Modeling and Simulating the Italian Wheat Production System: A Parallel Agent-Based Model to Evaluate the Sustainability of Policies

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Keywords: Farm Crop Management, Mathematical Optimization, Yield-Gap, Cluster Analysis.

Abstract: This work presents the modeling steps to build a tool for policymakers to orient policies toward more sustainable wheat production. Starting from a sample survey of Italian farms, we identify, with the help of clustering techniques, the farm types present in the sample. The clustering phase reveals a significant heterogeneity among farms that we handle building an agent-based model. Sampling from the clusters allows for including a number of farms comparable to those operating in Italy in the agent-based model. Moreover, we build a mathematical programming model with which farms (i.e., agents) decide the target production level and the mix of inputs needed to obtain such production. Considered inputs are 1) the use of fertilizers, 2) the use of herbicides, and 3) the use of pesticides. Policies are introduced as incentives or deterrents, driving production decisions and the input mix choice towards more sustainable production.

1 INTRODUCTION

The increasing global demand for food, particularly wheat, highlights its critical role as a staple crop feeding billions of people worldwide. Wheat is central to human diets and a key ingredient in various processed foods (Asseng et al., 2018; Ketema et al., 2023). Driven by population growth and evolving dietary preferences, global demand for wheat is expected to rise significantly, necessitating a substantial increase in production to maintain food security (Sheikh et al., 2014; Tilman et al., 2011; Lethin et al., 2020; Hannah Ritchie, 2020). However, achieving this growth is complicated by multiple constraints, chief among them the limited availability of arable land due to urbanization, climate change, and environmental degradation (Tilman et al., 2011; Costanzo and Bàrberi, 2013).

Decreasing land availability presents a dual challenge: meeting rising food demand while ensuring environmental sustainability (Fischer and Connor, 2018). Intensified agricultural practices, if unmanaged, can lead to soil degradation, biodiversity loss, and increased greenhouse gas emissions (Liu et al., 2013; Costanzo and Bàrberi, 2013; Poore and Nemecek, 2018). Projections indicate that wheat production must increase by approximately 70% by 2050 to meet global demand (Allen et al., 2016; Lethin et al., 2020). Yet, current agricultural systems are experiencing yield plateaus, further intensifying the need for innovative and sustainable farming strategies (Ray et al., 2012; Ibrahim and Baqutayan, 2023).

Many wheat-producing countries have introduced environmental policies promoting sustainable agricultural practices in response to these challenges. The European Union introduced significant changes in the Common Agricultural Policy (CAP), which became effective in January 2023. The CAP focuses on ten specific objectives, linked to common EU goals for social, environmental, and economic sustainability in agriculture and rural areas (EU CAP Network, 2022). Egypt has adopted strategies to achieve wheat self-sufficiency while addressing climate adaptation and resource limitations (Asseng et al., 2018). Policy frameworks increasingly emphasize soil health, eco-friendly farming techniques, and efficient irrigation methods to reduce water consumption and enhance resilience to environmental stressors (Liu et al., 2013; McMillan et al., 2018). By embedding sustainability into agricultural policy, these countries aim to rec-

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Giulioni, G., Di Giuseppe, E., Di Paola, A. and Ceccarelli, A.
Modeling and Simulating the Italian Wheat Production System: A Parallel Agent-Based Model to Evaluate the Sustainability of Policies.
DOI: 10.5220/0013568000003970
In *Proceedings of the 15th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH 2025)*, pages 337-343
ISBN: 978-989-758-759-7; ISSN: 2184-2841

oncile productivity with ecological preservation, ensuring the wheat supply can meet future demands without compromising environmental health (Tilman et al., 2011; Ray et al., 2012).

The effect of a policy introduction depends on how farmers respond to the measure. Because of the complexity of the decision process, these responses are usually heterogeneous. This work uses the agent-based approach to handle such complexity and heterogeneity. Agent-based simulation (ABS) has emerged as a powerful tool for evaluating policy design due to its ability to realistically model complex interactions among autonomous agents. The flexibility of ABS also supports the modeling of diverse agents with unique decision-making processes, enabling the exploration of unforeseen consequences of proposed policies. Beheshti et al. discuss how agent-based modeling facilitates this exploration, suggesting that simulations can reveal important insights into the impacts of policy initiatives, particularly in sustainable decision-making scenarios (Beheshti et al., 2015). By allowing changes in agent decision rules, researchers can also simulate various governance models, elucidating behavioral determinants that may significantly affect environmental management efforts (Jager and Mosler, 2007).

Several studies use agent-based models to tackle the issue of environmental impacts and for agricultural policy evaluation (see (Kremmydas et al., 2018), for a survey). According to the authors, the agent-based approach has the advantage of accounting for the different effects of policies due to farm heterogeneity. Similarly, to investigate sustainable paths of wheat production, (Khan et al., 2020) uses a computational approach to predict the economic impact of climate change-induced loss of agricultural productivity in Pakistan. In contrast, using an agent-based model, (Siad et al., 2017) focuses on price formation in South Italy. This work presents the framework of an agent-based model built to assess the economic and environmental sustainability of the wheat production system in Italy. To this end, we first build a model for individual farmer decision-making based on economic principles (Section 2).

In Section 3, we perform a cluster analysis on data from an Italian sample survey database. This phase aims to detect the diverse environmental profiles of firms producing wheat in Italy. It allows the introduction of heterogeneity in our agent-based model by estimating the parameters of the individual model for each cluster.

Section 4 details the agent-based model architecture. In particular, aiming to provide a valuable tool to policymakers, we intend to provide a model similar to the Italian wheat production system, including a number of farms comparable to those observed in reality. Data from the agriculture census is used to initialize simulations.

Section 5 concludes and describes future directions for our research.

2 MODELING FARM INPUTS DECISION

2.1 Farm Crop Management

Modeling a farm's input decision belongs to the broader farm management field. Farm management has several aspects: financial management, crop and livestock management, equipment management, labor management, and risk management (see (Kay et al., 2020) or (Kunz, 2022)). Because we deal with wheat production, we will build on tools used in the crop management field. In particular, we are interested in modeling a situation in which a product (wheat) is produced using several inputs. This choice is usually analyzed by applying economic principles ((Kay et al., 2020) chapter 8 page 144). Indeed, the problem of choosing an input combination is a mathematical minimization, i.e., the farmer selects the cost that minimizes the input combination. The dual problem of cost minimization is profit maximization (see (Carpentier et al., 2015) for a review of economic modeling of agriculture production). We analyze the problem of maximizing profit for one hectare of wheat, which is generally posed as follows:

$$\pi = p_w y(x_1, x_2, ...) - \sum_i p_{x_i} x_i \tag{1}$$

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

Because this work focuses on environmental sustainability, we consider fertilizer, herbicide, and insecticide relevant inputs for wheat production. A key role in the economic modeling of input combination choice is input substitution ((Kay et al., 2020) chapter 8). The input substitution degree has been studied for several decades (see, for example, chapter 5 in (Heady and Tweeten, 1963)). When inputs can be considered substitutes, the Cobb-Douglas or the CES (constant elasticity of substitution) are used as functional forms for $y(x_i)$.

In the model developed below, we will provide a new modelization of the yield function based on the yield gap concept. Because we are analyzing profit per hectare, it is reasonable to work under the zero degree of input substitution. Substitution normally occurs between acreage and other production inputs, i.e., it is possible to obtain the same production, for example, by increasing acreage and reducing fertilization. In cultivating a single hectare, each input is specialized in improving a specific condition that favors the plant's health. Therefore, the Leontief-type production function models the zero substitution input case.

2.2 Yield-Gap

This approach starts by identifying the potential yield, the maximum yield obtainable depending on solar radiation, temperature, atmospheric CO2, and genetic traits. These features govern the length of the growing period. Thus, the potential yield is location-specific because of the climate (see (Fischer, 2015) and (ClimaTalk, 2024) for more detailed definitions and explanations). The yield realized by the farm is lower than the potential yield, and the difference between the potential and the actual yield is the yield gap. The yield gap is caused by limiting factors such as water and nutrient availability and reducing factors such as weeds, pests, diseases, and pollutants. Usually, a farm's yield does not exceed 80% Farm management practices are important to reduce the yield gap. In Table 2, (Devkota et al., 2024) identifies the management factors that primarily affect the yield.

2.3 A Model

We set up a model based on the yield-gap concept as a tool for management decisions. The model envisages stress factors and actions to relieve the stress. Each production input can relieve one specific stress factor. Therefore, the farmer's action consists of weighing out the input quantity. Let us index stress factors by i. We denote the conditional yield with y_i, i.e., the yield obtained when only the stress factor i is binding. Our first step is to set up a functional form for y_i. Let us denote the potential yield with $\bar{y}$. In addition, we define $s_i \in (0,1)$ to identify the share of the potential yield lost due to the stress and x_i as the strength of the measure taken to counteract the stress. We also define $g_i(x_i) \in (0,1)$ as a function of x_i that gives the effectiveness of the undertaken measure. Furthermore, we assume that g_i is increasing in x_i according to the functional form $g_i(x_i) = 1 - e^{-\lambda_i x_i}$. We further introduce the maximum share of yield that can be recovered at the maximum effectiveness of the measure. Let us identify it with $\bar{s}_i$.

Under these definitions, the conditional yield can be written as

$$y_i(x_i) = \bar{y}[(1-s_i) + \bar{s}_i(1-e^{-\lambda_i x_i})] \tag{2}$$

When several stress factors are binding, the realized yield corresponds to the most binding stress factor: $y = \min(y_i)$.

As mentioned above, the economic theory of production uses the Leontief type function. Its main feature is that relieving one stress factor can be ineffective because of the constraints of the other stress factors. The optimal strategy in this case is to level out the conditional yields: $y_i = \hat{y}$.

Using equation (2), the $y_i = \hat{y}$ condition can be written as

$$\bar{y}[(1-s_i) + \bar{s}_i(1-e^{-\lambda_i x_i})] = \hat{y} \tag{3}$$

Solving x_i, we get:

$$\hat{x}_i = -\frac{1}{\lambda_i} \ln\left(\frac{(1+\bar{s}_i - s_i)\bar{y} - \hat{y}}{\bar{s}_i \bar{y}}\right) \tag{4}$$

With this result, we can go to the profit function (equation 1), which in our case is

$$\pi = p_w \min(\hat{y}_i) - \sum_i p_{x_i} \hat{x}_i \tag{5}$$

Because all the $\hat{x}_i$ deliver a yield equal to $\hat{y}$, we have $\min(\hat{y}_i) = \hat{y}$ and equation (5) simplifies to:

$$\pi = p_w \hat{y} - \sum_i p_{x_i} \hat{x}_i \tag{6}$$

Remembering that $\hat{x}_i$ depends on $\hat{y}$, the whole profit function depends on $\hat{y}$. Therefore, the farmer's problem is to maximize profit with respect to $\hat{y}$:

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

The first order condition (FOC) for a maximum is:

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

Numerical methods can solve the FOC. Let us denote the solution with $\hat{y}^*$. Plugging $\hat{y}^*$ in equation (4), we obtain the optimal level of each input $\hat{x}_i^*$.

The one stress factor case can help understanding because of its analytic solution. In the one stress factor case, we can drop the i subscript from equations, and the sum symbol is unnecessary. Solving the farmer's maximization problem in this case, we obtain: $\hat{y}^* = (1+\bar{s}-s)\bar{y} - p_x/(p_w\lambda)$ and plugging into equation (4) we get the optimal input level: $\hat{x}^* = -\frac{1}{\lambda}\ln\left(p_x/(p_w\lambda\bar{s}\bar{y})\right)$.

3 MODELING THE WHEAT SYSTEM

The model presented in the previous section will be used to to shape the behavior of agents in the agent-based model. As is known, one of the advantages of agent-based models is the possibility they offer to handle heterogeneity. Even though there are other ways to allow for heterogeneity in our context (we will talk about them in the conclusions and future research directions section below), our first device is to identify types of farms in the Italian system. We let all the farms decide according to the functional forms displayed in the previous section. Still, the parameters involved in the equations ($\bar{y}$, λ, s, $\bar{s}$) are estimated conditioning on the type. The different types of farms are identified by implementing a cluster analysis on real farm data.

This study utilizes the RICA (Rete d'Informazione Contabile Agricola) database, a comprehensive dataset representing 9048 Italian farms that have cultivated durum wheat for 16 years. The RICA database is essential for evaluating agricultural production systems, offering detailed information on farm characteristics, inputs, and outputs. For the following analysis, the dataset was filtered to focus exclusively on wheat-producing farms for 2016, resulting in a dataset encompassing 2140 distinct farms. The choice of 2016 relies on the fact that seasonal weather conditions strongly influence wheat production, input use, costs, and revenues. Favourable agro-climatic conditions in Italy characterized the year 2016. Thus, we assume—at least in a first approximation—to be working under stable and favourable climatic conditions, effectively disregarding the impact of adverse weather. Key variables extracted from the dataset include: 1) Produced Quantity (the total quantity of wheat produced), 2) Crop Acreage (the area dedicated to wheat cultivation), 3) Herbicide Use (quantities of various herbicides applied), 4) Nutrient Applications (quantity per hectare of nitrogen, phosphorus, and potassium, and 5) Machinery Use (hours of machine operation per hectare).

A clustering analysis was performed to group farms into distinct categories based on their input-use efficiency and productivity. Firstly, input-to-yield ratios were calculated to normalize farm differences and enable comparison. Then, three key performance indicators (herbicide ratio over yield, elements ratio over yield, and machinery hours per hectare over yield) were selected as input variables for clustering. We refer to the mentioned ratios as inefficiency because they increase as the inputs increase and the yield decreases, i.e., the farmer obtains less product with more inputs. A range of cluster numbers (k) from 2 to 15 was tested using the k-means algorithm. The elbow method was applied to identify the optimal number of clusters, leveraging the inertia metric, which reflects cluster compactness. In particular, the chosen k maximizes the second difference of the inertia. Figure 1 displays a visual representation of the method. In our case, the process suggests $k = 5$. The final clustering analysis let us classify the Italian wheat farms into five distinct clusters, with cluster sizes ranging from 155 to 813 farms. Figure 2 provides boxplots of each cluster's distribution of the key inefficiency ratios.

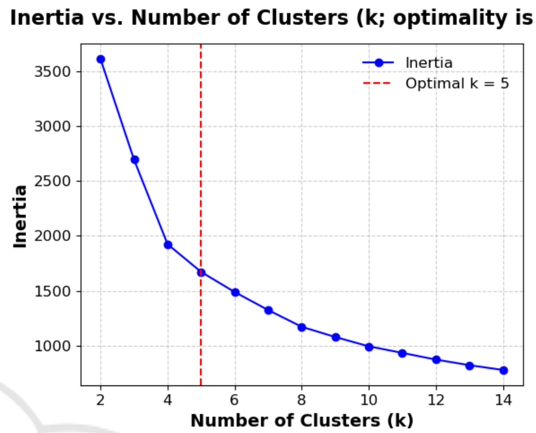

Figure 1: Inertia as a function of the number of clusters.

In the figure, clusters are sorted for increasing inefficiency levels of fertilizers. The inefficiency ranking is confirmed for herbicides and machine use in the other clusters, except for clusters 1 and 2. Clusters 1 and 2 have a higher dispersion of fertilizer inefficiency and less regular behavior of the other inefficiencies. Prominent is the high level of tractor use in cluster 1. The interpretation of these odd clusters' behavior deserves further investigation.

4 DISTRIBUTED AGENT-BASED SIMULATIONS

The research presented in this paper aims to simulate the reaction of the Italian wheat production system to events such as changes in policies or shocks. To have reliable results, we require the simulation to meet the features of the Italian system, especially the number of farms. To this aim, we classify wheat farms in clusters and magnify each cluster so that the total number of farms in the simulation is comparable to the number of farms producing wheat in Italy. According to the latest Italian agriculture census holding data for 2020, the number of grain producers in Italy is 325313 ((Gismondi, 2022) p. 11). Filtering the census data by grain type, we count 195735 observations for durum wheat. The magnification is implemented

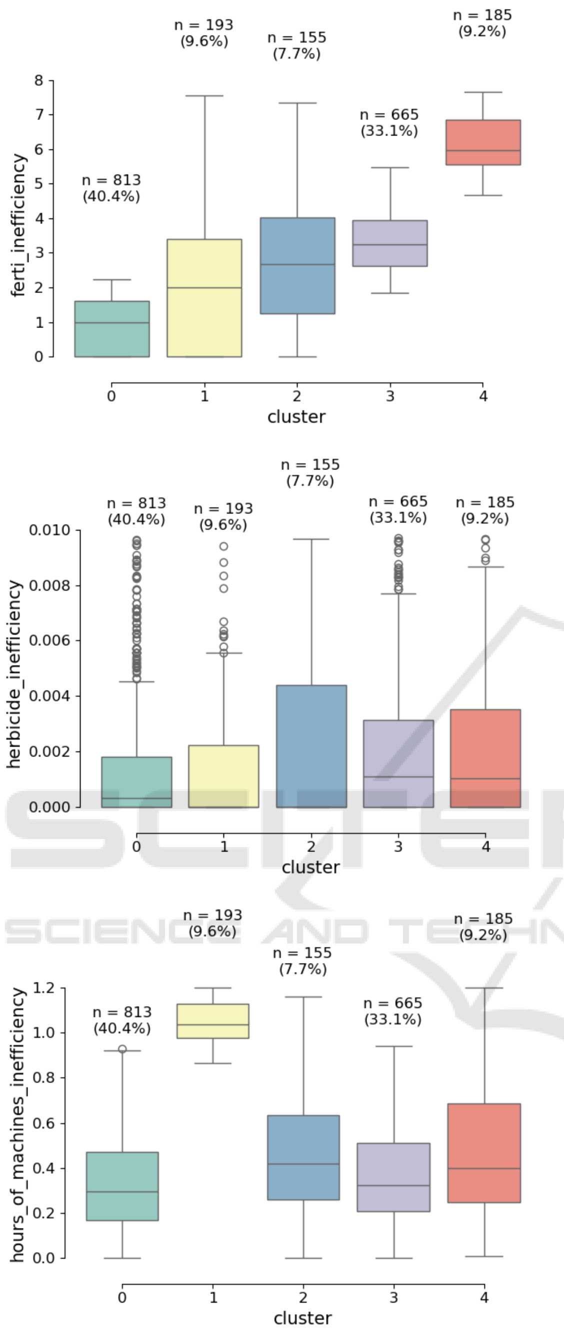

Figure 2: The clustering of Italian wheat farms according to their fertilizer, herbicide, and machinery use.

by estimating the statistical distribution of relevant clusters' variables and sampling from these distributions, keeping the relative cluster size unchanged until the scale of the Italian system is reached. The magnification using artificially generated agents is a practice needing some care (Roxburgh et al., 2025); however, in our view, it brings benefit because we could provide more significant simulation results even at a regional or provincial scale.

The considerable size of the system prompted us to consider the possibility of running our simulation in parallel using high-performance computing technologies. From this point of view, the Repast Suite (https://repast.github.io) offers interesting opportunities. Repast provides facilities to run agent-based simulations. It comes in three different toolkits. The classic one is "Repast Simphony," a Java-based toolkit designed for use by personal computers and small clusters. The increase in computer availability led the development team to release the "Repast for High-Performance Computing" toolkit, a "C++-based distributed agent-based modeling toolkit designed for use on large computing clusters and supercomputers." The most recent toolkit is Repast for Python. It is a Python-based distributed agent-based modeling toolkit for applying large-scale distributed ABM methods.

The simulator is currently under development using "Repast for Python", which, in addition to other facilities, builds some of its functions on mpi4py to ease the management of parallel computation. Presently, the simulator implements the `Farm` and the *PolicyMaker* classes. The `Farm` class has the `decide_production_inputs` function that performs the calculations presented in section 2.3. The code is executed with parameters sampled using the estimated cluster distribution. In other words, the statistical analysis of the clusters found in section 3 allows the calibration of the model. This preserves the relevant farm heterogeneity seen in reality. The `PolicyMaker` class affects farm decisions by managing input prices, i.e., by charging taxes on detrimental inputs. It will be enriched by International, National, or local policies in the future. To simulate in parallel, the policy maker is created in the master rank, and a copy of the original agent is sent to all the other ranks. In Repast jargon, we say that the original agent is ghosted to all other ranks. A second important issue is load balancing among ranks at initialization. To this aim, we partition clusters between two ranks where needed to keep proportionality with the n displayed in Figure 2 among clusters and an equal number of agents across ranks.

5 CONCLUSION AND FUTURE RESEARCH

The present work describes the plan to build a model representing the Italian wheat production system. We first built a model for the single-farm production and input decision. We then identified the heterogeneity of farms with a clustering analysis performed using a sample survey database. Finally, we used the detected heterogeneity to populate an agent-based model to evaluate the effects of policy introduction or the occurrence of significant exogenous shocks. To allow the possibility to simulate with as many agents (farms) as needed, we decided to implement the simulator using parallel simulation techniques. This will allows to scale to the Italian system size (which is in the order of a few hundred thousands), or more in case the model would be used to analyze wider areas.

The choice to implement in a parallel computation-enabled environment is convenient because the model is part of a wider project that aims to include modules that require additional computational power.

One of these modules aims to introduce the endogenous computation of the wheat price. As one expects, this price is heavily affected by international trade conditions. The module we intend to add represents the international wheat markets, where agents are large subcontinental geographic areas. The international prices are then computed by balancing the international demand of excess demand areas and the excess supply of areas with production higher than domestic demand. We plan to develop this module following our previous research (Giulioni, 2019; Giulioni et al., 2019). This task will allow accounting for the double-sided interaction between wheat price and individual farmers' production decisions. In Section 2, the wheat price is a variable affecting wheat production decisions. In turn, wheat production affects demand and supply in international markets, and therefore international prices.

A second module allows the computation of the environmental impact of the wheat production activity. We apply the Life Cycle Assessment (LCA) methodology to the wheat production process. The methodology can be applied both at the farm and aggregate levels. Performing the LCA individually, we can endow agents with environmental awareness. As an example, the ReCiPe LCA methodology outputs endpoint indicators measuring the damages to human health in terms of the shortening of healthy life, i.e., the "Disability Adjusted Life Years" (DALY), or the damages to ecosystem quality measured by the number of local species lost per year. Integrating this information in the farmers' decision process could nudge agents to adopt more sustainable production strategies. The model presented in section 2 has to be revised to account for this effect. The LCA at the aggregate level will mainly inform policymakers of the potential environmental effects of the policies they plan to introduce.

As a technical note, we developed the LCA module in Python using the Brightway LCA Software Framework. This fully complies with our choice of the Repast for Python toolkit and will allow us to deliver the whole software bundle in Python.

ACKNOWLEDGEMENTS

This research was conducted as part of the project "ECOWHEATALY: Evaluation of policies for enhancing sustainable wheat production in Italy" funded by the European Union-Next Generation EU under the call issued by the Minister of University and Research for the funding of research projects of relevant national interest (PRIN) grant n. PRIN 202288L9YN.

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