
Causality and Explainability for Trustworthy Integrated Pest Management

Ilias Tsoumas^{*1,2} Vasileios Sitokonstantinou^{*4} Georgios Giannarakis¹
Evagelia Lampiri³ Christos Athanassiou³ Gustau Camps-Valls⁴
Charalampos Kontoes¹ Ioannis Athanasiadis²

¹BEYOND Centre, IAASARS, National Observatory of Athens

²Wageningen University & Research

³University of Thessaly

⁴Image Processing Laboratory (IPL), Universitat de València

{i.tsoumas, giannarakis, kontoes}@noa.gr

{ilias.tsoumas, ioannis.athanasiadis}@wur.nl

{elampiri, athanassiou}@uth.gr

{sitokons, gustau.camps}@uv.es

Abstract

Pesticides serve as a common tool in agricultural pest control but significantly contribute to the climate crisis. To combat this, Integrated Pest Management (IPM) stands as a climate-smart alternative. Despite its potential, IPM faces low adoption rates due to farmers' skepticism about its effectiveness. To address this challenge, we introduce an advanced data analysis framework tailored to enhance IPM adoption. Our framework provides i) robust pest population predictions across diverse environments with invariant and causal learning, ii) interpretable pest presence predictions using transparent models, iii) actionable advice through counterfactual explanations for in-season IPM interventions, iv) field-specific treatment effect estimations, and v) assessments of the effectiveness of our advice using causal inference. By incorporating these features, our framework aims to alleviate skepticism and encourage wider adoption of IPM practices among farmers.

1 Introduction

Conventional pest management has been shown to contribute to climate change. Raising temperatures, intensifying ultraviolet radiation, and reducing relative humidity, are expected to increase pest outbreaks and undermine the efficacy of pest control methods like host-plant resistance, bio-pesticides, and synthetic pesticides [37, 41]. Pervasive pesticide use in agriculture, despite climate experts' warnings, adversely affects public health [9] and contributes to the climate crisis. This impact includes: i) greenhouse gas (GHG) emissions from pesticide production, packaging, and transportation [6], ii) compromised soil carbon sequestration [48], iii) elevated GHG emissions from soil [27, 18, 42], and iv) contamination of adjacent soil and water ecosystems, resulting in biodiversity loss [35].

Thus, a vicious cycle has been established between pesticides and climate change [36]. In response, the European Commission (EC) has taken action for the reduce of all chemical and high-risk pesticides by 50% by 2030. Achieving such reductions requires adopting integrated pest management (IPM), which promotes sustainable agriculture and agroecology. IPM consists of 8 principles inspired by the Food and Agriculture Organization (FAO) description. The authors in [8] condense these principles

*Equal contribution.

into prevention and suppression, monitoring, decision-making, non-chemical methods, pesticide selection, reduced pesticide use, anti-resistance strategies, and evaluation.

Data-driven methods have played a crucial role in optimizing pest management decisions. Some employ supervised machine learning (e.g., Random Forests, Neural Networks) with satellite Earth observations (EO) and in-situ data for pest presence prediction [49, 4], some incorporating weather data [40]. Recurrent Neural Networks (RNNs) are used to capture temporal features from weather data, effectively handling unobservable counterfactual outcomes [47]. Filho et al. extract fine-scale IPM information from meteorological data, insect scouting, remote sensing and machine learning [21]. Nanushi et al. propose an interpretable machine learning solution for *Helicoverpa armigera* presence in cotton fields [30], enhancing IPM decision-making beyond traditional thresholds.

2 Proposal

As Barzman et al. point out, threshold-based and "spray/don't spray" advice is not enough [8]. There is a need for a new class of digital tools that take into account the entire set of IPM principles in order to truly enhance decision-making. In this direction, we propose a data analysis framework for IPM based on causality and explainability. It consists of short-term actionable advice for in-season interventions and long-term advice for supporting strategic farm planning (Figure 1).

This way, we will upgrade the *monitoring* and *decision-making* IPM principles leading to actionable advice for direct pest control interventions and assist the selection of practices relevant to other IPM principles, such as *use non-chemical methods* and *reduce pesticide dosage*. Additionally, the proposed framework will better inform farmers with respect to the potential impact of practices that, in turn, will enhance the IPM principle of *prevention and suppression*, e.g., crop rotation, day of sowing, and no-tillage. Furthermore, our framework employs observational causal inference to continuously assess the aforementioned recommendations and thereby satisfy the IPM principle of *evaluation*.

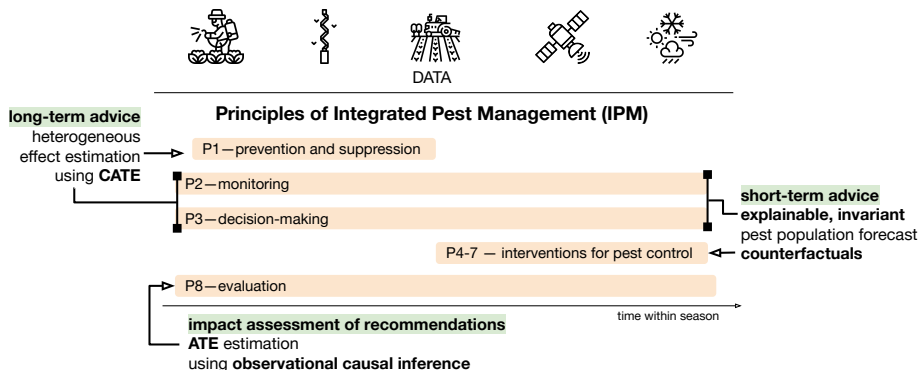


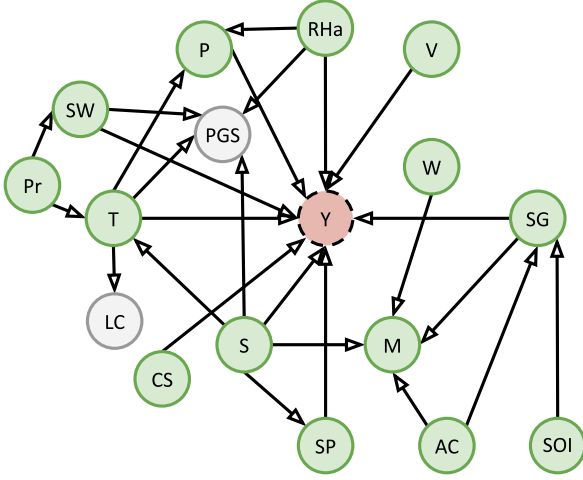
Figure 1: Causal and explainable data analysis framework for enhanced IPM

Data: Our strategy hinges on utilizing a variety of data to gain a holistic understanding of historical, current, and future agro-environmental conditions, thereby enhancing our ability to model and comprehend pest dynamics. We use EO data on factors like vegetation, soil moisture. Terrain and soil characteristics data are incorporated for long-term area-specific traits. We also utilize weather forecasts and ground measurements, including pest abundance (details in A.1 of Appendix).

3 Approach & Methods

Causal Graph for representing domain knowledge. We constructed a causal graph (Figure 2), denoted as G , that represents the underlying causal relationships within the pest-farm ecosystem for the *H. armigera* case. The graph G comprises vertices V , which represent the variables in the system, and directed edges E , which symbolize the cause-and-effect relationships between these variables (details about graph building in A.2 of Appendix). Besides helping us articulate domain knowledge, the causal graph G will benefit the downstream technical analyses in various ways. G

serves as an amalgamation of domain knowledge and a foundational schema that can be leveraged variably depending on the methodological requirements of the analytical techniques in play.



Id	Variable Description
T	Temperature
SW	Soil water
RHa	Air relative humidity
SG	Size of generation
Pr	Precipitation
LC	Life cycle
P	Parasitism
V	Variety
Sp	Spraying
CS	Cropping System
M	Migration
AC	Adjacent crops
W	Wind
S	Season
SOI	South oscillation index
PGS	Plant growth stage
Y	H. armigera population

Figure 2: Causal graph of pest-farm ecosystem.

Table 1: Pest-farm ecosystem variables.

Invariant & Causal Learning for Robust Pest Prediction. Our goal is to predict near-future pest populations (Y_{t+1}) using EO and environmental data (X_t) and weather forecasts (W_{t+1}) by learning the function $y_{t+1} = f(x_t, w_{t+1})$. Conventional machine learning methods [49, 4, 40, 47] struggle with non-i.i.d. data, hindering generalization and adaptation. We turn to causal learning [34], grounded in independent causal mechanisms that remain stable despite environmental changes. To achieve this, we integrate invariant learning with causality, categorizing data into environments E (e.g., agroclimatic zones). While E influences features (x_t, w_{t+1}), it does not directly affect the target (Y_t). Invariant Causal Prediction (ICP) [19], DAGs, and Invariant Risk Minimization (IRM) [5] help select causal features, identify potential relationships, and capture latent causal structures.

Explainability & Counterfactual Reasoning for Short-term Advice. We define the problem as a binary classification of pest presence or absence, at the next time step, using EO data (X_t) and weather forecasts (W_{t+1}). We employ Explainable Boosting Machines (EBM) [31] to enhance predictions with explanations at global and local levels. EBM’s additive model allows visualization of feature contributions, enhancing trust. To bolster trust, we propose generating counterfactual examples as recommended interventions. We follow the setup of [29], searching for minimal feature perturbations in (x_t, w_{t+1}) that alter predictions using the same model f . These counterfactual examples represent proposed actions for real farm systems, ensuring practicality and feasibility [45, 29].

Heterogeneous Treatment Effects for Long-term Advice. We provide long-term advice for pest prevention and suppression by assessing how practices (e.g., crop rotation, balanced fertilization, sowing dates) affect pest harmfulness and yield indices. Different agro-environments may yield varying responses to the same practice. We estimate the conditional average treatment effect (CATE) [17] using the potential outcomes framework [33]. CATE quantifies the difference in potential outcomes ($\mathbb{E}[Y(T = 1) - Y(T = 0)|X]$), controlling for field characteristics that drive heterogeneity.

Causal Inference for Evaluating Advice Effectiveness. We employ causal inference techniques to assess the effectiveness of our pest control recommendations, building on a recent approach introduced in the context of cotton farming [44]. Adapting this method to pest control interventions, we turn to difference-in-differences [1]. Our aim is to quantify the average treatment effect of adhering to our framework’s recommendations (*treated units*) compared to those who did not (*control units*). Historical intervention data, annotated as recommended or not, will be used for the evaluation. Causal inference will be conducted on a per-environment basis, ensuring similarity between treatment and control groups, following the parallel trends assumption [23]. Depending on data volume and time series length, other methods like synthetic control or panel data may also be considered.

4 Conclusions

Breaking the harmful cycle between pesticides and climate change is essential. In this direction, IPM aims to successfully control pests while minimizing the adverse effects of conventional pest management on human health and the environment. We propose an AI-driven framework for IPM that provides short- and long-term advice, promoting sustainable practices and timely control methods. Additionally, we employ observational causal inference to evaluate the framework's effectiveness. Finally, our approach ensures effective pest control and enhances trust and transparency.

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A Supplementary Material

A.1 Data

Our approach relies on diverse data sources as a key leverage to capture a comprehensive picture of the past, present, and future agro-environmental conditions. In turn, this will enable us to improve the modeling and comprehension of pest dynamics.

Earth Observations: We leverage biophysical and biochemical properties such as Leaf Area Index (LAI), Normalized Difference Vegetation Index (NDVI), chlorophyll content, as well as data on evapotranspiration and soil moisture. These factors play a crucial role in monitoring pest population dynamics. The data is derived from the Sentinel-1/2 and Terra/Aqua (MODIS) satellite missions that provide open access to optical multi-spectral and Synthetic Aperture Radar (SAR) images.

Terrain & soil characteristics: We incorporate data from open-access digital elevation models, as well as information on topsoil physical properties and soil organic carbon content [10, 7]. This allows us to include fixed or long-term characteristics specific to the area of interest.

Numerical weather predictions (NWP) and reanalysis environmental datasets: We utilize a custom configuration of WRF-ARW [39] at a spatial resolution of 2 km. Hourly predictions are made, and for each trap location, we obtain daily values for air (2 m) and soil temperature (0 m), relative humidity (RH), accumulated precipitation (AP), dew point (DP), and wind speed (WS). These parameters have been widely used in related work and are extremely valuable for learning from past (reanalysis) and future (NWP) pest states.

In-field measurements: In-field measurements involve ground observations of pest abundance using pheromone traps specifically designed for monitoring the cotton bollworm, known by the scientific name *Helicoverpa armigera* (*H. armigera*). These traps contain the active ingredients Z-11-hexadecen-1-al and Z-9-hexadecenal. The traps are used from the beginning of the first generation until the end of the season, with regular replacement every 4 to 6 weeks. The company Corteva Agriscience Hellas has established a dense (in time and space) trap network (Figure 3) that covers almost all areas in the Greek mainland where cotton is cultivated. The traps are strategically positioned at suitable distances from each other to prevent interference and ensure accurate data collection. An agronomist examines the traps and counts the trapped insects at regular intervals every 3-5 days. Corteva Agriscience Hellas provides us with historical data consisting of 398 trap sequences and 8202 unique data points since 2019 (Table 2). They also provide auxiliary data on pesticide application, potential crop damage from pests, the severity of the damage, trap replacements, and scouter comments.

Year	Traps	Measurements	Mean	std	Sprays	Sprayed fields %
2022	126	2507	19.73	4.22	30	18.25
2021	109	2245	20.30	1.79	17	11.01
2020	81	1693	20.54	4.77	12	8.64
2019	82	1757	21.29	6.43	21	21.95

Table 2: Summary of Trap Data.

A.2 Domain Knowledge and Graph Building.

In the current case about the pest-farm ecosystem of *H. armigera*, various biotic and abiotic factors (Table 1) can influence the population dynamics Y of *H. armigera* [38]. Temperature T plays a crucial role, affecting the growth, development, fecundity, and survival of the insect [20]. The size SG of the first generation is related to the size of the second generation, and the Southern Oscillation Index SOI has a significant correlation with the size of the first spring generation [25, 26]. Additionally, the life cycle LC of *H. armigera* is temperature-dependent, with completion occurring between 17.5°C and 32.5°C [28]. Depending on the season, the life cycle can be completed within 4–6 weeks in summer, increasing to 8–12 weeks in autumn [2]. The presence of parasitoids and natural enemies in cotton cultivation, is a crucial component of many IPM programs, including the control of *H. armigera* [32]. Many egg parasitoids of the different families are known for their high parasitism P rates and

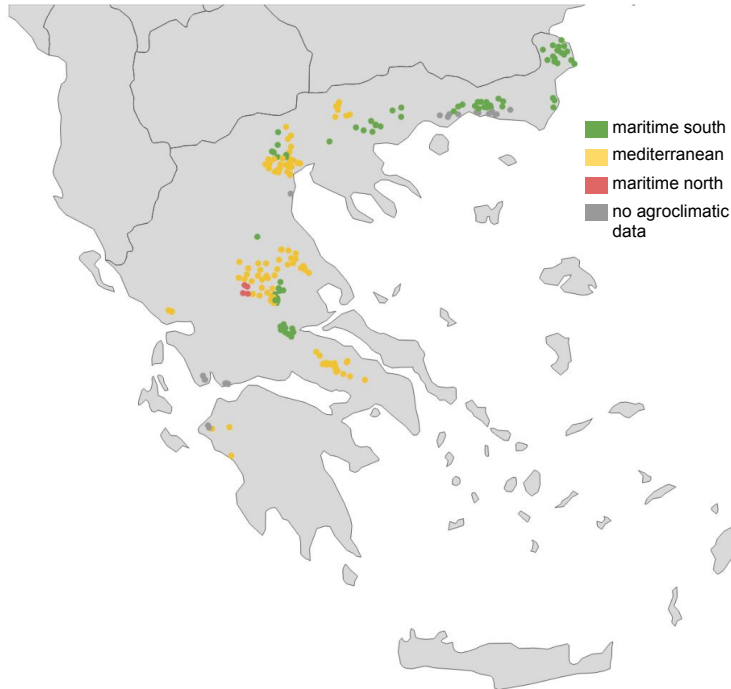


Figure 3: Traps distribution in the Greek mainland for the period 2019-2022. Colors indicate the different agroclimatic zones in which traps from the dataset belong. These zones have been identified based on the study conducted by Ceglar et al. [11].

their effectiveness in reducing the population of *H. armigera* [3]. Nevertheless, parasitism rates are influenced by temperature and relative humidity [22, 3]. Moreover, the efficacy of spray application Sp also impacts population dynamics [46].

Other environmental factors come into play as well. Precipitation Pr affects the population size, with heavy precipitation leading to a decrease in the population [16]. It also increases air relative humidity RHa and soil water content SW , that in their turn affect the emergence rate of *H. armigera* [12]. The presence of fruiting organs during the plant growth stage PGS is important for population dynamics, as it serves as the oviposition site for females [14]. Crop variety V , such as transgenic Bt cotton, can suppress the second generation of *H. armigera*, while both different cropping systems CS and adjacent crops AC can influence the population structure [46, 15, 24]. Finally, wind W and wind direction play a significant role in the seasonal migration M of *H. armigera*, impacting the distance covered during migration [43, 13]. These various factors collectively shape the population dynamics of *H. armigera* in a complex and interconnected manner.