AESTIMUM 75, Dicembre 2019: 235-255

Chiara Mazzocchi*, Anna Borghi, Federica Monaco, Anna Gaviglio, Rosalia Filippini, Eugenio Demartini, Guido Sali

University of Milan, Italy

E-mail: *chiara.mazzocchi1@unimi.it, anna.borghi@unimi.it, federica.monaco@unimi.it, anna.gaviglio@unimi.it, rosalia.filippini@unimi.it, eugenio.demartini@unimi.it, guido.sali@unimi.it*

Keywords: *farmland rent values, hedonic model, climate*
Parole chiave: *valore affitti fondiari, modello edonico, clima*
JEL codes: *Q15, Q54*

* *Corresponding Author*

Land rent values determinants: a Hedonic Pricing approach at local scale

Farmland values are driven by a complex set of factors. Starting from the idea that land rent values may reflect several characteristics both internal and external to agricultural sector, the paper has implemented a hedonic model based on land rent values in the metropolitan area of Milan, Northern Italy, assessing the influence of climate, soil, territorial and farm variables on a sample of farms. The model is based on data at rent contract level, matched with data at farm and municipal scale retrieved from different sources. Results confirm that land rent prices are affected by some climate variables, along with territorial and farm characteristics.

1. Introduction

Farmland values are driven by a complex set of factors. Farmland price determinants are multiple and heterogeneous, and their evaluation have interested many scholars and disciplines. As a market good, farmland generate returns from agricultural production (Borchers et al., 2014), although market value often exceeds use value in agricultural production (Flanders et al., 2004). That is, farmland values reflect other sources of return on investment.

In trying to define farmland determinants, authors have focused their studies on two major groups of causal factors: the internal/agricultural and the external factors (Feichtinger and Salhofer, 2013). According to Feichtinger and Salhofer (2013) the first group includes variables concerning the return of agricultural production and institutional payments. In this sense some authors (Gioia and Mari, 2012, Swinnen et al., 2008) has identified the price of agricultural goods as farmland determinants, as they may change the farmer's propensity to invest in land based on the return expected from the investment. In fact, since the most important factor affecting land market is the farmers' profit maximization, the willingness to pay for land is directly related to its expected profitability, depending on land use capability.

Similarly, the agricultural productivity of lands reflects the land profitability and it is closely linked to the farm characteristics (Pirani et al., 2016). Thus, the agricultural land value is a proxy of the potential productivity value of the land and is found to be a driver for land rent values (Pirani et al., 2016).

DOI: 10.13128/aestim-8152

Furthermore, the farm tenure system related to land, could play a role on farmland values, considering that the farmers are less encouraged to adopt long-term and conservation practices on land rented than on land owned (Choumert and Phélinas, 2015).

As for government payments, the external subsidies have been found to be fundamental drivers of farmland values by many researchers (see Feichtinger and Salhofer, 2013). Nevertheless, Mela et al. (2012) affirm that Common Agricultural Policy (CAP) funding exerts a modest effect if compared with external factors, especially where land values are high (Ciaian et al., 2011). Also the environmental policy could influence land rent prices: in Italy the Nitrate Directive (Directive 91/676/EEC) obliges farmers to spread manure only up to a fixed quantity per hectare; the higher land demand for manure disposal, the more pressure on farmland values (Mela et al., 2012).

The second group of studies includes variables describing the market conditions, macroeconomic factors, urban pressure indicators (Feichtinger and Salhofer, 2013). In fact, although agricultural "internal" factors as soil fertility (Delbecq et al., 2014), climate conditions (Maddison, 2000), irrigation facilities play an important role in determining farmland prices, other external factors impact on them. According with Tempesta (2011) territorial features as the economic development of the territory and its urbanization degree (Mazzocchi et al., 2014) are drivers of land rent prices. Also, in the case of land rented, the length of the contract can influence land price, as affirmed by DeMartini et al. (2016).

Although the huge number of studies focused on this issue, to the best of our knowledge there is a lack of researches that consider together land rent determinants and climate change factors at local scale in metropolitan areas. Hence, the aim of this research is to assess the influence of territorial, farm, climate variables on land rent market. To do so, given that land rent may reflect climate factors, the paper has implemented a Hedonic Price model based on agricultural land rent values in the metropolitan area of Milan, Northern Italy. In the next paragraphs, section two explores the literature background on land rent market and HP model, section three focuses on methodology, section four shows results and section five the discussion. Conclusions are drawn in the sixth paragraph.

2. Background and research question

For several years Hedonic Price (HP) method has become the standard empirical approach for modelling agricultural land values drivers (De Noni et al., 2019, Delbecq et al., 2014), with many researches based on this approach focusing on the different group of determinants. The popularity of the HP method among real estate and land use analysts is reflected in the vast, and still growing, literature on HP studies (Des Rosiers, 2013, Iacobini and Lisi, 20). Borchers et al. (2014) examine the non-agricultural factors influencing farmland values by using USA national data. They implement a HP including several external drivers, to analyze the share of farmland market values not explained by a model of agricultural returns, finding, among other variables, that recreational and natural amenities, such as hunting leases or proximity to golf courses and college campuses, also contribute to the market value. Given that the value of land derives from its use, Maddison (2000) implements a HP approach to measure the productivity of farmland characteristics, based the analysis on land transaction data in England and Wales. He found that structural attributes of farmland as assigned milk quota, but also climate and soil quality factors, influence farmland rental values.

Delbecq et al. (2014) estimated a HP model for Illinois farmland searching for differences in the contributions of characteristics associated with urban or rural submarkets (Kuethe, 2014). The study found that parcel characteristics, such as land quality, had a significant effect on farmland values in both rural and urban contexts. A study focused on the territorial factors influencing the value of farmhouses in Veneto region, in Italy, was carried on by Tempesta (2011), with different results depending on the economic development of the territory and its environmental and landscape features. Since the economic growth has boosted real estate prices which effects have spilled over the farmland market (Mela et al., 2012, Mazzocchi et al., 2013), some researches based on HP model have demonstrated the influence of urban proximity to the farmland value, especially in periurban or metropolitan areas where urban pressure is particularly strong (Plantinga et al., 2002, Guiling et al., 2009) and the urban land value is always higher than the agricultural one (Mazzocchi, 2013).

Moreover, during the last years the overall impact of climate change (CC) has affected the economic, environmental and social sphere. Climate trends and extremes affect air, land, and water resources, and the knowledge of these effects are crucial to achieve sustainable agricultural production, food and water security (Wheaton and Kulshreshtha, 2017). A substantial literature to better define CC impact on agriculture exists and involves a wide spectrum of disciplines. As for the agronomic performances, the sensitivity of agriculture to climate variations results in altered crop yields and yield stability, thus likely affecting food security (Diacono et al., 2017), altered physiological crops responses, higher respiration rates, changes in photosynthesis rate, changed phenology (Malkotra, 2017). The agronomical response to CC depends on several factors as crop typology, soil structure, chemical soil characteristics, cropping rotation (Tambo, 2016). Concerning the agronomical adaptability, a recent literature has deepened specific case studies both in the North (Diacono et al., 2017, Nguyen et al., 2016) and in the South (Zamasiya et al., 2017, Mahmood et al., 2017, Tambo, 2016) of the world, and on specific crops analysis (Dettori et al., 2017, Xu et al., 2017, Kent et al., 2016). They apply different methodological approaches, from composite indicator (Tambo, 2016) to logit model regressions (Zamasiya et al., 2017), crop growth models (Dettori et al., 2017), climate model simulations (Kent et al., 2017), mainly addressing the best agronomical adaptation strategies at local scale.

As for the economic performance of agricultural sector following CC, linear programming models have been implemented at farm level in several geographical areas, to solve optimization problems under a limited availability of resources and the pressure of extreme events, which means allocating the resources in the most efficient way (Nguyen et al., 2016). Some authors (Tambo, 2016) tried to assess the determinants of farmers' adaptability to CC using multivariate probit regression models to mitigate the adverse impacts of climate change and variability on agricultural sector. Faced with increasing incidence of climate stress, farmers have often tried to adopt a range of adaptation strategies, as permanent and seasonal migrations or new crop varieties and irrigation practices.

In terms of economic impact of CC in the agricultural sector, one of the most interesting approach is the Ricardian model (Migliore et al., 2019, Bozzola et al., 2017, Van Passel et al., 2017, Chatzopoulos and Lippert, 2015, De Salvo et al., 2013), implemented at regional or municipal scale. The method starts from the assumption that land rents reflect the expected productivity of agriculture and measure the long run impacts of climate change considering the ability of each farmer to adapt, and it is based on local data. The idea is to estimate how much of the cross-sectional variation of land values can be explained by climate or other factors (Bozzola et al., 2017). At the same time, HP approaches have been implemented to assess the impact of climate factors on land and housing prices. Recently, HP model have been proposed to assess the impact of temperature change on wine quality and prices (Aschenfelter and Storchmann, 2018), to estimate the effect of climatic variables on house prices in the USA (Galinato and Tantihkarnchana, 2018), to assess the impact of flood risk on residential accommodations costs (Pilla et al., 2019).

3. Methodology

3.1 Case study and data

Milan and Monza e Brianza provinces are the most urbanized areas of the North of Italy, located on the Po plain in one of the most intensively agricultural regions in Europe (Pretolani et al., 2017). The two Provinces maintained wide agricultural areas, with 74,546 ha of Utilized Agricultural Area (UAA) (Istat, 2010). Here, agriculture is mainly based on practices with high water requirements: in fact, Milan and Monza e Brianza Provinces covered the 11% (39,421 ha) of the total surface of Lombardy region cultivated with cereals, mainly with corn and rice (SIARL, 2016). Livestock sector is represented by cattle, poultry and pigs, although in the last ten years a decreasing trend has been registered (Pretolani et al., 2017, SIARL, 2016). Moreover, the South Milan Agricultural Park (PASM) a regional metropolitan agricultural park with about 37,000 hectares of agricultural surface, is exclusively placed in the Milan Province municipalities (Città Metropolitana, 2019).

Data have been collected from several sources, and dataset has been assembly at contract scale. Land rent contract data come from Association of Milan Province Landowners. Data describing farms characteristic have been principally drawn from SIARL (Sistema Informativo Agricolo Regione Lombardia) (Table 1) that collects the annual data by Lombardy Region to process the application of farmers for European grants. Farm level data permit a more accurate measure of farm level variables. Climate data derive from direct measurements conducted by the University of Milan by using the Lombardy weather stations, and they are been collected at municipal scale. Moreover, also the DUSAF (Database Uso del Suolo Agricolo e Forestale) has been employed, a georeferenced database used to build climate variables and linked them to municipalities by a spatialization procedure. Territorial data are drawn by the Istat 6^{th} Agricultural Census of Italy (2010) at municipal scale.

The dataset is based on contracts signed between 2010 and 2013 by landowners and farmers from Milan and Monza e Brianza Provinces, including land rental prices and some other cadastral information. Each farm can have more than one contract signed. The database included 669 contracts but only 604 are complete with all the necessary information, for a total of 354 farms tenants (Table 2).

Below, the description of the *Climate* variables SPEI, AWCI, HGI, CRI. The SPEI[1] is computed by summing water deficit (defined as precipitation minus reference evapotranspiration ET_0) over an accumulation period, and fitting the accumulated values for the meteorological time series considered (i.e. 24 years, that means 24 values) to a parametric statistical distribution from which non-exceedence probabilities can be transformed to the standard normal distribution (μ=0,σσ=1; Beguería et al. 2014; Vicente-Serrano et al. 2010). Hence, the SPEI value for each accumulation period of a specific year, represents the number of standard deviations from the long-term mean of the standard distribution (i.e. the mean deficit; Kingston et al. 2015).

The fitting distribution for describing the cumulated deficit (i.e. the) is the three-parameter log-logistic (Beguería et al. 2014):

$$f(D_n) = \frac{\beta}{\alpha}\left(\frac{D_n-\gamma}{\alpha}\right)^{\beta-1}\left[1+\left(\frac{D_n-\gamma}{\alpha}\right)^{\beta}\right]^{-2} \quad (1)$$

where $D_n=\sum_n(P\text{-}ET_0)_i$ is the deficit (*mm*), calculated as the difference between the precipitation P and the reference evapotranspiration ET_0, computed on a daily basis using the Penman-Monteith equation (Allen et al. 1998), for the accumulation period n, and α, β and γ are scale, shape and origin parameters, respectively, for D_n values in the range (γ,+∞) (Vicente-Serrano et al. 2010).

The parameters are obtained following Singh et al. (1993)probability weighted moments (PWM:

$$\hat{\beta} = \frac{2w_1-w_0}{6w_1-w_0-6w_2}$$
$$\hat{\alpha} = \frac{(w_0-2w_1)\hat{\beta}}{\Gamma(1+1/\hat{\beta})\Gamma(1-1/\hat{\beta})} \quad (2)$$
$$\hat{\gamma} = w_0 - \hat{\alpha}\Gamma\left(1+\frac{1}{\hat{\beta}}\right)\Gamma\left(1-\frac{1}{\hat{\beta}}\right)$$

where $\hat{\alpha}$, $\hat{\beta}$ and $\hat{\gamma}$ are the shape, scale and origin parameters estimated for the *SPEI* indices, Γ(x) is the gamma function of x and w_s are the probability weighted moments (PWMs) of order s.

---

1 For computational model see http://spei.csic.es/home

In equation (2) the PWMs of order are calculated as:

$$w_s = \frac{1}{N}\sum_{i=1}^{N}(1 - F_i)^s D_i \tag{3}$$

where $F_i = \frac{i-0.35}{N}$ is a frequency estimator calculated following the approach of Hosking (1990), i is the range of observations arranged in increasing order and is the number of data points.

The cumulative probability $H(D)$ is finally transformed into the standard normal random variable (zero mean and unit variance), which gives the value of the *SPEI* (Vicente-Serrano et al. 2010). This is obtained by using the approximation of Abramowitz and Stegun (1964):

$$Z = \begin{cases} -\left(t - \frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}\right) & 0 < H(x) \leq 0.5 \\ +\left(t - \frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}\right) & 0.5 < H(x) < 1 \end{cases} \tag{4}$$

Where

$$t = \begin{cases} \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} & 0 < H(x) \leq 0.5 \\ \sqrt{\ln\left(\frac{1}{(1.0-H(x))^2}\right)} & 0.5 < H(x) < 1 \end{cases}$$

c_0=2.515517, c_1=0.802853, c_2=0.010328, d_1=1.432788, d_2=0.189269 and d_3=0.001308.

Positive *SPEI* values indicate deficit greater than the median, while negative values indicate deficit lower than the median; the magnitude of departure from zero represents both drought intensity and a probability of occurrence. In this work, the SPEI has been calculated considering the hydrological year 2015-2016 (1 October 2015 - 30 September 2016), at a municipal scale for Milan and Monza e Brianza provinces, using direct data collection by Meteorological Centers of Milan University, related to municipal surfaces.

The Available Water Capacity Index (AWCI) is another cliate variable. More in detail, available water capacity is the water held in soil between its field capacity and permanent wilting point. Water capacity is usually expressed as a volume fraction or percentage, or as a depth. In this work, the soil hydrological parameters were derived by applying Rawls and Brakensiek (1989) pedotransfer functions separately to each layer of soil profiles. Subsequently, weighted soil hydrological parameters for each soil profile were derived for the layers 0-10 cm and 10-100 cm on a raster grid. Then, the connection of raster to vector data was made, and for each type of layer the value of humidity to the field capacity and the drying point starting from the type of soil, has been computed. The AWCI has been calculated at municipal level as weighted average between the different values of AWCI, which fall in the same municipality.

Hydrologic Group Indicator (HGI) is the third climate index used. Soils were originally assigned to hydrologic soil groups based on measured rainfall, runoff, and infiltrometer data (Musgrave, 1955). Most of the groupings are based on the premise that soils found within a climatic region that are similar in depth to a restrictive layer or water table, transmission rate of water, texture, structure, and degree of swelling when saturated, will have similar runoff responses. The classes are based on the following factors: intake and transmission of water under the conditions of maximum yearly wetness (thoroughly wet); soil not frozen; bare soil surface; maximum swelling of expansive clays. The hydrologic soils groups are four, from the best performance to the worst in term of runoff potential; our index is from 0 (worst performance) to 1 (best performance).

A Crop Risk Indicator (CRI) has been built to define the more vulnerable crops to some CC events. The crop typologies of the case study area have been divided in seven typologies: Permanent Crops, Horticultural Crops, Rice, Wheat, Barley, Grain Maize, Grasslands. To each typology a score has been assigned, according to Olesen et al. (2011) classification, referring to drought and heat stress events. The lower the CRI value, the higher the crop sensibility to heat stress and drought.

Then, each farm parcel cultivated with a crop potentially affected by moderate or major problems in terms of drought and heat stress has been considered as "at risk". So, for each farm, the number of "at risk" land parcels have been divided by the total number of farm parcels, obtaining the Crop Risk Indicator (CRI):

$$CRI_i = pr_i/pt_i \tag{5}$$

where i is the farm, pr is the number of parcels "at risk" and pt is the total number of farm parcels.

3.2 Conceptual framework and modeling

Land rent prices depend from several factors. Starting from the idea that land rent values may reflect the expected productivity of agriculture, thus climate factors can influence them, we choose to implement a hedonic pricing model (HP) using as dependent land rent values (€/ha/year), and as explanatory variables *Farm*, *Territorial* and *Climate* characteristics.

In HP method linear regression analysis is usually employed to assess the impact of explanatory variables on farmland price. According to Borchers et al. (2014, pp. 1310), long-standing evidence have suggested as for HP model "*simpler functional forms, linear and semi-log, are often preferred to more flexible-form models, when attributes are unobserved, represented by proxies, or have measurement error as is often the case in hedonic analysis*". Moreover, in our case, also because of the dependent variable does not follow a normal distribution, we use a log-log ordinary least squares (OLS) model that is the logarithm of the dependent variable and the continuous variables, except for those variables constituted by either indexes or dummies. In fact, the explanatory variables (Table 1) have different measure units; hence, for

Table 1. Descriptive statistics.

Variable *(measure unit)* Obs=604	Name of the variable	Spatial scale of the variable	Reference period	Average	Standard deviation	Source
Rent Value[a] *(€/ha/year)*	RV *(dependent)*	Contract	2010, 2011, 2012, 2013	441.35	177.57	Association of Milan Province Landowners
Population Density *(Inhabitants/m²)*	POP *(Territorial variable)*	Municipal	2011	1220.97	1148.64	XV Census of Population and Habitat
Utilized Agricultural Area (ha)	UAA *(Territorial variable)*	Municipal	2010	707.38	666.57	VI Census of Agriculture
Agricultural Land Value[b] (dummy)	ALV *(Territorial variable)*	Municipal	2015	0.53	0.50	Milan and Monza e Brianza Provinces
Farmer's age *(age)*	FA *(Farm variable)*	Farm	2015	59.14	11.82	SIARL
Year 2010[c] (dummy)	Y2010 *(Farm variable)*	Farm	2010	0.24	0.43	Association of Milan Province Landowners
Year 2011 *(dummy)*	Y2011 *(Farm variable)*	Farm	2011	0.22	0.41	Association of Milan Province Landowners
Year 2012 *(dummy)*	Y2012 *(Farm variable)*	Farm	2012	0.24	0.43	Association of Milan Province Landowners
Year 2013 *(dummy)*	Y2013 *(Farm variable)*	Farm	2013	0.30	0.46	Association of Milan Province Landowners
More than one contract signed per farm -Contract Plus (dummy)	CP *(Farm variable)*	Farm	2010, 2011, 2012, 2013	0.63	0.48	Association of Milan Province Landowners
Single Payment *(€)*	SP *(Farm variable)*	Farm	2014	44491.90	76227.22	SIARL

Variable *(measure unit)* Obs=604	Name of the variable	Spatial scale of the variable	Reference period	Average	Standard deviation	Source
Rural Development Funds *(dummy)*	RDF *(Farm variable)*	Farm	2014	0.14	0.34	SIARL
Length of the contract (number of year)	CL *(Farm variable)*	Contract	2010, 2011, 2012, 2013	4.50	3.80	Association of Milan Province Landowners, 2010-2013
Standardized Precipitation-Evapotranspiration Index *(index 0-1)*	SPEI *(Climate variable)*	Municipal	2016	0.58	0.27	Unimi metereological centers
Available Water Content Index *(index 0-1)*	AWCI *(Climate variable)*	Municipal	2016	0.71	0.12	DUSAF
Hydrogeological Group Index *(index 0-1)*	HGI *(Climate variable)*	Municipal	2016	0.80	0.18	DUSAF
Crop Risk Index (index 0-1)	CRI *(Climate variable)*	Municipal	2014	0.32	0.25	SIARL

[a] As specified in the text, the dependent variable (RV) and the explanatory variables expressed in continuous forms (POP, UAA, FA, SP, CL) have been translated in natural logarithm forms.

[b] The variable ALV is expressed in dummy form, where ALV=1 corresponds to the municipality where ALV>=7.3 €/mq and ALV=0 corresponds to the municipality where ALV<7.3 €/mq.

[c] The variables Y2010, Y2011, Y2012, Y2013 refer to the year in which each contract was been signed.

Table 2. Breakdown of farms divided per number of contracts signed.

Number of contracts	Farms
Only one	236
More than one	118
Total farms	354

the continuous variables POP, UAA, FA, SP, CL, their natural logarithm form has been considered. Indeed, for the other variables we used the interval 0-1; they are the *Climate* variables constituted by indexes and the RDF, ALV, CP, Y2010, Y2011, Y2012, Y2013 variable, codified as dummy.

The following general specification of the model has been applied:

$$\ln(y_{\_ifm}) = \alpha + \beta_{i\text{-}th}(\ln x_{i\text{-}th}) + \beta_{i\text{-}th}(x_{i\text{-}th}) + u_{i\text{-}th} \quad (6)$$

where $y_{\_ifm}$ is the dependent variable that indicates the rent land price for the i-th parcel of land paid by the f-th farm placed in the m-th municipality.

α is the constant term of the OLS regression, $\beta_{i\text{-}th}$ indicates the coefficients of explanatory variables for the i-th parcel of land. $x_{i\text{-}th}$ represents the independent variables expressed in dummy and index form, $\ln x_{i\text{-}th}$ represents the logarithm form variables, and $u_{i\text{-}th}$ is the error term.

More in detail, the model using the variables summarized in Table 1, is specified as:

$$\ln(y_{\_fm}) = \alpha + \beta_{i\text{-}th}(\ln POP_{i\text{-}th}) + \beta_{i\text{-}th}(\ln UAA_{i\text{-}th}) + \beta_{i\text{-}th}(ALV_{i\text{-}th})\ \beta_{i\text{-}th}(\ln SP_{i\text{-}th})_{+}\ \beta_{i\text{-}th}(RDF_{i\text{-}th}) + \beta_{i\text{-}th}(\ln CL_{i\text{-}th}) + \beta_{i\text{-}th}(\ln FA_{i\text{-}th}) + \beta_{i\text{-}th}(CP_{i\text{-}th}) + \beta_{i\text{-}th}(Y2010_{i\text{-}th}) + \beta_{i\text{-}th}(Y2011_{i\text{-}th}) + \beta_{i\text{-}th}(Y2012_{i\text{-}th}) + \beta_{i\text{-}th}(Y2013_{i\text{-}th}) + \beta_{i\text{-}th}(SPEI_{i\text{-}th}) + \beta_{i\text{-}th}(AWCI_{i\text{-}th}) + \beta_{i\text{-}th}(HGI_{i\text{-}th}) + \beta_{i\text{-}th}(CRI_{i\text{-}th}) + u_{i\text{-}th} \quad (7)$$

The *Territorial* variables are: Population density (POP), Utilized Agricultural Area (UAA), Agricultural Land Value (ALV). The population density (POP) is a proxy of the urban pression on the territory; in the case study area one of the main determinants of land use is the urban pressure, due to the land demand for residential use that strongly influences the land market (Mazzocchi et al., 2013, Demartini et al., 2016). Thus, POP may influence rent values of these municipalities, although there is not yet evidence of this trend in the case of land rent. A higher rurality may positively influence land rent prices (Corsi and Mazzocchi, 2019) and to test this the model includes UAA at municipal level.

The Agricultural Land Value (ALV) is the average value of agricultural lands with irrigated arable crops, indicated by the Land Expropriation Commissions of Milan and Monza e Brianza Provinces, for the year 2015. We used the value of the irrigated arable crops as benchmark for the variation in land productivity in the different municipality. In fact, the productivity index varies among municipalities according to the agronomical land quality of the different agricultural regions within provinces. In this sense, ALV is a proxy of the potential productivity value of the land, proposed in the literature as a driver for land rent values (Pirani et al., 2016).

The *Farm variables* are: CAP Single Payment (SP) received by the farm for the year 2014, measured in euros, Rural Development Program funds (RDF) of the 2014 year included as a dummy, Length of the contract (CL) in years and Farmer's Age (FA). Our hypothesis is that the higher is CAP single payment, the higher is the land rent value, because this is a payment strictly linked to CAP land titles, yet (Feichtinger and Salhofer, 2016, Arzeni and Sotte, 2013). RDF is a proxy of the farm need to implement project to earn money, so it could be negatively related to land prices; we used this variable as a dummy in order to avoid the lack of this parameter in the farm sample, because only a limited number of farms received RDP funds. We have employed RDF and SP of the 2014 year, because landowners' data refer to the 2010-2013 period, and in past years delays in farmers' CAP payments have often occurred. Thus, for the 2010-2013 period the year 2014 was chosen, hypothesizing that CAP payments referring to 2012-2013, also were carried out in 2014. According to Demartini et al (2016), the lenght of the contract (CL) is an important parameter in assessing land rent values determinants; we hypothesized that this factor can lead to a negotiation of land rent price and can influence it. Concerning the farmer's age (FA), land contracts are often the result of an economic relationship that the farmer may have started with the landowner for many years. This means that the farmer may have established a privileged relationship with the landowner for a long time, which could lead to lower land rent prices. For this reason, considering the farmer's age a proxy of the farm activity, it has been hypothesized that older farmers could have obtained renewals on the contract stipulated long before, so they could keep lower prices than younger farmers.

The *Climate variables* are: Standardized Precipitation Drought Index (SPEI) (Vicente-Serrano et al., 2010), Available Water Content Indicator (AWCI), Hydrological Group Indicator (HGI) and Crop Risk Indicator (CRI). SPEI is used as a measure of the potential reaction of soil types to the seriousness and radicalization of the drought events. It is based on the monthly difference between precipitation and Potential Evapo-Transpiration (PET), in turn representing a simple climatic water balance calculated at different time scales. The AWCI is an important indicator because plant growth and soil biological activity depend on water for hydration and delivery of nutrients in solution (Rawls and Brakensiek, 1989). In fact, in areas where plants remove more water than is supplied by precipitation, the amount of water held by the soil may be critical. HGI is a proxy of the farm capacity to react to alluvial and floods events, depending on the soil characteristics on which farm is located. The CRI has been assessed, identifying the most vulnerable crops to drought and heat stress. In fact, crops water and climatic needs influence the sustainability of production in case of climate change, making them unsuitable for cultivation in case of extreme events (Olesen et al., 2011).

4. Results

A correlation higher than 0.5 has been taken as threshold to consider the variables in the analysis. In our case variables were not correlated among them.

The regression analysis (Table 3) has been implemented on each group of variables, starting from the control variables. In fact, as a base model to compare our results against, we first presented the outcome with only the control variables (Model 1), that is Territorial variables. Then, gradually the others have been added to evaluate the effect of each variable group on the regression (Model 2, 3). In fact, in Model 2 we add to Territorial variables also Farm variables, in order to verify the model stability. Then, in Model 3 we add to Territorial variables the Climate variables, to test the stability of this group of variables. Then, in Model 4, we presented the full model with the three group of variables together.

Table 3. Regression results.

	Model 1 (Territorial variables)	Model 2 (Farm variables)	Model 3 (Climate variables)	Model 4 (Full model)
Territorial variables (control)				
Population Density (POP)	-0.126*** (0.019)	-0.141*** (0.019)	-0.0852*** (0.0192)	-0.100*** (0.019)
Utilized Agricultural Area (UAA)	0.0246 (0.0156)	0.0262 (0.0163)	0.0024 (0.0155)	0.00613 (0.0163)
Agricultural Land Value (ALV)	0.217*** (0.0298)	0.253*** (0.0291)	0.167*** (0.0322)	0.194*** (0.0305)
Farm variables				
Farm age (FA)		-0.188*** (0.0550)		-0.165** (0.0526)
Length of the contract (CL)		0.110*** (0.0175)		0.108*** (0.0173)
Year 2011 (Y11)		0.0516 (0.0374)		0.0565 (0.0363)
Year 2012 (Y12)		0.148*** (0.0362)		0.151*** (0.0339)
Year 2013 (Y13)		0.130*** (0.0345)		0.131*** (0.0327)
Contract Plus (CP)		0.0340 (0.0306)		0.0446 (0.0292)
Rural Development Funds (RDF)		-0.130*** (0.0435)		-0.175*** (0.0410)
Single Payment (SP)		0.0164* (0.0081)		0.0077 (0.0090)

	Model 1 (Territorial variables)	Model 2 (Farm variables)	Model 3 (Climate variables)	Model 4 (Full model)
Climate variables				
Available Water Content Index (AWCI)			0.473 (0.352)	0.521 (0.345)
Hydrogeological Group Index (HGI)			0.109 (0.0763)	0.122 (0.0777)
Standardized Precipitation-Evapotranspiration Index (SPEI)			-0.136*** (0.0208)	-0.153*** (0.0207)
Crop Risk Index (CRI)			0.165* (0.0691)	0.118 (0.064)
Intercept	6.612*** (0.183)	7.061*** (0.332)	6.205*** (0.193)	6.640*** (0.338)
Obs.	604	604	604	604
R^2	0.15	0.25	0.23	0.33
Wald test		9.97*** (Model1-Model2)	16.17*** (Model1-Model3)	13.54*** (Model1-Model4)
AIC	428.97	369.83	380.13	311.38
BIC	446.59	422.67	415.37	381.84
Breusch Pagan test				6.66 (0.0098)
Fisher test	32.61***	19.64***	27.19***	21.48***
Ramsey reset test			F = 2.64 Prob > F =0.05	
Jarque Bera test			1.842	

The Breusch-Pagan test for heteroschedasticity shows that it could be present heteroschedasticity in residuals, and for this reason we run a log-log OLS with robust standard errors, using a Huber-White error estimator. This estimator is robust to some types of misspecification, as heteroschedasticity of residuals, allowing us to perform correctly the analysis. Then, to test the importance of each group of variables, the Wald Chi-test has been employed, because this test is employed in presence of robust standard errors. As explained in Table 3, the Wald value increases from the basic model (1) to the full model (4). That is, both farm variables and climate variables improve significantly the degree of information of the base model. It is possible also to note the improvement of the R^2 parameter, because the full model with all the explanatory variables (Model 4) continuously increased compared to the 1,2,3 model, reaching the acceptable value of R^2=0.32 (Hair et al., 2019). Thus, the addition of independent terms is important in explaining our dependent variable. Moreover, the coefficients and signs of the control variables remained stable across the different models, showing robust results. As could be seen in Table 3, the Ramsey's test depicts the absence of misspecification of functional form in the model, so it could be considered reliable. To check the reliability of the non-linear relationships among dependent and explanatory variables, together with the Ramsey's RESET test an F-test of joint non-significance of parameter estimates have been performed. The joint results of these tests indicate the log-linear as an acceptable specification.

Then, although the significance of the constant has been shown in Table 3, we run the Jarque Bera test to verify the residuals distribution; the result confirms the normality of residuals. Lastly, moving from Model 1 to Model 2, form Model 1 to Model 3 and finally from Model 1 to Model 4 the reduction in the AIC and BIC statistics have been noticed, highlights that Model 4 is the best fitting model.

Considering our full model (Model 4) eight of the sixteen explanatory variables result to be significant. As for the *Territorial* variables, the population density (POP) of the municipalities in which the land under contract is situated, had a negative relationship with the land rent values; that is, the higher the population density is, the lower the land rent prices are. At the opposite, the agricultural land value (ALV) positively influences the contract price, so, in a municipality with a higher ALV a higher price of land rent has been verified.

Length of the contract (CL), Farmer's age (FA), Rural Development Funds (RDF) and the years 2012 and 2013 in which the contract was signed (Y2012; Y2013) resulted to be the *Farm* factors influencing the land rent values (RV). CL is positively related to the dependent, thus the longer the contract duration is, the higher the price of the signed contract. As hypothesized the FA factor negatively affects the RV, so the youngest the farmer, the higher the land rent price. The RDF variable negatively influences land rent price, so the participation of a farm to the Rural Development Program, seemed to affect the contract price. Y2012 and Y2013 variables show a positive sign, that is the land rent price in 2012 and in 2013 is higher than the price in 2010, that is the benchmark level on which the subsequent years of signed contracts (2011-2012-2013) must be compared.

Among the *Climate* variables Standardized Precipitation-Evapotranspiration Index (SPEI) result to be significant, negatively influencing the dependent variable.

5. Discussion

Several authors agree that territorial factors influence agricultural land prices (Mazzocchi et al., 2013, Bozzola et al., 2017). In our model we have found out that population density negatively affected land rent prices. This can be interpreted by the fact that a high urban pressure, exemplified by population density itself, has led to a continuous urbanization of the rural territory, a progressive fragmentation of farmlands (Mazzocchi et al., 2017), a strong reduction in farms' efficiency and breaking up of farm property, with the arise of several management problems (Kalantari and Abdollazeh, 2008). Another issue to be considered is that a low population density is usually directly proportional to the distance from urban center, representing a measure of the influence of urban areas on the surrounding places (Mazzocchi et al., 2013, Carrion-Flores and Irwin, 2004). In the case of farmland values many authors found population density to positively influence land prices (Borchers et al., 2014, Plantinga et al., 2002, Maddison, 2000); however, this may be not valid when dealing with farmland rent because the price of land rent usually follows the market of agricultural rent land, which is not necessarily linked to land use dynamics (Polelli and Corsi, 2008) and the potential conversion from agricultural to urban use. This is the reason why, in our model, land rent values decrease with the augmentation of population density.

Agricultural Land Value variable is a proxy of agriculture productivity and the expected returns on land investment, positively affecting land rent values. As affirmed by Pirani et al. (2016), agriculture productivity is one of the main drivers of land prices because when this factor assumes high values, there are more probabilities to have a better-quality harvest (Gioia and Mari, 2012). So, expected returns from the agricultural use of land are shown to be influential determinants of the agricultural land prices (Nilsson and Johanssen, 2013).

According to our hypothesis, when the contract duration is longer than one year, the owner could take the decision to raise the rental prices, following the demand-supply market rules. Longer term leases are desirable since they reduce the uncertainty and insecurity experienced by the tenant and encourage him to farm the land properly (Saskatchewan government, 2018).

Still, higher farmers' age results to have a positive influence on the land rent price, probably because old farmers have obtained renewals of the contract signed, paying lower prices than younger farmers.

RDP factor results to be negatively related to land rent prices. Because the SP are parameterized on land productivity, many farms with low productivity or want to address their activity to other markets with new products and services, also turn to RDP funds. Since the single payment is mainly granted on the basis of land titles, farms that get little funding through the SP are likely more interested in applying for and obtaining RDP funding. Thus, it is possible that the farms receiving higher RDP contributions have lower land rent values, given that these funds are dedicated to rural areas with less intensive agriculture. Similar conclusions can be found in Nilsson and Johanssen (2013), with regard to agri-environmental meausures; authors argue that farmers are not overcompensated for preservation efforts tied to agri-environmental payments, and also our results could be explained by the same reason, with farmers not compensated enough for their decision in applying for RDP subsidies.

Y2012 and Y2013 variables show a positive sign, that is the land rent price in 2012 and in 2013 is higher than the price in 2010. As affirmed in literature (Demartini et al., 2016) the variable's coefficient may change over years as an effect of change in policies. Effectively, in 2011 the Lombardy Region approved the Regional Action Programme for nitrate vulnerable zones (dgr 2208/2011), bringing once again the attention of the market - and farmers - on the problem of pollution by nitrates, with a potential increase in the land demand for manure disposal and a further pressure on farmland rent price (Mela et al., 2012) in the immediately subsequent years.

Finally, results confirm that some climate variables influenced land rent values (Bozzola et. al, 2017, Van Passel et al., 2017, Pirani et al., 2016), especially using very precise micro-data at local scale. Contract level data permitted to employ micro-level data, quite rare both in the case of land values and territorial analyses. Moreover, the climate indexes (i.e. climate variables) we built for the assessment of climate influence on land rent prices, allowed to reach accurate estimations, deriving from direct measurements on soil and water condition in the case study area. In our model, SPEI negatively influences land rent prices; positive SPEI values indicate deficit greater than the median, that is the higher the SPEI value is, the higher the deficit of crops evapotranspiration/precipitations condition are. Thus, the results show a negative relation between SPEI and RV, meaning that the more the decreasing of SPEI is, revealing a low evapotranspiration/precipitation deficit for crops, the higher the land contract prices are. In fact, Van Passel et al. (2017) have confirmed that better conditions of climate are reflected by high rent values. The impact of climate variables can be interesting also in terms of policy guidelines. In fact, the best lands for climate characteristics should be preserved to maintain agriculture in the most suitable lands, since one of the main problems in metropolitan areas is the land consumption due to urbanization aims (Zasada, 2011).

6. Conclusions

In conclusions, our analysis was aimed to estimate the influence of several variables related, amongst others, to climate factors on agricultural land rent values in the Provinces of Milan and Monza e Brianza, Northern Italy. Results confirm some evidences already found in literature, with climate variables playing a role in land rent prices regulation, together with farm and territorial factors. Thus work carries on an innovative approach owing to the use of micro-data, by making use of data at contract scale level and land rent values often rare to obtain, at least for Italian cases. Another novelty lies in the implementation of climate indicators for a more comprehensive assessment of land rend values determinants, and the availability of accurate data. Limitations of the study primarily regards the sample of farms used, which requires as further steps of the research the inclusion of both a wider number of farms and new or additional variables to test. Finally, for what concerns potential problems of spatial correlation of land values, the follow up of this approach could be focused on spatial analysis of data and, with panel data available, it will also be possible to implement a model to assess the time trend of climate change impact at micro scale.

7. References

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration - Guidelines for computing crop water requirements. *FAO Irrigation and Drainage Paper*, 56, 174.

Arzeni, A., & Sotte, F. (2013). Imprese e non-imprese nell'agricoltura italiana: una analisi sui dati del Censimento dell'Agricoltura 2010. *Coldiretti*, 4(1), 1-15.
Aschenfelter, O., & Storchmann, K. (2018). Using hedonic models of solar radiation and weather to assess the economic effect of climate change: the case of mosel valley vineyards. *World Scientific Handbook in Financial Economics Series*, 6, 59-96.
Beguería, S., Vicente-Serrano, S. M., Reig, F., Latorre, B. (2014). Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. *International Journal of Climatology*, 34, 3001-3023.
Bischetti, G., Chiaradia, E., Gandolfi, C., Monaco, F., & Sali, G. (2014). Irrigation water resource: economic evaluation and scenario analysis in a rice-cult, 98-125. In Bournaris, T., Berbel J., Manos B., Viaggi D. (Eds.), *Economics of water management in agriculture*, Boca Raton, Taylor and Francis.
Borchers, A., Ifft, J., & Kuethe, T. (2014). Linking the price of agricultural land to use values and amenities. *American Journal of Agricultural Economics,* 96(5), 1307-1320.
Bozzola, M., Massetti, E., Mendelshon, R., & Capitanio, F. (2017). A Ricardian analysis of the impact of climate change on Italian agriculture. *Centro Euro-Mediterraneo sui Cambiamenti Climatici, Research Papers*, Issue RP0283.
Chatzopoulos, T., & Lippert, C. (2015). Adaptation and climate change impacts: a structural Ricardian analysis of farm types in Germany. *Journal of Agricultural Economics*, 2, 537-554.
Choumert, J., & Phélinas, P. (2015). Determinants of agricultural land values in Argentina. *Ecological Economics*, 110, 134-140.
Città metropolitana (2019). http://www.cittametropolitana.mi.it/parco_agricolo_sud_milano/
Corsi, S., & Mazzocchi, C. (2019). Alternative Food Networks (AFNs): determinants for consumer and farmer participation in Lombardy, Italy. *Agricultural Economics -Czech*, in press.
Cotula, L., Vermeulen, S., Leonard, R., & Keeley, J. (2009). *Land grab or development opportunity? Agricultural investment and international land deals in Africa*. London/Rome, IIED/FAO/IFAD.
Debonnet, N., van Vliet, J., & Verburg, P. (2019). Future governance options for large-scale land acquisition in Cambodia: impacts on tree cover and tiger landscapes. *Environmental science and policy*, 94, 9-19.
Deininger, K. (2003). Land Policies for Growth and Poverty Reduction. In *A World Bank Policy Research Report*. Oxford, UK, World Bank and Oxford University Press.
Delbecq, B. A., Kuethe, T. H., & Borchers, A. M. (2014). Identifying the extent of the urban fringe and its impact on agricultural land values. *Land Economics*, 90 (4), 587-600.
Demartini, E., Gaviglio, A., Gelati, M., and Cavicchioli, D. (2016). The effect of biogas production on farmland rental prices: empirical evidences from Northern Italy. *Energies*, 9(11), 965.
Dettori, M., Cesaraccio, C., & Duce, P. (2017). Simulation of climate change impacts on production and phenology ofdurum wheat in Mediterranean environments using CERES-Wheatmodel. *Field Crops Research* 206, 43-53.
De Noni, I., Ghidoni, A., Menzel, F., Bahrs, E., & Corsi, S. (2019). Exploring drivers of farmland value and growth in Italy and Germany at regional level. *Aestimum*, (74), 77-99.
De Salvo, M., Raffaelli, R., & Moser, R. (2013). The impact of climate change on permanent crops in an Alpine region: A Ricardian analysis. *Agricultural Systems* 118, 23-32.
Des Rosiers, F. (2013). Market efficiency, uncertainty and risk management in real estate valuation – how hedonics may help. *Aestimum*, XLI Incontro di Studio del Ce.S.E.T., 511-533.
FAO (2010). Measuring Resilience: A Concept Note on the Resilience Tool. Food Security Information for Decision Making concept note. EC-FAO Programme on Linking Information and Decision Making to Improve Food Security.
Feichtinger, P., & Salhofer, K. (2013). What do we know about the influence of agricultural support on agricultural land prices?. *German Journal of Agricultural Economics*, 62, 71-85.
Hair, J. F., Risher, J. J., Sarstedt, M., &Ringle, C.M. (2019). When to use and how to report the results of PLS-SEM, *European Business Review*, 31 (1), 2-24.
Hosking, J. R. M. (1990). L-Moments: analysis and estimation of distributions Using Linear Combinations of Order Statistics, *Journal of the Royal Statistical Society B*, 52, 105-124.

Iacobini, M., & Lisi, G. (2013). Estimation of a Hedonic House Price Model with Bargaining: Evidence from the Italian Housing Market. *Aestimum*, XLI Incontro di Studio del Ce.S.E.T., 41-54.
Key, N., & Roberts, M. J. (2006). Government payments and farm business survival. *American Journal of Agricultural Economics*, 88, 382-392.
Kent, C., Pope, E., Thompson, V., Lewis, K., Scaife, A., & Dunstone, N. (2017). Using climate model simulations to assess the current climate risk to maize production. *Environmental Research Letters*, 12, 054012.
Kingston, D. G., Stagge, J. H., Tallaksen, L. M., & Hannah, D. M. (2015). European-scale drought: understanding connections between atmospheric circulation and meteorological drought indices. *Journal of Climate*, 28, 505-516. doi: 10.1175/JCLI-D-14-00001.1
Klein, R. J. T., Schipper, E. L. F., & Dessaid, S. (2005). Integrating mitigation and adaptation into climate and development policy: three research questions. *Environmental Science and Policy*, 8, 579-588.
Kuethe, T., Delbecq, B., & Borchers, A. (2014). The impact of urban areas on farmland prices in Illinois. *Farmdoc daily*, 4, 224. Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.
Galinato, G.I., & Tantihkarnchana, P. (2018). The amenity value of climate change across different regions in the United States. *Applied Economics*, 50(37), 4024-4039.
Gioia, M., & Mari, F. (2012). *Il valore della terra. Un contributo alla conoscenza del mercato italiano dei terreni agricoli attraverso i dati della RICA*. INEA, collana RICA, Quaderni, Roma.
Land Matrix (2017). http://www.landmatrix.org
Maddison, D. (2000). A hedonic analysis of agricultural land prices in England and Wales. *European Review of Agricultural Economics*, 27(4), 519-532
Mahmood, F., Belhouchette, H., Nasim, W., Shahzad, T., Hussain, S., Therond, O., Fahad, S., Refat, Sultana, S., & Wery, J. (2017). Economic and environmental impacts of introducing grain legumes in farming systems of Midi-Pyrenees region (France): a simulation approach. *International Journal of Plant Production*, 11 (1), 65-87.
Malkotra, S. K. (2017). Horticultural crops and climate change: a review. *Indian Journal of Agricultural Sciences*, 87 (1), 12-22.
Mazzocchi, C., Salvan, M., Orsi, L., & Sali, G. (2018). The determinants of Large-Scale Land Acquisitions (LSLAs) in Sub-Saharan Africa (SSA): a case study. *Agriculture*, 8, 194.
Mazzocchi, C., Sali, G., & Corsi, S. (2013). Land use conversion in metropolitan areas and the permanence of agriculture: Sensitivity Index of Agricultural Land (SIAL), a tool for territorial analysis. *Land Use Policy,* 35, 155-162.
Menzel, F., Ghidoni, A., De Noni, I., Bahrs, E., & Corsi, S. (2016). Factors influencing German and Italian farmland prices – A spatial econometric analysis. *Journal of the Austrian Society of Agricultural Economics*, 26, 189-198.
Mela, G., Longhitano, D., & Povellato, A. (2016). Agricultural and non-agricultural determinants of Italian farmland values. In *Fifth AIEAA Congress, June 16-17, 2016, Bologna, Italy*. Italian Association of Agricultural and Applied Economics (AIEAA).
Migliore, G., Zinnanti, C., Schimmenti, E., Borsellino, V., Schifani, G., Di Franco, C. P., & Asciuto A. (2019). A Ricardian analysis of the impact of climate change on permanent crops in a Mediterranean region, *New Medit*, 18(1), 41-52
Nguyen, T. P. L., Mula, L., Cortignani, R., Seddaiu, G., Dono, G., Virdis, S. G. P., Pasqui, M., & Roggero, P. P. (2016). Perceptions of present and future climate change impacts on water availability for agricultural systems in the Western Mediterranean Region. *Water*, 8, 523, 1-18.
Nilsson, P., & Johansson, S. (2013). Location determinants of agricultural land prices. *Jahrbuch für Regionalwissenschaft*, 33(1), 1-21.
Oberthür, S., & Taenzler, D. (2007). Climate policy in the EU, 255-278. In Harris, P. G. (Ed.), *Europe and global climate change*. Cheltenham, U.K., Edward Elgar.
Pilla, F., Gharbia, S. S., & Lyons, R. (2019). How do households perceive flood-risk? The impact of flooding on the cost of accommodation in Dublin, Ireland. *Science of the Total Environment*, 650, 144-154.

Plantinga, A., Lubozski, R., & Stavins R. (2002). The effects of potential land development on agricultural land prices, *Journal of Urban Economics*, 52, 561-581.

Pirani, A., Gaviglio, A., Demartini, E., Gelati, M., & Cavicchioli, D. (2016). Studio delle determinanti del valore degli affitti agrari. Potenzialità dell'uso di microdati e applicazione del metodo dei prezzi edonici. *Aestimum*, 69, 131-151.

Polelli, M., & Corsi, S. (2008). Nuovi modelli interpretativi delle dinamiche del mercato fondiario. *Aestimum*, Atti del XXXVII Incontro di studio del Ce. SET, 51-66.

Pretolani, R., & Rama, D. (Eds.) (2017). *Il sistema agroalimentare della Lombardia: rapporto 2017*. Milano, Franco Angeli.

Rayner, T., & Jordan, A. (2016). Climate Change Policy in the European Union. In *Oxford Research Encyclopedia of Climate Science*. (oxfordre.com/climatescience).

Rawls, W. J., & Brakensiek, D. L. (1989). Estimation of Soil Water Retention and Hydraulic Properties. In Morel-Seytoux, H.J. (Ed). *Unsaturated Flow in Hydrologic Modeling*. NATO ASI Series (Series C: Mathematical and Physical Sciences), 275. Dordrecht, Springer.

Saskatchewan government (2018). Land rental arrangements. https://publications.gov.sk.ca

Singh, V. P., Guo, H., & Yu, F. X. (1993). Parameter estimation for 3-parameter log-logistic distribution (LLD3) by Pome. *Stochastic Hydrology and Hydraulics*, 7, 163-177. doi: 10.1007/BF01585596

Steinebach, Y., & Knill, C. (2017). Still an entrepreneur? The changing role of the European Commission in EU environmental policy-making, *Journal of European Public Policy*, 24(3), 429-446.

Swinnen, J., Ciaian, P., & Kancs, D.A. (2008). Study on the Functioning of Land Markets in the EU Member States under the Influence of Measures Applied under the Common Agricultural Policy. Unpublished Report to the European Commission. Brussels, Belgium, Centre for European Policy Studies.

Tambo, J. (2016). Adaptation and resilience to climate change and variability in north-east Ghana. *International Journal of Disaster Risk Reduction*, 17, 85-94.

Tempesta, T. (2011). Un'analisi dei fattori che influenzano il valore dei rustici a destinazione residenziale nel Veneto. *Aestimum*, 58, 59-74.

UNISDR (2009), Terminology on Disaster Risk Reduction, United Nations International Strategy for Disaster Reduction, Geneva.

Van Passel, S., Massetti, E., & Mendelshon, R. (2017). A Ricardian analysis of the impact of climate change on European agriculture. *Environmental Resource Economics*, 67 (4), 725–760.

Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A Multiscalar Drought Index Sensitive to Global Warming: the Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, 23, 1696-1718. doi: 10.1175/2009JCLI2909.1

Vicente-Serrano, S. M., Lopez-Moreno, J. I., Beguería, S., Lorenzo-Lacruz, J., Sanchez-Lorenzo, A., García-Ruiz, J. M., Azorin-Molina, C., Revuelto, J., Trigo, R., Coelho, F., & Espejo, F. (2014). Evidence of increasing drought severity caused by temperature rise in southern Europe. *Environmental Research* Letters, 9, 44001. doi: 10.1088/1748-9326/9/4/044001

Vicente-Serrano, S. M., Van der Schrier, G., Beguería, S., Azorin-Molina, C., & Lopez-Moreno, J. I. (2015). Contribution of precipitation and reference evapotranspiration to drought indices under different climates. *Journal of Hydrology*, 526, 42-54. doi: 10.1016/j.jhydrol.2014.11.025

Wheaton, E., & Kulshreshtha, S. (2017). Environmental Sustainability of Agriculture Stressed byChanging Extremes of Drought and Excess Moisture: a Conceptual Review. *Sustainability*, 9, 970.

Zamasiya, B., Nyikahadzoi, K., & Billiard Mukamuri, B. (2017). Factors influencing smallholder farmers' behavioural intention towards adaptation to climate change in transitional climatic zones: a case study of Hwedza District in Zimbabwe. *Journal of Environmental* Management, 198, 233-239.

Zasada, I. (2011). Multifunctional peri-urban areas – a review of societal demands and agricultural provision of goods and services. *Land Use Policy*, 28(4), 639-648.

Xu, X., Wang, L., Sun, D., Liu, L., & Banson K. E. (2017). The Impact of Climate Change on Yield Potential of Maize across China. *International Journal of Plant Production*, 11 (1), 47-63.

Appendix

Appendix 1. Farms per municipality in Milan and Monza and Brianza Provinces.

Municipality	Province	Number of farms
Abbiategrasso	MI	9
Albairate	MI	9
Arese	MI	1
Arluno	MI	15
Assago	MI	4
Baranzate	MI	2
Bareggio	MI	7
Basiano	MI	9
Basiglio	MI	1
Bellinzago Lombardo	MI	11
Bernate Ticino	MI	7
Besate	MI	4
Binasco	MI	2
Boffalora sopra Ticino	MI	1
Bollate	MI	1
Bresso	MI	1
Brugherio	MI	1
Buccinasco	MI	1
Cambiago	MI	5
Caponago	MI	1
Carpiano	MI	2
Carugate	MI	1
Cassano d' Adda	MI	10
Cassina de' Pecchi	MI	3
Cassinetta di Lugagnano	MI	1
Castano Primo	MI	2
Cernusco Sul Naviglio	MI	4
Cerro Al Lambro	MI	1
Cerro Maggiore	MI	5
Cesano Boscone	MI	1
Cisliano	MI	1
Colturano	MI	2

Municipality	Province	Number of farms
Corbetta	MI	9
Cormano	MI	1
Cornaredo	MI	2
Cuggiono	MI	1
Cusago	MI	2
Dresano	MI	2
Gaggiano	MI	4
Gorgonzola	MI	3
Gudo Visconti	MI	3
Inzago	MI	2
Lacchiarella	MI	3
Liscate	MI	7
Locate di Triulzi	MI	4
Magenta	MI	1
Mediglia	MI	6
Melzo	MI	5
Milano	MI	10
Morimondo	MI	2
Motta Visconti	MI	1
Nerviano	MI	1
Noviglio	MI	3
Ossona	MI	1
Peschiera Borromeo	MI	6
Pessano Con Bornago	MI	3
Pioltello	MI	2
Pozzuolo Martesana	MI	1
Rho	MI	1
Rodano	MI	3
Rosate	MI	2
San Colombano al Lambro	MI	4
San Giuliano Milanese	MI	7
San Zenone Al Lambro	MI	1

Municipality	Province	Number of farms
Settala	MI	1
Settimo Milanese	MI	6
Trezzo Sull'adda	MI	2
Triuggio	MI	1
Truccazzano	MI	5
Usmate Velate	MI	1
Vanzago	MI	3
Vaprio D'adda	MI	1
Vernate	MI	2
Vignate	MI	1
Vittuone	MI	1
Vizzolo Predabissi	MI	2
Zelo Surrigone	MI	1
Zibido San Giacomo	MI	3
Agrate Brianza	MB	9
Aicurzio	MB	2
Albiate	MB	4
Arconate	MB	6
Arcore	MB	4
Bellusco	MB	8
Bernareggio	MB	2
Besana in Brianza	MB	11
Biassono	MB	1
Buscate	MB	4
Busnago	MB	5
Busto Garolfo	MB	4
Calvignasco	MB	1
Canegrate	MB	1
Carnate	MB	2
Casorezzo	MB	4
Cavenago di Brianza	MB	1
Ceriano Laghetto	MB	2
Cesano Maderno	MB	1
Cesate	MB	2

Municipality	Province	Number of farms
Concorezzo	MB	2
Cornate D'adda	MB	8
Giussano	MB	1
Inveruno	MB	1
Lainate	MB	2
Lazzate	MB	2
Legnano	MB	1
Lentate Sul Seveso	MB	1
Limbiate	MB	1
Parabiago	MB	1
Pregnana Milanese	MB	1
Rescaldina	MB	1