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# Estimating the Impact of Crop Diversity on Agricultural Productivity in South Africa

Cecilia Bellora, Élodie Blanc, Jean-Marc Bourgeon, and Eric Strobl

## 6.1 Introduction

Diversity plays a key role in the resilience to external stresses of farm plants and animals. In particular, crop species diversity increases productivity and production stability (Tilman, Polasky, and Lehman 2005; Tilman and Downing 1994; Tilman, Wedin, and Knops 1996) in the sense that the probability to find at least one individual that resists to an adverse meteorological phenomenon (for example, a drought or a heatwave), or pests and diseases, increases with the diversity within a population. Furthermore, the larger a homogeneous population, the larger the number of parasites that use this population as a host and therefore the larger the probability of a lethal infection (Pianka 1999). Diversity also allows for species complementarities and, as a consequence, a more efficient use of natural resources (Loreau and Hector 2001). In short, crop biodiversity has the potential to

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enhance resistance to strains due to biotic and abiotic factors and to improve crop production and, possibly, farm revenues.[1]

For these reasons, after the large development of monocultures in the last decades, crop biodiversity is making a comeback. During the last century, farming activities specialized on the most productive crops, in particular in developed countries and in large areas of emerging economies. The decrease in crop biodiversity resulted in increased pest attacks (Landis et al. 2008) and has been compensated by the heavy use of agrochemicals. Nevertheless, chemicals generate negative externalities, irreversible in many cases, on water and soil quality, on wildlife, and on human health (Pimentel 2005; Foley et al. 2011; Jiguet et al. 2012; Beketov et al. 2013), which engender large economic costs (Gallai et al. 2009; Sutton et al. 2011). One of the main challenges for the future is to drastically reduce externalities while satisfying an increasing and changing food demand (Gouel and Guimbard 2018). In this context, crop biodiversity is seen more and more as a promising way to raise, or at least maintain, agricultural yields while decreasing the use of chemicals (McDaniel, Tiemann, and Grandy 2014). However, more estimations of the actual impacts of crop biodiversity on agricultural yields are needed to build solutions for farmers and to adopt relevant public policies. To this end, we empirically investigate the role of crop biodiversity on crop productivity.[2] We build a probabilistic model based on ecological mechanisms to describe crop survival and productivities according to diversity. From this analytic model, we derive reduced forms that are estimated using data on South African agriculture.

Our results contribute to the existing literature in three main ways. First, we confirm that diversity has a positive and significant impact on produced quantities. An increase in biodiversity is equivalent to a third of the benefits of a comparable increase in irrigation, where irrigation is known to be an important impediment to crop productivity in South Africa, due to unreliable precipitation. Previous empirical investigations on the role of biodiversity on production has produced sometimes contrasted results. Positive impact of biodiversity is found by Di Falco and Chavas (2006) and Carew, Smith, and Grant (2009) in wheat production in Italy and Canada, respectively. Smale et al. (1998) also focus on wheat yield and find a positive impact of biodiversity in rain-fed regions of Pakistan, while in irrigated areas, higher concentration on few varieties is associated with higher yields. Second, we adopt an approach based on ecology literature, while previous contribu-

1. The variation of farm revenues depends on the trade-off between the increase in biomass production and the opportunity cost of a larger crop diversity.

2. Crop biodiversity can be implemented in different ways and at various scales. Mixing several species in the same plot increases interspecific biodiversity, while the association of different varieties of the same crop increases intraspecific biodiversity. Agronomists and ecologists also explore the impact of a diversified landscape, where cultivate fields and uncultivated areas alternate. Our investigation is about interspecific crop diversity at the landscape level, as detailed in the following chapter.

tions used pure econometric methods, mainly moment-based approaches (Di Falco and Chavas 2006, 2009) stressing the crucial role played by skewness in addition to mean and variance. In these cases, the functional forms are disconnected from the ecology literature and therefore do not allow us to go into deep details on the way biodiversity impacts productivity. In the economic literature, models of endogenous interaction between biodiversity and crop production have been developed in theoretical papers that analyze the role and value of biodiversity against specialization on the most productive crops (Weitzman 2000; Brock and Xepapadeas 2003; Bellora and Bourgeon 2016) but have never been coupled with empirical investigations. In contrast, we build a probabilistic model that makes explicit the relationship between biodiversity and biotic and abiotic factors that affect agricultural production Stochastic shocks affecting agricultural production are endogenous, in accordance with ecology findings. This model can easily be linked to data and grounds our analysis on findings of ecology studies. This approach can also be extended to account for noncrop biodiversity (pastures, fallow land, noncultivated areas), which appears to also play a key role (Tscharntke et al. 2005), and to characterize the impacts on production variability. Third, we draw from the increasingly available satellite data (Donaldson and Storeygard 2016) to build a rich data set allowing us to estimate the impact of biodiversity on crop productivity based on our probabilistic model. A Normalized Difference Vegetation Index (NDVI) derived from the SPOT 5 satellite images, coupled with land-use classification, allow us to quantify the crop biomass produced on nearly 65,000 fields covering around 6.5 million hectares in South Africa. We quantify biodiversity using an index taken from the ecological literature, based on species richness (i.e., the total number of species) and their relative abundance, the Shannon index (Shannon 1948). This index captures the fact that biodiversity is high when the total number of species is large and the distribution of their relative abundances is homogeneous. We are then able to quantify the impacts of interspecific diversity on the productivity of various crops, while previous studies mainly looked at genetic diversity (i.e., intraspecific diversity of a single crop). We confirm that biodiversity has mainly a local impact: biodiversity is a significant predictor of crop productivity on perimeters having a radius smaller than 2 km.

In the remainder of the chapter, the theoretical model that motivates our empirical investigations is developed in section 6.2, and section 6.3 details its empirical implementation. Then the database on South African agriculture is presented in section 6.4. In section 6.5, we empirically investigate the impact of crop biodiversity on crop production.

## 6.2 The Model

A very robust stylized fact in ecology describes the impact of biotic factors on agricultural production: the more area dedicated to the same crop, the higher the number of pests specializing on this crop and the higher the frequency of their attacks (Pianka 1999). Relying on this stylized fact, we build a general probabilistic model of crop production where crops are affected by both abiotic (i.e., weather, water availability, soil properties) and biotic (i.e., pests) factors causing preharvest losses.[3] More precisely, we consider that the total agricultural production depends on the survival probability of each crop, which is directly linked to the probability of a pest attack. The frequency at which pest attacks occur is linked to the way crops are produced: the more diverse the crops, the lower the probability of a pest attack, the higher the survival probability, and therefore the higher the expected agricultural production. To describe the diffusion of pests, or equivalently the survival probabilities, we follow the literature in ecology and plant physiology and adopt a beta-binomial distribution, which is usual to depict spatial distributions that are not random but clustered, patchy, or heterogeneous (Hughes and Madden 1993; Shiyomi, Takahashi, and Yoshimura 2000; Chen et al. 2008; Bastin et al. 2012; Irvine and Rodhouse 2010).

We assume that a region (or a country) produces $Z$ different crops on $I$ fields of the same size, each field being sowed with one crop only.[4] Characteristics of field $i$ are gathered in vector $X_i = (x_{i1},\ldots,x_{iK})$ and are related to both abiotic factors and biotic factors. In particular, $\mathbf{X}_i$ contains information on the way crops are cultivated (irrigation but also soil quality and field location) and on biodiversity conditions. Depending on the crop cultivated, each field is divided in $n(z)$ patches that are subject to potential lethal strains due, for example, to adverse meteorological conditions or pathogens. We suppose that a patch on field $i$ is destroyed with probability $1-\lambda_i$ from one (or several) adverse condition and that otherwise it produces the potential yield $a(z)$ independently of the fate of the other patches on field $i$ or elsewhere.[5] With $n(z)$ patches, the probability of $t$ patches within field $i$ remaining unaffected (and thus $n(z)-t$ destroyed) follows a binomial distribution

$$\Pr\{\tilde{T}_i = t \mid z, \lambda_i\} = \begin{pmatrix} n(z) \\ t \end{pmatrix} \lambda_i^t (1-\lambda_i)^{n(z)-t},$$

where $\tilde{T}_i$ is the random variable that corresponds to the number of patches that are indeed harvested among the $n(z)$ patches of field $i$ sowed with crop

3. Losses due to biotic factors can be significant. Oerke (2006) finds that, from 2001 to 2003, without crop protection, losses in major crops due to pests comprised between 50 percent and 80 percent, at the world level. Thanks to crop protection, they fall between 29 percent and 37 percent. Similar results are found for the United States by Fernandez-Cornejo et al. (1998).

4. The model can be thought at different scales. It could represent a mixed intercropping system (Malézieux et al. 2009) or a diversified agricultural landscape, for instance. In the following empirical exercise, we apply it at a large geographic scale.

5. Obviously, this is a strong assumption. Pests and/or weather do not necessarily totally destroy a patch but rather affect the quantity of biomass produced. But in order to maintain tractability, we consider that a patch is either unaffected or totally destroyed, rather than partially affected, by adverse conditions. Thus our random variable is the number of harvested patches rather than the share of biomass that is lost on each patch.

$z$. We consider that the survival probability of the patches of a field, $\lambda_i$, is identically and independently distributed across patches. However, this probability may vary across fields of the same crop (we generally have $\lambda_i \neq \lambda_j$ for any couple of fields $(i, j)$ sowed with the same crop): it depends on natural conditions but also on the characteristics $\mathbf{X}_i$ of the field. More precisely, the survival probability of patches on a given field is a draw from a beta distribution given by

$$\Pr(\lambda_i = \lambda | \mathbf{X}_i, z) = \frac{\Gamma[S_{ui}(z) + S_{di}(z)]}{\Gamma[S_{ui}(z)]\Gamma[S_{di}(z)]} \lambda^{S_{ui}(z)-1}(1 - \lambda)^{S_{di}(z)-1},$$

where $\Gamma(\cdot)$ is the gamma function, $S_{ui}(z) \equiv e^{\gamma(z)+\theta_u(z)X_i}$ and $S_{di}(z) \equiv e^{\beta(z)+\theta_d(z)X_i}$, $\gamma(z)$ and $\beta(z)$ are positive parameters that determine the randomness of the survival probability of a patch of crop $z$ absent any field-specific effect, and the vectors $\boldsymbol{\theta}_u(z) = \{\theta_{uk}(z)\}_{k=1,\ldots,K}$ and $\boldsymbol{\theta}_d(z) = \{\theta_{dk}(z)\}_{k=1,\ldots,K}$ capture the influence of each field-specific effect $X_i$ on the survival probability of crop $z$. The expected number of patches among $n(z)$ that are harvested on field $i$ is given by $E[\tilde{T}_i | X_i, z] = n(z)\psi(z, X_i)$, where

$$(1) \qquad \psi(z, X_i) = E[\lambda_i | X_i, z] = \frac{S_{ui}(z)}{S_{ui}(z) + S_{di}(z)}$$

is the expected probability that a particular patch of field $i$ of crop $z$ is harvested given its characteristics $X_i$. Absent field-specific effects ($\boldsymbol{\theta}_u(z) = \boldsymbol{\theta}_d(z) = 0$), the expected resilience of a particular stand of crop is given by $\exp\gamma(z)/(\exp\gamma(z) + \exp\beta(z))$. An increase in coefficient $\theta_{uk}(z)$ increases this resilience, while an increase in $\theta_{dk}(z)$ diminishes it, the extent of these effects depending on the corresponding field characteristics $x_{ik}$. The variance of the number of harvested patches on field $i$ is given by $\sigma_i^2 = n(z)V(z, X_i)$, where

$$(2) \qquad V(z, X_i) = \psi(z, X_i)[1 - \psi(z, X_i)]\{1 + [n(z) - 1]\rho(z, X_i)\}$$

with

$$\rho(z, X_i) = [1 + S_{ui}(z) + S_{di}(z)]^{-1}.$$

Equation (2) corresponds to the variance of the survival probability of one patch on a field with characteristics $X_i$. Compared to the Bernoulli distribution, (2) contains an additional term that accounts for the correlation between patches induced by the common distribution of the survival probability, the correlation coefficient being given by $\rho(z, X_i)$.

The production on field $\tilde{Y}_i = a(z)\tilde{T}_i$ is given by $\tilde{Y}_i = a(z)\tilde{T}_i$. It can be equivalently written as

$$(3) \qquad \tilde{Y}_i = E[\tilde{Y}_i](1 + \tilde{\varepsilon}_i),$$

where $E[\tilde{Y}_i] = a(z)n(z)\psi(z, X_i)$ and $\tilde{\varepsilon}_i = (\tilde{T}_i - E[\tilde{T}_i])/E[\tilde{T}_i]$ has a mean equal to 0 and a variance given by

$$(4)\qquad \sigma^2_{\varepsilon_i} = \frac{1-\psi(z,X_i)}{\psi(z,X_i)}\left(\frac{1}{n(z)} + \frac{n(z)-1}{n(z)}\rho(z,X_i)\right) \approx \frac{1-\psi(z,X_i)}{\psi(z,X_i)}\rho(z,X_i)$$

when $n(z)$ is large. This variance is mainly due to the correlation between patches on a field that share the same survival probability, captured by $\rho(z, X_i)$. Indeed, $\lambda_i$ follows a beta distribution, but the parameters of the distribution depend on the field characteristics $\mathbf{X}_i$ and are thus different across fields. In other words, with a sufficiently large number of patches on each field, the difference in the quantities produced is mainly driven by field characteristics.

This simple ecological model of crop production can thus be summarized as follows: the number of patches that are harvested on field $i$, $\tilde{T}_i$, follows a beta-binomial distribution determined by the parameters $\gamma(z)$, $\beta(z)$, $\theta_{uk}$, and $\theta_{dk}$. Parameters $\theta_{uk}$ and $\theta_{dk}$ determine the impact of the $k^{th}$ field characteristic $x_{ik}$ on $\tilde{T}_i$, in addition to the parameters $\lambda(z)$ and $\beta(z)$ that are shared by all fields that grow crop $z$. Depending on the values of $\theta_{uk}$ and $\theta_{dk}$, each characteristic $x_{ik}$ can increase or decrease the expected number of harvested patches on field $i$ and skew the distribution of $\tilde{T}_i$ to the right or to the left, modifying the probability of extreme events like the loss of all the patches in a field.

In the following section, we build an empirical strategy to estimate the impact of the characteristics of a field on the distribution of $\tilde{T}_i$. In particular, we are interested in the impact on crop production of the crop biodiversity surrounding the field considered and expect this impact to be positive, according to findings and mechanisms described in the ecology literature.

## 6.3 Empirical Strategy

Starting from the probabilistic model, our aim is to estimate the parameters $\theta_u(z)$, $\theta_d(z)$, $\gamma(z)$, and $\beta(z)$ of the distribution of the survival probability $\tilde{T}$. We first have to derive from each field production the corresponding survival probability $\lambda_i$. They are obtained by dividing the production level by the potential maximum production $a(z)n(z)$ level. This potential production is not observed in practice; it is derived in the following from the maximum observed production level $Y_M(z) \equiv \max Y_i(z)$ using $a(z)n(z) = (1 + \alpha) Y_M(z)$, where $\alpha \geq 0$.[6] With a linear regression of the equation

$$(5)\qquad \ln\left(\frac{\hat{\lambda}_i}{1-\hat{\lambda}_i}\right) = \delta + \Delta X_i$$

for each type of crop, we obtain the estimate $\hat{\delta}(z)$ of $\gamma(z) - \beta(z)$ and $\hat{\mathbf{\Delta}}(z)$ of $\mathbf{\theta}_u(z) - \mathbf{\theta}_d(z)$. This first regression estimates the contribution of biodiversity (and other field characteristics) to the ratio of survival and death probabilities. Coefficients $\Delta$ show the variation of the growth rate of the odds

6. In the following, we consider $\alpha = 0.5$. Robustness checks for $\alpha = 0.1$ are available in the appendix.

associated with a marginal increase in each explanatory variable. These first results are interesting per se but also allow us to derive an expected patch survival rate for each field $i$ using

$$\hat{\psi}_i = 1/(1 + e^{-\hat{\delta}(z) - \hat{\mathbf{\Delta}}(z)X_i})$$

and a series of dispersion values

$$\hat{\varepsilon}_i = (\hat{\lambda}_i - \hat{\psi}_i)/\hat{\psi}_i.$$

From (4), which can be written as

$$\sigma^2_{\varepsilon_i} = \frac{1 - \psi(z, X_i)}{\psi(z, X_i) + S_{ui}},$$

we get, solving for $S_{ui}$,

$$S_{ui} = \frac{1 - \psi(z, X_i)(1 + \sigma^2_{\varepsilon_i})}{\sigma^2_{\varepsilon_i}}.$$

As $S_{ui} = \exp(\gamma + \mathbf{\theta}_u(z)X_i)$, we construct the variable

$$\hat{Z}_i = \frac{1 - \hat{\psi}_i(1 + \hat{\varepsilon}_i^2)}{\hat{\varepsilon}_i^2},$$

and we perform an OLS estimation of the equation

$$\ln(\hat{Z}_i) = \gamma(z) + \mathbf{\theta}_u(z)X_i \tag{6}$$

to obtain $\hat{\gamma}(z)$ and $\hat{\mathbf{\theta}}_u(z)$. We then get $\hat{\beta}(z) = \hat{\gamma}(z) - \hat{\delta}(z)$ and $\hat{\mathbf{\theta}}_d(z) = \hat{\mathbf{\theta}}_u(z) - \hat{\mathbf{\Delta}}(z)$.

## 6.4 Data

Combining different data sources, we construct a very detailed original database on South African agriculture that quantifies the production and describes the characteristics of a very large number of fields using satellite data. First, field boundaries are identified, then agricultural production is characterized on each field by identifying the crops that are grown and measuring the biomass produced. Field characteristics are then collected, addressing particular water balance, length of the growing season, and crop interspecific biodiversity.

### 6.4.1 Crop Fields

Field boundaries, available for South African provinces of Free State, Gauteng, North West, and Mpumalanga, are determined using the Producer Independent Crop Estimate System (PICES), which combines satellite imagery, a geographic information system (GIS), point frame statistical platforms, and aerial observations (Ferreira, Newby, and du Preez 2006). Satellite imagery of cultivated fields is obtained from the SPOT 5 satellite at

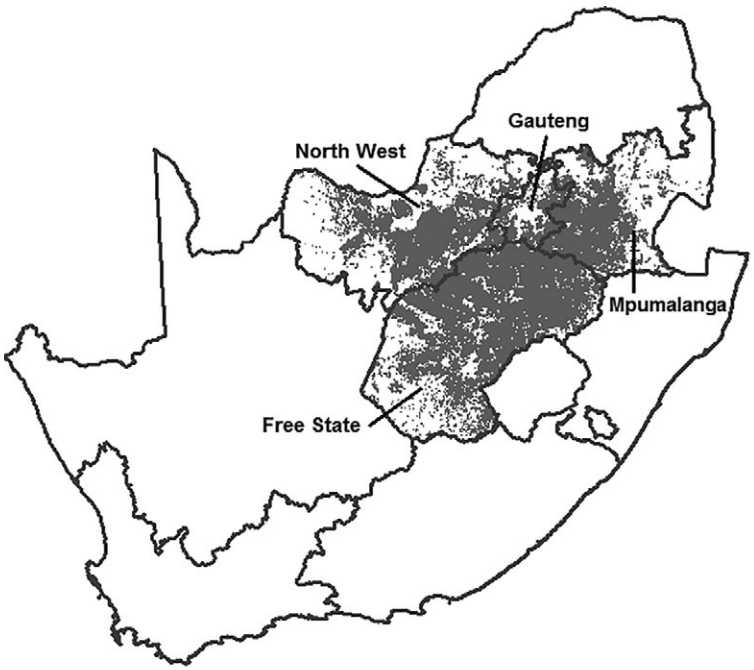


**Fig. 6.1 Localization of the considered fields in South Africa**

a 2.5 m resolution. Plot boundaries are then digitized using GIS, and field cloud covered polygons are removed before processing. Over the four regions of interest, PICES distinguishes circa 280,000 fields covering an area of around 6.5 million hectares. To approximately match the resolution of the crop production indicator we use (see section 6.4.2), which is only available at the 250 m resolution, the analysis is limited to fields larger than 6.25 ha. Additionally, we exclude pasture and fallow land. This restricts the sample to 64,682 fields. Figure 6.1 presents the location of the considered crop fields in South Africa. While the summary statistics in table 6.1 show that fields are on average about 28.4 ha, the large standard deviation (24.8) indicates that they vary substantially in size (the largest field is 720 ha large).

Using the digitized satellite images previously described, the Agricultural Geo-referenced Information System (AGIS) developed by the South African Department of Agriculture provides information on the crop cultivated on each field. To do so, sample points were selected randomly and surveyed by trained observers from a very light aircraft in order to determine crop type (Ferreira, Newby, and du Preez 2006). Crop information collected during the aerial surveys on the sample points was subsequently used as a training set for crop-type classification for each field and for accuracy assessment. These estimated crop classifications were then checked against a producer-

**Table 6.1** **Plot summary statistics**

| Variable | Mean | Standard deviation | Variable | Mean | Standard deviation |
|---|---|---|---|---|---|
| All crops | | | Maize | | |
| NDVI | 0.61 | 0.13 | NDVI | 0.61 | 0.13 |
| Water balance | –41.07 | 11.73 | Water balance | –42.60 | 11.89 |
| Season length (days) | 129.64 | 35.48 | Season length (days) | 126.98 | 35.33 |
| Plot area (ha) | 28.36 | 23.47 | Plot area (ha) | 22.72 | 2.04 |
| Farm area (ha) | 315.2 | 500.00 | Farm area (ha) | 193.63 | 3.53 |
| Irrigation (%) | 5.05 | – | Irrigation (%) | 4.94 | 21.67 |
| Cotton | | | Sorghum | | |
| NDVI | 0.73 | 0.05 | NDVI | 0.69 | 0.10 |
| Water balance | –28.61 | 14.54 | Water balance | –33.54 | 7.70 |
| Season length (days) | 130.94 | 52.00 | Season length (days) | 125.20 | 26.17 |
| Plot area (ha) | 15.63 | 1.66 | Plot area (ha) | 19.27 | 1.91 |
| Farm area (ha) | 184.41 | 2.32 | Farm area (ha) | 45.63 | 2.79 |
| Irrigation (%) | 56.60 | 49.80 | Irrigation (%) | 1.96 | 13.87 |
| Dry bean | | | Soybean | | |
| NDVI | 0.62 | 0.14 | NDVI | 0.71 | 0.09 |
| Water balance | –38.96 | 12.39 | Water balance | –32.18 | 7.59 |
| Season length (days) | 145.58 | 38.66 | Season length (days) | 129.19 | 30.14 |
| Plot area (ha) | 21.43 | 2.03 | Plot area (ha) | 19.09 | 1.91 |
| Farm area (ha) | 68.50 | 3.10 | Farm area (ha) | 95.98 | 2.95 |
| Irrigation (%) | 3.75 | 19.00 | Irrigation (%) | 5.89 | 23.55 |
| Groundnuts | | | Sunflower | | |
| NDVI | 0.52 | 0.11 | NDVI | 0.59 | 0.13 |
| Water balance | –55.56 | 6.34 | Water balance | –44.20 | 12.10 |
| Season length (days) | 115.40 | 34.67 | Season length (days) | 131.27 | 38.01 |
| Plot area (ha) | 28.61 | 2.03 | Plot area (ha) | 20.54 | 2.01 |
| Farm area (ha) | 73.91 | 2.96 | Farm area (ha) | 80.59 | 3.14 |
| Irrigation (%) | 4.10 | 19.84 | Irrigation (%) | 7.80 | 26.81 |

based survey for the Gauteng region. The Gauteng census survey showed that less than 1.8 percent of crop types had been misclassified. All in all, seven summer crops were distinguished for the provinces of Free State, Gauteng, North West, and Mpumalanga for the summer season 2006/2007: cotton, dry beans, groundnuts, maize, sorghum, soybeans, and sunflowers. An example of the distribution of crop types is provided in figure 6.2. The summary statistics for the entire sample in table 6.2 show that maize was the dominant crop cultivated in the three provinces: maize fields represent nearly 70 percent of the total number of fields we consider. Other important crops were sunflowers and soybeans, standing at 15 and 11 percent, respectively. In contrast, all other crop types constituted less than 2 percent individually. One should note that even if one were to adjust the crop-type shares by their areas, a similar ranking remains, with a slight redistribution of shares toward the smaller crop types. For instance, the share of maize dropped to 62 percent of the total crop area.

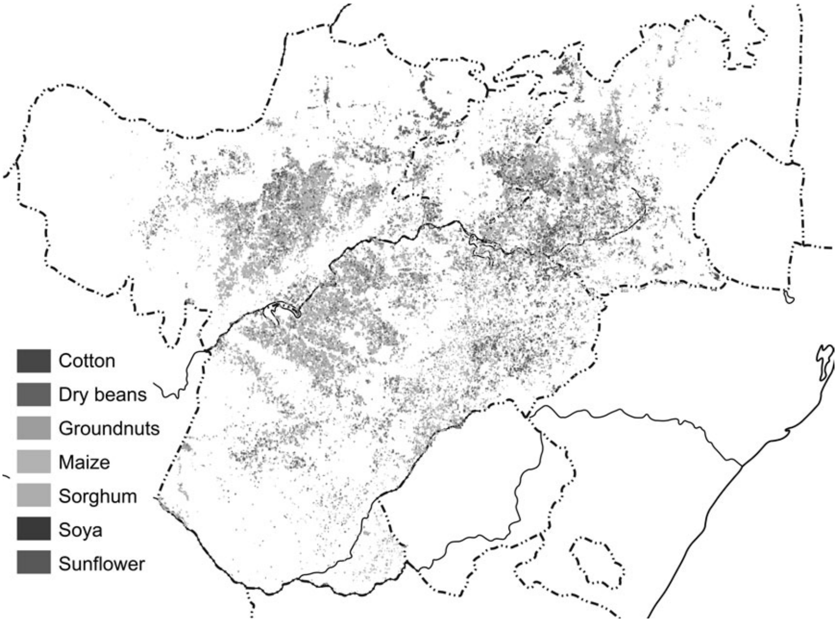


**Fig. 6.2 Distribution of the studied crops in South Africa**

**Table 6.2 Distribution of the considered crops**

| Crop | Number of fields | Share of total fields (%) | Share of total area (%) |
|---|---|---|---|
| Dry beans | 1,227 | 1.88 | 1.88 |
| Groundnuts | 1,292 | 2.5 | 2.50 |
| Maize | 45,256 | 69.77 | 72.27 |
| Sorghum | 715 | 1.10 | 0.93 |
| Soybeans | 6,825 | 10.52 | 8.80 |
| Sunflowers | 9,441 | 14.56 | 13.51 |
| Cotton | 106 | 0.16 | 0.10 |
| Total | 64,862 | 100.00 | 100.00 |

The AGIS crop-boundaries data set also provides information regarding irrigation, from which only 5 percent of the fields considered benefit (table 6.1).

Finally, all fields can be linked to their respective farms with a unique farm identifier. In total, the fields were owned by 12,462 different farms, where on average each farm was proprietor of five fields. However, ownership differed substantially, with the largest ownership gathering 193 fields and 3,704 single field farms.

### 6.4.2 Crop Production Measure

We estimate crop biomass production using the satellite-derived Normalized Difference Vegetation Index (NDVI). Vegetation indexes provide consistent spatial and temporal representations of vegetation conditions when locally derived information is not available. As a matter of fact, numerous studies have demonstrated that NDVI values are significantly correlated with biomass production, and therefore yields, of various crops, including wheat (Das, Mishra, and Kalra 1993; Gupta et al. 1993; Doraiswamy and Cook 1995; Hochheim and Barber 1998; Labus et al. 2002), sorghum (Potdar 1993), maize (Hayes and Decker 1996; Prasad et al. 2006), rice (Nuarsa et al. 2011; Quarmby et al. 1993), soybeans (Prasad et al. 2006), barley (Weissteiner and Kuhbauch 2005), millet (Groten 1993), and tomatoes (Koller and Upadhaya 2005). Moreover, NDVI has also been shown to provide a very good indicator of crop phenological development (Benedetti and Rossini 1993).

The NDVI index is calculated using ratios of vegetation spectral reflectance over incoming radiation in each spectral band. The NDVI data are extracted from the MOD13Q1 data set,[7] which gathers reflectance information collected by the MODerate-resolution Imaging Spectroradiometer (MODIS) instrument operating on NASA's Terra satellite (Huete et al. 2002). From these data, NDVI can be formulated as

$$\text{NDVI} = \frac{\text{NIR} - \text{VIS}}{\text{NIR} + \text{VIS}},$$

where the difference between near-infrared reflectance (NIR) and visible reflectance (VIS) values is normalized by the total reflectance and varies between $-1$ and 1 (Eidenshink 1992). The more biomass is produced, the more the NDVI is close to 1. Negative and very low values corresponding to water and barren areas were excluded from the analysis by design. Nevertheless, NDVI has some limitations. In particular, it enters an asymptotic regime for high values of biomass. It reaches its maximum when leaves totally cover the soil and does not allow us to distinguish between dense or very dense vegetation, contrary to other vegetation indexes that do not saturate over densely vegetated regions (Huete et al. 1997). In that sense, NDVI is less reliable in estimating the biomass production of dense vegetation, like forests. However, it is very sensible to photosynthetic activity and therefore remains highly indicative of the biomass produced in cultivated fields. Carlson and Ripley (1997) precisely describe the asymptotic regime of NDVI and Ma et al. (2001) confirm this analysis and relate biomass produced to NDVI using the following relationship, extrapolated for soybeans,

7. Available online at https://lpdaac.usgs.gov/lpdaac/content/view/full/6652.

$$Y = d + b\mathrm{NDVI}^c, \tag{7}$$

where $Y$ represents the quantities produced (or the yield) and $d$, $b$, and $c$ are three parameters. The only parameter needed in the following is $c$, taken equal to 4.54, following Ma et al. (2001).[8] Denoting

$$N_i = \mathrm{NDVI}_i - \mathrm{NDVI}_0 \tag{8}$$

with $\mathrm{NDVI}_0 = |d/b|^{1/c}$, $bN_i^c$ gives an estimation of the quantities produced on field $i$, $Y(i)$.[9]

Crop-growing seasons are characterized by the planting date and the phenology cycle, which determines the length of the season. In South Africa, planting generally occurs between October and December in order to reduce the vulnerability to erratic precipitation (Ferreira, Newby, and du Preez 2006). However, phenology cycles, and hence growing seasons, can differ substantially among crop types and even for fields of the same crop type. In order to take account of this, we used the TIMESAT program[10] (Jönsson and Eklundh 2002, 2004) to determine crop- and field-specific growing seasons. We are then able to approximate the start and end of growing seasons based on distribution properties of the NDVI. Summary statistics in table 6.1 show that growing seasons are on average 130 days, with a standard deviation of 35 days.

Finally, as is standard in the literature of satellite-derived plant-growth measures, we use the maximum NDVI over the growing season as an indicator of crop production (Zhang, Friedl, and Schaaf 2006). It takes on an average value of 0.61 with a standard deviation of 0.13 (see table 6.1).

### 6.4.3 Crop–Water Balance

An important determinant of crop growth is water availability. A common simple proxy for it is the difference between rainfall and the evaporative demand of the air,—that is, evapotranspiration. To calculate this, we use gridded daily precipitation and reference evapotranspiration data taken from the USGS Early Warning Famine climatic database.[11] More specifically, daily rainfall data, given at the 0.1-degree resolution (approximately 11 km), are generated with the rainfall estimation algorithm RFE (version 2.0) data set implemented by the National Oceanic and Atmospheric Administration (NOAA)-Climate Prediction Center (CPC) using a combination of rain gauges and satellite observations. Daily reference evapotranspiration data, available at a 1-degree resolution (approximately 111 km), were calculated

8. We take the estimate coming from the regression showing the best fit on data used by Ma et al. (2001).

9. For values smaller than $\mathrm{NDVI}_0$, the produced quantities are equal to 0, the NDVI capturing the light reflected by the bare soil.

10. The algorithm within the TIMESAT software is commonly used to extract seasonality information from satellite time-series data.

11. http://earlywarning.usgs.gov/fews.

using a six-hour assimilation of conventional and satellite observational data of air temperature, atmospheric pressure, wind speed, relative humidity and solar radiation extracted from the NOAA Global Data Assimilation System. Using these gridded data, each field was then assigned a daily precipitation and potential evapotranspiration value over its growing season to then calculate out its average daily water balance. The mean and standard deviation of this measure are given in table 6.1.

### 6.4.4 Biodiversity Index

Among field characteristics, we are particularly interested in crop biodiversity. Diversity measures, extensively used in biology and ecology literature, take into account species richness (i.e., the number of species present) and evenness (i.e., the distribution of species). In the following, we quantify biodiversity at the field level, adopting one of the most widely used indicators, the Shannon index (Shannon 1948),

$$H_\ell = -\sum_z B_\ell(z) \ln B_\ell(z), \tag{9}$$

where $\ell$ defines the size of the perimeter considered as relevant and $B_\ell(z)$ is the proportion of area within perimeter $\ell$ that is of crop $z$ type. $H_\ell$ is then calculated for a given perimeter $\ell$, defined by its radius, applied to the centroid of the field considered. The more diverse the crops are and the more equal their abundances, the larger the Shannon index. When all crops are equally common, all $B(z)$ values will equal $1/Z$ ($Z$ being the total number of crops), and $H$ will be equal to ln $Z$. On the contrary, the more unequal the abundances of the crops, the smaller the index, approaching 0 (and being equal to 0 if $Z = 1$). With respect to other common indicators, like the Simpson's index,[12] the Shannon index is known to put less weight on the more abundant species and to be more sensitive to differences in total species richness and in changes in populations showing small relative abundances (Baumgärtner 2006). In our specification, the distance threshold for the radius $\ell$ is 0.75 km; the distance is then increased 250 m by 250 m to reach 3 km, the maximum distance considered. We provide summary statistics for the Shannon index in table 6.3. Widening the perimeter under consideration increases the value of the Shannon index substantially. For example, the 3 km index is nearly five times larger than the 0.75 km index. This suggests that crop types are strongly spatially agglomerated and thus locally less diverse.

## 6.5 Empirical Analysis

Our first empirical task is to investigate whether biodiversity affects crop field production. To this end, we rely on the strategy defined in section 6.3.

12. With our notations, the Simpson's index is given by $1 - \sum_z B_\ell^2(z)$.

Table 6.3 Summary statistics for the Shannon index

| | All crops | | Dry bean | | Groundnuts | | Maize | | Sorghum | | Soybeans | | Sunflowers | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\ell$ | $\bar{H}$ | $\sigma_H$ | $\bar{H}$ | $\sigma_H$ | $\bar{H}$ | $\sigma_H$ | $\bar{H}$ | $\sigma_H$ | $\bar{H}$ | $\sigma_H$ | $\bar{H}$ | $\sigma_H$ | $\bar{H}$ | $\sigma_H$ |
| 0.75 km | 0.03 | 0.14 | 0.17 | 0.31 | 0.21 | 0.31 | 0.08 | 0.21 | 0.11 | 0.25 | 0.17 | 0.29 | 0.14 | 0.26 |
| 1.00 km | 0.06 | 0.18 | 0.27 | 0.37 | 0.35 | 0.35 | 0.14 | 0.26 | 0.20 | 0.31 | 0.28 | 0.33 | 0.23 | 0.31 |
| 1.25 km | 0.07 | 0.21 | 0.36 | 0.39 | 0.43 | 0.35 | 0.19 | 0.29 | 0.28 | 0.35 | 0.37 | 0.35 | 0.30 | 0.33 |
| 1.50 km | 0.09 | 0.23 | 0.45 | 0.41 | 0.48 | 0.34 | 0.23 | 0.30 | 0.35 | 0.36 | 0.44 | 0.36 | 0.35 | 0.34 |
| 1.75 km | 0.10 | 0.24 | 0.50 | 0.42 | 0.51 | 0.34 | 0.27 | 0.31 | 0.40 | 0.37 | 0.49 | 0.35 | 0.40 | 0.34 |
| 2.00 km | 0.12 | 0.25 | 0.55 | 0.43 | 0.53 | 0.32 | 0.31 | 0.32 | 0.45 | 0.37 | 0.54 | 0.35 | 0.43 | 0.33 |
| 2.25 km | 0.13 | 0.26 | 0.60 | 0.43 | 0.55 | 0.31 | 0.33 | 0.32 | 0.49 | 0.37 | 0.58 | 0.34 | 0.46 | 0.33 |
| 2.50 km | 0.13 | 0.27 | 0.63 | 0.43 | 0.56 | 0.30 | 0.36 | 0.32 | 0.52 | 0.37 | 0.61 | 0.33 | 0.48 | 0.32 |
| 2.75 km | 0.14 | 0.28 | 0.66 | 0.43 | 0.57 | 0.30 | 0.38 | 0.31 | 0.56 | 0.36 | 0.63 | 0.32 | 0.50 | 0.32 |
| 3.00 km | 0.15 | 0.28 | 0.68 | 0.43 | 0.58 | 0.29 | 0.40 | 0.31 | 0.59 | 0.36 | 0.65 | 0.32 | 0.52 | 0.31 |

*Note:* The table reports the mean ($\bar{H}$) and the standard deviation ($\sigma_H$) of the distribution of the Shannon index, measured for the different crops considered, on different perimeters, characterized by their radius, $\ell$.

In short, we build data on crop production using (7) and (8). We use them to calculate the survival probability in each field, $\hat{\lambda}_i$. Then with a linear regression on specification (5), we estimate the impact of biodiversity on the odds—that is the ratio of the probability for a given field to survive to the probability of death.

Crop productivity depends not only on crop biodiversity but also on more general natural conditions (weather, season length), field attributes (irrigation, area), and farm management attributes (pesticides, mechanization, economies of scale). Therefore, the vector of control variables **X** includes crop fixed effects, crop–water balance (*WB*) and its squared value ($WB^2$), an irrigation dummy indicator (*IR*), the season length (*SEAS_LENGTH*), the logarithm of the field area in hectares (ln (*AREA*)), the latitude (*LAT*) and longitude (*LON*) of the centroid of the field, the percentage of cropland within a defined perimeter that is irrigated (*PC_AREA_IR*), and the percentage of land devoted to the same crop that belongs to the same farm, within a defined perimeter (*PC_AREA_FARM*). We also include farm fixed effects to capture crop management techniques that are common within farms as well as farmwide economies of scale. Crop-specific dummies allow us to control for the fact that different crops will have different vegetation growth intensity as captured by satellite reflectance data. Our identifying assumption is that after controlling for climatic factors and within-farm fixed effects, there are no other within-farm time-varying omitted factors that determine plant productivity and are correlated with biodiversity.

The results of the regression on equation (5) for all crops pooled are presented in table 6.4. In the first column, we simply include our field-specific control variables (vector *X*). The first column shows results for a perimeter defined by a radius $\ell$ equal to 0.75 km. As can be seen, crop–water balance

**Table 6.4** **Regression results, all crops pooled**

| Variables | $\ell = 0.75$ km | $\ell = 1.00$ km | $\ell = 1.25$ km | $\ell = 1.50$ km | $\ell = 1.75$ km | $\ell = 2.00$ km | $\ell = 2.25$ km | $\ell = 2.50$ km | $\ell = 2.75$ km | $\ell = 3.00$ km |
|---|---|---|---|---|---|---|---|---|---|---|
| H | 3.6*** | 2.67** | 3.73*** | 1.88** | 1.68** | 1.4* | 0.16 | 0.29 | –0.4 | –1.02 |
| | (1.16) | (1.04) | (1.05) | (0.72) | (0.82) | (0.8) | (0.91) | (0.83) | (1.00) | (0.93) |
| WB | 0.59*** | 0.59*** | 0.58*** | 0.58*** | 0.59*** | 0.59*** | 0.61*** | 0.61*** | 0.61*** | 0.61*** |
| | (0.14) | (0.14) | (0.14) | (0.13) | (0.14) | (0.14) | (0.14) | (0.14) | (0.14) | (0.14) |
| $WB^2$ | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| WB × IR | –0.93*** | –0.96*** | –0.96*** | –0.97*** | –0.96*** | –0.95*** | –0.95*** | –0.95*** | –0.96*** | –0.96*** |
| | (0.29) | (0.29) | (0.28) | (0.28) | (0.28) | (0.28) | (0.28) | (0.28) | (0.28) | (0.28) |
| $WB^2$ × IR | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| SEAS_LEN | –0.27*** | –0.27*** | –0.27*** | –0.27*** | –0.27*** | –0.27*** | –0.27*** | –0.27*** | –0.27*** | –0.27*** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| ln(AREA) | –2.85*** | –2.98*** | –3.01*** | –3.08*** | –3.08*** | –3.13*** | –3.12*** | –3.14*** | –3.16*** | –3.17*** |
| | (0.4) | (0.4) | (0.4) | (0.39) | (0.39) | (0.39) | (0.4) | (0.4) | (0.4) | (0.4) |
| IR | 31.63*** | 30.99*** | 30.51*** | 30.96*** | 31.73*** | 32.35*** | 32.73*** | 32.83*** | 32.83*** | 32.99*** |
| | (5.05) | (5.09) | (5.11) | (5.12) | (5.12) | (5.12) | (5.1) | (5.06) | (5.09) | (5.09) |
| LON | 72.94*** | 73.24*** | 74.39*** | 74.06*** | 73.87*** | 73.02*** | 72.34*** | 72.59*** | 72.54*** | 72.24*** |
| | (14.53) | (14.49) | (14.45) | (14.53) | (14.55) | (14.53) | (14.52) | (14.43) | (14.41) | (14.47) |
| LAT | –22.44 | –22.82 | –23.01 | –22.7 | –22.56 | –22.64 | –22.74 | –22.26 | –21.84 | –22.01 |
| | (26.28) | (26.39) | (26.55) | (27.79) | (28.07) | (28.58) | (28.62) | (29.33) | (29.7) | (29.65) |
| PC_AREA_IR | 12.22*** | 14.44*** | 17.93*** | 19.14*** | 18.27*** | 17.73*** | 14.86*** | 14.76*** | 14.73*** | 11.91*** |
| | (1.64) | (1.77) | (1.54) | (1.83) | (2.13) | (2.02) | (2.36) | (2.19) | (2.69) | (2.61) |
| PC_AREA_FARM | 1.39** | 0.93 | 0.48 | –0.42 | –0.19 | –0.74 | –0.43 | –1.36 | –1.9 | –2.16 |
| | (0.63) | (0.63) | (0.78) | (0.9) | (0.84) | (0.93) | (1.12) | (1.3) | (1.43) | (1.65) |

*Note:* ***, **, and * indicate 1 percent, 5 percent, and 10 percent significance levels, respectively. Robust standard errors are in parentheses, clustered at field level. Farm and crop fixed effects are included but not reported. Sample: 64,862 fields, 12,462 farms. Results for individual crops are reported in the appendix. For ease of reporting, all coefficients are scaled by a factor of $10^2$.

has a significant positive and exponentially increasing impact on the survival rate of crops. However, having an irrigation system acts more to increase the survival rate of crops and therefore fields' productivity. It also makes crops less reliant on water balance (in a linear fashion) as would be expected. The coefficient on season length suggests that the longer the season lasts, the lower the crop survival rate. In other words, the longer the season, the higher the probability that an adverse event affects crops. Larger fields have lower survival rates than smaller ones. Finally, being located further east results in crop survival probability, possibly because of more favorable climatic or soil conditions, while being further south or north is inconsequential for field productivity within our sample.

If we consider now the degree of crop diversity, as measured by the Shannon index, we observe that an increase in surrounding biodiversity improves the survival ratio in a given field, and consequently its productivity. Arguably, however, our diversity index may just be capturing the fact that neighboring areas are different in ways that are correlated with the diversity of crops. To take account of these factors, we thus control for the percentage of the surrounding area that is irrigated and the percentage of the surrounding area of fields of the same crop type that belongs to the same farm.

When increasing the defined perimeter to calculate the Shannon index to 1 km, adjusting the variables *PC_AREA_IR* and *PC_AREA_FARM* in an analogous fashion, the impact of crop biodiversity on survival rate remains statistically significant but decreases by 26 percent. As far as control variables are concerned, the share of area irrigated unequivocally increases the biomass production, while the share of area belonging to the same farm within the perimeter we consider seems to have no significant impact on the biomass production. Further increasing the perimeter similarly continues to produce a significant positive impact of biodiversity, the coefficient increasing by 40 percent. However, when further expanding the threshold of our definition of the relevant neighborhood, biodiversity still acts as a significant predictor of survival probability, but its contribution decreases and finally disappears for a perimeter's radius greater than 2 km.[13] This suggests that biodiversity is relatively locally defined—that is, within less than 2 km but likely close to 1.25 km.

To better appreciate the contribution of the theoretical model specification, we compare the results to a reduced-form model specified as

$$\text{NDVI}_i = \beta_1 H_i + \beta_2 Rain_i + \beta_3 ET_i + \theta_{Farm} + \varepsilon_i. \tag{10}$$

This simple correlation model only considers the effect of the Shannon index and simple weather variables (rain and evapotranspiration, which are used to calculate water balance) and the farm fixed effect. The results of the reduced-

13. We also experimented with increasing the perimeter up to 10 km, but the coefficient on *H* remains insignificant in all cases.

**Table 6.5 Impact of biodiversity on the odds of survival probabilities**

| $\ell$ | Pooled crops | Dry beans | Groundnuts | Maize | Soya | Sunflowers |
|---|---|---|---|---|---|---|
| 0.75 | 3.6*** | –1.68 | 5.84 | 4.93*** | –0.67 | 2.91 |
| | (1.16) | (6.85) | (9.02) | (1.69) | (2.1) | (3.32) |
| 1.00 | 2.67** | –0.23 | –4.54 | 3.01** | 0.52 | 4.59* |
| | (1.04) | (5.91) | (9.3) | (1.17) | (2.15) | (2.72) |
| 1.25 | 3.73*** | 4.04 | –5.38 | 3.15*** | 4.77** | 2.57 |
| | (1.05) | (5.57) | (10.51) | (1.16) | (2.22) | (2.41) |
| 1.50 | 1.88** | 7.68 | –20.42* | 0.8 | 5.74** | –1.05 |
| | (0.72) | (6.73) | (11.02) | (0.94) | (2.22) | (3.14) |
| 1.75 | 1.68** | 4.98 | –9.1 | 1.11 | 8.48*** | –0.91 |
| | (0.82) | (7.17) | (11.6) | (1.01) | (2.17) | (3.3) |
| 2.00 | 1.4* | –4.28 | 4.96 | 0.84 | 9.6*** | –3.08 |
| | (0.8) | (7.14) | (11.42) | (0.91) | (2.6) | (3.62) |
| 2.25 | 0.16 | 0.06 | –1.59 | –0.04 | 6.83** | –6.2** |
| | (0.91) | (6.95) | (13.47) | (1.05) | (2.59) | (3.11) |
| 2.50 | 0.29 | 3.12 | –2.44 | 0.71 | 6.47*** | –9.12*** |
| | (0.83) | (7.35) | (17.65) | (0.84) | (2.3) | (3.13) |
| 2.75 | –0.4 | 2.45 | –1.96 | 0.69 | 5.73** | –11.9*** |
| | (1.00) | (7.98) | (18.36) | (1.05) | (2.53) | (4.44) |
| 3.00 | –1.02 | –3.28 | –3.48 | 0.41 | 5.47* | –15.58*** |
| | (0.93) | (7.44) | (18.64) | (1.21) | (2.8) | (4.59) |
| Fields | 64,682 | 1,227 | 1,292 | 45,256 | 6,825 | 9,441 |

*Note:* ***, **, and * indicate 1 percent, 5 percent, and 10 percent significance levels, respectively. Robust standard errors are in parentheses, clustered at field level. Farm and crop fixed effects are included but not reported. Sample: 64,862 fields, 12,462 farms. The table shows the coefficients for the variable $H_\ell$ for each of the six crops considered. Complete regression results are reported in the annex. For ease of reporting, all coefficients are scaled by a factor $10^2$.

form regression presented in table 6.6 show a strong and positive effect of biodiversity on NDVI for all perimeter radii up until 2000 m. These results are consistent with those obtained using the probabilistic model based on ecological mechanisms.

We then look at the heterogeneity of impacts across crops, considering sequentially each of the six crops for which data are available (cotton is not considered in the regressions by crop, since the available sample—106 fields, 0.16 percent of the total available fields and 0.1 of the total cropland considered—is too small). The results show that, on the one hand, biodiversity has a significant impact on survival probability of maize, soybeans, and sunflowers, and that the relevant perimeter size of the biodiversity index depends on the crop. Table 6.5 also reveals that biodiversity has no significant impact on dry beans, groundnuts, and sorghum. This can be explained by the fact that each of the latter crops represents less than 2 percent of the total number of fields. In other words, the area dedicated to these crops is small, and the fields are probably sufficiently scattered and don't suffer from the proliferation of their pests. Therefore, the biodiversity variation on the

**Table 6.6** **Regression results for the reduced form model, all crops pooled**

| Variables | $\ell$ = 0.75 km | $\ell$ = 1.00 km | $\ell$ = 1.25 km | $\ell$ = 1.50 km | $\ell$ = 1.75 km | $\ell$ = 2.00 km | $\ell$ = 2.25 km | $\ell$ = 2.50 km | $\ell$ = 2.75 km | $\ell$ = 3.00 km |
|---|---|---|---|---|---|---|---|---|---|---|
| H | 79.59*** | 61.83*** | 62.71*** | 38.74*** | 31.09*** | 23.21*** | 7.029 | 5.255 | –5.287 | –13.54 |
| | (12.13) | (11.69) | (11.83) | (8.873) | (9.115) | (8.439) | (9.227) | (8.097) | (10.13) | (10.00) |
| Rain | 0.0684 | 0.0677 | 0.0678 | 0.0674 | 0.0669 | 0.0669 | 0.0669 | 0.0668 | 0.0668 | 0.0667 |
| | (0.0499) | (0.0499) | (0.0501) | (0.0501) | (0.0502) | (0.0502) | (0.0502) | (0.0502) | (0.0502) | (0.0502) |
| ET | 379.9*** | 380.2*** | 379.8*** | 379.7*** | 379.5*** | 379.4*** | 379.3*** | 379.3*** | 379.3*** | 379.2*** |
| | (41.32) | (41.27) | (41.39) | (41.43) | (41.49) | (41.47) | (41.46) | (41.44) | (41.44) | (41.43) |

*Note:* ***, **, and * indicate 1 percent, 5 percent, and 10 percent significance levels, respectively. Robust standard errors are in parentheses, clustered at field level. Farm fixed effects are included but not reported. Sample: 64,862 fields, 12,462 farms.

perimeter that we consider has a negligible marginal effect on the biomass production. When looking at how crop biomass production is affected by crop biodiversity, we see that the relevant perimeter for biodiversity varies: biodiversity has a positive and significant impact on the production of maize only for perimeters equal to or smaller than 1.25 km, whereas the relevant perimeter for soybeans is equal to or greater than 1.25 km. Surprisingly, biodiversity has a negative and significant impact on sunflower biomass production on perimeters with a radius larger than 2.25 km; a positive significant impact is found only for $\ell$ equal to 1.00 km. This heterogeneity is probably linked to the fact that pests responsible for biomass losses differ among the three crops we consider. Generally, the main potential crop losses are caused by weeds, but thanks to the improvement in weed control techniques, the main actual losses come from animals (mainly insects) and pathogens (Oerke 2007). More precisely, in South Africa, maize is mainly attacked by insects (DAFF 2014a), while sunflowers and soybeans are mainly attacked by diseases caused by fungi and viruses (DAFF 2009, 2014b).

The impact of irrigation also varies and depends on crop characteristics, as shown in tables 6A.1, 6A.2, and 6A.3 in the appendix to this chapter. Maize is one of the most efficient cultivated plants in South Africa as far as water use is concerned (DAFF 2014a), hence a positive and significant impact of irrigation. On the contrary, sunflowers are highly inefficient in water use and, as well as soybeans, are mostly rain-fed grown.[14] This could explain the absence of a significant impact of irrigation on biomass production for these crops. Finally, soybean biomass production is positively affected by the size of the field, while sunflower survival rates are inversely related to field size, and maize is unaffected. These effects could be related to plant physiology or to higher mechanization allowed by larger fields and having a positive impact on the final yield of soybean.

These results confirm the positive impact of crop biodiversity on agricultural production and underline its heterogeneity across crops, with sunflowers being an exception. Additional regressions considering land-use types surrounding the crop plots did not provide significant results. Furthermore, it is important to note that we estimate biodiversity effects in the presence of pesticides, for which we do not totally control. Indeed, farm fixed effects capture practices that are common to all the fields within the same farm, and crop fixed effects capture practices common to all crops, but the level of pesticides actually applied remains unknown. Then the effects we observe can be considered residual. The positive impact of biodiversity on crop survival, only second to the one of irrigation and more generally water management, is all the more important in that respect. Even when

14. Soybeans are mostly rain-fed grown because of low profitability and difficult water management. Indeed, water shortage is critical during the pod set stage, while excessive water supply prior to or after the flowering may jeopardize the final yield.

pesticides are possibly applied, biodiversity still has the capacity to improve crop survival rate.

The results presented detail the impact of crop biodiversity on crop survival rates. Our approach through a probabilistic model can be used to add a step to disentangle more precisely the mechanisms at stake. In particular, the parameters of the beta-binomial distribution of the survival probability of fields can be estimated, following the approach detailed in section 6.3. We perform an OLS regression on equation (6) to directly estimate the value of $\theta_d$; $\theta_u$ is given by the difference between the coefficients found in the linear regressions on equations (5) and (6).

Results are presented in table 6.7, which reports the values of parameters $\theta_u$ and $\theta_d$ for all the explanatory variables for selected values of $\ell$, and table 6.8, which shows the values of the parameters for the Shannon index, computed on all the possible perimeters. As is visible from table 6.7, in practice, significant individual values for the parameters of the beta-binomial distribution can be found in a limited number of cases. In particular, it is interesting to note that biodiversity has a positive impact on the survival rate of maize by increasing $S_u$ more than $S_d$ (see equation (1)), while the positive impact found for sunflowers comes from a larger decrease in $S_d$ than in $S_u$. This difference in mechanisms at stake confirms the important role played by crop specificities (plant physiology as well as predominant pests) on the possible impacts of crop biodiversity on agricultural production.

## 6.6 Conclusion

Using a new large database built from satellite imagery, we confirm that crop biodiversity has a positive impact on agricultural production, which is heterogeneous across crops, sunflower being an exception. Maintaining a large diversity of crops in the landscape increases agricultural production level. These impacts, which were previously described at regional scales, are robust when we consider a larger area. We show the consistency of these results with the underlying ecologic and agricultural mechanisms. For this purpose, we build a probabilistic model in which stochastic factors linked to biodiversity—namely, pests—are endogenous, as is shown in the ecology literature, while previous results were derived using functional forms arbitrarily chosen.

In the absence of data on pesticide use, their effects are not precisely measured in this model, which only evaluates the residual effects of biodiversity. However, our approach can be easily extended to pesticides. This would have the advantage of measuring their effects not on an isolated field but rather within a varied set of agricultural productions. Nevertheless, our analysis shows that residual effects are important and that a better spatial distribution of crops could lead to a significant improvement in crop yields. This could be achieved if farmers distribute their crops on their farms to not only

**Table 6.7** **Estimated values of the parameters of the distribution of the survival probabilities: All explanatory variables, for selected perimeters**

| | Pooled crops ($\ell$ = 1.25 km) | | Maize ($\ell$ = 1.25 km) | | Soya ($\ell$ = 2.00 km) | | Sunflower ($\ell$ = 1.00 km) | |
|---|---|---|---|---|---|---|---|---|
| Exp. variable | $\theta_u$ | $\theta_d$ | $\theta_u$ | $\theta_d$ | $\theta_u$ | $\theta_d$ | $\theta_u$ | $\theta_d$ |
| H | 14.09*** | 10.36*** | 14.55*** | 11.4*** | 4.78 | –4.82 | –23.77** | –28.36*** |
| WB | –0.42 | –1.00 | –0.45 | –0.68 | –3.70* | –4.19** | –0.65 | –1.73 |
| $WB^2$ | –0.01 | –0.02** | 0.00 | –0.01 | –0.05 | –0.06 | 0.00 | –0.01 |
| WB × IR | 0.21 | 1.17 | 0.23 | 0.67 | 2.11 | 2.40 | –3.59* | –1.16 |
| $WB^2$ × IR | 0.00 | 0.00 | 0.01 | 0.01 | 0.05 | 0.04 | –0.06** | –0.03 |
| SEAS_LEN | 0.05 | 0.32*** | 0.11* | 0.42*** | –0.37*** | –0.05 | 0.10 | 0.22** |
| ln(AREA) | –1.99 | 1.02 | –7.58*** | –4.86** | 1.81 | –1.3 | –6.64 | 2.39 |
| IR | 10.14 | –20.38 | –29.75 | –81.89** | 40.04 | 25.03 | –5.21 | –31.58 |
| LON | 9.13 | –65.26 | 112.78 | 52.28 | 283.91* | 116.49 | –542.78*** | –741.69*** |
| LAT | –55.79 | –32.78 | –49.67 | –55.66 | –182.43 | –94.14 | –132.6 | 94.82 |
| PC_AREA_IR | –4.72 | –22.65*** | –0.23 | –23.70*** | –11.01 | –21.60 | 17.85 | 22.75 |
| PC_AREA_FARM | 3.26 | 2.78 | 4.75* | 4.24 | 20.89** | 19.91** | –10.17 | –11.26 |

*Note:* ***, **, and * indicate 1 percent, 5 percent, and 10 percent significance levels, respectively. Standard t–tests are used for $\theta_d$, estimated with equation (5), and a Z-test is used for $\theta_u$, calculated using the coefficients produced by equations (5) and (6), as detailed in section 3. The values of $\ell$ presented correspond to the largest and most significant impact of crop biodiversity on the survival rate. For ease of reporting, all coefficients are scaled by a factor $10^2$.

Table 6.8 **Estimated values of the parameters of the distribution of the survival probabilities: Biodiversity parameters**

| Parameter | $\ell = 0.75$ | $\ell = 1.00$ | $\ell = 1.25$ | $\ell = 1.50$ | $\ell = 1.75$ | $\ell = 2.00$ | $\ell = 2.25$ | $\ell = 2.50$ | $\ell = 2.75$ | $\ell = 3.00$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Maize | | | | | | | | | | |
| $\gamma$ | –13.53** | –14.59** | –18.33*** | –16.49** | –18.12*** | –16.69** | –15.15** | –15.45** | –15.28** | –17.26*** |
| $\beta$ | 21.86*** | 20.72*** | 16.85** | 18.84*** | 17.22** | 18.71*** | 20.35*** | 20.04*** | 20.2*** | 18.24*** |
| $\theta_u$ | 8.25 | 15.55*** | 14.55*** | 13.73*** | 15.5*** | 10.87** | 9.36** | 8.72** | 6.94 | 2.65 |
| $\theta_d$ | 3.32 | 12.55*** | 11.4*** | 12.93*** | 14.4*** | 10.03** | 9.4** | 8.01* | 6.24 | 2.24 |
| Soybeans | | | | | | | | | | |
| $\gamma$ | 0.01 | –1.97 | –4.2 | –3.58 | –5.84 | –4.11 | –4.17 | –4.55 | –5.07 | –6.66 |
| $\beta$ | 11.88 | 9.77 | 7.51 | 8.21 | 5.96 | 7.73 | 7.74 | 7.36 | 6.82 | 5.25 |
| $\theta_u$ | 30.28*** | 24.05*** | 7.02 | –1.9 | 12.77 | 4.78 | –0.86 | 4.65 | –0.92 | 8.73 |
| $\theta_d$ | 30.95*** | 23.53*** | 2.25 | –7.64 | 4.29 | –4.82 | –7.69 | –1.81 | –6.65 | 3.25 |
| Sunflower | | | | | | | | | | |
| $\gamma$ | –11.37 | –11.37 | –15.29** | –13.29* | –14.83* | –12.94 | –12.2 | –12.22 | –11.75 | –13.14 |
| $\beta$ | –3.56 | –3.65 | –7.66 | –5.5 | –7.07 | –5.17 | –4.33 | –4.37 | –3.9 | –5.26 |
| $\theta_u$ | –21.72 | –23.77** | –14.21 | –12.29 | –15.01 | –6.72 | –19.69* | –28.42** | –27.24 | –35.53** |
| $\theta_d$ | –24.63* | –28.36*** | –16.77 | –11.24 | –14.1 | –3.64 | –13.48 | –19.29 | –15.34 | –19.95 |

*Note:* ***, **, and * indicate 1 percent, 5 percent, and 10 percent significance levels, respectively. Standard t-tests are used for $\theta_d$, estimated with equation (5), and a Z-test is used for $\theta_u$, calculated using the coefficients produced by equations (5) and (6), as detailed in section 3. $\theta_u$ and $\theta_d$ presented here are those related to the Shannon index. For ease of reporting, all coefficients are scaled by a factor $10^2$.

take account of these effects on their own yields but also take into account their surroundings, which supposes that they coordinate.

Describing the mechanisms governing the impact of biodiversity on crop survival, our model can also be extended to consider wild biodiversity. Indeed, maintaining uncultivated small areas in agricultural landscapes is considered to diminish pests attacks. Adding data on uncultivated areas to our data set, the contribution of these initiatives could be easily evaluated.

Furthermore, enriching the data set, in particular with data on pesticide use, could help precisely estimate the parameters of the beta-binomial distribution of survival probabilities. Characterizing the distribution could bring elements of the impacts of crop biodiversity on the variance and the skewness of the distribution—that is, on the probability of extreme events, in particular, the complete loss of the harvest. These results are rarely analyzed in the literature (Di Falco and Chavas 2009), while they are particularly relevant for farmers.

Notwithstanding these limitations, our results confirm that crop diversification can be seen as a possible strategy to increase agricultural productivity or maintain its level while decreasing the use of pesticides.

# Appendix

**Table 6.A1** **Regression results, maize**

| Variables | $\ell$ = 0.75 km | $\ell$ = 1.00 km | $\ell$ = 1.25 km | $\ell$ = 1.50 km | $\ell$ = 1.75 km | $\ell$ = 2.00 km | $\ell$ = 2.25 km | $\ell$ = 2.50 km | $\ell$ = 2.75 km | $\ell$ = 3.00 km |
|---|---|---|---|---|---|---|---|---|---|---|
| H | 4.93*** | 3.01** | 3.15*** | 0.8 | 1.11 | 0.84 | –0.04 | 0.71 | 0.69 | 0.41 |
| | (1.69) | (1.17) | (1.16) | (0.94) | (1.01) | (0.91) | (1.05) | (0.84) | (1.05) | (1.21) |
| WB | 0.26 | 0.23 | 0.23 | 0.23 | 0.26 | 0.27 | 0.27 | 0.27 | 0.27 | 0.28 |
| | (0.2) | (0.21) | (0.21) | (0.21) | (0.21) | (0.21) | (0.21) | (0.21) | (0.21) | (0.21) |
| $WB^2$ | 0.01** | 0.01** | 0.01* | 0.01* | 0.01** | 0.01** | 0.01** | 0.01** | 0.01** | 0.01** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| WB × IR | –0.4 | –0.4 | –0.43 | –0.45 | –0.45 | –0.44 | –0.43 | –0.43 | –0.43 | –0.44 |
| | (0.38) | (0.38) | (0.38) | (0.38) | (0.38) | (0.38) | (0.38) | (0.38) | (0.38) | (0.38) |
| $WB^2$ × IR | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| SEAS_LEN | –0.31*** | –0.31*** | –0.31*** | –0.31*** | –0.31*** | –0.31*** | –0.31*** | –0.31*** | –0.31*** | –0.31*** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| ln(AREA) | –2.51*** | –2.66*** | –2.72*** | –2.78*** | –2.8*** | –2.86*** | –2.85*** | –2.88*** | –2.91*** | –2.93*** |
| | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) | (0.49) | (0.5) | (0.5) | (0.5) | (0.51) |
| IR | 52.59*** | 52.61*** | 52.14*** | 52.36*** | 53.26*** | 53.82*** | 54.09*** | 54.23*** | 54.24*** | 54.27*** |
| | (6.78) | (6.82) | (6.89) | (6.81) | (6.77) | (6.74) | (6.77) | (6.8) | (6.79) | (6.79) |
| LON | 59.25*** | 59.89*** | 60.5*** | 60.51*** | 59.83*** | 59.09*** | 58.65*** | 59.06*** | 58.95*** | 58.85*** |
| | (16.43) | (16.44) | (16.56) | (16.69) | (16.73) | (16.72) | (16.65) | (16.6) | (16.55) | (16.52) |
| LAT | 6.01 | 5.64 | 5.98 | 6.14 | 6.32 | 6.32 | 6.33 | 6.75 | 6.35 | 6.58 |
| | (29.09) | (29.11) | (29.47) | (30.45) | (31.06) | (31.88) | (31.99) | (32.57) | (32.87) | (33.09) |
| PC_AREA_IR | 16.18*** | 20.01*** | 23.46*** | 24.99*** | 18.94*** | 18.1*** | 18.43*** | 17.64*** | 14.38*** | 12.91*** |
| | (2.09) | (2.46) | (2.85) | (3.52) | (2.91) | (3.22) | (2.98) | (3.26) | (3.7) | (4.12) |
| PC_AREA_FARM | 1.66*** | 1.1 | 0.51 | –0.28 | –0.27 | –1.42 | –1.33 | –2.48* | –3.21** | –4.17*** |
| | (0.63) | (0.74) | (0.9) | (0.87) | (0.83) | (0.96) | (1.17) | (1.38) | (1.33) | (1.44) |

*Note:* ***, **, and * indicate 1 percent, 5 percent, and 10 percent significance levels, respectively. Robust standard errors are in parentheses, clustered at field level. Farm and crop fixed effects are included but not reported. Sample: 45,256 fields. For ease of reporting, all coefficients are scaled by a factor $10^2$.

**Table 6.A2** **Regression results, soybeans**

| Variables | $\ell$ = 0.75 km | $\ell$ = 1.00 km | $\ell$ = 1.25 km | $\ell$ = 1.50 km | $\ell$ = 1.75 km | $\ell$ = 2.00 km | $\ell$ = 2.25 km | $\ell$ = 2.50 km | $\ell$ = 2.75 km | $\ell$ = 3.00 km |
|---|---|---|---|---|---|---|---|---|---|---|
| H | –0.67 | 0.52 | 4.77** | 5.74** | 8.48*** | 9.6*** | 6.83** | 6.47*** | 5.73** | 5.47* |
| | (2.1) | (2.15) | (2.22) | (2.22) | (2.17) | (2.6) | (2.59) | (2.3) | (2.53) | (2.8) |
| WB | 0.46 | 0.46 | 0.47 | 0.5 | 0.49 | 0.5 | 0.49 | 0.49 | 0.49 | 0.48 |
| | (0.45) | (0.44) | (0.45) | (0.46) | (0.45) | (0.46) | (0.46) | (0.45) | (0.45) | (0.45) |
| $WB^2$ | 0.02* | 0.02* | 0.02* | 0.02* | 0.02* | 0.02* | 0.02* | 0.02* | 0.02* | 0.02* |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| WB × IR | –0.29 | –0.31 | –0.32 | –0.28 | –0.34 | –0.29 | –0.32 | –0.35 | –0.36 | –0.33 |
| | (0.67) | (0.68) | (0.67) | (0.68) | (0.68) | (0.67) | (0.67) | (0.68) | (0.67) | (0.67) |
| $WB^2$ × IR | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.00 | 0.00 | 0.01 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| SEAS_LEN | –0.31*** | –0.32*** | –0.32*** | –0.32*** | –0.32*** | –0.32*** | –0.32*** | –0.32*** | –0.32*** | –0.32*** |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| ln(AREA) | 3.41*** | 3.23*** | 3.22*** | 3.11*** | 3.19*** | 3.11*** | 3.07*** | 3.08*** | 3.06*** | 3.05*** |
| | (1.06) | (1.04) | (1.04) | (1.02) | (1.01) | (1.01) | (1.02) | (1.03) | (1.04) | (1.04) |
| IR | 15 | 14.64 | 13.87 | 15.39 | 14.1 | 15.01 | 14.92 | 14.77 | 14.51 | 14.97 |
| | (10.42) | (10.3) | (10.38) | (10.57) | (10.64) | (10.63) | (10.63) | (10.6) | (10.5) | (10.56) |
| LON | 162.75*** | 163.82*** | 165.6*** | 164.95*** | 164.08*** | 167.43*** | 165.77*** | 165.3*** | 164.49*** | 165*** |
| | (47.3) | (46.98) | (46.97) | (46.85) | (46.5) | (46.4) | (47.55) | (47.3) | (47.18) | (47.34) |
| LAT | –81.62 | –85.66 | –87.16 | –87.27 | –89.05 | –88.29 | –87.28 | –85.28 | –81.96 | –82.61 |
| | (55.94) | (56.42) | (55.8) | (55.55) | (54.97) | (56.05) | (57.28) | (57.78) | (59.72) | (59.12) |
| PC_AREA_IR | 3.93 | 4.13 | 6.47 | 0.25 | 11.89* | 10.59 | 4.9 | 13.09* | 16.41** | 10.6 |
| | (5.19) | (4.65) | (5.24) | (6.27) | (6.46) | (6.84) | (7.24) | (7.12) | (8.22) | (8.97) |
| PC_AREA_FARM | 4.61*** | 4.28*** | 2.85* | 2.39 | 3.09 | 0.99 | 0.43 | 1.25 | –0.94 | –1.25 |
| | (1.68) | (1.37) | (1.67) | (2.27) | (2.3) | (2.8) | (3.14) | (3.07) | (2.95) | (3.54) |

*Note:* ***, **, and * indicate 1 percent, 5 percent, and 10 percent significance levels, respectively. Robust standard errors are in parentheses, clustered at field level. Farm and crop fixed effects are included but not reported. Sample: 6,825 fields. For ease of reporting, all coefficients are scaled by a factor $10^2$.

**Table 6.A3** **Regression results, sunflowers**

| Variables | $\ell = 0.75$ km | $\ell = 1.00$ km | $\ell = 1.25$ km | $\ell = 1.50$ km | $\ell = 1.75$ km | $\ell = 2.00$ km | $\ell = 2.25$ km | $\ell = 2.50$ km | $\ell = 2.75$ km | $\ell = 3.00$ km |
|---|---|---|---|---|---|---|---|---|---|---|
| H | 2.91 | 4.59* | 2.57 | –1.05 | –0.91 | –3.08 | –6.2** | –9.12*** | –11.9*** | –15.58*** |
| | (3.32) | (2.72) | (2.41) | (3.14) | (3.3) | (3.62) | (3.11) | (3.13) | (4.44) | (4.59) |
| WB | 1.09*** | 1.08*** | 1.07*** | 1.07*** | 1.06*** | 1.06*** | 1.08*** | 1.08*** | 1.09*** | 1.09*** |
| | (0.31) | (0.31) | (0.31) | (0.31) | (0.31) | (0.31) | (0.32) | (0.31) | (0.31) | (0.31) |
| $WB^2$ | 0.01** | 0.01** | 0.01** | 0.01** | 0.01** | 0.01** | 0.01** | 0.01** | 0.01** | 0.01** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| WB × IR | –2.41** | –2.43** | –2.43** | –2.44** | –2.43** | –2.43** | –2.44** | –2.48** | –2.49** | –2.5** |
| | (1.06) | (1.08) | (1.09) | (1.1) | (1.1) | (1.11) | (1.11) | (1.09) | (1.08) | (1.07) |
| $WB^2$ × IR | –0.03* | –0.03* | –0.03* | –0.03* | –0.03* | –0.03* | –0.03* | –0.03* | –0.03* | –0.03* |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| SEAS_LEN | –0.11** | –0.12** | –0.12** | –0.12** | –0.12** | –0.12** | –0.12** | –0.12** | –0.12** | –0.12** |
| | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) |
| ln(AREA) | –8.83*** | –9.02*** | –8.99*** | –9.07*** | –9.00*** | –8.92*** | –8.9*** | –8.95*** | –8.87*** | –9.00*** |
| | (1.23) | (1.28) | (1.24) | (1.25) | (1.26) | (1.25) | (1.26) | (1.25) | (1.25) | (1.25) |
| IR | 27.76 | 26.37 | 24.03 | 24.52 | 24.03 | 24.05 | 24.36 | 23.75 | 23.35 | 24.08 |
| | (21.24) | (21.37) | (21.57) | (21.92) | (21.8) | (21.89) | (21.59) | (21.07) | (21.08) | (20.79) |
| LON | 199.61*** | 198.91*** | 198.71*** | 195.38*** | 194.93*** | 191.12*** | 188.4*** | 187.68*** | 186.17*** | 187.15*** |
| | (45.09) | (45.04) | (44.73) | (45.24) | (44.77) | (45.38) | (45.43) | (45.15) | (44.03) | (43.69) |
| LAT | –227.75*** | –227.42*** | –227.48*** | –225.22*** | –227.59*** | –229.49*** | –224.67*** | –221.18*** | –218.81*** | –213.74*** |
| | (69.58) | (69.82) | (69.95) | (70.78) | (70.51) | (69.39) | (69.36) | (69.26) | (69.12) | (69.74) |
| PC_AREA_IR | –13.48** | –4.9 | 6.43 | 4.53 | 10.34 | 14.07 | 10.17 | 12.42 | 20.2** | 9.4 |
| | (5.73) | (5.68) | (7.44) | (7.62) | (9.06) | (9.01) | (9.66) | (9.72) | (10.16) | (10.17) |
| PC_AREA_FARM | 3.73* | 1.09 | 0.78 | 0.43 | 1.74 | 4.36 | 5.35 | 5.02 | 6.3 | 7.09 |
| | (2.12) | (1.89) | (2.8) | (3.46) | (3.51) | (4.19) | (4.52) | (5) | (5.25) | (5.55) |

*Note:* ***, **, and * indicate 1 percent, 5 percent, and 10 percent significance levels, respectively. Robust standard errors are in parentheses, clustered at field level. Farm and crop fixed effects are included but not reported. Sample: 9,441 fields. For ease of reporting, all coefficients are scaled by a factor $10^2$.

**Table 6.A4** **Robustness check: Regression results, all crops pooled, $\alpha = 0.1$**

| Variables | $\ell = 0.75$ km | $\ell = 1.00$ km | $\ell = 1.25$ km | $\ell = 1.50$ km | $\ell = 1.75$ km | $\ell = 2.00$ km | $\ell = 2.25$ km | $\ell = 2.50$ km | $\ell = 2.75$ km | $\ell = 3.00$ km |
|---|---|---|---|---|---|---|---|---|---|---|
| H | 4.03*** | 3.03*** | 4.19*** | 2.24*** | 2.02** | 1.7* | 0.32 | 0.42 | –0.35 | –1.01 |
| | (1.24) | (1.13) | (1.1) | (0.77) | (0.89) | (0.88) | (0.98) | (0.89) | (1.1) | (1.03) |
| WB | 0.65*** | 0.64*** | 0.64*** | 0.63*** | 0.64*** | 0.65*** | 0.67*** | 0.67*** | 0.67*** | 0.67*** |
| | (0.15) | (0.15) | (0.15) | (0.15) | (0.15) | (0.15) | (0.15) | (0.15) | (0.15) | (0.15) |
| $WB^2$ | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** | 0.01*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| WB × IR | –1.00*** | –1.03*** | –1.04*** | –1.05*** | –1.04*** | –1.03*** | –1.03*** | –1.03*** | –1.03*** | –1.03*** |
| | (0.32) | (0.32) | (0.31) | (0.31) | (0.31) | (0.31) | (0.31) | (0.31) | (0.31) | (0.31) |
| $WB^2$ × IR | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| IR | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| SEAS_LEN | –0.29*** | –0.29*** | –0.29*** | –0.29*** | –0.29*** | –0.29*** | –0.29*** | –0.29*** | –0.29*** | –0.29*** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| ln(AREA) | –2.67*** | –2.82*** | –2.86*** | –2.94*** | –2.94*** | –2.99*** | –2.99*** | –3.01*** | –3.02*** | –3.04*** |
| | (0.42) | (0.42) | (0.41) | (0.41) | (0.41) | (0.41) | (0.41) | (0.41) | (0.41) | (0.42) |
| IR | 36.71*** | 36.00*** | 35.48*** | 35.96*** | 36.79*** | 37.48*** | 37.92*** | 38.03*** | 38.03*** | 38.2*** |
| | (5.82) | (5.86) | (5.88) | (5.89) | (5.89) | (5.88) | (5.88) | (5.82) | (5.85) | (5.85) |
| LON | 83.27*** | 83.62*** | 84.9*** | 84.55*** | 84.39*** | 83.44*** | 82.66*** | 82.94*** | 82.9*** | 82.57*** |
| | (16.13) | (16.08) | (16.04) | (16.11) | (16.12) | (16.09) | (16.08) | (15.97) | (15.95) | (16.01) |
| LAT | –27.31 | –27.76 | –27.97 | –27.64 | –27.47 | –27.54 | –27.64 | –27.11 | –26.62 | –26.82 |
| | (28.76) | (28.87) | (29.11) | (30.5) | (30.84) | (31.43) | (31.53) | (32.31) | (32.75) | (32.71) |
| PC_AREA_IR | 13.52*** | 16.08*** | 19.91*** | 21.44*** | 20.86*** | 20.42*** | 17.00*** | 16.97*** | 17.24*** | 14.18*** |
| | (1.76) | (1.96) | (1.76) | (2.00) | (2.32) | (2.17) | (2.58) | (2.39) | (2.97) | (2.9) |
| PC_AREA_FARM | 1.68** | 1.16* | 0.61 | –0.42 | –0.17 | –0.81 | –0.52 | –1.51 | –2.14 | –2.47 |
| | (0.69) | (0.68) | (0.86) | (0.97) | (0.91) | (1.00) | (1.19) | (1.39) | (1.53) | (1.76) |

*Note:* ***, **, and * indicate 1 percent, 5 percent, and 10 percent significance levels, respectively. Robust standard errors are in parentheses, clustered at field level. Farm and crop fixed effects are included but not reported. Sample: 64,862 fields. For ease of reporting, all coefficients are scaled by a factor $10^2$.

## References

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