 0$. This means that the k -th lagged production $y_{i,t-k}$ enters the production function up to lag $k = p$. It also allows the k -th lagged inputs $x_{i,t-k}$ to affect production y_{it} up to lag $k = q$. As a result, the production process is represented by $y_{it} = f_{it}(x_{it}; y_{i,t-1}, \dots, y_{i,t-p}, x_{i,t-1}, \dots, x_{i,t-q})$. After taking logarithms, a first-order approximation of the production function gives

$$\ln(y_{it}) = A(i, t) + \alpha \ln(x_{it}) + \sum_{k=1}^p \beta_k \ln(y_{i,t-k}) + \sum_{k=1}^q \gamma_k \ln(x_{i,t-k}), \quad (1)$$

where α and γ_k are respectively vectors of parameters associated with the current and k -th lagged input vector x , and β_k is the parameter of the k -th lagged dependent variable. Note that the specification (1) reduces to a Cobb-Douglas specification in the absence of dynamics (where $\beta_k = 0$ and $\gamma_k = 0$ for all k). Knowing that the Cobb-Douglas specification is not a flexible functional form (e.g., it imposes unitary elasticity of substitution among inputs), we seek a generalization of (2) that allows for a more general representation of the underlying technology. This can be done by introducing second-order interaction terms between inputs in (1). In our analysis, we are

particularly interested in the effects of rainfall and of biodiversity on productivity. Considering that both rainfall and biodiversity are among the inputs x , we introduce the additional terms $[\ln(\text{rainfall}) \ln(\text{diversity})]$ in (1). This gives a flexible specification of the production function, representing dynamics as well interaction effects between rainfall and diversity. As a result, we consider the following econometric specification

$$\ln(y_{it}) = A + \alpha \ln(x_{it}) + \sum_{k=1}^p \beta_k \ln(y_{i,t-k}) + \sum_{k=1}^q \gamma_k \ln(x_{i,t-k}) + \delta_0 \ln(\text{biodiversity}_t) \ln(\text{rainfall}_t) + \delta_1 \ln(\text{biodiversity}_t) \ln(\text{rainfall}_{t-1}) + \mu_i + v_{it}, \quad (2)$$

where μ_i and v_{it} are independently distributed error terms, each with mean zero and finite variance. The term μ_i measures region-specific effects, while the error term v_{it} denotes the remainder disturbance that can vary over time as well as across regions. Equation (2) is a panel data model, combining cross sectional data across regions as well as time series data. The panel nature of the analysis has several advantages. First, it can control for cross-section heterogeneity and unobservable or missing values (Baltagi, 2001). Second, it can improve the efficiency of the parameter estimates. Finally, panel data analysis provides a basis to study dynamics and the estimation of short run, intermediate run as well as long run effects of the explanatory variables. Equation (2) can be alternatively written as

$$\Delta \ln(y_{it}) = \alpha \Delta \ln(x_{it}) + \sum_{k=1}^p \beta_k \Delta \ln(y_{i,t-k}) + \sum_{k=1}^q \gamma_k \Delta \ln(x_{i,t-k}) + \delta_0 \Delta [\ln(\text{biodiversity}_t) \ln(\text{rainfall}_t)] + \delta_1 \Delta [\ln(\text{biodiversity}_t) \ln(\text{rainfall}_{t-1})] + \Delta v_{it}, \quad (3)$$

where $\Delta z_t = z_t - z_{t-1}$ is the first-difference operator. The first-difference transformation in (3) eliminates the individual effects (Baltagi, 2001) and reduces serial correlation. Equation (3) provides a basis for estimating the parameters in (2). When some of the explanatory variables are endogenous, a generalized method of moments (GMM) estimator can generate consistent parameter estimates. When the error terms v_{it} are serially uncorrelated, valid instruments in the

estimation of the first-difference model (3) include lagged values of the dependent variable (see Arellano and Bond, 1991). And given an appropriate choice of the instruments and weights, GMM can provide asymptotically efficient parameter estimates. Ahn and Schmidt (1995), and Blundell and Bond (1998) explored how using the initial conditions in levels, in addition to (3), can generate efficiency gains. This involves using a system GMM estimator that uses lagged differences as instruments for equations in levels, in addition to lagged dependent variables as instruments for equations in first-difference. Both the usual GMM estimator of (3) and the system GMM estimator were used in the empirical analysis.

When applied to our data, the two estimation methods gave similar results. We found that the system approach did not provide significant efficiency gains. As a result, our discussion below focuses on the Arellano-Bond GMM estimator of (3). Table 3 reports the associated econometric results. The estimated system GMM is available from the authors upon request.

3. Agroecosystem description

The area considered in this study includes 8 regions in southern Italy. Cultural and climatic characteristics of southern Italy make agriculture an important sector. Indeed, this area agriculture accounts for 8% of overall European Union agricultural land and the average ratio of added value in agriculture against added value in industry has been persistently 0.4 from 1960 to 1993. Cereals are among the most important crops in this agroecosystem. Between 1990 and 2000 it accounted on average of about 4 per cent of the overall European cereal production. And cereals account for up to 69 per cent of the total land use in some of the regions. In the past twenty years, 68 per cent of national durum wheat production, a staple product in Italy, came from regions in southern Italy. Durum and soft wheat production is spread uniformly, with some

areas producing large quantities of output. For instance, the Abruzzo and Campania regions have produced respectively 72,144 and 75,838 tons of soft wheat (using roughly 25 different cultivars). The Sicily and Puglia regions produced the largest part of the durum wheat with the latter accounting for 482,689 tons and the former for 434,730 tons.

The production of cereals is particularly favored since the dry and warm weather in this area suits this family of crops. Cold, frosty winters and sudden changes in the temperature affect yields negatively. These weather conditions may also reduce the spread and proliferation of pests. Pests are more likely to spread when the degree of humidity is high. In some areas the soil is sandy. This reduces the ability of plant roots to absorb fertilizers, and hence the benefit in using nutrients. In the time span considered in this paper, institutional conditions were quite homogeneous. The entire region was classified as “objective one” by the European Common Agricultural Policy, implying that agricultural assistance involved the same set of policy instruments.

4. Data sources and variables description

Data were obtained from ISTAT, the Italian National Institute of Statistics, and the INEA, the National Institute for Agricultural Economics. The series are drawn from the *Statistiche Agrarie and Annuario* for eight regions in Southern Italy (Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicily and Sardegna), including the years from 1970 to 1993. As mentioned in the previous section, during this time span all the regions in the studies were under the same institutional framework (objective one of the Common Agricultural Policy, CAP). This implies that the set of financial instruments aimed to support farm income were

homogeneous. Thus, farms would face the same incentives (i.e. price support, grants etc) for growing different cereals.

Table 1 and table 2 present the descriptive statistics and the definitions of the variables used in this empirical analysis. The quantity (biomass) of cereal produced is in tons. Fertilizer applications per hectare and labor force participation are conventional inputs. Capital is measured as investment in structure and machineries (at constant prices). The quantity of rainfall per year captures the weather impact on productivity.

One of the most commonly recognized concepts of diversity refers to the amount of diversity found in a given geographical area (e.g., Smale et al., 1998; Smale et al., 2003). The ecological literature has developed many metrics to represent diversity concepts and methods for calculating them. In agricultural systems, one of the most commonly adopted measures of diversity is spatial diversity. Spatial diversity refers to the amount of diversity found in a fixed geographical area. In this study, the Shannon index is used to measure the crop biodiversity of the agroecosystem. The Shannon index is

$$H = - \sum_i p_i \cdot \log(p_i)$$

where p_i is the planted area share of the i -th species in a reference region. Note that alternative diversity indices have appeared in previous literature. They include the commonly-used Simpson index. However, the Simpson index is “heavily weighted toward the most abundant species in the sample while being less sensitive to species richness” (Magurran, 1988: p. 40). On that basis, the Simpson index appears ill suited to represent spatial diversity in interspecies crop biodiversity because of the dominance of one crop (durum wheat). By construction these spatial indices are a source of endogeneity bias. Indeed, the share of land to be allocated to the i -th species is a choice variable.

Assumptions underlying the use of the Shannon index include random sampling from an infinitely large population and the representation of all species from the defined area in the sample. The adoption of a Shannon spatial index bears two important benefits. First benefit of the Shannon index in this context is that it is sensitive to both evenness and richness. A contested issue in biodiversity analysis is the existence of the so-called “sampling” effect (Tilman et al., 2005). Such effect can reflect the performance of one particular crop species rather than the effect of heterogeneity. Given that the spatial Shannon index increases with evenness in land allocation, it can help control for such effect. A second benefit is that it captures the restricted economic substitution for cereals. This takes account of the potential bias can arise in production function approaches that model one single crop (Mendelsohn et al., 1994). Indeed, the index implicitly incorporates information on possible economic substitutions among cereals.

Finally, it is important to stress that other measure of biodiversity have been used in the literature (i.e. genetic distance index). This includes Weitzman (1992) who proposed a distance measure that maximizes diversity among the surviving members of the set. This also includes Solow et al. (1993) who proposed that the distance measures should take into account the size of the set (to capture richness) as well as the distance among members. However, given the complexity of biodiversity valuation, at this point, no specific measure has been identified that appears always superior (e.g., Mainwaring, 2001; Brock and Xepapadeas, 2003).

5. Empirical results

The dynamic production function given in (3) is estimated using GMM. Two lags are included for the dependent variable ($p = 2$), and one lag for the explanatory variables ($q = 1$). This provides a reasonable flexible representation of the dynamics of productivity. Rainfall is

considered strictly exogenous, conventional inputs are considered as predetermined variables and the lagged values of the dependent variable and the biodiversity index are considered endogenous. To test for endogeneity for the diversity index, we adopted a residual based test (Davidson and MacKinnon, 1993; Wooldridge, 2002). Lagged values of the index were used as instruments. We rejected the null hypotheses of exogeneity at the 10% significance level. This suggests the need to estimate the model using an instrumental variable method that can correct for endogeneity bias.

Equation (3) is estimated using the GMM approach proposed by Arellano and Bond (1991).⁴ The results are reported in Table 3. In the Arellano-Bond approach, the error term v_{it} is assumed to be serially uncorrelated. This is essential to generate the consistency of the parameter estimates. If v_{it} is not serially correlated, there should be no evidence of second-order serial correlation in Δv_{it} . Using the standardized average residual autocorrelation and following Arellano and Bond (1991), we tested whether Δv_{it} exhibited second-order serial correlation. The Arellano-Bond test statistic of second-order serial correlation was $z = -0.65$. Under the null hypothesis of no serial correlation in v_{it} , the associated p-value is 0.513. Therefore, we fail to reject the null hypothesis. This indicates that the assumption that the v_{it} are serially uncorrelated appears supported by the data. Next, we implemented a Sargan/Hansen test of the overidentifying restrictions. The hypothesis being tested with the Sargan/Hansen test is that the instrumental variables are uncorrelated with the residuals, a key assumption to support the consistency of the GMM estimator. The null hypothesis is not rejected. Thus, from the Sargan/Hansen test results, the instruments pass the test: they appear to satisfy the orthogonality conditions required by GMM.

⁴ As mentioned above, we also estimated the model using a system GMM estimator exploiting the initial conditions. The econometric results were similar.

Table 3 column (A) reports the model where lags are included for all variables. Many of the lagged explanatory variables are found to be statistically significant. This stresses the important role of dynamics. Both $y_{i,t-1}$ and $y_{i,t-2}$ are positive although only the latter is statistically significant. Crop biodiversity is positively related with production both in current and in lagged effects, indicating that maintaining a more diverse agro-ecosystem enhances agricultural productivity both in the short run and in the intermediate run. The interaction terms between crop biodiversity and rainfall are negative and significant in both current and lagged effects. This result stresses the relevance of a higher biodiversity regime as a means of coping with scarce rainfall. This provides evidence that crop biodiversity ensures that the agro-ecosystem remains productive when facing lower or scarce rainfall. The effects of land on production are found to be statistically significant both in current and in lagged effects. As expected, the estimated impact of land is relatively large. The coefficients for the current levels of other conventional inputs (fertilizer, capital and labor) are all positive and statistically significant. However, in column (A) of Table 3, the lagged effects of these conventional inputs are not statistically significant.

The dynamic panel data framework allows the assessment of dynamic responses, including the evaluation of short run and long run elasticities. The estimated coefficients from model (3) are used to calculate dynamic elasticities of production. Evaluated at sample means, the elasticity of production with respect to crop biodiversity is 0.87 in the short run, and 3.29 in the long run. This gives two important results. First, crop biodiversity has a positive and fairly large impact on productivity both in the short run and in the long run. This provides evidence that crop biodiversity plays an important role in supporting agroecosystem productivity. Second,

the long run impact is much larger than its short run impact. This stresses the importance of dynamics in the functioning of the agroecosystem.

The interaction effects in model (3) imply that the role of biodiversity varies with rainfall. To illustrate, consider the production elasticity with respect to crop biodiversity when rainfall is 20 percent below the sample mean. Compared to the evaluation at sample means, this elasticity increases from 0.87 to 1.14 in the short run, and from 3.29 to 3.75 in the long run. This shows that the productivity benefits of biodiversity are larger when rainfall declines and the ecosystem faces environmental stress. This issue is further investigated in the following section by means of a simulation exercise.

The econometric estimates reported in Table 3 column (A) show that some of the lagged conventional inputs do not have statistically significant effects on production. To evaluate these effects, the model was also estimated without the lagged variables for fertilizer and capital. The results are presented in Table 3 column (B). Note that the results remain quantitatively as well as qualitatively similar. This indicates that our empirical findings appear to be fairly robust to the model specification.

6. Rainfall, resilience and diversity

This section investigates the implications of our analysis for the dynamics of agroecosystem productivity. The estimated model is used to simulate production under alternative scenarios. We start with a base scenario where the agroecosystem production is simulated forward in time, with all other variables set at their sample means. All scenarios have the same initial conditions (at time $t = 0$). At time $t \geq 1$, alternative scenarios face different conditions and

thus evolve along different paths. The comparison of these paths across scenarios provides useful insights into resilience and agroecosystem dynamics.

According to the IPCC projection, we can expect a rainfall decline in Southern Italy between 5% and 15% over the next decade. To evaluate these effects, we investigate the dynamic implications of *permanent* reductions in rainfall, holding other variables at their sample mean. The results are presented in Figure 1. Figure 1 shows simulations of the base scenario (where rainfall is set at its sample mean of the last two decades), and of four scenarios representing different levels of rainfall reductions: 5%, 10%, 20% and 40% *permanent* decreases in rainfall. Figure 1 illustrates the adverse effects of rainfall reduction on productivity. As expected, lower rainfall has a negative effect on agroecosystem production. It shows that drier environments make the system move from its original equilibrium to other paths that are less productive. The magnitude of productivity loss increases with the decline in rainfall, showing that adaptation is more difficult under greater stress. Finally, the productivity losses are higher in the long run than in the short run. This reflects the dynamics of the ecosystem: some of the adverse effects of rainfall reduction can be buffered in the short run and not in the long run. These results provide a useful illustration of the way environmental stress (i.e., lower rainfall) affects the dynamics of agroecosystem productivity. They show how the productive capability of the agroecosystem is adversely affected under increased environmental stress.

What about the effects of crop biodiversity? Figure 2 presents dynamic simulation results under alternative levels of diversity, holding all other variables at their sample means. Besides the base scenario, three scenarios are presented corresponding to a 5%, 10% and 20% *permanent* decline in biodiversity. Figure 2 shows how a reduction in biodiversity has a negative effect on the productivity of the agroecosystem. It illustrates that a loss of diversity makes the system less

productive. The magnitude of productivity loss increases with the decline in diversity. Figure 2 also indicates that the productivity losses are much higher in the long run than in the short run. For example, under a 20% reduction in diversity, production decreases by 17% in the short run (at time $t = 1$) but as much as 52% in the long run (for $t \geq 6$). This reflects the dynamics of the ecosystem. It shows that a large part of the benefits of biodiversity are obtained only in the longer term.

Finally, we use our estimated model to investigate the resilience benefits of diversity under climatic change. In our analysis, resilience comes from the dynamic interaction effects between rainfall and biodiversity. We investigate these issues by simulating the dynamic effects of biodiversity under alternative rainfalls, as shown in Figure 3. Besides the base scenario (where all variables are set at their sample means), Figure 3 presents two alternative scenarios: one where rainfall exhibits a 20% permanent decline while diversity equals its sample mean; and one where rainfall decreases 20% while diversity increases by 2%. Comparing these two scenarios provides useful insights into the resilience benefits of diversity. Figure 3 shows that, while a sharp decline in rainfall sees a decrease in system productivity, this decline can be reversed under higher diversity. Interestingly, this reversal does not occur in the short run. Indeed, at time $t = 1$, higher diversity cannot prevent the lower rainfall from decreasing agroecosystem production. However, the reversal does occur in the longer run ($t \geq 2$), where the benefits of biodiversity become large enough to compensate for the adverse effects of lower rainfall. This illustrates how biodiversity is buffering against the negative effects of adverse environmental conditions. This is the essence of how biodiversity supports the resilience of the system: at least in the longer term, it can help keep the agroecosystem at a level of productivity that is similar to the one obtained without the shock. It implies that crop biodiversity has an important role to play

in a changing environment. Both spatial abundance and evenness of the distribution of the crop species matter. On the one hand, oversimplified agroecosystems, such as a monoculture, may not be able to cope adequately with climatic change. On the other hand, under climatic changes, enhancing the biodiversity of an agroecosystem can help maintain its long term productivity and its ability to produce food.

7. Concluding remarks

Previous studies focusing on the determinants of crop biodiversity conservation have found that risk hedging, market integration, agro-ecological conditions are key variables in determining the level of agro-biodiversity. Yet, one of the major issues in the debate on biodiversity is to understand the potential role of crop diversity on the productivity of agro-ecosystems. This paper contributes to this understanding by presenting an empirical assessment of the effects of crop biodiversity on agro-ecosystem production, with a focus on cereals. Diversity is measured using a Shannon index of spatial diversity. Using data from southern Italy (an area classified as mega-diversity spot for cereals) over a twenty year period, we investigated empirically the dynamics of productivity. Relying on dynamic panel data econometrics and accounting for endogeneity in the diversity index, we investigated how rainfall, biodiversity and their interactions affect cereal production.

The econometric results show that levels of crop biodiversity is positively and significantly related to production. Reflecting the dynamics of ecosystem productivity, these positive effects are found to be stronger in the long term than in the short term. Thus, conserving in situ crop biodiversity enhances agricultural production in agro-ecosystems. Importantly, the positive contribution of crop biodiversity is found to be stronger when the level of rainfall in

lower. This result stresses that maintaining high crop biodiversity helps the productivity of the agro-ecosystem when a limiting physical factor becomes important. Moreover, simulations results highlight that the agro-ecosystem resilience to rainfall shocks depend heavily on the level of biodiversity. According to recent climate change projections in Southern Italy, rainfall will decrease at the rate between 5% and 15% in the next decade. We simulated the impact of different permanent changes in rainfall. While rainfall reductions have adverse effects on agro-ecosystem productivity, we found that these adverse effects can be buffered in the short term and possible reversed in the longer term under increased biodiversity. In other words, we find evidence that agro-biodiversity can buffer against negative environmental effects and support the resilience of the system under adverse weather conditions associated with anticipated climate changes.

References

- Ahn, S.C. and P. Schmidt (1995), Efficient estimation of models for dynamic panel data, *Journal of Econometrics* 68: 5-27.
- Arellano, M. and S. Bond (1991), Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *The Review of Economic Studies* 58: 277-297.
- Baltagi, B.H. (2001), *Econometric of panel data analysis*, John Wiley & Sons, Ltd. Chirchester, England.
- Blundell, R. and S. Bond (1998), Initial conditions and moment restrictions in dynamic panel data models, *Journal of Econometrics* 87: 115-143.
- Brock, W.A. and A. Xepapadeas (2003), Valuing biodiversity from an economic perspective: a unified economic, ecological and genetic approach, *American Economic Review*, 93(5): 1597-1614.
- Conway, G. R. (1985), Agroecosystem analysis, *Agricultural Administration* 20:31-55.
- Conway, G.R. (1986), *Agroecosystem analysis for research and development*, Winrock International Institute for Agricultural Development, Bangkok.
- Conway, G. R. (1987), The properties of agroecosystems, *Agricultural Systems* 24: 95-117.
- Conway, G.R. (1993), Sustainable agriculture: The trade-offs with productivity, stability and equitability, In: E.D. Barbier (ed.), *Economics and ecology new frontiers and sustainable development*, Chapman, London, 46-65.
- Conway, G.R. and E.B. Barbier (1990), *After the green revolution: Sustainable agriculture for development*, Earthscan, London.
- Davidson, R. and J.G. MacKinnon (1993), *Estimation and inference in econometrics*, New York: Oxford University Press.
- Di Falco, S., and C. Perrings (2005), Crop biodiversity, risk management and the implications of agricultural assistance, *Ecological Economics* 55(4): 459-466.

EEA report No 2/2004, Impacts of Europe's changing climate, European Environment Agency, European Topic Center for Air and Climate Change, Copenhagen.

Evenson, R. E. and D. Gollin (1997), Genetic resources, international organizations, and improvement in rice varieties, *Economic Development and Cultural Change* 45(3): 471-500.

Giller K.E., M.H. Beare, P.Lavelle, A.M.N. Izac and M.J. Swift (1997), Agricultural intensification, soil biodiversity and agro-ecosystem function, *Applied Soil Ecology* 6: 3-16.

Goeschl, T., and T. Swanson (2002), The social value of biodiversity for R&D, *Environmental and Resource Economics*, 22(4): 477-504.

Heal, G. (2000), *Nature and the Marketplace: Capturing the value of ecosystem services*, Island Press, New York.

Heisey, P.W., M. Smale, D. Byerlee and E. Souza (1997), Wheat rusts and the costs of genetic diversity in the Punjab of Pakistan, *American Journal of Agricultural Economics* 79: 726-737.

Holling, C.S. (1973), Resilience and stability of ecological systems, *Annual Review of Ecology and Systematics* 4: 1-23.

Hulme, M., E.M. Barrow, N.W. Arnell, P.A. Harrison, T.C. Johns, and T.E. Downing (1999), Relative impacts of human-induced climate change and natural climate variability, *Nature* 397: 688-691.

IPCC WGII Report (2003), *Climate change impacts, adaptation and vulnerability*, Intergovernmental Panel on Climate Change, World Meteorological Organization, Geneva.

ISTAT, *Annuario di Statistica Agraria*, various years.

Lenne J. and D. Wood (1999), Optimizing biodiversity for productive agriculture, In: Wood D. and Lenne J. (eds.), *Agrobiodiversity: Characterization, utilization and management*, CABI Publishing, Wallingford, UK, 447-470.

Magurran, A.E. (1988), *Ecological diversity and its measurement*, Croom Helm, London.

- Mainwaring, L. (2001), Biodiversity, biocomplexity, and the economics of genetic dissimilarity, *Land Economics* 77: 79-93.
- Mendelsohn, R., W.D. Nordhaus, and D. Shaw (1994), The impact of global warming on agriculture: A Ricardian analysis, *American Economic Review* 84(4): 753-771.
- Mundlak, Y. (2001), Production and supply, In Gardner, B.L. and Rausser, G.C. (eds.), *Handbook of Agricultural Economics*, North Holland, Amsterdam, 3-85.
- National Academy of Science (2001), *Climate change science: An analysis of some key questions*, Committee on the Science of Climate Change, National Academy Press, Washington, D.C.
- Parry, M.L. ed. (2000), *Assessment of the potential effects and adaptations for climate change in Europe: The Europe ACACIA project*, Jackson Environmental Institute, University of East Anglia, Norwich.
- Perrings C. and Stern D. I. (2000), Modelling loss of resilience in agroecosystems: Rangelands in Botswana, *Environmental and Resource Economics* 16: 185-210
- Perrings, C., K.G. Mäler, C. Folke, C.S. Holling and B.O. Jansson, eds.(1995), *Biodiversity loss: Economic and ecological issues*, Cambridge: Cambridge University Press.
- Qualset, C.O., P.E. McGuire and M.L. Warburton (1995), Agrobiodiversity: key to agricultural productivity, *California Agriculture* 49(6): 45-49.
- Simpson, R. D., R. A. Sedjo and J.W. Reid (1996), Valuing biodiversity for use in pharmaceutical research, *Journal of Political Economy* 104(1): 163-185.
- Smale, M., J. Hartell, P.W. Heisey and B. Senauer (1998), The contribution of genetic resources and diversity to wheat production in the Punjab of Pakistan, *American Journal of Agricultural Economics* 80: 482-493.
- Smale, M., M.R. Bellon and J.A. Aguirre Gomez (2001), Maize diversity variety attributes and farmers' choices in Southeastern Guanajuato, Mexico, *Economic Development and Cultural Change* 50(1): 201-225.
- Smale, M. E. Meng, J.P. Brennan and R. Hu (2003), Determinants of spatial diversity in modern wheat: Examples from Australia and China, *Agricultural Economics* 28(1): 13-26.

- Solow, A., S. Polasky and J. Broadus (1993), On the measurement of biological diversity, *Journal of Environmental Economics and Management* 24(1): 60-68.
- Tilman, D. and J. A. Downing (1994), Biodiversity and stability in grasslands, *Nature* 367: 363–365.
- Tilman, D., D. Wedin and J. Knops (1996), Productivity and sustainability influenced by biodiversity in grassland ecosystems, *Nature* 379: 718–720.
- Tilman, D., S. Polasky and C. Lehman (2005), Diversity, productivity and temporal stability in the economies of humans and nature, *Journal of Environmental Economics and Management* 49(3): 405-426.
- Tisdell, C. (1996), Economic indicators to assess the sustainability of conservation farming projects: An evaluation” *Agriculture, Ecosystems and Environment* 57(2): 117-131.
- Weitzman, M.L. (1992), On diversity, *Quarterly Journal of Economics* 107: 363-405
- Widawsky, D., and S. Rozelle (1998), Varietal diversity and yield variability in Chinese rice production, in M. Smale ed., *Farmers, Gene Banks, and Crop Breeding*, Boston: Kluwer.
- Wooldridge, J. (2002) *Econometric analysis of cross section and panel data*, Cambridge, MA: MIT Press.

Table 1 - Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Ln(Labour)	3.974	0.7245	2.16	5.8
Ln(Fertilizer)	0.3383	0.7966	-1.6	1.643
Ln(Capital)	6.167	0.5997	4.48	7.139
Ln(Land)	6.34	0.6042	5.17	7.404
Ln(Biodiversity)	-0.068	0.4773	-1.469	0.36846
Ln(Rain)	6.354	0.37	5.199	7.3338

Table 2 - Variables definition

Variable	Definition
Labour	Labor force in cereal production
Fertilizer	Quantity of fertilizers and chemicals
Capital	Expenditure in machinery and buildings
Land	Land size to cereal production in ha
Biodiversity	Index for biodiversity
Rain	Annual rainfall in mm

Table 3 - Dynamic panel data (GMM) estimation result

Variables	Dynamic Model Arellano-Bond GMM estimation of (3) (A)	Estimation of (3) Selected Regressors (B)
y_{t-1}	0.12 (0.2)	0.129 (0.18)
y_{t-2}	0.12* (0.07)	0.156* (0.08)
Biodiversity _t	10.4*** (3.82)	9.87*** (3.65)
Biodiversity _{t-1}	4.24* (2.5)	3.94* (2.4)
Interaction Biodiversity _t & Rain _t	-1.5*** (0.56)	-1.4*** (0.53)
Interaction Biodiversity _t & Rain _{t-1}	-0.41** (0.2)	-0.35* (0.2)
Land _t	2.82*** (1.1)	3.02*** (1.2)
Land _{t-1}	-1.36* (0.8)	-1.2* (0.7)
Labor _t	1.18* (0.7)	1.107* (0.62)
Labor _{t-1}	-0.38 (0.5)	-0.5 ^a (0.4)
Fertilizer _t	1.18*** (0.29)	1.17*** (0.36)
Fertilizer _{t-1}	0.14 (0.2)	-
Capital _t	1.41** (0.67)	1.38** (0.61)
Capital _{t-1}	-0.184 (0.7)	-
Rain _t	0.06 (0.15)	0.248 (0.36)
Constant	0.43 (0.99)	0.0145 (0.071)

Significance levels: *** = 1%, ** = 5%, * = 10%; “a” = 10% one tailed test.

Robust standard errors are in parentheses.

Arellano-Bond test, H_0 of no first-order serial correlation in the residuals: $z = -5.85$.

Arellano-Bond test, H_0 of no second-order serial correlation in the residuals: $z = -0.65$, p -value = 0.513.

Dynamic production under alternative rainfall scenarios

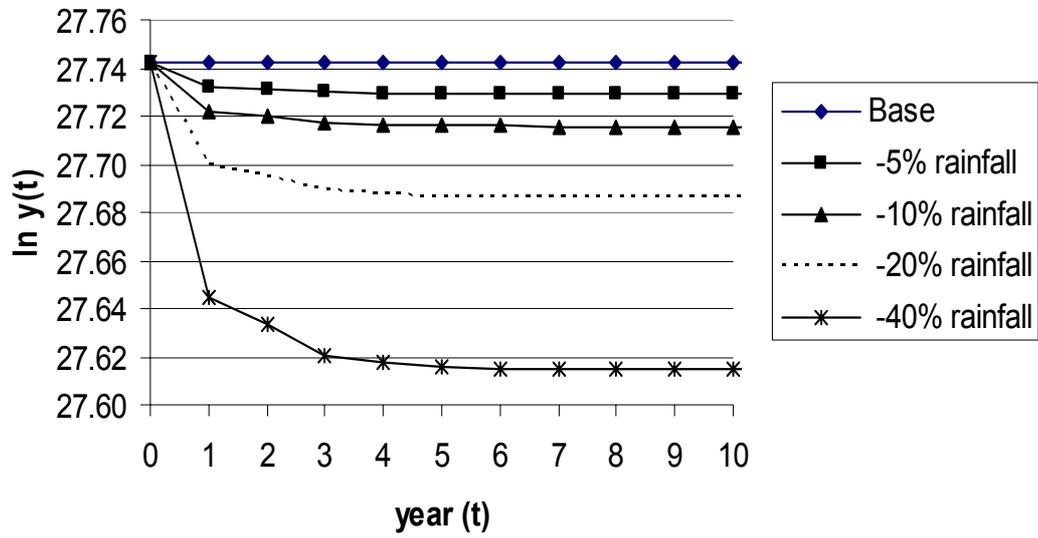


Figure 1 – The dynamic impact of rainfall reduction on productivity

Dynamic production under alternative biodiversity scenarios

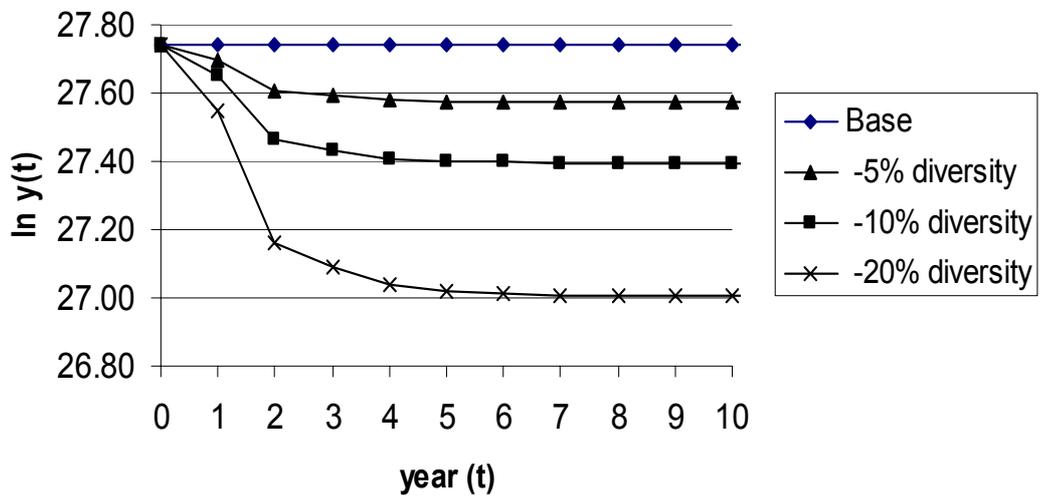


Figure 2 – The dynamic impact of biodiversity on productivity

Dynamic resilience: the role of diversity

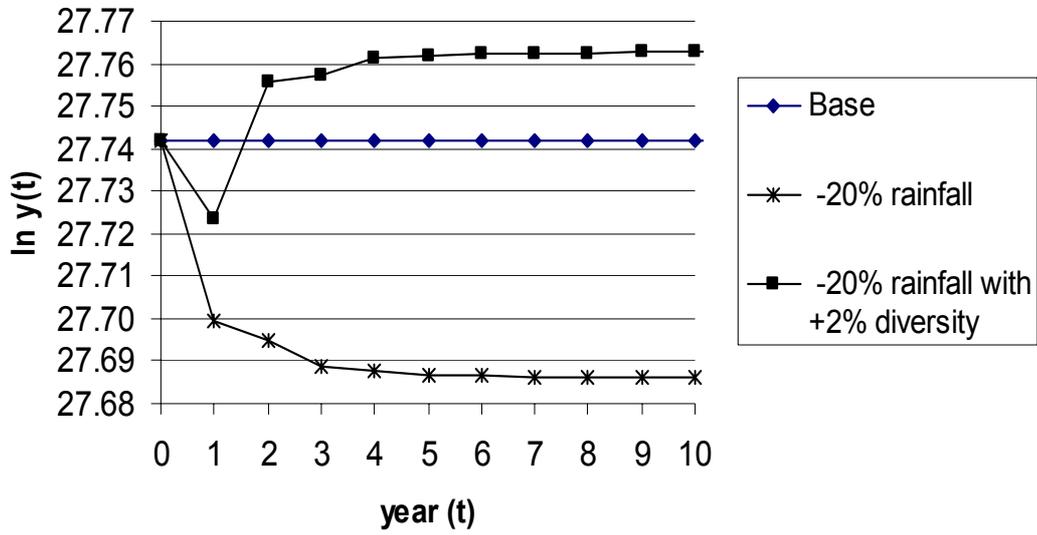


Figure 3 - The resilience role of diversity under reduced rainfall