Research on World Agricultural Economy

https://journals.nasspublishing.com/index.php/rwae

ARTICLE

Performance of Agroforestry versus Conventional Rice Farms under a Changing Climate: Evidence from Western Po Plain

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ABSTRACT

Climate change trends and the ongoing environmental crisis are anticipated to significantly affect crop production, particularly rice, which is highly sensitive to these changes. This study explores adaptive strategies for ensuring long-term food security through agri-environmental farm management practices, focusing on a polyculture rice production model (POLY), which emphasizes crop diversification, land races, resource management, and environmental stewardship. We compare the POLY model with local organic (ORG) and conventional (CV) models in northern Italy's western Po Plain, particularly during the extreme climatic event of 2022 and the preceding five years. Although POLY and ORG farms exhibited lower average rice yields (3.9 and 4.3 Mg/ha, respectively) compared to CV (6.7 Mg/ha), they demonstrated better resilience to the 2022 climate anomaly. POLY farms achieved yield increases of 21–22% for the top performers, while ORG farms saw a 20% increase, contrasting with a 10% decrease in CV yields. Yield variability was higher in POLY and ORG farms due to cultivar diversity, providing insurance against climatic unpredictability. Regression analysis revealed a significant correlation between total annual precipitation and CV yields, whereas POLY and ORG yields showed less sensitivity to climate fluctuations. Economically, POLY farms outperformed in efficiency, indicating a viable model for addressing agri-environmental challenges without necessarily increasing land productivity. This study highlights the importance of integrating such models into comprehensive strategies to mitigate the interconnected crises of environment, climate, and food supply.

Keywords: Rice Polyculture; Crop Rotation and Diversification; Climate Change Adaptation; Farm Scale; Northern Italy

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ARTICLE INFO

Received: 30 October 2024 | Revised: 20 January 2025 | Accepted: 6 February 2025 | Published Online: 15 April 2025
DOI: https://doi.org/10.36956/rwae.v6i2.1367

CITATION

Chiaffarelli, G., Vagge, I., 2025. Performance of Agroforestry versus Conventional Rice Farms under a Changing Climate: Evidence from Western Po Plain. Research on World Agricultural Economy. 6(2): 304–326. DOI: https://doi.org/10.36956/rwae.v6i2.1367

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1. Introduction

The most recent climate change scenarios developed by the Intergovernmental Panel on Climate Change (IPCC) project an increase in global temperatures from 2.5 to 4.5 °C by the year 2100 [1]. Climate change current and potential impacts on crop production are deeply evidenced [2–7]. The Intergovernmental Panel on Climate Change projected the loss of 10% of currently suitable area for major crops on a global scale by 2050 due to future climate unsuitability, under the high-emissions scenario [1]. This should be coupled to the rising risk of simultaneous yield losses due to climate extremes across major crop-producing regions [8]. Such impacts are multiplied when considering the projected increase of global population to 9.7 billion by 2050, with consequent rise of world food supply demand [9]. This poses severe threats to food security. Rice, with wheat and maize, is one of the major crops contributing to global food security [10]. In Europe, it is the 6th most produced cereal; besides its economic load, its cultivation is here associated to important social-cultural [11] and ecological values [12]. Italy is the first European rice-producer, supplying two thirds of Europe rice [13]. Global rice yield is predicted to decrease by 17% by 2050 under the highest scenario of warming [14]. Zhao et al. estimated that each degree-Celsius increase in global mean temperature would reduce global rice yields by 3.2%, if no specific adaptation strategies were implemented [15]. Previous studies projected a 7–10% loss in rice yield per each degree-Celsius increase [16, 17]. Rice is a primarily drought-sensitive plant and water availability is the most serious constraint to rice production [18]; future droughts are predicted to be more frequent and extreme [19]. Plant diseases are also projected to be facilitated by climate change by inducing favourable conducive environmental conditions for new pathogens, whilst rising plants sensitivity [20, 21].

Climate change impacts add up with current agri-environmental crisis consequent to 20th and 21st century anthropogenic disturbance: the ecosystem services delivering capacity of land is further impelled because of climate instability; the impacts and threats to food security other than the climate-related ones are consequently widened [3, 21–25]. Crop production adaptation measures are needed to moderate or avoid harm of the ongoing climate change or take advantage of beneficial opportunities [7]. Specifically, increase in crops adaptive capacity should be targeted, i.e. "the ability of systems [...] to adjust to potential damage, to take advantage of opportunities, or to respond to consequences" [7]. Rice yield stabilisation throughout the current and projected unstable environment demands on one side to reduce the adverse consequences of the environmental change and, on the other, to reduce the impact of biotic stress on rice (i.e. to enhance rice resistance and resilience capacity to environmental instability and to projected environmental changes) [19]. Multi-spectra strategies both involving crop cultivar choice and agri-environmental farm management choices are needed. Crop diversification through rotations, the use of stress-tolerant land races and locally selected cultivars, weed mechanical control through green mulching, improved soil management, reduced chemicals, recycling of farm waste into organic fertilisers, and, generally, organic agriculture practices can improve the environmental performance of rice production [26, 27] and also rice production adaptive capacity to climate change [28, 29].

In Europe, the impacts of climate change on rice yield are not so deeply investigated. Ray et al. study showed climate variability to be responsible for 13–43% of rice yield variability in the Mediterranean region; 0–30% in Po Plain district, where normal rainfall data showed the most significant relationship with rice yield (compared to extreme precipitation, normal and extreme temperature) [30]. The Mediterranean basin is a hotspot of expansion of drylands due to the increased frequency of droughts [31, 32]. This region is facing a progressive decrease in mean precipitation and an increase in rainfall variability during the dry season [33]; summer climate variations are the main contributors to aridification [32, 34]. Concerning northern Italy, different studies have already investigated the impacts of climate change on crop production. Straffelini et al. study [34] reports the ongoing shift of Northeast Italy climate towards drier conditions, significantly threatening rice cultivation and other irrigated crops. Northern Italy Po Plain district faced a significant number of drought events since 2000 [35]; 2022 was an extraordinary dry and high-temperature year, with several months of insufficient rainfall and record summer high temperatures, which significantly affected the entire Po river basin [36]. Such extreme climate conditions affected agricultural productions too, causing total yield loss in some areas: rice yield decreased by 30% on average [37].

Po Plain district is parallelly currently facing intense and widespread environmental impacts consequent to decades of intensive agriculture and industrialisation: from soil health deterioration [38] to water [39] and air pollution [40], landscape over-simplification, natural habitat loss and fragmentation [41] and consequent alien species spread [42]. This makes the Po Plain a biodiversity-loss hotspot [43–45]. Ricefield biodiversity is affected too, especially where conventional practices are applied [46, 47]. To date, high-input conventional monoculture represents the most spread rice production model in Po Plain. The persistent and prevailing conventional agriculture model, coupled to intense urbanisation and industrialism, transformed the entire Po Plain agricultural landscape, impairing the Po basin regulating processes and land ecosystem services delivering capacity [48]. This entails higher vulnerability and lower adaptation capacity to climate change conditions, exacerbating its impacts. This poses important challenges for Po Plain next future, demanding for multi-functional strategies to be implemented to reinforce crop production adaptive capacity to climate change.

Organic rice production is generally characterized by higher yield variability and higher productivity gaps under limiting conditions, compared to conventionally managed rice [49]. Delmotte et al. study on the source of variability of southern France rice production identified, among the main factors affecting rice yield, weed competition (both for conventional and organic farms). Late sowing was the mostly applied adaptation strategy for weed control under organic management, but also variety choice, water irrigation management, crop rotations and cover crops were identified as valuable alternatives, to also counterbalance adverse climatic and soil conditions [49]. Arcieri et al. identified the following key challenges for Italian rice cultivation (mostly coming from the Po Plain district): optimism resources use, coping with growing costs of agricultural inputs, improving small farm production efficiency by promoting ecosystem-based agriculture, sustainable intensification and climate change resilience strategies [12]. The following practices are identified by Arcieri et al. [12] to face current Italian rice production issues: improve soil fertility, multi-cropping rotations, site-specific nutrient management, use of organic fertilizers, integrated pest management, harvest and post-harvest management optimism, intermittent flooding and alternate wet/dry water-saving techniques, information systems supporting irrigation scheduling, farming system diversification to increase farm incomes, improve family nutrition and enhance climate resilience.

Within this framework, the present study aims to report and provide local evidence on the agronomic and economic performance of a rice production model based on polyculture practices in the western Po Plain (northern Italy), within a climate change and environmental instability framework. The rice polyculture model (POLY) is founded on high crop diversification and the adoption of land races, on-farm resource management and minimized or zero external inputs, and farm landscape management through agroforestry, with a specific focus on agrobiodiversity support. This is achieved by comparing the POLY model to local organic (ORG) and conventional (CV) models, the latter of which is the most prevalent among the alluvial context under study. The study aims to provide a valuable addition to existing and future assessments by offering context-specific case histories related to a symbolic period with respect to the climate change issue (i.e. the 2022 extreme climatic event and the five previous years). The 2022 extreme climatic event was characterized by exceptional conditions of aridity and elevated summer temperatures. This prompts the question of how aridity affects rice cultivation in the Po Valley, as previously examined by other authors in works concerning aridity in cereal production in other regions of the world [34, 50–52]. Additionally, the investigation explores how the three distinct cultivation methods (polyculturae, organic and conventional) respond to aridity and which method is most effective. This aspect has not been explored by other researchers and there is a paucity of evidence in the literature. Specifically, our study aims at:

(1) comparison of the agronomic (yield) performance of the three different rice farms management mod-

els: POLY, ORG, CV. A particular emphasis will be placed on the response of the three models to the 2022 climate anomaly that occurred in northern Italy (an extremely dry and hot year).

(2) we will investigate the potential relationships between the three management models' yield performance and climate change evidence (2018-2022 data), with the aim of highlighting any potential climate change sensitivity and/or adaptive traits exhibited by specific farm management models.

(3) a comparison of the economic performance of the three different rice farms management models (POLY, ORG, CV) will be made, in order to complement the agronomic performance analysis with the analysis of farm sustainability components depending on different degrees of farming system diversification.

2. Materials and Methods

2.1. Case Studies

Rice polyculture farms (POLY) were selected among the western Po Plain alluvial district (Vercelli and Pavia districts, Piedmont and Lombardy regions, northern Italy) among three different sites: site 1 45°32'53.2"N 8°19'11.0"E (G farm); site 2 45°17'17.4"N 8°39'07.9"E (C farm); site 3 45°11'54.6"N 8°20'00.8"E (P farm) (**Figure 1**). Among site 1, two local rice organic farms (ORG: A, T farms) and two rice conventional farms (CV: M, B farms) were selected for agronomic model comparison.

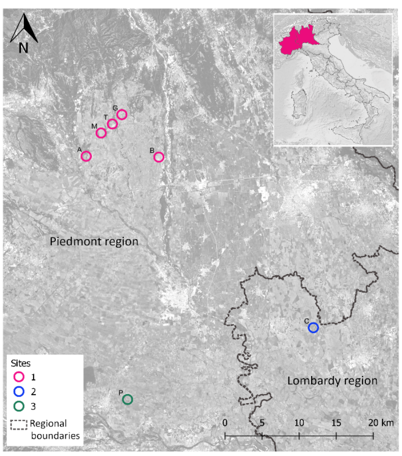

Figure 1. Location of the farms belonging to the three study sites among the western Po Plain alluvial district (Piedmont and Lombardy regions). Site 1 (45°32'53.2"N 8°19'11.0"E): G POLY farm, A and T ORG farms, M and B CV farms; site 2 (45°17'17.4"N 8°39'07.9"E): C POLY farm; site 3 (45°11'54.6"N 8°20'00.8"E): P POLY farm.

Table 1 synthesizes the main traits of each site environmental context (geomorphology, pedology, landscape ecology [48, 53]) and of each POLY, ORG and CV farm.

Site 1 farms are located among Riss alluvial terraces with predominant fine texture Alfisols with low permeability and fertility, except for B_CV farm, which partly stands on Wurm alluvial deposits with Inceptisols of lower pedogenesis intensity [48, 53]. This ancient geomorphological background makes this land a unicum for rice qualitative and nutritional traits (denomination protected under PDO regulation: "Biella and Vercelli Baraggia rice") [54]. Site 2 and 3 belong to more recent fluvial deposits with low to medium pedogenesis, lower soil acidity, coarser soil texture and consequent low-to-medium permeability (i.e. lower suitability to rice cultivation, despite its deep local historical background as rice-land) [48, 53]. All sites belong to highly simplified and low diversified agricultural landscape systems (**Table 1**) [48]. This is especially true for site 2 and 3, where the agricultural matrix covers 87–89% of the surrounding extra-local landscape system and forest and semi-natural components are strongly reduced and fragmented (5–7% of total extra-local landscape surface) [48]. Site 1 shows a slightly better landscape ecological configuration, thanks to its higher geomorphological variety which made possible to preserve a higher portion of natural and semi-natural components (31% of total extra-local landscape surface). Landscape diversity and mean biological territorial capacity (a measure of the landscape ecological meta-stability traits) are very low in site 2 and 3 (diversity: 1–1.1; biological territorial capacity: 1.2–1.3 Mcal/ha/yr). Site 1 has higher landscape diversification (1.7) and biological territorial capacity (2.4 Mcal/ha/yr), but still values are low if compared to more balanced and diversified agricultural landscapes [48]. These landscape ecology traits impair the life support and regulating functions of the agricultural landscape, thus weakening the resilience and resistance capacity of landscape components, and rising the vulnerability of landscape components to environmental and climate change, with knock-on effects on food provisioning functions [48]. Hence, study sites represent agricultural areas currently demanding for agri-environmental re-balancing strategies, such as the one represented by organic agriculture and, even more, by a polyculture, highly diversified, farm management model.

Table 1. Main traits of each site territorial context (geomorphology, pedology, landscape ecology) and of each POLY (SITE 1: farm G; SITE 2: farm C; SITE 3: farm P), ORG (SITE 1: farms A, T) and CV (SITE 1: farms M, B) farm (surface, crops, agroforestry implementation, management model).

			Site	**SITE 2**	**SITE 3**	**SITE 1**				
			Model	POLY			ORG		CV	
			Farm	C	P	G	A	T	M	B
TERRITORIAL CONTEXT	GEOMORPHOLOGY, PEDOLOGY [48,53]		ST /WRB CLASSES	Luvisols; Arenosols	Inceptisols; Entisols	Alfisols (ancient terraces); Inceptisols				Alfisols (ancient terraces); Inceptisols
			Geomorphology	Fluvial terrace	Fluvial deposits	Riss alluvial terrace, Holocene fluvial terrace				Riss alluvial terrace, Wurm alluvial deposits
			Main soil texture	Loamy-sand; Sandy-loam	Loamy-coarse; Loamy-sand	Fine silty				Fine silty to loamy-sand
			Development	Medium pedogenesis	Low pedogenesis	Predominant intense pedogenesis				Both low and intense pedogenesis
			Permeability	Medium-low permeability	Medium permeability	Predominant surface hydromorphy				Mixed high and low permeability
			pH	Sub-acid [5.5–6.5]	Sub-alkaline to alkaline [7.4–8.4]	Acid [4.6–5.4]				Acid [4.6–5.4] to sub-acid [5.5–6.5]
			Land use capacity	IIw (waterlog)	II (oxygen availability)	III (oxygen availability)				?
	LANDSCAPE ECOLOGY TRAITS [41,48]	EXTRA-LOCAL SCALE	Matrix	Agricultura: 88.6%	Agricultural: 86.7%	Agricultural: 60.1%				
			Forest & semi-natural	5.2%	6.7%	30.6%				
			Artificial	6.3%	6.7%	9.3%				
			Landscape diversity	1.0	1.11	1.70				
			Biological territorial capacity	1.17	1.26	2.39				
			Farm	C	P	G	A	T	M	B
FARMS	SURFACE		SAU (ha)	47	65	128	65	86	160	300
	CROPS		Main annual crops	Rice in rotation with millet, black-eyed bean, rye, oat, pea	Rice in rotation with barley and soyabean	Rice in rotation with millet, black-eyed bean, rye, oat	Rice in rotation with soyabean	Rice in rotation with soyabean, buckwheat, oat	Rice in rotation with soyabean	Rice
			Rice land races and/or local cultivars	Yes	No	Yes	No	Yes	No	No
			Perennial crops	Apple						
	AGROFORESTRY		In-field hedgerows and treelines	No	No	Yes	No	No	No	No
			Between field hedgerows and treelines	Yes	Ongoing transition	Yes	Ongoing transition	Ongoing transition	No	No
	MANAGEMENT MODEL		Years since beginning of activity	7	8	21	21	27	32	39
			Years since conversion to ORG	7	8	21	21	6	/	/
			Years since conversion to POLY	7	8	21	/	/	/	/
			Completed conversion	Yes	Partially	Yes	Yes	Yes	/	/

POLY farms are distinguished from the ORG ones on: more widespread crop rotation, polyphyte cover crops, use of rice land races and/or local cultivars, almost complete substitution of external inputs (fertilizers, pesticides, herbicides) with on-farm resources, agroforestry and agrobiodiversity-support practices (**Table 1**). Among POLY farms, one farm still undergoing complete transition to the POLY model is included (site 3, P farm): a farm portion in still under low-impact conventional management (lower chemicals and soil management intensity compared to standard conventional farms). G farm (site 1) represents the most consistent POLY model implementation, resulting from longer POLY management history (more than 20 years). The two ORG farms represent typical local organic farms traits [27]. The two CV farms represent the most widespread local rice management model and stand for two different degrees of intensification: B farm is the most intensive, large size, CV model, based on rice monoculture for the past forty years, whereas M farm is lower-sized and partly includes rice rotation with soyabean.

2.2. Climate Data Collection and Analysis

Daily climate data over thirty years were collected from regional databases [55, 56], referring to the agri-meteorological monitoring station closest to each of the 3 sites (site 1: Albano Vercellese station; site 2: Castello d'Agogna station; site 3: Tricerro station). If not available, the minimum available dataset was used (site 2: 1991-2022 rainfall data, 1993–2022 temperature data; site 3: 2002–2022 rainfall and temperature data). Daily rainfall and temperature data (average, minimum and maximum) were cleaned of missing data and then used to calculate the variables shown in **Table 2**.

A linear trend line was calculated for all variables to highlight climate trends over the entire period. Sites were classified on their bioclimate [57, 58] referring to pre-existing bioclimate maps based on 1950-2000 data series [59, 60].

For 2018–2022 years, the following additional calculations were made:

- Monthly rainfall anomalies: for each year [2018–2022], difference between total monthly rainfall and the climatic monthly mean rainfall (MONTHLY MEAN), compared to the MONTHLY MEAN to get percentage anomality values
- Monthly mean temperature anomalities: for each year [2018–2022], difference between monthly mean of daily temperature and the climatic monthly mean temperature (MONTHLY MEAN).

In order to compare yield trends with climate trends, climate indices were obtained, in **Table 3**, for the 12 months preceding the rice harvest (September/year before harvest to August/year of harvest).

2.3. Agronomic Data Collection and Agronomic Performance Analysis

Agronomic data were collected at farm level through detailed face-to-face interviews. Data were collected for each crop, over 5 years (2018–2022); farm level data were taken as an average of the reported period. Specifically, information was gathered on: employed crops and cultivars, rotations, agroforestry practices, irrigation (type, water source, frequency, flooded period, water consumption, fees), soil management (type, depth, frequency), sowing (type, period, seed dose, seed source, seed cost: in-farm seed production cost, seed purchase cost), cover crops (incidence -percentage surface-, species, seed dose, seed cost), fertilizers-pesticides-herbicides (incidence, type, source, cost, compliance to organic agriculture), harvest (date, yield, maximum and minimum yield during last ten years, fate – sold, in-farm re-use, re-incorporation to soil-), post-harvest (in-farm storage cost, in-farm transformation cost, whole sale and direct sale ratios and selling prices, residues type, management and related costs and selling price), machinery and labour (total machinery power, fuel and lubricants consumption, electricity consumption and production, in-farm and paid labour units). For 2022, an exceptionally dry year, additional information was collected on water reductions due to drought and on the implemented adaptations.

These data allowed a preliminary synthesis on the main agronomic management traits distinguishing the different farms and the 3 models under study. Agronomic performance was assessed by using rice yield as indicator (2018–2022 data). POLY, ORG and CV yields were compared through ANOVA test (non-parametric Kruskal-Wallis rank test for not normally distributed data) and post-hoc test (Mann-Whitney pairwise test). Their yield variability was then compared, investigating the influence of the different employed rice cultivars. Then, the year mean rice yield trend from 2018 to 2022 were compared between farms and models, also including other crops trend (for the ones repeatedly used over the studied time frame). A comparison was made also with district, regional and national mean annual yields [61].

Table 2. Climate variables calculated and taken into account.

Climate Variables	Acronym	Definition
Total annual rainfall	(ANNUAL TOT)	sum of daily total rainfall for each year
Mean annual rainfall	(ANNUAL MEAN)	mean of total annual rainfall over the entire period (about 30 years)
Daily maximum rainfall	(DAILY MAX)	maximum daily rainfall for each year
Mean daily maximum rainfall	(DAILY MAX MEAN)	mean of maximum daily rainfall over the entire period (about 30 years)
Number of dry days	(DRY DAYS)	number of days per year with daily total rainfall lower or equal to 1 mm
Mean annual dry days	(MEAN DRY DAYS)	mean of number of dry days per year over the entire period (about 30 years)
Monthly mean rainfall	(MONTHLY MEAN)	Mean of the sum of daily rainfall for each month over the entire period (about 30 years)
Mean annual temperature	(ANNUAL MEAN)	Mean of each month mean temperature for each year
Minimum temperature annual mean	(MIN ANNUAL MEAN)	Mean of each month mean minimum temperature for each year
Maximum temperature annual mean	(MAX ANNUAL MEAN)	Mean of each month mean maximum temperature for each year
Annual absolute maximum temperature	(MAX ASS)	Maximum of monthly maximum temperature for each year
Annual absolute minimum temperature	(MIN ASS)	Minimum of monthly minimum temperature for each year
Monthly mean temperature	(MONTHLY MEAN)	Mean of monthly mean temperature over the entire period (about 30 years)

Table 3. Climate indices calculated for the 12 months preceding the rice harvest.

Index	Acronym	Definition
Late season months rainfall	(P_au)	sum of daily rainfall for months 09, 10, 11
Coldest months rainfall	(P_wi)	sum of daily rainfall for months 12, 01, 02
Mid-season rainfall	(P_sp)	sum of daily rainfall for months 03, 04, 05
Hottest months rainfall	(P_su)	sum of daily rainfall for months 06, 07, 08
Annual rainfall	(P_yr)	sum of daily rainfall for months 09-08
Absolute maximum temperature	(T_M_abs)	absolute maximum temperature value
Late season months mean temperature	(T_au)	mean of monthly mean temperature for months 09, 10, 11
Coldest months mean temperature	(T_wi)	mean of monthly mean temperature for months 12, 01, 02
Mid-season months mean temperature	(T_sp)	mean of monthly mean temperature for months 03, 04, 05
Hottest months mean temperature	(T_su)	mean of monthly mean temperature for months 06, 07, 08
Annual mean temperature	(T_yr)	mean of monthly mean temperature for months 09-08

2.4. Comparison between Climatic and Agronomic Data

To check for relationships between 2018–2022 climate trend and anomality (12 months prior to rice harvest) and agronomic performance of different management models (annual rice yields of POLY, ORG and CV farms), we first checked for normal distribution of climate and yield data (Shapiro-Wilk test) and consequently run a correlation analysis (Pearson or Spearman rs correlation coefficients, respectively for normally and not-normally distributed data) to identify possible significant relationships. We then run an ordinary least square regression analysis on the most influent climate variables (the ones showing significant, or close to significant, correlation patterns with yield), with yield as dependent variable. Reduced Major Axis algorithm (RMA) or Ordinary Least Square algorithm (LS) were alternatively chosen, depending on model robustness (p value and coefficient of determination value). 95% bootstrapped confidence intervals were used for RMA algorithm, 95% regression confidence intervals for the LS algorithm (if residuals are normally distributed).

2.5. Economic Performance Analysis

Farm economic performance was addressed by comparing the costs and income types composition among each farm and by computing indicators on the economic flows and technical and economic indices, as detailed in **Table 4**. Indicators choice was based on previous works focusing on farm sustainability assessment on similar territorial context (already applied on Po Plain or Italian case studies) [62, 63]. Economic flows indicators include: gross income (GI), variable costs (VC), gross margin (GM) and efficiency (EF) [62]. Technical and economic indicators include: land use intensity degree (INT), family working weight (FAM), land mechanization degree (MEC_SAU) and mechanization intensity (MEC_ULT), work gross productivity (PROD_WORK) and land gross productivity (PROD_LAND) [63]. A variant was introduced in the evaluation of variable costs to better represent real farm case histories: VC (the original one, including fuels, lubricants, pesticides, herbicides, fertilisers, and seeds), VC2 (also including irrigation water fees, storage costs, residues management costs, electricity costs) ad VC3 (like VC2, also including harvest in-farm transformation costs). Consequently, gross margin and efficiency were calculated for these three variants (GM, GM2, GM3; EF, EF2, EF3).

Table 4. Detail on the applied indicators on economic performance.

ECONOMIC FLOWS					
Indicator name	Acronym	Definition	Equation	udm	Reference
GROSS INCOME	GI	Yield of harvested product multiplied by its price + income from residuals management + electricity production income	$GI = \sum income_x$	euro/yr	[62]
VARIABLE COSTS	VC	Sum of costsx: fuels, lubricants, pesticides, herbicides, fertilisers, seeds	$VC = \frac{(\sum cost_x)}{GI} \times 100$	%	[62]
	VC2	Sum of costsy: fuels, lubricants, pesticides, herbicides, fertilisers, seeds, irrigation water fees, storage costs, residues management costs, electricity	$VC = \frac{(\sum cost_y)}{GI} \times 100$	%	*Re-adapted from* [62]
	VC3	Sum of costsz: fuels, lubricants, pesticides, herbicides, fertilisers, seeds, irrigation water fees, storage costs, residues management costs, electricity, harvest in-farm transformation costs	$VC = \frac{(\sum cost_z)}{GI} \times 100$	%	*Re-adapted from* [62]
ECONOMIC BALANCE (GROSS MARGIN)	GM	Difference between gross income and variable costs (VC)	$GM = \frac{GI-VC}{GI} \times 100$	%	[62]
	GM2	Difference between gross income and variable costs (VC2)	$GM = \frac{GI-VC2}{GI} \times 100$	%	*Re-adapted from* [62]
	GM3	Difference between gross income and variable costs (VC3)	$GM = \frac{GI-VC3}{GI} \times 100$	%	*Re-adapted from* [62]
EFFICIENCY	EF	Ratio between gross income and variable costs (VC)	$EF = \frac{GI}{VC}$	-	[62]
	EF2	Ratio between gross income and variable costs (VC2)	$EF = \frac{GI}{VC2}$	-	*Re-adapted from* [62]
	EF3	Ratio between gross income and variable costs (VC3)	$EF = \frac{GI}{VC3}$	-	*Re-adapted from* [62]
TECHNICAL & ECONOMIC INDICES					
Indicator name	Acronym	Definition	Equation	udm	Reference
Land use intensity degree	INT	Ratio between used agricultural surface (SAU) and total labour units (ULT)	$INT = \frac{SAU}{ULT}$	sau/working units	[63]
Family working weigth	FAM	Ratio between family labour units (ULF) and total labour units (ULT)	$FAM = \frac{ULF}{ULT}$	in-farm labour units/paid labour units	[63]
Land mechanization degree	MEC_SAU	Ratio between machinery power (KW) and used agricultural surface (SAU)	$MEC_{SAU} = \frac{KW}{SAU}$		[63]
Mechanization intensity	MEC_ULT	Ratio between machinery power (KW) and total labour units (ULT)	$MEC_{ULT} = \frac{KW}{ULT}$		[63]
Work gross productivity	PROD_WORK	Ratio between farm gross income (GI) and total labour units (ULT)	$PROD_{WORK} = \frac{GI}{ULT}$	Total incomes/working unit	[63]
Land gross productivity	PROD_LAND	Ratio between gross saleable production (PLV) and used agricultural surface (SAU)	$PROD_{LAND} = \frac{GI}{SAU}$	Gross production to sell/SAU	[63]

3. Results and Discussion

3.1. Climate Change Evidence

3.1.1. Climate Trend [1990–2022]

Table 5 synthetises the main climatic and bioclimatic traits of the three sites. Despite being in the same alluvial district, a climatic gradient is evident between the three sites. Site 1 shows higher annual rainfall, lower annual mean temperature and average minimum temperature, whereas site 2 shows the lowest annual rainfall (**Table 5**). Annual mean temperature, mean maximum and minimum ones do not significantly differ between sites 2–3 (**Table 5**). **Figure 2** details the climatic trend of rainfall (annual total rainfall, daily maximum rainfall, number of dry days) and temperature (mean annual temperature, maximum and minimum temperature annual means) for each year since 1990 for the three sites. Rainfall shows a decreasing trend during last thirty years in all sites, with great variability between years, the lowest absolute value registered in 2022; site 3 shows the most influent decrease ratio (−7.69 trendline slope) (**Figure**

2a). Site 2 shows the highest increase in annual dry days (+2.02 trendline slope), whereas site 1 is almost stable (−0.002 trendline slope). Daily maximum rainfall trend does not show significant increasing and or decreasing patterns; it highlights a significant positive anomality in 2020. Annual mean temperature shows an increasing trend in all sites (site 1: + 0.047; site 2: +0.056; site 3: +0.067 trendline slope), with even steeper increasing trends in site 1 and 2 maximum temperature annual mean (respectively, +0.071 and +0.076 trendline slope) (**Figure 2b**). Minimum temperature annual mean increase is influent too (site 1: +0.031; site 2: +0.042; site 3: +0.061 trendline slope). The registered trend towards dryer and hotter condition is coherent to the most recent climate-change scenarios built for northern Italy [34, 64].

Table 5. Main differences between the 3 sites climate variables and bioclimatic traits [59, 60].

		SITE 2	SITE 3	SITE 1
CLIMATE [1990–2022 data]	Annual rainfall [mm]	668	737	872
	Annual mean Temperature [°C]	13.1	13.2	12.3
	Average Maximum Temperature [°C]	18.6	18.8	18.9
	Average Minimum Temperature [°C]	8.19	8.5	7.0
BIOCLIMATE [1950–2000 WorldClim data]	Bioclimate (variant)	Temperate oceanic (submediterranean)	Temperate oceanic (steppic)	Temperate oceanic
	Bioclimatic belt	Lower supratemperate Lower humid	Lower supratemperate Upper subhumid	Lower supratemperate Lower humid

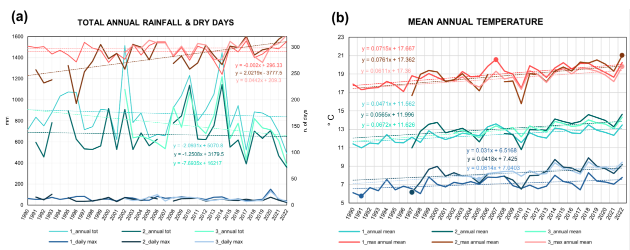

Figure 2. Rainfall and temperature climatic data (1990–2022 data series) for each site (1, 2, 3): (**a**) total annual rainfall (annual_tot), daily maximum rainfall (daily_max), number of dry days (dry_days); (**b**) mean annual temperature (annual_mean), maximum temperature annual mean (max_annual_mean), minimum temperature annual mean (min_annual_mean). Linear trend line (dotted line) and equation is reported for all variables highlighting climate trends over the entire period.

All sites belong to the same macro-bioclimate, temperate oceanic, with some variants: site 2 is temperate oceanic (submediterranean), site 3 is temperate oceanic (steppic). All sites belong to the same thermotype, lower supra-temperate. The ombrotype slightly changes in site 3 (upper sub-humid), compared to sites 1–2 who show higher ombrothermic index values (lower humid hombrotype).

3.1.2. Last Five Years Trend and Anomality [2018–2022]

Figure 3 reports a detail on rainfall and temperature data of 2018-2022 years among the three sites, with a specific focus on 2022 anomalous behaviour, compared to each site climatic mean. All sites show a significant anomality in 2022 monthly rainfall, across almost all months (except for July in sites 1 and 3). The seasonal rainfall pattern (spring and autumn peaks) is weakly detectable in 2022. The strong reduction of winter and spring rainfall caused knock-on effects on rice cultivation (delayed sowing, spread dry sowing, reduced cover crops development) due to the impaired soil water reserve and reduced irrigation water availability. Concerning temperature, 2022 mean monthly temperature exceeds the climatic mean among all three sites, during almost every month (except for early spring months). The highest gaps are registered in July and, generally, during summer; October also showed significant deviation from climatic mean. This significantly raised evapotranspiration processes, hydric deficit and heat stress.

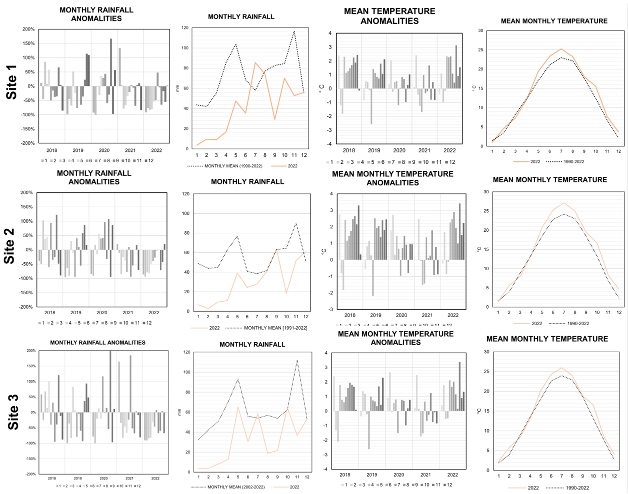

Figure 3. For each site (1, 2, 3): 2018–2022 monthly rainfall anomality (percentage deviation from the 1990–2022 climate mean values) and 2022 monthly rainfall trend, compared to the climate mean monthly values; 2018–2022 monthly temperature anomality (percentage deviation from the 1990–2022 climate mean values) and 2022 monthly temperature trend, compared to the climate mean monthly values.

3.2. Agronomic Performance

3.2.1. Main Agronomic Management Traits

Crop diversification distinguishes POLY and ORG farms from CV ones: POLY farms mean surface used for crops other than rice is 40%; 58% in ORG farms; 11% in CV ones (**Figure 4a**). P farm (POLY) represents a mixed model, in that its transition to the POLY model is still ongoing, and 65% of cultivated surface is under conventional rice production; if excluding P farm, POLY mean other crops surface rises to 52.5%. These diversified productions (OTHER_CROPS) are mostly aimed at on-farm resources conservation and external inputs reduction: their relative weight on total farm income coming from crops is low, ranging from 14% in POLY farms (19.5% if excluding P farm under transition) to 16% in ORG ones (**Figure 4b**). **Table 6** synthetises the main agronomic management traits distinguishing the POLY, ORG and CV farms (mean values of 2018–2022 data).

The studied 7 farms generally apply continuous flooding conditions on rice fields, but differ in rice rotations, which are reduced (or absent) in CV farms. Mean irrigated surface is 63%in POLY farms, 44% in ORG farms, 89% in CV farms, because of lower crop diversification. Tillage intensity and frequency is higher in CV farms. CV farms completely depend on off-farm purchased seeds, whereas both POLY and ORG farms also rely on seeds auto-production (G farm completely relies on the latter). Multi-species cover crops are used only among POLY and ORG farms, with POLY farms showing higher cover crops species diversification and incidence (POLY: 82% of cultivated surface; ORG: 75%). No fertilizers are applied among POLY farms, where fertilization is obtained through cover cropping and green manuring practices [27], except for P farm which is still under transition to POLY model. ORG farms apply organic fertilizers on about 33% of cultivated surface, whereas among CV farms 93% of cultivated surface is fertilized, mainly with non-organic fertilizers. POLY farms do not use pesticides or herbicides (except 60% of P farm cultivated surface, still under transition, where chemical weed control integrates green manuring practices); ORG farms apply organic compliant pesticides among 15% of cultivated surface but no herbicides; CV farms employ both pesticides and herbicides on 87% of cultivated surface. No residues management occurs among CV farms, whereas they are re-incorporated to soil in POLY and ORG farms (G farm also partially sells them).

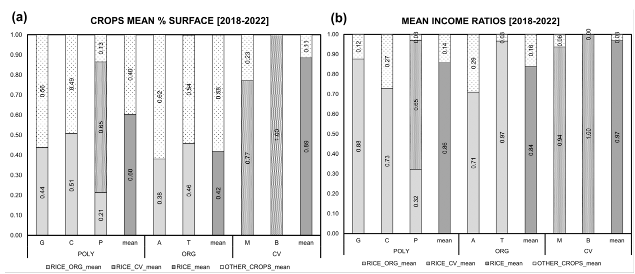

Figure 4. (**a**) 2018–2022 mean percentage surface of different crop types; (**b**) 2018–2022 mean income ratio related to different crop types. Data are reported for each POLY, ORG and CV farm, also reporting mean values for each management model. Organic/polyculture rice: RICE_ORG_mean; conventional rice: RICE_CV_mean; total rice: RICE_mean; other crops: OTHER_CROPS_mean.

Table 6. Comparison of the main agronomic management traits among the studied farms (mean values of 2018-2022 data): POLY farms (SITE 1: farm G; SITE 2: farm C; SITE 3: farm P); ORG farms (SITE 1: farms A, T); CV farms (SITE 1: farms M, B).

			SITE 2	**SITE 3**	**SITE 1**				
			POLY			**ORG**		**CV**	
CATEGORY	DESCR	udm	C	P	G	A	T	M	B
ROTATIONS	Rice rotations* R=rice; C=other crops	*yrs*	R, C, C, R, C, C	R, C, R, C, R	R, C, R, C	R, C, R, C	R, C, R, C	R, R, R, R, C, C	R, R, R, R
IRRIGATION	Rice irrigation type		continuous flooding	continuous flooding	continuous flooding	continuous flooding	continuous flooding	continuous flooding	continuous flooding
	Irrigated surface	*% SAU*	57%	87%	44%	38%	49%	78%	100%
TILLAGE	tillage	-	minimum tillage (partly no tillage, rarely tillage)	minimum tillage	minimum tillage; ripper subsoiling	tillage; arrowing	tillage, ripper subsoiling (completely substituting tillage in some years), leveling (not all years)	Tillage, levelling, arrowing,ripper subsoiling	Tillage, levelling, arrowing (where row sowing))
	tillage depth	*cm*	10-15	15-20	20	15-18	20	25	18-20
	tillage frequency	*n./yr*	1 / 2	1	2	1	2	4	2
SOWING	rice sowing type		broadcast	broadcast	broadcast	broadcast	broadcast	Rows, partially broadcast	Rows, broadcast
	other crops sowing type	-	rows	broadcast	rows	broadcast	rows	rows	rows
	seed source		autoproduction; purchase	purchase; limited autoproduction	Autoproduction	purchase; autoproduction	autoproduction; purchase	purchase	purchase
COVER CROPS	incidence*	*% SAU*	82%	64%	100%	50%	100%	0%	0%
	species composition	-	*Vicia villosa* Roth, *Vicia sativa* L., *Trifolium repens* L., *Trifolium incarnatum* L., *Avena sativa* L., *Brassica napus* L.	*Vicia villosa* Roth, *Trifolium incarnatum* L., *Lolium perenne* L.	*Vicia villosa* Roth, *Brassica rapa* L., *Secale cereale* L., *Avena sativa* L., *Lolium perenne* L.	*Lolium perenne* L., partly *Vicia villosa* Roth	wild weeds (ricefields); *Lolium perenne* L. (dry crops)	-	-
	number of species	*n.*	6	3	5	2	1		
FERTILISERS	incidence	*% SAU*	0%	60%	0%	20%	45%	86%	100%
	type	-		Mineral NPK (2 doses/yr)		cornunghia (only sandy soils; 1 dose/3 yrs)	manure, cornunghia	Mineral NPK	Cornunghia(1 dose/yr); Mineral slow-release NPK (2 doses/yr)
	Other strategies*		Cover crops green manuring	Cover crops green manuring	Cover crops green manuring	Cover crops green manuring	winter grazing on cover crops; soybean green manuring		
	BIO compliant	*Y/N*	Yes	No	Yes	Yes	Yes	No	No
PESTICIDES	incidence	*% SAU*	0%	0%	0%	4%	26%	73%	100%
	type	-				Sulphur, copper; 1 dose/yr (fruit trees)	Sulphur	Fungicides; Pesticides	Fungicides; Pesticides
	BIO compliant	*Y/N*				Yes	Yes	No	No
HERBICIDES	incidence	*% SAU*	0%	60%	0%	0%	0%	73%	100%
	type			3 doses/yr				n.d.	n.d.
	BIO compliant	*Y/N*		No				No	No
RESIDUES	residues fate*	-	Re-incorporated to soil	Re-incorporated to soil	Re-incorporated to soil; sold	Re-incorporated to soil	Re-incorporated to soil	Unmanaged	Unmanaged

3.2.2. Agronomic (Yield) Performance [2018–2022]

Considering 2018-2022 rice yields, POLY and ORG farms have similar mean rice yields, with lower values for POLY farms (respectively, 3.9 and 4.3 Mg/ha), whereas CV farms show significantly higher values (6.7 Mg/ha) (**Table A1**, **Appendix A**; **Figure 5**). Organic farms mean yield is higher than the one detected in previous studies on the same territorial context (3.7 Mg/ha) [27]; CV farms mean yield is similar to the ones detected by previous local studies [27, 65] and is the closest to the mean rice yields of the Vercelli district (6.7 Mg/ha), the regional mean values (6.8 Mg/ha) and the national ones (6.5 Mg/ha) [61] (**Figure 5**). Significance of differences between models is confirmed by the Kruskal-Wallis ANOVA test for equal medians: data are not normally distributed; p(same) = 2.938×10^{-16}; Mann-Whitney pairwise test showed significant differences between POLY-CV and ORG-CV (respectively: p = 9.588×10^{-13}; p = 1.082×10^{-11}). When separating P farm yields (site 3) between the POLY managed cultivars and the conventionally managed ones, differences between POLY and ORG farms mean rice yields rise (respectively, 3.5 and 4.3 Mg/ha) (**Table A1**, **Appendix A**) and difference is significant (Kruskal-Wallis ANOVA test: p(same) = 1.43×10^{-17}; Mann-Whitney pairwise test between POLY-ORG yields: p = 0.00998).

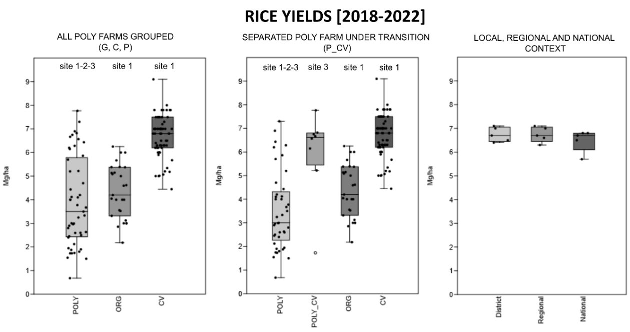

Figure 5. Rice yield across 2018–2022 years of POLY, ORG and CV farms, first by grouping all POLY farms togheter (left side boxplots); secondly by separating P farm yields between the POLY managed ones (under POLY group) and the conventionally managed ones (under POLY_CV group) (middle boxplots); compared to the district, regional and national mean annual rice yields (right side boxplots).

Generally, 2018–2022 rice yield shows higher variability in POLY and ORG farms compared to CV ones (respectively, σ = 1.65; 1.13; 0.88) (**Table A1**, **Appendix A**; **Figure 5**), in line with literature evidences [49]. Previous studies on organic farms in the same territorial context detected slightly higher variability values in organic farms (σ = 1.6) [27]. The detected variability can be linked to several interacted and interconnected factors, among which farmer know-how certainly plays a key role (e.g. by limiting farm management errors in weed competition, one of the major yield variability source), followed by the optimization capacity of the timely and punctuality of operations and the controlling capacity on soil seed bank (depending on soil management, crop rotations and local agroecosystem characteristics) [27, 49]. Rice variety choice can also influence weed competition capacity and yield response to weather instability [27]. In our study, the employ of a diversified set of cultivars among POLY, ORG and CV farms showed different responses to the diverse years' conditions (different intra-cultivar variability) (**Figure 6**), which might result in higher yield unpredictability but also in higher yield insurance thanks to the multiple responses offered by a diversified set of cultivars. **Figure 6** reports a selection of 2018–2022 yield values for those cultivars being repeated at least 4 consecutive years during the studied time frame. For instance, Rosa Marchetti cultivar (a local traditional land race introduced in 1972) shows the highest variability both under POLY and ORG management, ranging from 1.7 to 7.3 Mg/ha (mean: 4.3 Mg/ha). Among the cultivars cultivated under POLY model, Dellarole, Chinese and Bertone are ancient land races of conservation interest: intra-cultivar variability is lower, especially for Dellarole and Bertone (the latter also showing the lowest yields); Chinese shows a more variable behaviour. Carnaroli, a local cultivar selected in 1939–1945, also shows a more stable behaviour across years; the same is observed for Cammeo variety, whose variability is intermediate (with a significant increase shifting from ORG management to the CV one).

We further investigated the mean year rice yield trend during 2018–2022 time frame, to check for possible difference in yield responses to climate instability, depending on farm management model (**Figure 7a**). Regional and national rice yields were significantly impacted by 2022 climate anomality (respectively, −7% and −15%, compared to 2018–2021 mean) (**Figure 7**); district level mean yields remained almost stable (−4%). Differently, POLY farms showed a mean stable trend of rice yields across 2018–2022, with a slight increase in 2022, compared to previous year (P farm conventionally managed cultivars are excluded from POLY mean yield calculation) (**Figure 7a**). Nonetheless, separated behaviours are detected among the three POLY farms: G farm (the one implementing the POLY model more strictly and long-term; see **Table 1**) shows a clear increase in mean rice yields going from 2020 to 2021 to 2022 (2022: +21%, compared to 2018–2021 mean). This suggests an increased adaptability capacity to climate anomality of the farm model. Differently, C farm shows a clear decrease in 2022 (−35%), which was balanced by other crops higher yields (millet +19%, black-eyed bean +86%). This highlights the role of crop diversification in building a robust farm adaptation strategy. P farm polyculture fields mean yield show a clear increase in 2022 (+22%), following the low-yield previous year and exceeding all yields of previous years (absence of continuity of other crops cultivation over the studied time frame did not allow to check for their yield trend). Orlando et al. 2020 study on organic farms belonging to the same context highlighted how farmers know-how is the most critical factor influencing yield variability, reflecting the need for site-specific agroecological practices customization [27]. Among POLY farms, G is the oldest in terms of conversion to the POLY model (more then 20 years), and this certainly contributed to site-specific POLY practices tuning (i.e., cultivars selection, cover crops and green manuring management, timely operations setting) coupled to soil health promotion depending on long-term cumulative processes [27].

With regard to site 1 (**Figure 7b**), ORG farms showed a quite stable (slight decrease) mean rice yield in 2022, with different performances of the two farms: A farm clearly increases (+20%), T farm slightly decreases (−6%), coupled to an increase in buckwheat yield (+75%). POLY and ORG farms 2022 mean rice yields are similar (respectively, 4.2 Mg/ha; 4.4 Mg/ha). Differently, CV farms experienced a decrease in 2022 mean rice yields, in line with regional and national trends (M: 5.1 Mg/ha, compared to 6.1 Mg/ha average yield; B: 6.9 Mg/ha, compared to 7.1 Mg/ha average yield). Other crops did not balance such loss: M farm 2022 soyabean yield decreased too, compared to previous years (**Figure 7b**).

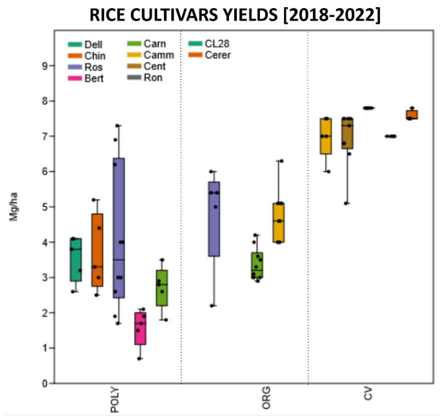

Figure 6. Selection of 2018-2022 yield values for those cultivars being repeated at least 4 consecutive years during the studied time frame, grouped for farm management models (POLY, ORG, CV). Included cultivars: Dell=Dellarole; Chin=Chinese; Ros=Rosa Marchetti; Bert=Bertone; Carn=Carnaroli; Camm=Cammeo; Cent=Centauro; Ron=Ronaldo; CL28=CL28; Cerer=Cerere.

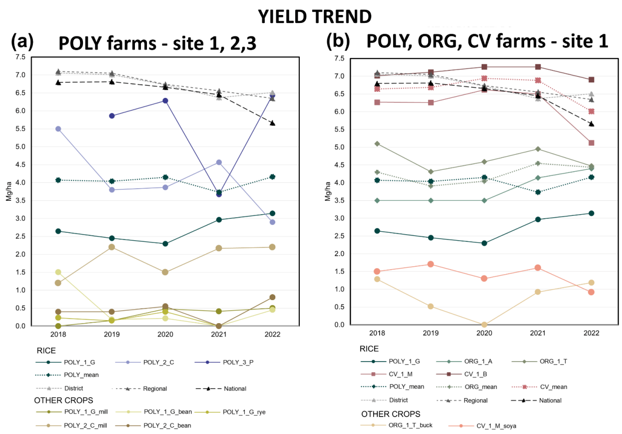

Figure 7. 2018-2022 rice and other crops yield trends of: (**a**) POLY farms (site 1 – POLY_1_G), site 2 -POLY_2_C, site 3 - POLY_3_P); (**b**) site 1 POLY (POLY_1_G), ORG (ORG_1_A, ORG_1_T) and CV (CV_1_M, CV_1_B) farms. In each graph, district, regional and national mean rice yield is reported.

3.3. Farms Response to Climate Change

3.3.1. Agricultural Practices Adaptations to Climate Anomality (2018–2022)

Table 7 resumes the adaptation on agricultural practices experienced by the studied farms, in consequence to 2022 climate anomality. Water sources scarcity was experienced by all farms, even though the access to private pit and reservoirs, added to consortium water, was a winning strategy, in that water provisioning was less affected (see C farm and ORG farms, **Table 7**). Among site 1, G POLY farm and the CV ones experienced the highest irrigation water shortage (−50%), ORG farms had lower shortages (−30%). All farms (except A farm) turned continuous flooding conditions to alternate flooding and drying ones due to water scarcity, with a noticeable reduction on rice field flooding length.

Table 7. Synthesis on the agricultural practice adaptations experienced by POLY, ORG and CV farms in consequence to 2022 climate anomality (X: Yes/applied; <: reduction in 2022; >: increase in 2022; ≈:no significant changes in 2022; n.d.: not determined).

	Time frame	USUAL [2018–2021]							2022						
	Sites	SITES 2-3			SITE 1 - ROVASENDA FARMS				SITES 2-3			SITE 1 - ROVASENDA FARMS			
	Model		POLY		ORG		CV			POLY		ORG		CV	
	Farm	C	P	G	A	T	M	B	C	P	G	A	T	M	B
WATER SOURCES	rivers/consortium ditches	X	X	X		X	X		<	<	<		<	<	
	private pit/floodgate	X		X					≈		≈	>	≈		
	consortium pit			X							≈				
	dike				X	X	X					<	>	>	
	private reservoir				X								>		
WATER USE	WATER SHORTAGE								-10%	X	-50%	-30%	-30%	-50%	-50%
	FLOODING LENGHT (months)	3.5	3	2.5	2	3.5	4	n.d.	3	1.5	1.5	2	2.5	2.5	n.d.
IRRIGATION TYPE	continuous flooding	X	X	X	X	X	X	X	X			X			
	alternate flooding and drying								X	X	X		X	X	X
YIELDS	Rice trend	≈	≈	>	≈	≈	≈	≈	<	>	>	<	<	<	<
	Other crops trend	>	≈	≈	n.d.	≈	<		>	n.d.	>	n.d.	>	<	

3.3.2. Yields Trends versus Climate Trends

Figure A1 (**Appendix A**) reports 2018-2022 trends of the rainfall and temperature variables selected to represent the 12 months prior to rice harvesting among each site. **Table 8** reports the results of correlation analysis run between each farm (site 1, 2, 3) and the climate variables. Only CV farms (M, B) registered significant correlation patterns. Both CV farms rice yields are strongly positively correlated to total rainfall of the 12 months prior to rice harvest (P_yr). That is, lower total rainfall tended to impair rice yields in CV farm. This relation is not found in POLY and ORG farms; the ones showing higher correlation coefficients (POLY_G and ORG_A farms) show an opposite trend (higher rice yield with lower P_yr), but this relationship is not significant (respectively, p(uncorr) = 0.24;0.50), suggesting other factors also contributed to higher 2022 rice yields (see **Figure 7**).

A similar pattern is evidenced for yield response to mean temperature of the hottest months (T_su): CV farms (B, M) are the only ones showing a significant, negative, correlation patterns, testifying for a dependence of rice yields on temperature behaviour (lower rice yield with higher mean temperature in the hottest months of the year). This dependence is not significant for POLY and ORG farms, but still POLY_G and ORG_A farms show the highest positive correlation coefficients, reflecting a higher adaptation capacity to higher mean temperatures in the hottest months. POLY_C and ORG_T farms show low and not significant correlation patterns. The following additional patterns are evidenced, although not significant from a statistical point of view and hence demanding further investigation: generally, POLY and ORG farms show negative correlation patterns to total rainfall during late season (P_au), coldest season (P_wi) and mid-season (P_sp) months, suggesting a lower sensitivity to rainfall shortage compared to CV farms; differently, rainfall shortage in the hottest months (P_su) is related to lower rice yields independently from farm management model, but correlation is low and this doesn't allow any inference; all farms show negative correlation coefficients to absolute maximum temperature; higher temperature in the hottest months (T_su) seems to have lower impact on POLY_G and ORG_A farms yields.

The most relevant patterns were further investigated through ordinary least square regression of farm mean year yield values as dependent variable (**Table 9**, **Figure 8**, **Figure A2 Appendix A**): P_sp, P_yr and T_su showed few significant relationships with sound model descriptive capacity (i.e. with coefficient of variation r2>0.6). CV farms yield positive relationship with P_sp

Table 8. Correlation analysis results between mean year rice yields and the rainfall and temperature variables representing the 12 months prior to rice harvesting: late season months rainfall (P_au); coldest months rainfall (P_wi); mid-season rainfall (P_sp); hottest months rainfall (P_su); annual rainfall (P_yr); absolute maximum temperature (T_M_abs); late season months mean temperature (T_au); coldest months mean temperature (T_wi); mid-season months mean temperature (T_sp); hottest months mean temperature (T_su); annual mean temperature (T_yr). *: p(uncorr)≤0.05; **: p(uncorr)≤0.01.

				Rainfall					Temperature					
SITE	MODEL	FARM	Correlation coefficient	P_au	P_wi	P_sp	P_su	P_yr	T_M_abs	T_au	T_wi	T_sp	T_su	T_yr
2	POLY	C	Linear r (Pearson)	0.43	0.48	0.73	−0.06	0.36	−0.72	0.21	−0.02	−0.10	−0.26	−0.48
2	POLY	C	p(uncorr)	0.4738	0.4118	0.1653	0.9224	0.5522	0.1717	0.7300	0.9730	0.8702	0.6756	0.4157
3	POLY	P	Linear r (Pearson)	−0.63	−0.45	−0.20	0.08	−0.26	−0.47	0.29	0.26	0.94	0.30	0.63
3	POLY	P	p(uncorr)	0.3720	0.5485	0.7954	0.9249	0.7416	0.5332	0.7103	0.7393	0.0551	0.7026	0.3669
1	POLY	G	Linear r (Pearson)	−0.78	−0.06	−0.73	0.35	−0.65	−0.23	0.30	0.01	−0.07	0.46	−0.36
1	POLY	G	p(uncorr)	0.1176	0.9197	0.1633	0.5670	0.2362	0.7118	0.6298	0.9812	0.9099	0.4370	0.5512
1	ORG	A	Spearman rs	−0.89	−0.22	−0.89	0.34	−0.45	−0.45	0.11	0.11	−0.11	0.45	−0.11
1	ORG	A	p(uncorr)	0.1000	0.8000	0.1000	0.6000	0.5000	0.5000	1.0000	1.0000	1.0000	0.5000	1.0000
1	ORG	T	Linear r (Pearson)	−0.13	−0.02	0.35	0.11	0.27	−0.41	0.23	0.57	0.09	−0.15	−0.80
1	ORG	T	p(uncorr)	0.8370	0.9777	0.5663	0.8643	0.6598	0.4965	0.7149	0.3131	0.8837	0.8097	0.1039
1	CV	M	Spearman rs	0.10	0.50	0.50	0.40	1.00	−0.60	−0.70	0.80	−0.30	−0.90	0.00
1	CV	M	p(uncorr)	0.9500	0.4500	0.4500	0.5167	0.0167*	0.2917	0.1833	0.1333	0.6000	0.0500*	1.0000
1	CV	B	Linear r (Pearson)	0.33	0.63	0.08	0.21	0.88	−0.58	−0.83	0.64	−0.57	−0.98	−0.29
1	CV	B	p(uncorr)	0.5894	0.2502	0.8969	0.7346	0.0472*	0.3090	0.0819	0.2400	0.3147	0.0038**	0.6391

and P_yr was confirmed but only P_yr model was significant and with reliable descriptive capacity for both CV farms ($r2=[0.74–0.78]$). This confirms the limited adaptation capacity of CV yields to rainfall shortage, the most influencing climate factor on rice yield for Po Plain district, as identified by Ray et al. study [30]. Considering the other site 1 farms, both POLY_G and ORG_A showed opposite P_sp and P_yr relationships to yields (negative slope of regression line): models are partially significant (respectively: p(slope)=0.086; 0.028) and have medium to high descriptive capacity (respectively, r2=0.53;0.81). ORG_T farm shows intermediate, not significant, patterns, suggesting a stronger dependence on factors others then rainfall. Concerning the hottest months temperature (T_su) influence on rice yields, still CV farms show a clear negative relationship, with higher T_su values being related to lower CV_M and CV_B yields (respectively, p(slope)=0.0595; 0.0038; and r2=0.66; 0.96). No significant regression models are found for the other farms, but still POLY_G and ORG_A show opposite patterns compared to CV farms, suggesting lower impacts on yields of higher T_su, if compared to CV farms. Still ORG_T farm shows intermediate (not significant) patterns, as well as POLY_C and POLY_P farms.

3.4. Economic Performance

The business structure of POLY, ORG and CV farms varies significantly, depending on different cost types, incomes diversification and selling strategies (ratio of wholesale, direct sale, unsold) (**Figure 9a**); this influences the economic performance of the three management models, which only partly depends on yields. In POLY farms (excluding P farm, still under transition) seed production costs are partly substituted by seed auto-production costs (from 14% to 16% of total costs), and a portion varying from 7% to 18% of total costs is covered by cover crops seeds costs, which represent an agri-environmental investment on farm natural capital (soil health). Parallelly, fertilizers, pesticides and herbicides costs are null in POLY farms (excluding P farm, which represent a mixed strategy, with 12% of costs covering herbicides purchase). Differently, ORG farms invest from 2% to 12% in fertilizers, with one farm also covering a 5% of pesticides costs. In CV farms, fertilizers, pesticides and herbicides cover from 45% to 60% of total costs (higher than P farm, which covers 35% of total costs for external inputs). Fuel and lubricants costs portion do not significantly change between the three models (with the exception of A ORG farm). Incomes mainly consist in crop selling; among POLY farm, a portion is also made of electricity production and crop residues selling (G farm, which represents the most diversified business structure). The ratio of direct selling (absent in CV farms and in the P one) varies from 24% to 88% in POLY farms, from 30% to 70% in ORG ones. An unsold portion is reported in T ORG farm, representing yields occasionally re-adapted to agri-environmental functions (soil improvement through crop residues reincorporation to soil).

Table 9. Results of Ordinary Least Square regression run on farm mean year yield values as dependent variables and summer mean temperature (T_su), spring total rainfall (P_sp) and total year rainfall (P_yr) as independent variables. In bold: p(slope)<0.05; r2>0.6. *: p(uncorr)≤0.05; **: p(uncorr)≤0.01.

				REGRESSION						RESIDUALS			
SITE	MODEL	FARM	CLIMATE VARIABLE	Slope a	Std. error a	Intercept b	Std. error b	p (slope)	r2	p (no pos. Autocorr.)	p (homoskedasticity)	Shapiro-Wilk W	p (normal)
2	POLY	C	P_sp	0.010	0.004	2.39	0.761	0.0864	0.53	0.9946	0.7180	0.94	0.648
3	POLY	P	P_sp	−0.010	0.007	7.33	1.159	0.2854	0.04	1.0000	0.4274	0.93	0.630
1	POLY	G	P_sp	−0.003	0.001	3.32	0.272	0.0857	0.53	0.3320	0.0392	0.91	0.479
1	ORG	A	P_sp	−0.004	0.001	4.57	0.209	0.0282*	0.81	0.5715	0.0636	0.98	0.939
1	ORG	T	P_sp	0.003	0.002	4.10	0.359	0.1619	0.12	0.4610	0.3453	0.98	0.950
1	CV	M	P_sp	0.005	0.003	5.09	0.580	0.1342	0.28	0.4943	0.8725	0.98	0.947
1	CV	B	P_sp	0.001	0.001	6.83	0.188	0.1806	0.01	0.1557	0.4573	0.96	0.826
2	POLY	C	P_yr	0.006	0.003	0.52	2.002	0.1604	0.13	0.8196	0.0365	0.86	0.220
3	POLY	P	P_yr	−0.004	0.003	8.66	1.997	0.2808	0.07	1.0000	0.1275	0.90	0.392
1	POLY	G	P_yr	−0.002	0.001	4.27	0.701	0.1073	0.42	0.6067	0.9243	0.99	0.968
1	ORG	A	P_yr	−0.003	0.001	5.73	0.973	0.1370	0.26	0.3185	0.5433	0.94	0.664
1	ORG	T	P_yr	0.002	0.001	3.21	0.842	0.1698	0.07	0.5618	0.1329	0.96	0.813
1	CV	M	P_yr	0.004	0.001	3.48	0.793	0.0417*	0.74	0.8716	0.5896	0.90	0.383
1	CV	B	P_yr	0.001	0.000	6.40	0.195	0.0345*	0.78	1.0000	0.1347	0.87	0.247
2	POLY	C	T_su	−1.030	0.575	29.72	14.287	0.1709	0.07	0.2441	0.6966	0.92	0.537
3	POLY	P	T_su	0.926	0.625	−16.08	14.797	0.2767	0.09	1.0000	0.3361	0.86	0.236
1	POLY	G	T_su	0.409	0.210	−6.71	4.828	0.1464	0.21	0.3555	0.3920	0.89	0.361
1	ORG	A	T_su	0.502	0.279	−7.74	6.421	0.1699	0.07	0.2113	0.5746	0.95	0.758
1	ORG	T	T_su	−0.386	0.220	13.56	5.069	0.1781	0.02	0.4169	0.8982	0.97	0.896
1	CV	M	T_su	−0.698	0.236	22.19	5.420	0.0595	0.66	0.1123	0.1530	0.88	0.322
1	CV	B	T_su	−0.181	0.022	11.26	0.508	0.0038**	0.96	0.9160	0.7080	0.53	0.271

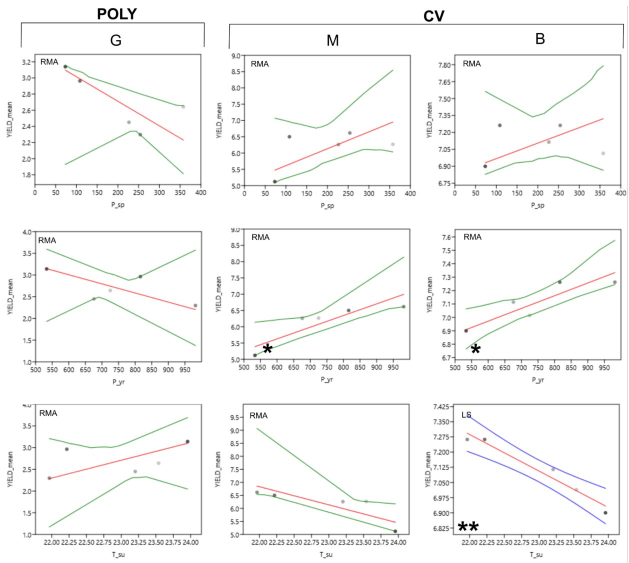

Figure 8. Site 1 G POLY farm and CV farms (M, B): Ordinary Least Squares Regression run on mean year rice yield (2018–2022) as dependent variable; summer mean temperature (T_su), spring total rainfall (P_sp) and total year rainfall (P_yr) as independent variables. RMA=Reduced Major Axis algorithm; LS=Ordinary Least Square algorithm; green line=95% bootstrapped confidence intervals (N=1999); blue line=95% regression confidence intervals; *=p<0.05; **=p<0.01.

Considering site 1 data, the ratio of variable costs (VC1: fuels, lubricants, pesticides, herbicides, fertilisers, seeds) is lower in POLY model, and increases from ORG to CV model (**Figure 9b**). Site 1 and 2 POLY farms similarly show low values, whereas the mixed P farm (site 3) is close to ORG farms (site 1) values. When considering the total variety of costs covered by the diversified POLY and ORG models (VC3: VC1 costs plus irrigation water fees, storage costs, residues management costs, electricity, harvest in-farm transformation costs), POLY model still shows the best performance (lower costs ratio), whereas ORG farms costs exceed the CV model ones due to the high ratio of in-farm transformation costs (not included in the intermediate VC2). The gross margin indicator (GM1) reflects the higher efficiency of the POLY model, both among site 1 farms and when including site 2 POLY farm. P farm (site 3) has a similar performance to the ORG farms; CV farms have the lowest GM1 ratio (**Figure 9b**). The same pattern (with lowered differences between models) is found when considering the total variety of costs covered by the diversified POLY and ORG models (GM2 and GM3, the latter also including harvest in-farm transformation costs), with the only difference of ORG model showing lower performance than the CV one in GM3 due to in-farm transformation costs. The efficiency indicator (EF) reflects the same patterns (**Figure 9b**). Among site 1, the farm economic efficiency (EF1: ratio between gross income and variable costs) in the highest in POLY model, also when considering the total variety of costs (EF2; EF3). A decreasing trend is highlighted going from POLY to ORG to CV. POLY mean values (sites 1,2) have the highest EF1-EF2-EF3 values too, which decrease in the farm P (site 3) POLY farm mixed model. ORG model efficiency decreases when considering the total variety of costs (EF3: ORG values lower than CV ones).

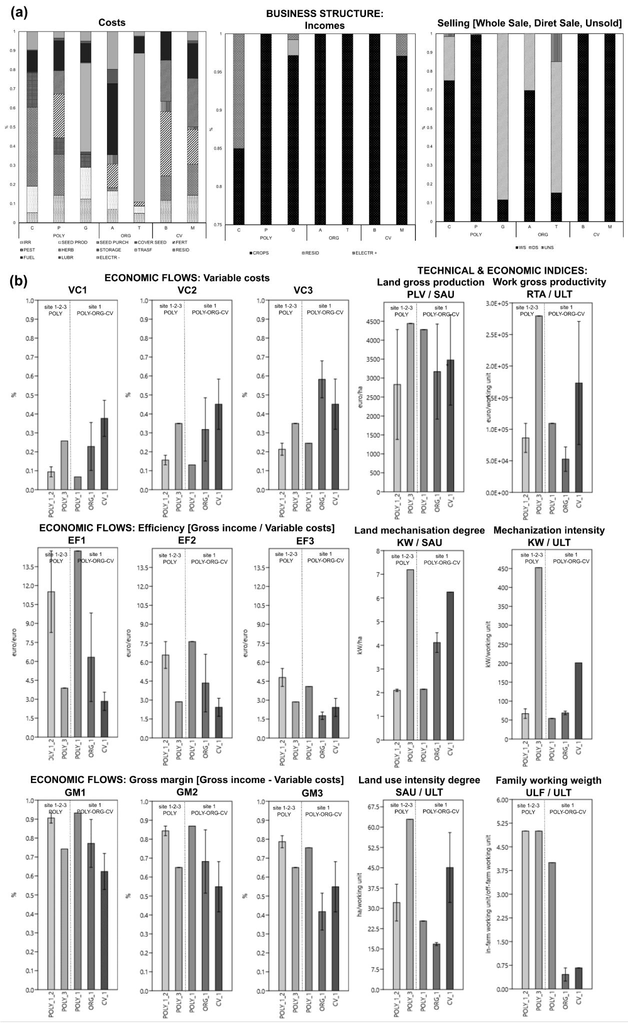

Figure 9. Results on the economic performance indicators. (**a**) cost types, income types and selling types ratio. (**b**) Economic flows indicators: variable costs (VC1, VC2), Efficiency (EF1, EF2), Gross margin (GM1, GM2); technical and economic indicators: land gross production (PLV/SAU), work gross productivity (RTA/ULT), land mechanisation degree (KW/SAU), Mechanisation intensity (KW/ULT), land use intensity degree (SAU/ULT), family working weight (ULF/ULT).

The technical and economic indices show a higher performance, among site 1, of the POLY model land gross production (PLV/SAU; €/ha), whereas the work gross productivity (RTA/ULT; €/working unit) is the highest in CV model, followed by POLY and then ORG (**Figure 9b**). Site 2 C POLY farm lowers the POLY mean land gross production (i.e., a significant variability is detected between POLY farms). Land mechanisation degree (kW/SAU; kW/ha) and mechanisation intensity (kW/ULT; kW/working unit) are the highest in CV model and the lowest in POLY model, reflecting the lower dependence on machinery of the POLY model (less treatments and lighter soil management). Land use intensity degree (SAU/ULT; ha/working unit) is the highest in the wider scale and highly mechanized CV model, whereas family working weight (ULF/ULT; in-farm working units/off-farm working units) clearly distinguishes the POLY model from the other ones, which rely the most on in-farm working units (**Figure 9b**).

These data offer a synthetic overview on the sustainability components of the POLY model, compared to ORG and CV ones, highlighting possible pathways sustaining the economic balance of such a diversified farm management model, which relies on investments on farm natural capital which are sustained thanks to higher business model efficiency (higher land profitability), based on reduced off-farm resources use (external inputs, machinery-related costs), in-farm resources valorisation, and high-quality products. Such a business model does not provide increased land productivity (yield/ha), but whilst guaranteeing a farm economic viability it addresses pivotal agri-environmental issues which deal with medium-long term food supply securing through the capacity to mitigate and adapt to the changing climate and environmental conditions. In this analysis, we purposely excluded external funding (CAP, rural development program, etc.), in that our aim was to specifically address in-farm economic sustainability components of crop production, to complement the assessment on adaptation capacity to climate change of the three studied farm models. Obviously, this analysis excludes wider investments on farm natural capital (such as agroforestry and landscape features management), which are generally covered by public funding.

4. Conclusions

Our study, despite being time and space limited (Po Plain, western northern Italy), complements the in-building knowledge framework on the possible role of the organic and polyculture rice farm management in building adaptive strategies for climate change. Despite the significantly lower absolute yields, compared to the conventional ones, ORG and POLY farms showed a better adaptation capacity to the 2022 extreme climate event. Climate change projections forecast an increase in mean temperature and a decrease in rainfall for the studied region by 2050 [34, 35], intensifying current trends, which were confirmed among the studied sites. In the Po Plain, projected climate change impacts will be strictly interweaved with the ongoing environmental crisis, exacerbating the current impairment of agricultural land ecosystem services delivering capacity. This raises the need for multi-spectra solutions from the agricultural sector. Organic agriculture and, further more, integrated farm models targeting multiple ecosystem services, such as the POLY model [48], can play a major role in balancing such impacts, whilst guaranteeing farm economic sustainability. Our study testified for a positive response of POLY model to weather negative trends and extreme climate events (2022 aridity and extreme high temperature), highlighting the variable response of different cultivars and the role of crop and cultivar diversification (which acts as an insurance towards climate unpredictability). Such traits were not recognized on CV farms, suggesting a higher dependence on weather instability. This was also confirmed by yields regression on 2018–2022 climate data, which highlighted a significant positive relation between total precipitation of the 12 months before harvest (CV yields decreasing with rainfall shortage); and a significant negative relation between summer mean temperature (CV yields being significantly affected by summer mean temperature increase). This relation was not significant when considering POLY or ORG yields, reflecting a lower sensitivity to climate instability of these farm management models, compared to the CV ones. Even if not significant from a statistical point of view, the opposite trend detected for G farm is illustrative. Indeed, G farm is the one managed under POLY model for the longest term, and it showed increasing mean rice yields with decreasing annual rainfall and increasing mean summer temperature. From an economic perspective, POLY farms showed best performance, when considering economic flows efficiency indicators, thanks to the business structure based on lower machinery and external inputs costs, in-farm resources valorisation, higher incomes diversification and mixed selling strategies (direct sale/wholesale ratio). These business strategies can complement and balance the investment on natural capital associated to the POLY model (agri-environmental practices based on the support of the health of the agroecosystem health, its agrobiodiversity, and soil health), which leads to lower yields but parallelly addresses social and economic issues of public domain (i.e., the agricultural land capacity to mitigate and adapt to the changing climate and environmental conditions and consequently to long-term delivering ecosystem services to the human society). Obviously, POLY and ORG farms performance could not sustain current rice production demand for the Po Plain basin, due to lower absolute yield per surface unit. Nonetheless, they should be part of an integrated strategy to parallelly address environmental and climate change related impacts. The here-presented study offered some new context-specific highlights on such roles and might positively be integrated by wider-scale assessments, involving more farms belonging to similar territorial contexts.

Author Contributions

Conceptualization, I.V. and G.C.; methodology, I.V. and G.C.; software, G.C.; validation, I.V. and G.C.; formal analysis, G.C.; investigation, G.C.; resources, G.C.; data curation, G.C.; writing—original draft preparation, I.V. and G.C.; writing—review and editing, I.V. and G.C.; visualization, I.V.; supervision, I.V.; project administration, I.V. All authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The datasets generated during and/or analysed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

Appendix A

Table A1. Descriptive statistics of yield values (2018–2022) of POLY (site 1, 2, 3), ORG (site 1) and CV (site 1) farms; first by grouping all POLY farms values (G, C, P) and then by separating the values of the P POLY farm conventionally managed fields, partly still under transition to the POLY model (POLY_CV).

	ALL POLY FARMS GROUPED (G, C, P)			SEPARATED POLY FARM UNDER TRANSITION (P_CV)			
	POLY	ORG	CV	POLY	POLY_CV	ORG	CV
N	49	27	67	41	8	27	67
Min	0.68	2.18	4.45	0.68	1.73	2.18	4.45
Max	7.76	6.25	9.10	7.30	7.76	6.25	9.10
Mean	3.90	4.35	6.70	3.50	5.96	4.35	6.70
Standard error	0.27	0.22	0.11	0.26	0.65	0.22	0.11
Variance	3.61	1.27	0.77	2.72	3.42	1.27	0.77
Standard deviation	1.90	1.13	0.88	1.65	1.85	1.13	0.88
Median	3.50	4.20	6.80	3.00	6.62	4.20	6.80
25 percentil	2.43	3.32	6.20	2.26	5.45	3.32	6.20
75 percentil	5.78	5.38	7.50	4.32	6.80	5.38	7.50
Skewness	0.42	−0.06	−0.34	0.68	−2.06	−0.06	−0.34
Kurtosis	−1.05	−1.08	0.29	−0.32	4.80	−1.08	0.29

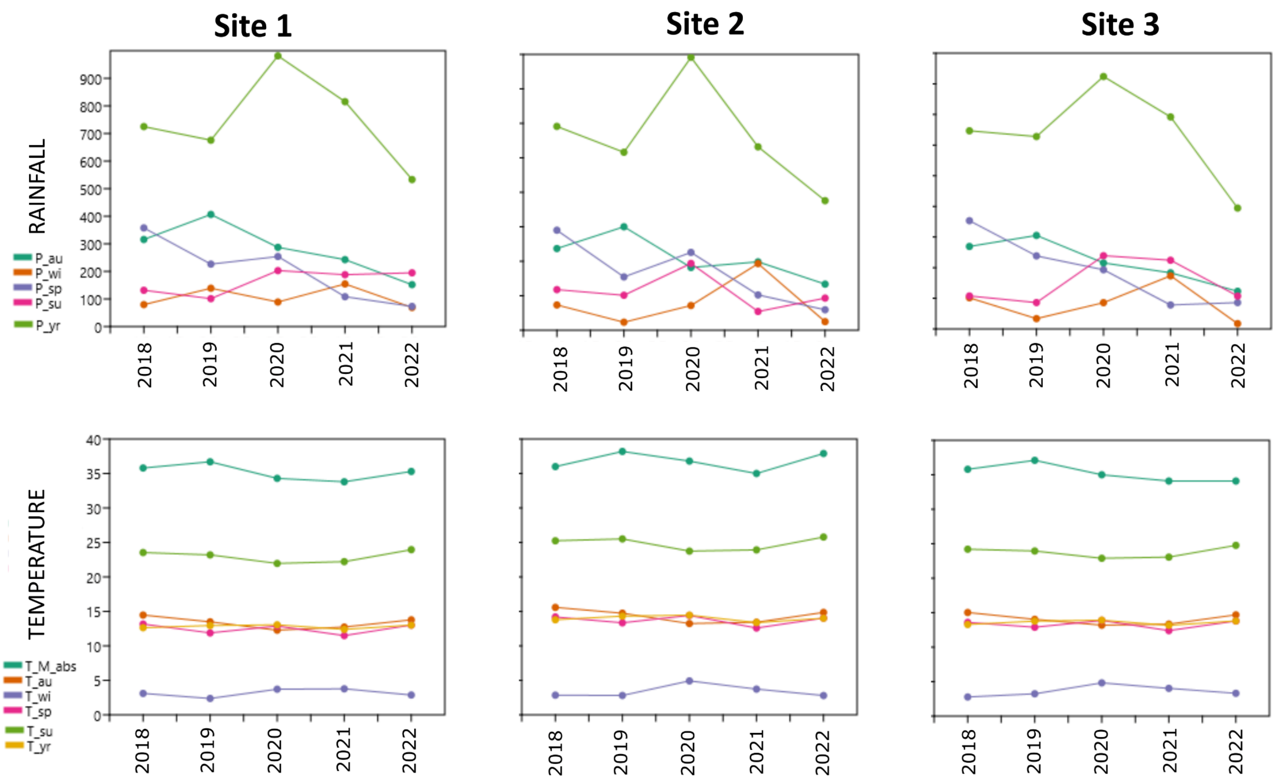

Figure 10. 2018–2022 trends of the rainfall and temperature variables selected to represent the 12 months prior to rice harvesting: late season months rainfall (P_au); coldest months rainfall (P_wi); mid-season rainfall (P_sp); hottest months rainfall (P_su); annual rainfall (P_yr); absolute maximum temperature (T_M_abs); late season months mean temperature (T_au); coldest months mean temperature (T_wi); mid-season months mean temperature (T_sp); hottest months mean temperature (T_su); annual mean temperature (T_yr).

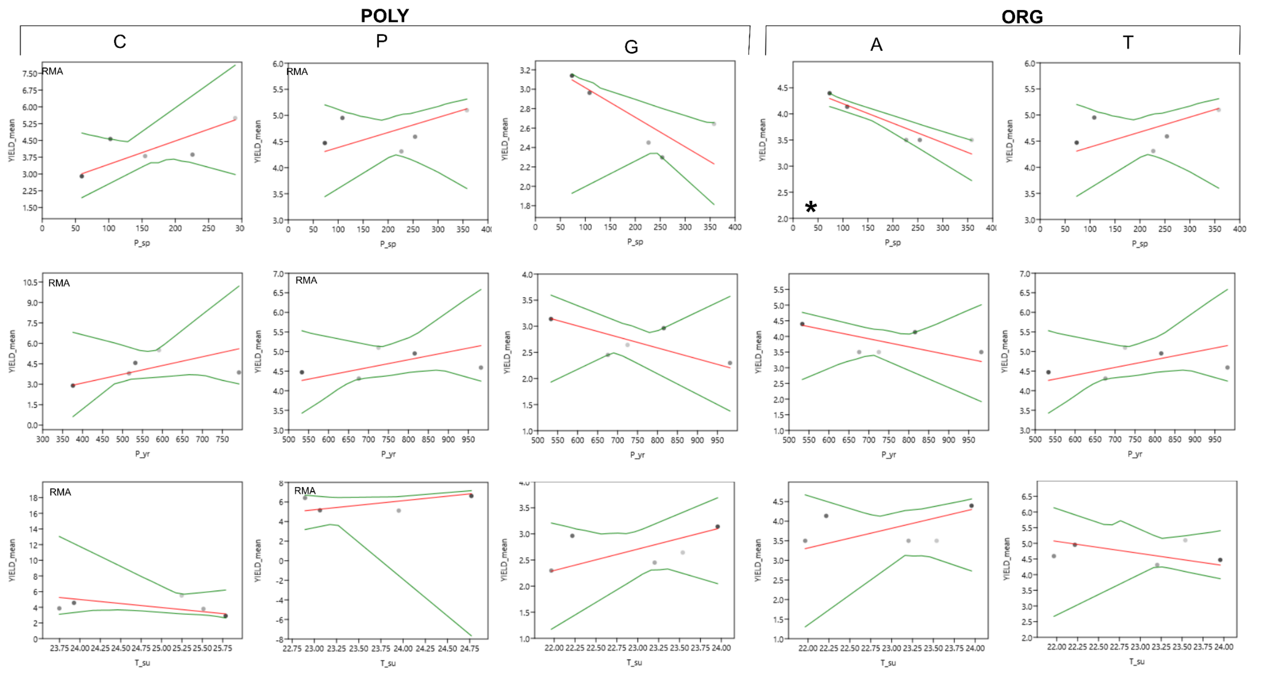

Figure 11. Ordinary Least Squares Regression run on POLY (C, P, G) and ORG (A, T) farms mean year rice yield (2018-2022) as dependent variable, summer mean temperature (T_su), spring total rainfall (P_sp) and total year rainfall (P_yr) as independent variables. RMA= Reduced Major Axis algorithm; LS= Ordinary Least Square algorithm; green line= 95% bootstrapped confidence intervals (N=1999); blue line= 95% regression confidence intervals; *=p<0.05.

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