



# Evaluation of policies for enhancing sustainable wheat production in Italy

Work Package 2: Model development  
**Deliverable D1**

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## Modeling Italian Wheat System

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# Modeling Italian Wheat System

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## Executive Summary

This report presents the results of Task 2.2 of the ECOWHEATALY project, which develops the microeconomic modelling framework used to represent the Italian wheat production system within the project's simulation architecture. The objective of this task is to construct a farm-level model capable of reproducing the observed heterogeneity of Italian wheat farms and to provide a scalable representation of the sector suitable for integration with the global market model developed in Task 2.1.

The modelling approach follows the agent-based computational economics paradigm, in which aggregate outcomes emerge from the decentralized decisions of heterogeneous agents. In this context, individual farms are represented as economic agents that make production decisions under technological, economic, and policy constraints.

The core of the model is a static microeconomic optimization problem in which farms choose input levels in order to maximize profits given market prices and production technologies. Crop yields are modeled as a function of complementary production inputs, allowing the model to capture the interaction between fertilizers, other production factors, and agronomic conditions. The solution of this optimization problem provides the optimal input use and expected yield for each farm type.

The parameters of the production function and cost structure are estimated using farm-level microdata from the RICA/FADN database. To ensure consistency with the structural characteristics of the Italian agricultural system, these estimates are complemented with information derived from the 2020 ISTAT agricultural census. The census data are used to construct a synthetic population of farms that reproduces the empirical distributions of farm size, yields, and input intensities observed in Italian wheat production.

An additional feature of the model is the introduction of behavioral heterogeneity through an environmental awareness component. This extension allows the model to represent the possibility that farmers may partially account for environmental impacts when making production decisions, thereby providing a mechanism through which environmental policies can influence farm behaviour.

Overall, Task 2.2 establishes the microeconomic foundation of the ECOWHEATALY modelling framework. By combining profit-based decision rules, empirically estimated production parameters, and realistic structural heterogeneity, the model provides a detailed representation of the Italian wheat production system that can be used for policy simulations and environmental impact analysis.

# 1 Objective and Conceptual Framework

The objective of Task 2.2 report is to document the modeling strategy used to represent the Italian wheat production system at the micro level and to scale it up to the sectoral level while preserving empirically observed heterogeneity. The core idea is to start from a microeconomic description of an individual farm—grounded in profit maximization under agronomic and economic constraints—and then construct an ensemble of heterogeneous farms such that the simulated population reproduces key structural and technological features of Italian wheat production (e.g., dispersion in yields, input intensities, and farm size patterns). This approach is motivated by the well-known limitation of representative-farm models in contexts where policy impacts are heterogeneous and non-linear, especially when environmental instruments target specific inputs or practices.

Methodologically, the framework follows the agent-based computational economics paradigm, which studies aggregate outcomes as emergent properties of decentralized decision-making by heterogeneous agents interacting within a defined institutional environment [Tesfatsion \(2006\)](#); [Tesfatsion and Judd \(2006\)](#). In the agricultural domain, agent-based models have been widely used to assess policy interventions, structural change, and technology diffusion in the presence of heterogeneous farm structures and spatial or market constraints [Happe et al. \(2006\)](#); [Berger \(2001\)](#). These contributions highlight that modeling farm heterogeneity is not only a descriptive improvement but also a necessary condition for credible policy evaluation when responses depend on farm-specific cost structures, production technologies, and local constraints.

In ECOWHEATALY, the Italian wheat system component is therefore constructed as a micro-founded farm model enriched with empirically calibrated heterogeneity. The farm-level module provides (i) a transparent mapping from prices and policy instruments to optimal input choices and yields, and (ii) a disciplined way to interpret environmental policies as modifications of incentives and constraints at the farm level. The heterogeneity layer then ensures that aggregate simulated outcomes are consistent with the empirical distribution of farm types, rather than being driven by an average or representative behavior.

A further objective of this report is to clarify the empirical grounding of the Italian module. Parameter values entering the microeconomic farm model are estimated using Italian farm accounting microdata (RICA/FADN) and structural information from the 2020 agricultural census (ISTAT). The RICA survey is the harmonized European source for farm management and economic variables, coordinated in Italy by CREA [CREA-RICA \(2026\)](#). The ISTAT agricultural census provides a comprehensive picture of the structure of Italian agricultural holdings at the national and sub-national level [ISTAT \(2026\)](#). Together, these sources support both the estimation of technological and behavioral parameters and the construction of a synthetic farm population aligned with the observed Italian production system.

To improve clarity and replicability, the model documentation in the following sections is organized according to standard best practices in agent-based modeling, emphasizing transparent specification of entities, state variables, decision rules, and initialization procedures. In this respect, the Overview–Design concepts–Details (ODD) protocol provides a widely used reference standard for communicating ABMs in a structured and reproducible way [Grimm et al. \(2010\)](#).

The modeling strategy unfolds in three steps. First, we introduce a simple microeconomic framework grounded in static profit maximization. At this stage, each farm is modeled as solving a standard economic problem in which output is determined by

agronomic constraints and input choices respond to prices and technological parameters. This static formulation provides a clear analytical structure linking prices, costs, and optimal input decisions. It also allows us to identify target yield levels and corresponding optimal input combinations under different economic scenarios.

Second, we introduce farm heterogeneity in a systematic and empirically grounded manner. Using farm-level microdata from the Italian RICA (FADN) database and structural information from the 2020 ISTAT agricultural census, we estimate technological parameters at the provincial level and perform a clustering procedure to identify distinct farm types. The resulting parameter distributions enable the construction of a synthetic population of farms that reproduces observed differences in production conditions, yield dispersion, and structural characteristics. This step ensures that aggregate outcomes emerge from a heterogeneous ensemble of agents rather than from a representative-farm abstraction.

Third, we extend the baseline microeconomic model to incorporate an environmental awareness parameter. This extension allows farms to depart from pure profit maximization and to internalize environmental considerations in their decision-making process. The introduction of this behavioral dimension is crucial for the analysis of green policies and sustainability-oriented interventions, as it permits modeling differentiated responses to environmental regulation and incentives.

Methodologically, the framework is aligned with the agent-based computational economics paradigm, where aggregate outcomes arise from decentralized decisions by heterogeneous agents interacting within a defined economic and institutional environment [Tesfatsion \(2006\)](#); [Tesfatsion and Judd \(2006\)](#). In the agricultural context, agent-based approaches have proven particularly suitable for studying policy impacts and structural adjustment processes in heterogeneous farm populations [Berger \(2001\)](#); [Happe et al. \(2006\)](#). The present model follows this tradition while maintaining a transparent microeconomic foundation and explicit empirical calibration.

Finally, consistent with best practices in agent-based modeling, the following sections describe in detail the entities, state variables, decision rules, calibration procedures, and heterogeneity mechanisms used to construct the Italian wheat system module, following structured documentation standards such as the ODD protocol [Grimm et al. \(2010\)](#).

## 2 Static Microeconomic Farm Model

We begin with a static representation of the wheat-producing farm. The farm is assumed to operate at the hectare level and to choose input levels in order to maximize current-period profit. Inter temporal considerations are abstracted from at this stage in order to isolate the technological and economic mechanisms governing input choice and yield formation. Hereafter, we will give the essentials of the model. A full detailed version is reported in [Appendix B](#).

### 2.1 Profit Maximization Problem

Let  $x_i$  denote the quantity per hectare of input  $i = 1, \dots, I$ , and let  $p_{x_i}$  be its price. Wheat is sold at price  $p_w$ , which is taken as exogenous at the farm level. Profit per hectare is defined as

$$\pi = p_w y(x_1, \dots, x_I) - \sum_{i=1}^I p_{x_i} x_i. \quad (1)$$

The key modeling choice concerns the specification of the production technology  $y(\cdot)$ .

## 2.2 Complement-Input Yield Structure

Each input is interpreted as mitigating a specific stress factor affecting production (e.g., nitrogen deficiency, weed pressure, insect damage). The model assumes that each input alleviates only one stress factor and that stress factors are technologically non-substitutable. In economic terms, inputs are treated as complements.

For each stress factor  $i$ , define the conditional yield:

$$y_i(x_i) = \bar{y}(1 - s_i) + \bar{y}s_i (1 - e^{-\lambda_i x_i}), \quad (2)$$

where:

- $\bar{y}$  is the attainable yield under full stress control,
- $s_i \in (0, 1)$  is the proportional yield loss associated with stress  $i$  in the absence of treatment,
- $\lambda_i > 0$  measures the effectiveness of input  $i$ .

The functional form implies diminishing marginal productivity of each input and a saturation level at  $\bar{y}$ .

Because stress factors are complements, realized yield is determined by the most binding constraint:

$$y = \min_{i=1, \dots, I} \{y_i(x_i)\}. \quad (3)$$

This “minimum” structure captures the agronomic idea that insufficient control of a single stress factor limits overall production, regardless of the level of other inputs.

## 2.3 Solution Strategy

The complement structure allows solving the problem in two stages.

First, define a common target yield  $\hat{y}$  such that for all  $i$ :

$$y_i(x_i) = \hat{y}. \quad (4)$$

Solving for input demand as a function of the target yield yields:

$$\hat{x}_i(\hat{y}) = -\frac{1}{\lambda_i} \ln \left( 1 - \frac{\hat{y} - \bar{y}(1 - s_i)}{\bar{y}s_i} \right). \quad (5)$$

Substituting these expressions into the profit function gives a reduced-form problem depending only on  $\hat{y}$ :

$$\pi(\hat{y}) = p_w \hat{y} - \sum_{i=1}^I p_{x_i} \hat{x}_i(\hat{y}). \quad (6)$$

The optimal target yield  $\hat{y}^*$  solves:

$$\hat{y}^* = \arg \max_{\hat{y} \in [y_{\min}, \bar{y}]} \pi(\hat{y}), \quad (7)$$

where  $y_{\min} = \bar{y}(1 - s_i)$  represents the minimum achievable yield when a stress factor is untreated.

The optimal input mix is then obtained by evaluating  $\hat{x}_i(\hat{y}^*)$ .

## 2.4 Economic Interpretation

This formulation separates technological constraints from economic optimization. The “min” structure ensures that production is limited by the weakest controlled stress factor, while the exponential response functions guarantee smooth marginal adjustments. Changes in output prices or input prices affect the optimal target yield  $\hat{y}^*$ , which in turn determines the complete vector of optimal input intensities.

Importantly, the static structure provides a transparent benchmark against which the effects of shocks, policies, and behavioral extensions can be evaluated in subsequent sections.

## 3 Parameter Estimation from RICA Data

This section describes the estimation strategy used to calibrate the parameters of the static microeconomic farm model. The objective is to estimate input–yield response relationships for a set of key wheat inputs using Italian farm microdata (RICA/FADN), while preserving geographic and structural heterogeneity. The empirical strategy follows the logic of yield-gap and frontier-based estimation: observed yield outcomes reflect both the response to inputs and a variety of unobserved limiting factors, so the agronomic input response is most appropriately identified from the upper envelope of the yield–input relationship rather than from the conditional mean [Food and Agriculture Organization of the United Nations \(FAO\) \(2015\)](#). This idea is illustrated by the canonical response pattern in [Figure 1](#): yield increases with input use but saturates, while many observations lie below the attainable response due to other constraints [Hochman et al. \(2013\)](#).

### 3.1 Inputs and Data Integration

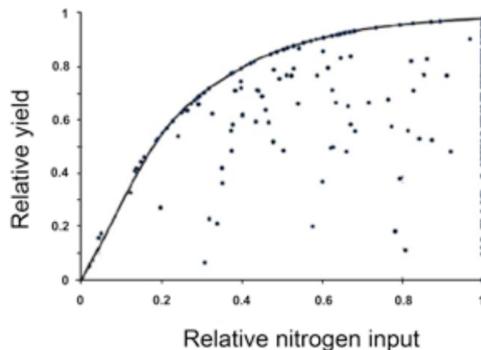
We focus on three production inputs available in distinct RICA tables: (i) nitrogen from fertilizers, (ii) herbicides, and (iii) insecticides. For each farm-year observation, these variables are matched to wheat yield (per hectare) and to the relevant structural descriptors used for stratification. The estimation is performed separately for each input dimension, consistent with the technological interpretation adopted in [Section 2](#): each input mitigates a specific stress factor and has a saturating effect on yield.

### 3.2 Functional Form and Parameters

For each input  $x_i$  (nitrogen, herbicides, insecticides), the model adopts a saturating response function consistent with the microeconomic framework:

$$y_i(x_i) = y_{\min,i} + \Delta y_i (1 - e^{-\lambda_i x_i}), \quad (8)$$

FIGURE 27  
**Normalised relationship between yield and nitrogen input for 334 wheat crops in Australia. The solid line is a nitrogen-response curve representing the upper limit of the relationship.**



Source: Hochman et al. (2013).

Figure 1: Illustrative yield–input response with an upper-envelope frontier (solid line). Many observations lie below the frontier due to other limiting factors. Source: Hochman et al. (2013), reproduced in Food and Agriculture Organization of the United Nations (FAO) (2015).

where  $y_{\min,i}$  is a baseline yield level when the stress factor is untreated,  $\Delta y_i$  is the attainable yield gain attributable to controlling stress  $i$ , and  $\lambda_i > 0$  is an effectiveness parameter controlling curvature. In the notation of Section 2, the mapping is  $y_{\min,i} = \bar{y}(1 - s_i)$  and  $\Delta y_i = \bar{y}s_i$ .

### 3.3 Frontier (Upper-Envelope) Estimation Rationale

A direct regression of yield on input use typically underestimates technological response because a large share of observations is affected by constraints unrelated to the input under consideration (e.g., weather, soil quality, management, pests not covered by the input, liquidity constraints). Therefore, following the yield-gap methodology, the response curve is identified from high-performing observations representing the upper bound of the yield–input relationship Food and Agriculture Organization of the United Nations (FAO) (2015). Operationally, the estimation targets the observations that lie close to the upper envelope of the scatter plot, in the spirit of the solid curve shown in Figure 1 Hochman et al. (2013).

### 3.4 Cascade Estimation Across Spatial Scales and Altimetry

To incorporate spatial heterogeneity while ensuring statistical feasibility, parameters are estimated through a hierarchical cascade with fallback rules. Estimation strata are defined by the cross-classification of geography and altimetry. Altimetry is grouped into three levels: *mountain*, *hill*, and *flat*. The cascade proceeds as follows:

1. **National × altimetry.** Data are pooled at the national level and stratified by altimetry. Parameters  $(y_{\min,i}, \Delta y_i, \lambda_i)$  are estimated separately for each altimetry

class.

2. **Regional × altimetry.** The same estimation is then attempted for each Italian region within each altimetry class. If the estimation for a specific region–altimetry cell is infeasible (e.g., insufficient observations or failure to identify a stable frontier), the corresponding parameters are replaced by the national estimate for the same altimetry class.
3. **Provincial × altimetry.** Finally, estimation is attempted at the province–altimetry level. If infeasible, parameters are replaced by the corresponding region–altimetry estimate; if that is also unavailable, the procedure falls back to the national altimetry estimate.

This cascade ensures that (i) the model uses the most granular feasible parameterization, while (ii) maintaining complete parameter coverage across the Italian territory. The result is a coherent set of technological parameters that vary by province and altimetry whenever supported by data, but remain anchored to broader aggregates when local estimation is unreliable.

### 3.5 Practical Identification of the Upper Envelope

Within each estimation cell (e.g., a given province and altimetry class), the upper envelope is identified using a frontier selection step consistent with yield-gap practice [Food and Agriculture Organization of the United Nations \(FAO\) \(2015\)](#). In practical terms, candidate frontier observations are selected as those forming the upper boundary of the yield–input scatter plot (i.e., “high-yield for given input” points). Parameters in 8 are then obtained by minimizing the squared distance between observed yields and the response curve over the selected frontier points:

$$\min_{y_{\min,i}, \Delta y_i, \lambda_i} \sum_{j \in \mathcal{F}} [y_{ij} - (y_{\min,i} + \Delta y_i (1 - e^{-\lambda_i x_{ij}}))]^2, \quad (9)$$

where  $\mathcal{F}$  denotes the set of frontier observations within the cell. Estimated parameters are then mapped to the structural microeconomic model described in Section 2.

### 3.6 Outputs for the Simulation Model

The outcome of the estimation stage is a set of input-specific response parameters indexed by geography and altimetry. These parameters define the technological response functions used by farm agents in the static microeconomic module, and they provide the basis for introducing empirically grounded heterogeneity across Italian farms in the subsequent sections.

## 4 Structural and Demographic Heterogeneity from the ISTAT 2020 Census

While the RICA-based estimation described in Section 3 identifies technological response parameters, a further level of heterogeneity is introduced using microdata from the 7th Italian Agricultural Census (2020). Access to census microdata was granted

through the ISTAT ADELE Laboratory within the ECOWHEATALY project framework [Di Giuseppe et al. \(2025\)](#).

The objective of this additional analysis is to reproduce the structural composition of Italian durum wheat-producing farms, including farm size distribution, wheat-dedicated area, and demographic characteristics of farm managers. These elements are crucial for initializing the agent-based model with a population that matches the real distribution of farms across Italian territory.

## 4.1 Data Sources and Population

Two census datasets were used to build a framework of the Italian durum wheat cropping system:

- **Census of land localization** ("Censimento localizzazione terreni"),
- **General farm census dataset** ("Censimento dati generali").

From the land localization dataset, 195,735 durum wheat-producing farms were identified and aggregated by province/region and altimetry class [Di Giuseppe et al. \(2025\)](#). From the general census dataset, 136,041 durum wheat-producing farms were used for demographic and structural aggregation [Di Giuseppe \(2025\)](#). Moreover, altimetry classes were harmonized into three categories: a) mountain, b) hill, and c) plain.

Some descriptive statistics based on aggregated general census data are provided in the Appendix and on [this web page](#) of the official ECOWHEATALY website. It is worth highlighting that the web page also features interactive maps, which constitute one of the project deliverables.

## 4.2 Aggregated Structural Indicators

For each province–altimetry and region–altimetry cell, the following aggregated indicators were considered for each farm:

- Total agricultural area (SAU),
- Total wheat area (CER2\_ETTARI),
- Number of farms ( $N_{farmers}$ ),
- Share of female farm managers (Female\_quote),
- Share of young farm managers (Young\_quote, age  $\leq 40$ ),
- Average age of farm manager (Age\_avg).

These indicators provide structural moments that must be replicated by the synthetic farm population used in the simulation model.

### 4.3 Statistical Rationale for Parametric Distribution Fitting

The ISTAT microdata analysis produces distributional information that is used for *population synthesis* rather than econometric inference. The central task is to generate synthetic farms whose structural attributes (e.g., SAU and wheat area) reproduce the empirical shape of the census distributions within each spatial-altimetric cell. In this context, fitting parametric distributions provides three practical advantages.

First, parametric distributions offer a compact and transferable representation of heterogeneous farm structures. Instead of storing large empirical histograms for every province/region and altimetry class, each distribution can be summarized by a small set of parameters (typically 2–4). This is particularly useful in an agent-based modeling workflow, where initialization must be repeated across scenarios and replicated simulation runs.

Second, parametric representations facilitate controlled sampling and scaling. Once a distribution is selected and estimated within a given cell, synthetic farms can be generated by random draws that preserve key moments (mean, variance, skewness, tail weight) and that can be scaled to match census counts. This improves computational tractability and reproducibility, because initialization becomes a deterministic procedure conditional on a random seed and a finite set of parameters.

Third, the parametric approach supports harmonization across cells with very different sample sizes. Some provinces–altimetry cells may contain a limited number of wheat farms, leading to noisy nonparametric estimates. Parametric fitting regularizes the shape of the distribution by imposing economically interpretable constraints (e.g., non-negativity, right-skewness), while still allowing flexibility across families (lognormal, gamma, Weibull, etc.).

**Model selection and estimation.** For each variable of interest (SAU, wheat area, farm-manager age) and for each spatial-altimetric cell, candidate parametric families are fitted by maximum likelihood. The best-fitting model is selected using the `univariateML::model_select()` routine, which compares candidate distributions and returns the selected family together with its estimated parameters [Di Giuseppe \(2025\)](#). Model selection is based on standard information criteria that balance goodness-of-fit against model complexity, such as AIC or BIC [Akaike \(1974\)](#); [Schwarz \(1978\)](#). This is consistent with the goal of obtaining a parsimonious representation suitable for simulation.

**Support constraints and plausibility.** The fitted distributions are required to respect the natural support of each variable. In particular, SAU and wheat area are non-negative variables that typically display right-skewed distributions, while farm-manager age is bounded within a realistic range. When necessary, truncation or bounding rules are applied at the sampling stage to ensure that simulated values remain plausible and consistent with census definitions. This prevents synthetic farms from taking implausible extreme values driven by tail extrapolation.

**Validation and robustness checks.** Because fitted distributions are used to generate agents, the primary validation criterion is distributional fidelity within each cell. In practice, goodness-of-fit can be assessed by checking whether (i) key moments of the fitted distribution match empirical moments, and (ii) the fitted CDF reproduces the empirical CDF within acceptable tolerances. Where feasible, diagnostic tools include

Q–Q plots, Kolmogorov–Smirnov distances, or comparisons of selected quantiles (e.g., median, interquartile range, 90th percentile). If a cell exhibits unstable or weak identification (e.g., very small sample size or multi-modality), a fallback strategy is applied by using a higher aggregation level (region–altimetry or national–altimetry) or by selecting a simpler distributional family. These steps ensure complete territorial coverage while maintaining statistical reliability.

Overall, the parametric fitting approach provides a transparent bridge between census microdata and simulation initialization, yielding a compact, reproducible, and scalable representation of structural heterogeneity across Italian wheat farms, fully consistent with the LAB ADELE output requirements and aggregation constraints [Di Giuseppe et al. \(2025\)](#); [Di Giuseppe \(2025\)](#).

#### 4.4 Role in the Agent-Based Model

The estimated distributions are not used for econometric inference but for *population initialization*. Specifically:

1. For each province–altimetry cell, a synthetic set of farms is generated by sampling from the estimated SAU and wheat-area distributions.
2. Demographic characteristics (age class, gender share) are assigned probabilistically according to observed regional proportions.
3. The number of simulated farms in each cell is proportional to the census count  $N_{farmers}$ .

This ensures that the ensemble of simulated agents reproduces:

- The geographic distribution of wheat farms,
- The distribution of farm size,
- The structural weight of wheat cultivation within total farm area,
- The demographic composition of farm managers.

Importantly, all outputs released from the ADELE Laboratory are fully aggregated at province/region and altimetry level and are not traceable to individual statistical units [Di Giuseppe \(2025\)](#). The resulting distributions serve exclusively as initialization inputs for the agent-based model.

## 5 A possible future development: a behavioral extension with environmental awareness

The static microeconomic model presented in Section 2 assumes that farmers maximize profit. While analytically tractable, this benchmark abstracts from well-documented behavioral heterogeneity in agricultural decision-making. Empirical evidence suggests that production choices are influenced not only by economic incentives but also by environmental values, demographic characteristics, education, and exposure to information [Srebrennikov et al. \(2020\)](#); [Fanelli \(2022\)](#); [Liebert and et al. \(2022\)](#).

To account for these dimensions, we plan to introduce an environmental awareness parameter  $\Theta_i$  that modifies the farmer's objective function.

## 5.1 Utility Function with Environmental Impact

Let  $\pi(x)$  denote profit as previously defined and let  $DALY(x)$  denote the environmental and human-health impact associated with production choices  $x$ , as computed by the Life Cycle Assessment (LCA) module (see the report of Task 1.2). Environmental impact is measured in disability-adjusted life years (DALY).

Farmer  $i$  maximizes the utility function:

$$U_i(x) = \pi_i(x) - \Theta_i \cdot DALY_i(x), \quad (10)$$

where  $\Theta_i \geq 0$  represents the weight assigned to environmental damage in the decision process.

The interpretation of  $\Theta_i$  is straightforward:

- $\Theta_i = 0$ : the farmer behaves as a pure profit maximizer.
- $\Theta_i > 0$ : the farmer is willing to sacrifice profit to reduce environmental impact.

Thus,  $\Theta_i$  measures the marginal willingness to trade economic return for environmental improvement.

The first-order condition for a generic input  $x_k$  becomes:

$$\frac{\partial \pi_i(x)}{\partial x_k} = \Theta_i \frac{\partial DALY_i(x)}{\partial x_k}. \quad (11)$$

Relative to the profit-maximizing benchmark, a higher  $\Theta_i$  reduces optimal input intensities whenever environmental damage increases with input use.

## 5.2 Structural Determinants of Environmental Awareness

Environmental awareness is assumed to vary systematically with observable farmer characteristics. Let the baseline awareness level of farmer  $i$  be defined as:

$$\bar{\Theta}_i = \Theta_0 \exp(\beta_A Age_i + \beta_F Female_i + \beta_E Educ_i + \beta_S \ln(SAU_i)), \quad (12)$$

where:

- $Age_i$  denotes age (or age class),
- $Female_i$  is a gender indicator,
- $Educ_i$  captures education level,
- $SAU_i$  is utilized agricultural area (farm size),
- $\Theta_0$  is a baseline parameter,
- $\beta_A, \beta_F, \beta_E, \beta_S$  are behavioral coefficients.

The exponential specification ensures  $\Theta_i \geq 0$  and allows multiplicative heterogeneity. Demographic and structural variables are drawn from ISTAT census distributions (Section 4), ensuring empirical coherence.

This specification is consistent with findings suggesting that:

- younger farmers may be more receptive to sustainable innovation,
- female farm managers may display stronger environmental concern,
- more educated farmers may process environmental information more effectively,
- larger farms may have greater capacity to adopt sustainable technologies.

### 5.3 Policy Communication and Dynamic Evolution of Awareness

In addition to structural heterogeneity, environmental awareness may evolve over time in response to policy communication and outreach efforts.

Let  $C_t$  denote the intensity of policy communication at time  $t$  (e.g., information campaigns, extension services, advisory programs), and let  $Exp_{it} \in [0, 1]$  denote farmer-specific exposure to such communication. The evolution of awareness is modeled as:

$$\Theta_{i,t+1} = (1 - \rho)\Theta_{i,t} + \rho\bar{\Theta}_i + \gamma Exp_{it} C_t, \quad (13)$$

where:

- $\rho \in [0, 1]$  governs the speed of adjustment toward the structural baseline,
- $\gamma > 0$  measures the marginal impact of campaign intensity.

This dynamic specification separates:

1. Structural determinants of awareness (demographics and size),
2. Policy-induced shifts through communication,
3. Persistence of individual attitudes over time.

In the absence of campaigns ( $C_t = 0$ ), awareness converges toward its structural baseline  $\bar{\Theta}_i$ . Under active campaigns,  $\Theta_{i,t}$  may temporarily increase, thereby shifting optimal input choices.

### 5.4 Relation to Marvuglia et al. (2022)

The present behavioral extension shares conceptual similarities with the agent-based model proposed by [Marvuglia et al. \(2022\)](#), who simulate farmers' sustainable decisions by modeling the evolution of "green consciousness" through social interaction among agents. However, important differences arise.

First, the ECOWHEATALY specification embeds environmental awareness directly into a micro-founded optimization problem (Eq. 10), preserving a transparent mapping from economic incentives and environmental costs to optimal decisions. In [Marvuglia et al. \(2022\)](#), behavioral evolution plays a more central role, with green consciousness evolving primarily through peer interaction and network dynamics.

Second, the present model anchors heterogeneity in observable structural variables derived from census data. Environmental awareness is therefore empirically grounded and directly linked to demographic composition. In contrast, [Marvuglia et al. \(2022\)](#) emphasize endogenous diffusion of sustainable behavior within social networks.

Third, policy communication in ECOWHEATALY is modeled as an explicit exogenous lever affecting  $\Theta_{i,t}$  (Eq. 13), which facilitates counterfactual evaluation of outreach strategies alongside economic instruments. The focus remains on interpretable policy simulation rather than on modeling social norm evolution per se.

Overall, the two approaches are complementary. [Marvuglia et al. \(2022\)](#) emphasize the role of peer interaction and social learning, whereas ECOWHEATALY prioritizes microeconomic interpretability, empirical calibration to the Italian farm structure, and direct policy evaluation within a unified economic?environmental framework.

To clarify the conceptual positioning of the proposed behavioral extension, Table 1 summarizes the key differences between (i) the baseline profit-maximizing specification, (ii) the ECOWHEATALY environmental-awareness extension, and (iii) the agent-based framework proposed by [Marvuglia et al. \(2022\)](#). The comparison highlights how the present model preserves a micro-founded optimization structure while introducing empirically grounded behavioral heterogeneity linked to structural and demographic characteristics, and how it differs from models in which sustainable behavior primarily emerges through endogenous social interaction and diffusion mechanisms.

Table 1: Comparison of Behavioral Specifications

	Baseline Model	Economic	ECOWHEATALY Behavioral Extension	Behav- Marvuglia et al. (2022)
<b>Decision Objective</b>	Profit maximization $\max \pi(x)$		Utility maximization $\max [\pi(x) - \Theta_i DALY(x)]$	Sustainable decision driven by evolving "green consciousness"
<b>Environmental Consideration</b>	Not internalized		Internalized through preference weight $\Theta_i$	Internalized through evolving behavioral state variable
<b>Source of Heterogeneity</b>	Technological parameters only (RICA-based)		Technological + structural (ISTAT) + behavioral $\Theta_i$	Behavioral heterogeneity from social interaction
<b>Determinants of Environmental Attitude</b>	None		Age, gender, education, farm size, policy communication	Social network influence and peer interaction
<b>Dynamics of Awareness</b>	Not applicable		Baseline structural level with optional policy-driven updating (Eq. 13)	Endogenous evolution via interaction and diffusion
<b>Role of Policy Communication</b>	Indirect (via prices)		Explicit exogenous lever affecting $\Theta_i$	Indirect through influence on network behaviour
<b>Microeconomic Interpretability</b>	High		High (explicit FOC and optimization problem)	Moderate (behavioral evolution focus)
<b>Empirical Anchoring</b>	Calibrated on RICA technology		Calibrated on RICA + ISTAT demographic structure	Conceptual/behavioral calibration
<b>Primary Analytical Focus</b>	Economic efficiency		Joint economic-environmental trade-off	Social diffusion of sustainable behaviour

## 6 Conclusions

This report documented the development of the microeconomic modelling framework representing the Italian wheat production system within the ECOWHEATALY project. The objective of Task 2.2 was to construct a farm-level model capable of capturing the technological and structural heterogeneity of Italian wheat farms while remaining compatible with the broader simulation architecture of the project.

The modelling strategy begins with a microeconomic representation of individual farms based on profit maximization under technological and economic constraints. This framework provides a transparent mapping between market conditions, production technologies, and farmers' input choices. Crop yields are represented as the out-

come of complementary input use, allowing the model to capture the interactions between fertilizers, production practices, and agronomic conditions.

The empirical grounding of the model relies on two main data sources. Farm-level economic and technical parameters are estimated using microdata from the RICA/FADN database, while structural characteristics of the Italian agricultural sector are derived from the 2020 ISTAT agricultural census. Together, these sources allow the construction of a synthetic population of heterogeneous farms whose statistical properties are consistent with the observed distribution of farm sizes, yields, and input intensities in the Italian wheat sector.

An additional contribution of the modelling framework is the introduction of behavioral heterogeneity through an environmental awareness component. This extension enables the model to represent potential variations in farmers' responses to environmental policies, thereby improving the realism of policy simulations.

The resulting farm-level module provides the microeconomic foundation required to analyse how policy instruments, price changes, and environmental constraints affect production decisions at the farm level. When combined with the global wheat market model developed in Task 2.1 and the environmental assessment framework established in Work Package 1, this module will allow the ECOWHEATALY project to simulate the economic and environmental impacts of alternative agricultural policies.

Overall, Task 2.2 contributes a crucial component to the integrated modelling framework of the project, enabling a consistent link between farm-level decision-making, sectoral production dynamics, and environmental outcomes.

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## Appendix

### A Durum Wheat in Italy: Where and Who Produces It

Italy ranks among the world's leading producers of **durum wheat** (*Triticum durum*), the essential raw material for pasta and many traditional food products. According to analyses conducted using data from the 7th General Agricultural Census (ISTAT, 2020), more than 195,000 Italian farms cultivate durum wheat.

The data were processed at a regional, provincial, and altitudinal level, providing a detailed and an up-to-date portrait of the national cereal sector ? a foundation for evidence-based agricultural policy in the context of the CAP 2023–2027 and the broader ecological transition.

**Regional Distribution of Production: Puglia and Sicily are the Production Heartlands** As shown by the regional distribution map (Figure 2), Puglia stands out as Italy's true "capital of durum wheat," followed by Sicily. The bulk of cultivated areas is concentrated in the Central and Southern regions, where surfaces range between 40,000 and 105,000 hectares per region. Northern Italy plays a comparatively smaller role in terms of total acreage, but is characterised by higher mechanisation and productivity levels.

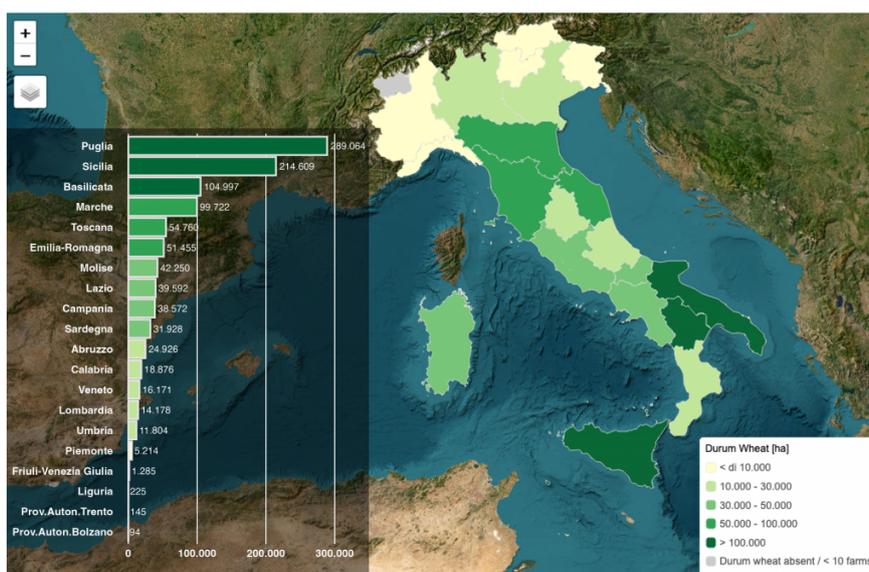


Figure 2: Regional distribution of durum wheat cultivation areas in Italy (hectares). Source: ISTAT, 7th Agricultural Census 2020 — Analysis: CNR.

**Distribution by Altitude Class.** The altitudinal analysis reveals that durum wheat is predominantly cultivated in hilly areas, where clay-rich soils and favourable climatic conditions ensure good yields with limited input requirements. Plains, more prevalent in Northern and Central-Northern Italy, host high-yield, often irrigated, industrially-oriented cereal systems. Mountain areas account for only a marginal share of national production.

**Leading Provinces: Foggia is Italy's Durum Wheat Capital.** At the provincial level, Foggia leads by a wide margin, with over 183,000 hectares cultivated, more than three times the area of the second-ranking province, Potenza. Other major producers include Sicilian and Lucanian provinces, but it is noteworthy that Marche provinces — *Ancona, Macerata, and Pesaro-Urbino* — also show relevant surfaces, indicating a broader national distribution well beyond the South.

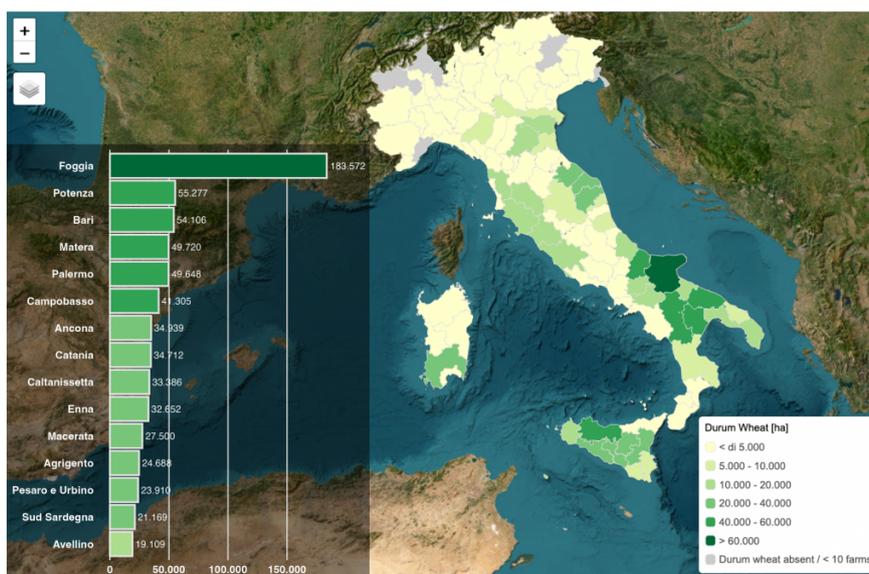


Figure 3: Ranking of Italian provinces by durum wheat cultivation area (hectares). Source: ISTAT, 7th Agricultural Census 2020 — Analysis: CNR.

**Socio-Economic Profile of Farm Managers: Women in Durum Wheat Farming.** Women remain underrepresented, rarely exceeding 25% of farm holders in the leading production regions. However, female presence is growing in areas such as Tuscany, Piedmont, and Marche, where durum wheat is often integrated into multifunctional farms.

**Young Farmers (Under 40)** Young farmers (under 40) are still a minority nationwide, though more numerous in Southern regions and innovation-oriented areas, where CAP incentives and regional programmes are actively fostering generational renewal in the wheat supply chain.

**Summary** The census data provide a comprehensive overview of Italy's durum wheat production structure. This analysis, presented at the 4th ECOWHEATALY Meeting at CREA headquarters in Rome, helps to identify the challenges and opportunities facing the Italian wheat supply chain within the framework of the ecological transition and the new CAP 2023–2027.

Here are the results of the census data analysis on durum wheat farms in Italy:

- **195,735 farms** cultivate durum wheat across the national territory.



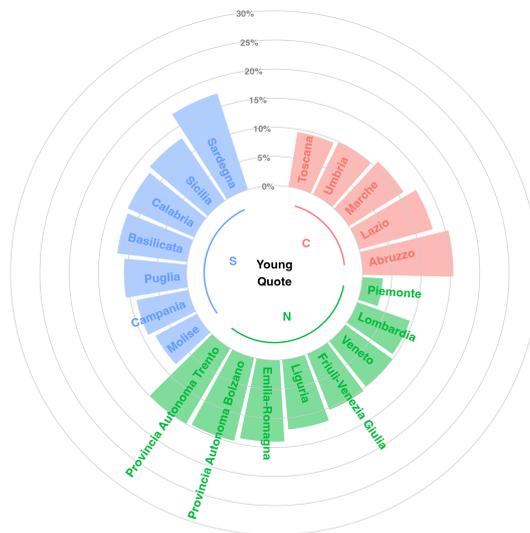


Figure 6: Distribution of young farm holders (under 40) growing durum wheat, by region. Source: ISTAT, 7th Agricultural Census 2020 — Analysis: CNR.

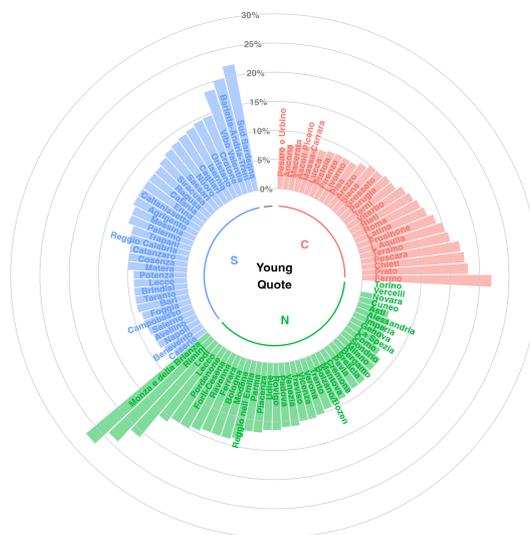


Figure 7: Distribution of young farm holders (under 40) growing durum wheat, by province. Source: ISTAT, 7th Agricultural Census 2020 — Analysis: CNR.

the second-ranked province (Potenza).

- **Puglia and Sicily** are the top regions, with production concentrated in Central and Southern Italy.

- **Women and young farmers** remain a minority but are gradually expanding their role, particularly in multifunctional and innovation-oriented farms.

It is worth recalling that "The data used in this work come from ISTAT and relate to the 7th General Census of Agriculture. The analyses were conducted at the Laboratory for the Analysis of Elementary Data of ISTAT (LAB ADELE), and in compliance with regulations regarding the protection of statistical secrecy and personal data. The results and opinions expressed are solely the responsibility of the author and do not constitute official statistics. It should be noted that the analyses were conducted without using the weights for universe extrapolation".

## B Italian Farm Agent: Microeconomics

### B.1 Farm management

Farm management encompasses several dimensions: (1) financial management, (2) crop and livestock management, (3) equipment management, (4) labor management, and (5) risk management, among others. See [Kay et al. \(2020\)](#) or [this blog](#) for more information.

Because we focus on wheat production, we draw on tools from the crop management literature. In particular, we are interested in modeling a situation in which a product (wheat) is produced using several inputs.

The textbook by [Kay et al. \(2020\)](#) examines this situation in Chapter 8, page 144, in a section titled "input combinations". This chapter is part of the broader section of the book called "applying economic principles". In this framework, the problem of choosing an input combination is formulated as a cost-minimization problem: the farmer selects the input combination that minimizes total cost.

A review of economic modeling of agriculture production is provided by [Carpentier et al. \(2015\)](#). The article presents a paragraph titled "Mathematical programming models" (p. 135). Among them, the "positive mathematical programming" is summarised (see also [Paris, 2017](#)). However, the author states:

Positive Mathematical Programming (PMP) framework. The PMP term is generally defined as quadratic. The PMP term still lacks economic rationalisation.

A key role in the economic modeling of input combination choice is input substitution ([Kay et al. \(2020\)](#) Chapter 8). The degree of input substitution has been studied for several decades. See, for example, Chapter 5 in [Heady and Tweeten \(1963\)](#). When inputs may be substituted to some extent, we use standard mathematical optimization:

$$\pi = p_w y(x_1, x_2, \dots) - \sum_i p_{x_i} x_i$$

where  $y$  is yield,  $x_i$  are inputs,  $p_w$  is the price of wheat and  $p_{x_i}$  are the inputs prices.

In the model developed below, we present a new specification of the yield function based on the concept of the *yield gap*. Moreover, we assume zero substitutability between fertilizers and herbicides and therefore adopt a Leontief production function.

## B.2 Yield gap

To explore the concept of the yield gap in more depth, see [van Ittersum et al. \(2013\)](#) (pp. 5?6) and the specialised blog [Climate Talk](#). Additional definitions are provided in [Fischer \(2015\)](#).

This approach begins by identifying the potential yield, which depends on solar radiation, temperature, atmospheric CO<sub>2</sub>, and genetic traits that determine the length of the growing period. Because these factors are climate-dependent, potential yield is location-specific.

The yield actually achieved on a farm is lower than the potential yield, and the difference between the potential and actual yield is termed the yield gap. The yield gap arises from limiting factors, such as water and nutrient availability, and from reducing factors such as weeds, pests, diseases, and pollutants. Typically, farm yields do not exceed 80% of the potential yield. The exploitable yield gap is therefore defined as the difference between 80% of the potential yield and the realized yield.

## B.3 A model to reduce the yield gap

Farm management practices play a key role in reducing the yield gap. [Devkota et al. \(2024\)](#), in Table 2 on page 4, identifies the management factors that most strongly affect yield. Following this approach, we develop a model based on the yield-gap concept as a tool to support management decisions.

In particular, the model incorporates stress factors and measures aimed at relieving these stresses. We first analyze a case with a single stress factor, and then extend the analysis to multiple stress factors.

We denote the potential yield by  $\bar{y}$ . Let the variable  $s \in (0, 1)$  indicate the share of potential yield lost due to the stress, and  $x$  the strength of the management measure implemented to counteract the stress. The function  $g(x) \in (0, 1)$  represents the effectiveness of the management measure. The function  $g$  is increasing in  $x$ ; specifically, we adopt the functional form  $g(x) = 1 - e^{-\lambda x}$ .

We further introduce the maximum share of yield that can be recovered at the maximum effectiveness of the measure, denoted by  $\bar{s}$ .

Under these assumptions, the yield can be written as

$$y(s, \bar{s}, x) = \bar{y}[(1 - s) + \bar{s}g(x)]$$

and using  $g(x) = 1 - e^{-\lambda x}$  we have

$$y(s, \bar{s}, \lambda, x) = \bar{y}[(1 - s) + \bar{s}(1 - e^{-\lambda x})]$$

One of the issues we must address is the reliability of our assumption regarding the function  $g(x)$ . Consider, for example, fertilization:  $g(x)$  can be interpreted as the relationship between yield and nitrogen uptake. This relationship has been examined extensively in the literature. For instance, [Berbel and Martínez-Dalmau \(2021\)](#) reports that a linear increase up to a plateau has frequently been adopted in the literature. However, the empirical relationship is not strictly linear (see [FAO and DWFI \(2015\)](#), p. 36, for yield and nitrogen uptake).

We can now proceed to the maximization in two ways:

- the standard way
- the cost function way

In particular, the cost function is useful when dealing with multiple stress factors.

We first present the standard maximization problem, then introduce the cost function to show how it leads to the same solution. Finally, we extend the cost function to the case of multiple stress factors.

## B.4 One stress factor

### B.4.1 Standard maximization

The farmer's profit is:

$$\pi(s, \bar{s}, x) = p_w y(s, \bar{s}, x) - p_x x$$

$$\pi(s, \bar{s}, x) = p_w \bar{y}(1 - s) + p_w \bar{y} \bar{s} g(x) - p_x x$$

The farmer's problem is therefore:

$$\max_x \pi(s, \bar{s}, x)$$

The FOC is obtainable by differentiating as follows:

$$\frac{d\pi(s, \bar{s}, x)}{dx} = p_w \bar{y} \bar{s} \frac{dg(x)}{dx} - p_x = 0$$

if  $g(x) = 1 - e^{-\lambda x}$  we have  $\frac{dg(x)}{dx} = \lambda e^{-\lambda x}$  and the FOC becomes:

$$p_w \bar{y} \bar{s} \lambda e^{-\lambda x} - p_x = 0$$

solving for  $x$  gives the farmer's optimal action:

$$e^{-\lambda x} = \frac{p_x}{p_w \bar{y} \bar{s} \lambda}$$

$$-\lambda x = \ln \left( \frac{p_x}{p_w \bar{y} \bar{s} \lambda} \right)$$

$$x = -\frac{1}{\lambda} \ln \left( \frac{p_x}{p_w \bar{y} \bar{s} \lambda} \right)$$

### B.4.2 Cost function

In this case, we compute the level of  $x$  needed to achieve a given level of yield  $\hat{y}$ . It will be denoted with  $\hat{x}$ . To solve, we start by imposing the condition:

$$\bar{y}[(1 - s) + \bar{s}g(x)] = \hat{y}$$

if  $g(x) = 1 - e^{-\lambda x}$  we have

$$\bar{y}[(1 - s) + \bar{s}(1 - e^{-\lambda x})] = \hat{y}$$

after some algebra, we have:

$$\hat{x} = -\frac{1}{\lambda} \ln \left( \frac{(1 + \bar{s} - s)\bar{y} - \hat{y}}{\bar{s}\bar{y}} \right)$$

The cost function is therefore:

$$c(p_x, \hat{y}) = p_x \hat{x} = p_x \left[ -\frac{1}{\lambda} \ln \left( \frac{(1 + \bar{s} - s)\bar{y} - \hat{y}}{\bar{s}\bar{y}} \right) \right]$$

The maximization problem can be posed as follows:

$$\max_{\hat{y}} \pi = p_w \hat{y} - c(p_x, \hat{y})$$

that is:

$$\max_{\hat{y}} \pi = p_w \hat{y} - p_x \left[ -\frac{1}{\lambda} \ln \left( \frac{(1 + \bar{s} - s)\bar{y} - \hat{y}}{\bar{s}\bar{y}} \right) \right]$$

FOC

$$p_w - p_x \left[ -\frac{1}{\lambda} \left( \frac{\bar{s}\bar{y}}{(1 + \bar{s} - s)\bar{y} - \hat{y}} \right) \left( -\frac{1}{\bar{s}\bar{y}} \right) \right] = 0$$

$$p_w - p_x \left[ \frac{1}{\lambda} \frac{1}{(1 + \bar{s} - s)\bar{y} - \hat{y}} \right] = 0$$

$$p_w [\lambda(1 + \bar{s} - s)\bar{y} - \lambda\hat{y}] - p_x = 0$$

$$p_w \lambda(1 + \bar{s} - s)\bar{y} - p_w \lambda\hat{y} - p_x = 0$$

$$-p_w \lambda\hat{y} = p_x - p_w \lambda(1 + \bar{s} - s)\bar{y}$$

$$\hat{y} = \frac{p_w \lambda(1 + \bar{s} - s)\bar{y} - p_x}{p_w \lambda}$$

$$\hat{y} = (1 + \bar{s} - s)\bar{y} - \frac{p_x}{p_w \lambda}$$

Take now the  $\hat{x}$  expression obtained above:

$$\hat{x} = -\frac{1}{\lambda} \ln \left( \frac{(1 + \bar{s} - s)\bar{y} - \hat{y}}{\bar{s}\bar{y}} \right)$$

and substitute  $\hat{y}$ :

$$\hat{x} = -\frac{1}{\lambda} \ln \left( \frac{(1 + \bar{s} - s)\bar{y} + \frac{p_x}{p_w \lambda} - (1 + \bar{s} - s)\bar{y}}{\bar{s}\bar{y}} \right)$$

$$\hat{x} = -\frac{1}{\lambda} \ln \left( \frac{\frac{p_x}{p_w \lambda}}{\bar{s}\bar{y}} \right)$$

$$\hat{x} = -\frac{1}{\lambda} \ln \left( \frac{p_x}{p_w \lambda \bar{s}\bar{y}} \right)$$

that is the same we obtained in the previous section.

### B.4.3 Numerical example

Under the following parametrization:

Wheat price per ton:  $p_w = 300$

Potential yield (ton/ha):  $\bar{y} = 5$

stress factor	$s$	$\bar{s}$	$p_x$	$\lambda$	$x$
Lack of Nitrogen	0.5	0.5	1.5	0.005	supply of N (kg)

The solution is:

$$\hat{x} = 183.26$$

$$\hat{y} = 4$$

$$\pi = 925$$

This means the farmer achieves the maximum profit by using 183.26 kg of Nitrogen fertilizer per hectare. With this level of fertilization, s/he obtains 4 tons of wheat per hectare. Note that the farmer obtains a yield that is 80% of the potential. Therefore, the exploitable yield gap is zero.

## B.5 Several stress factors

In this section, we allow for several stress factors indexed by  $i$ . We denote with  $y_i$  the conditional yield, i.e., the yield obtained when only stress factor  $i$  is binding. When several stress factors are binding, the realized yield is the one corresponding to the most binding stress factor:

$$y = \min(y_i)$$

In the economic theory of production, this is called the Leontief-type function. Its main feature is that relieving one stress factor can be ineffective because of the constraints of other stress factors. The optimal strategy in this case is to level out the conditional yields:

$$y_i = \hat{y}$$

### B.5.1 Cost function

The cost function is obtained by finding the needed inputs to obtain a given level of yield (say  $\hat{y}$ ). We start from the conditional yield function:

$$y_i(s_i, x_i) = \bar{y}[(1 - s_i) + \bar{s}_i g_i(x_i)]$$

As specified above, the Leontief type production function implies:

$$\bar{y}[(1 - s_i) + \bar{s}_i g_i(\hat{x}_i)] = \hat{y}$$

if  $g_i(x_i) = 1 - e^{-\lambda_i x_i}$

$$\bar{y}[(1 - s_i) + \bar{s}_i(1 - e^{-\lambda_i \hat{x}_i})] = \hat{y}$$

After some algebra (reported in the appendix) we get:

$$\hat{x}_i = -\frac{1}{\lambda_i} \ln \left( \frac{(1 + \bar{s}_i - s_i)\bar{y} - \hat{y}}{\bar{s}_i \bar{y}} \right)$$

note that the condition for a meaningful solution is:

$$(1 - s_i)\bar{y} \leq \hat{y} < (1 - s_i)\bar{y} + \bar{s}_i\bar{y}.$$

The cost function is given by:

$$c(p_{x_i}, \hat{y}) = \sum_i p_{x_i} \hat{x}_i.$$

### B.5.2 Maximization

The maximization problem can now be posed as follows:

$$\max_{\hat{y}} \pi = p_w \hat{y} - c(p_{x_i}, \hat{y})$$

substituting  $\hat{x}_i$

$$\max_{\hat{y}} \pi = p_w \hat{y} - \sum_i p_{x_i} \left[ -\frac{1}{\lambda_i} \ln \left( \frac{(1 + \bar{s}_i - s_i)\bar{y} - \hat{y}}{\bar{s}_i\bar{y}} \right) \right]$$

The corresponding FOC can be solved by numerical methods:

$$p_w - \sum_i p_{x_i} \frac{1}{\lambda_i(1 + \bar{s}_i - s_i)\bar{y} - \lambda_i\hat{y}} = 0$$

Now, having the solution  $\hat{y}^*$ , we can establish if there are binding stress factors by checking the conditions:

$$(1 - s_i)\bar{y} \leq \hat{y}^* < (1 - s_i)\bar{y} + \bar{s}_i\bar{y}$$

Let us put the previous expression in a compact way as

$$y_i^l \leq \hat{y}^* < y_i^h$$

### B.5.3 Numerical example

**Benchmark case** Wheat price per ton:  $p_w = 300$

Potential yield (ton/ha):  $\bar{y} = 5$

$i$	stress factor	$s$	$\bar{s}$	$p_x$	$\lambda$	$x$
0	Lack of Nitrogen	0.5	0.5	1.5	0.005	supply of N (kg)
1	weeds	0.4	0.4	8	0.2	herbicide (kg)
2	Insects	0.3	0.3	5	0.1	Insecticide (kg)

The solution is:

$$\hat{x}_0 = 130.79 \quad \hat{x}_1 = 2.15 \quad \hat{x}_2 = 1.43$$

$$\hat{y} = 3.7$$

$$\pi = 889$$

In words, the farmer applies 130.79 kg/ha of nitrogen fertilizers, 2.15 kg/ha of herbicides, and 1.43 kg/ha of insecticides. This input mix results in a yield of 3.7 tons/ha and a profit of 889 per hectare.

**A shock** Suppose now, a new type of insect reaches the farm area. This type of insect is more damaging and more resistant to current insecticides. In other words, current insecticides become less effective. We include this in the model by changing the insect stress parameters as follows:

$i$	stress factor	$s$	$\bar{s}$	$p_x$	$\lambda$	$x$
0	Lack of Nitrogen	0.5	0.5	1.5	0.005	supply of N (kg)
1	weeds	0.4	0.4	8	0.2	herbicide (kg)
2	Insects	0.5	0.1	5	0.1	Insecticide (kg)

the solution for  $\hat{y}$  is 2.6748

Now, we analyze if there are binding constraints:

$$y_0^l = 2.50, y_0^h = 5.00$$

$$y_1^l = 3.00, y_1^h = 5.00$$

$$y_2^l = 2.50, y_2^h = 3.00$$

We discover that at the current level of  $\hat{y}$ , the second input (herbicide) is not binding. Therefore, we set  $\hat{x}_1 = 0$  and proceed with a new maximization.

The new maximization gives  $\hat{y} = 2.7047$ . At this level, inputs 0 and 2 are binding. Therefore, the new solution is:

$$\hat{x}_0 = 17.08 \quad \hat{x}_1 = 0 \quad \hat{x}_2 = 5.27$$

$$\hat{y} = 2.7$$

$$\pi = 759$$

The following table can be used to compare the results

	$\hat{x}_1$	$\hat{x}_2$	$\hat{x}_3$	$\hat{y}$	$\pi$
benchmark	130.79	2.15	1.43	3.7	889
new insect	17.08	0	5.27	2.7	759

**Policy evaluation** Suppose now that a regulation imposes a tax on insecticides. The tax increases insecticide prices and affects farmers' input decisions. The following table shows how the results change due to this increase in the insecticide price.

$p_{x_3}$	$\hat{x}_1$	$\hat{x}_2$	$\hat{x}_3$	$\hat{y}$	$\pi$
5	130.79	2.15	1.43	3.7	889
7.5	118.36	1.84	0.81	3.62	887
10	106.66	1.55	0.22	3.53	885
$\geq 11$	102.17	1.44	0	3.5	885

It is useful to show what happens at a price level higher than 11. To do this, we analyze the boundaries corresponding to the three inputs.

$$y_0^l = 2.50, y_0^h = 5.00$$

$$y_1^l = 3.00, y_1^h = 5.00$$

$$y_2^l = 3.50, y_2^h = 5.00$$

At  $p_{x_3} = 15$  for example, we have  $\hat{y} = 3.3667$  that falls outside the third interval. If we remove the third input, we get  $\hat{y} = 3.8667$ ; however, this value is not consistent because if we do not apply insecticide, the production will be 3.5. Therefore, to have consistency, we set  $\hat{y} = 3.5$  that delivers the reported solution.

## B.6 Algebra to $\hat{x}$

$$\begin{aligned}\bar{y}[(1 - s_i) + \bar{s}_i(1 - e^{-\lambda_i x_i})] &= \hat{y} \\ (1 - s_i) + \bar{s}_i(1 - e^{-\lambda_i x_i}) &= \frac{\hat{y}}{\bar{y}} \\ \bar{s}_i(1 - e^{-\lambda_i x_i}) &= \frac{\hat{y}}{\bar{y}} - (1 - s_i) \\ 1 - e^{-\lambda_i x_i} &= \frac{\hat{y}}{\bar{s}_i \bar{y}} - \frac{(1 - s_i)}{\bar{s}_i} \\ -e^{-\lambda_i x_i} &= \frac{\hat{y}}{\bar{s}_i \bar{y}} - \frac{(1 - s_i)}{\bar{s}_i} - 1 \\ e^{-\lambda_i x_i} &= 1 + \frac{(1 - s_i)}{\bar{s}_i} - \frac{\hat{y}}{\bar{s}_i \bar{y}} \\ \ln(e^{-\lambda_i x_i}) &= \ln\left(1 + \frac{(1 - s_i)}{\bar{s}_i} - \frac{\hat{y}}{\bar{s}_i \bar{y}}\right) \\ -\lambda_i x_i &= \ln\left(1 + \frac{(1 - s_i)}{\bar{s}_i} - \frac{\hat{y}}{\bar{s}_i \bar{y}}\right) \\ x_i &= -\frac{1}{\lambda_i} \ln\left(1 + \frac{(1 - s_i)}{\bar{s}_i} - \frac{\hat{y}}{\bar{s}_i \bar{y}}\right) \\ x_i &= -\frac{1}{\lambda_i} \ln\left(\frac{\bar{s}_i \bar{y} + (\bar{y} - s_i \bar{y}) - \hat{y}}{\bar{s}_i \bar{y}}\right) \\ x_i &= -\frac{1}{\lambda_i} \ln\left(\frac{\bar{s}_i \bar{y} + \bar{y} - s_i \bar{y} - \hat{y}}{\bar{s}_i \bar{y}}\right) \\ x_i &= -\frac{1}{\lambda_i} \ln\left(\frac{(1 + \bar{s}_i - s_i)\bar{y} - \hat{y}}{\bar{s}_i \bar{y}}\right)\end{aligned}$$

## B.7 Condition for a meaningful solution

Given the solution obtained above:

$$\hat{x}_i = -\frac{1}{\lambda_i} \ln\left(\frac{(1 + \bar{s}_i - s_i)\bar{y} - \hat{y}}{\bar{s}_i \bar{y}}\right)$$

the condition for a meaningful solution is

$$1 \geq \frac{(1 + \bar{s}_i - s_i)\bar{y} - \hat{y}}{\bar{s}_i \bar{y}} > 0$$

that is

$$\frac{(1 + \bar{s}_i - s_i)\bar{y} - \hat{y}}{\bar{s}_i \bar{y}} > 0$$

$$(1 + \bar{s}_i - s_i)\bar{y} - \hat{y} > 0$$

that gives the levels of  $\hat{y}$  that can be achieved:

$$\hat{y} < (1 + \bar{s}_i - s_i)\bar{y}$$

while from

$$1 \geq \frac{(1 + \bar{s}_i - s_i)\bar{y} - \hat{y}}{\bar{s}_i\bar{y}}$$

$$\bar{s}_i\bar{y} \geq (1 + \bar{s}_i - s_i)\bar{y} - \hat{y}$$

$$\bar{s}_i\bar{y} \geq \bar{y} + \bar{s}_i\bar{y} - s_i\bar{y} - \hat{y}$$

$$0 \geq \bar{y} - s_i\bar{y} - \hat{y}$$

$$\hat{y} \geq (1 - s_i)\bar{y}$$

That is

$$(1 - s_i)\bar{y} \leq \hat{y} < (1 - s_i)\bar{y} + \bar{s}_i\bar{y}$$

## C Italian Farm Agent: Implementation

This appendix documents the implementation of the `Farm` agent, which represents an individual Italian wheat-producing farm within the `ECOWHEATALY` framework. The farm agent integrates microeconomic optimization, yield response functions, environmental life-cycle assessment (LCA), and stochastic production realization. This design enables consistent linkage between price signals, production decisions, and environmental outcomes.

### C.1 Agent Role and State Variables

Each `Farm` agent (`TYPE = 0`) is characterized by:

- Geographic attributes: province and altimetry class,
- Structural attributes: wheat acreage and farm acreage,
- Production parameters estimated at the province–altimetry level,
- Input price vector  $\mathbf{p}_x$ ,
- Yield response parameters  $\mathbf{s}$  and  $\lambda$ ,
- Environmental accounting matrices for LCA.

Key production variables include:

- Target yield per hectare  $\hat{y}$ ,
- Harvested yield  $y$ ,
- Nitrogen, herbicide, and insecticide inputs per hectare,
- Tractor hours per hectare,
- Environmental impact indicators (DALY and species loss).

Farm parameters are province–altimetry specific and reflect empirical estimation from `RICA` and `ISTAT` data.

## C.2 Microeconomic Optimization Problem

The farm solves a static input choice problem consistent with the first-order condition:

$$p_w = \sum_{i=1}^3 \frac{p_{x_i}}{\lambda_i [(1 + \bar{s}_i - s_i)\bar{y} - y]}$$

where:

- $p_w$  is the wheat price,
- $p_{x_i}$  are input prices,
- $\lambda_i$  are productivity parameters,
- $\bar{y}$  is maximum attainable yield,
- $s_i$  are yield share parameters.

The function `_foc_residual()` computes the residual of this condition, and the target yield  $\hat{y}$  is obtained by solving:

$$\text{fsolve}(\text{\_foc\_residual}, y_0).$$

Given  $\hat{y}$ , optimal input levels are derived as:

$$\hat{x}_i = -\frac{1}{\lambda_i} \log \left( \frac{(1 + \bar{s}_i - s_i)\bar{y} - \hat{y}}{\bar{s}_i \bar{y}} \right).$$

Negative values are truncated at zero.

## C.3 Yield Realization and Harvest

The biological yield function follows:

$$\hat{y} = \bar{y} [(1 - s_1) + s_1(1 - e^{-\lambda_1 x_1})].$$

Actual harvested yield is a stochastic or scaled realization of the target yield. In the current implementation:

$$y = \xi \hat{y}.$$

where  $\xi$  is the realization of a Gaussian random variable with mean  $0.5\hat{y}$  and standard deviation equal to the standard deviation of the yield computed on all the farms located at in the same province and at the same altimetry of the farm at hand;

Total production is:

$$Q = y \times \text{wheat acreage} \times 10.$$

## C.4 Life Cycle Assessment (LCA)

The farm performs a simplified process-based LCA using:

- Activity matrix **A**,
- Biosphere matrix **B**,
- Characterization matrices  $C_{DALY}$  and  $C_{species}$ .

The environmental computation proceeds as:

$$\mathbf{s} = \mathbf{A}^{-1}\mathbf{f},$$

$$\mathbf{i} = \mathbf{B}\mathbf{s},$$

$$DALY = \sum(C_{DALY}\mathbf{i}), \quad Species = \sum(C_{species}\mathbf{i}).$$

Tractor energy use and chemical inputs are inserted into matrices **A** and **B** before solving.

Environmental impacts are stored at the farm level and aggregated across ranks.

## C.5 Aggregation Mechanism

Each farm contributes to global aggregates:

- Production,
- Tractor hours,
- Nitrogen use,
- Herbicide use,
- Insecticide use.

These quantities are summed via MPI reduction at harvest.

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**Algorithm 1:** Italian Farm Annual Decision and Harvest

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**Input:** Wheat price  $p_w$ , farm parameters

**Output:** Production  $Q$ , environmental impacts

Solve first-order condition for target yield  $\hat{y}$ ;

**for**  $i = 1$  to 3 **do**

    Compute optimal input:

$$x_i = -\frac{1}{\lambda_i} \log \left( \frac{(1 + \bar{s}_i - s_i)\bar{y} - \hat{y}}{\bar{s}_i\bar{y}} \right)$$

**if**  $x_i < 0$  **then**

$x_i \leftarrow 0$ ;

Compute biological yield:

$$\hat{y} = \bar{y}[(1 - s_1) + s_1(1 - e^{-\lambda_1 x_1})]$$

Set realized yield  $y = \xi\hat{y}$ .

Compute production:

$$Q = y \times \text{acreage} \times 10$$

Insert inputs into LCA matrices;

Solve LCA system to compute DALY and species impact;

Return  $(Q, DALY, Species)$ ;

---