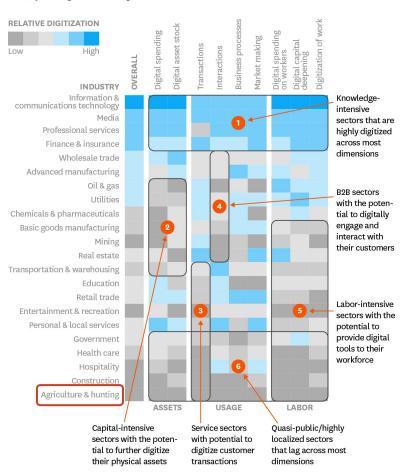
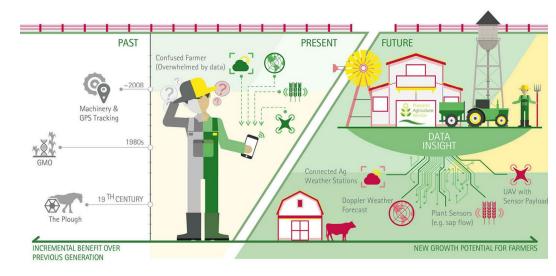


Motivation

How Digitally Advanced Is Your Sector?

An analysis of digital assets, usage, and labor.





smart farming technologies could drive to the application of required sustainable agriculture practices



Farmer needs:

- → actionable advices
- evidence about effectiveness & benefits

The case of a knowledge-based recommendation system for optimal cotton sowing

Answering on a real need of cotton farmers. **Is today a good day to sow?**

Collaboration with a farmer's cooperative (171 cotton fields) in Orchomenos, Viotia-Greece

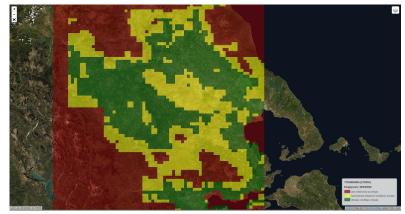
Cooperative have consolidated routines for interacting with their crops (e.g. common practices, homogeneous fertilizer application, jointly owned machinery)



pilot of sowing map for cotton for cultivation period of 2021 in Orchomenos, GR







Knowledge-based Recommendation System

Artificial 10-day at 2km forecast blending WRF & GFS

$$a_i = \frac{GFS_{day=i}}{GFS_{day=1}}, i \in \{3, ..., 10\}$$
 (1)

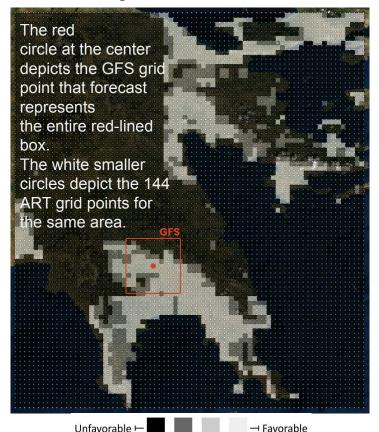
$$ART_{j} = \begin{cases} WRF_{day=j} & , j \in \{1, 2\} \\ WRF_{day=1} \cdot a_{j} & , j \in \{3, ..., 10\} \end{cases}$$
 (2)

Knowledge-based rules

Type of Temperature	Statistic	Condition	Condition Priority		
soil (0-10 cm)	mean	>18°C	optimum		
ambient (2 m)	max	$>26^{\circ}\mathrm{C}$	optimum		
soil (0-10 cm)	mean	$>15.56^{\circ}C$	mandatory		
soil (0-10 cm)	min	>10°C	mandatory		
ambient (2 m)	min	$>10^{\circ}$ C	mandatory		

All conditions refer to a time window between 5 to 10 days

Nearest neighbor



actionable advices



evidence about effectiveness & benefits

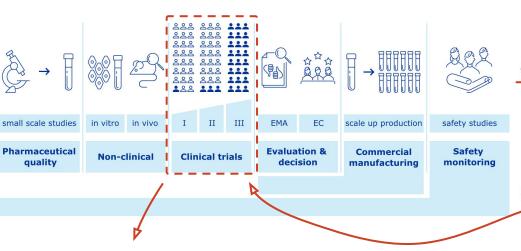
Hmm, but what is the actual impact of our recommended actions?

[BOOK] Evaluating decision support and expert systems

L Adelman - 1992 - dl.acm.org

Three approaches to evaluating decision support and expert systems are presented: subjective, technical, and empirical. Subjective evaluation assesses the decision support or expert system from the perspective of the system's users and sponsors. For subjective evaluation, the author presents several techniques including multiattribute utility technology, cost-benefit analysis, and decision analysis. Technical evaluation determines whether the delivered system is a good technical product. Technical evaluation techniques include ...

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Ok, lets run our experiments! But if there is no capacity for RCTs?

Table 1. Evaluation methods overviewed herein

Subjective evaluation methods for requirements validation and to obtain system performance and usability judgments

Multi-Attribute Utility Assessment (MAUA)

Task analysis

Interviews and questionnaires

Observation

Human factors checklists

User diaries

Technical evaluation methods

Static and dynamic analysis to assess the logical consistency and completeness of the knowledge base

Domain experts and the use of test cases to assess the functional completeness and predictive accuracy of the knowledge base Software testing methods to assess "service requirements"

Empirical evaluation methods to obtain objective measures of system

performance

Experiments

Quasi-experiments

Case studies (i.e., field tests)

Evaluating agricultural recommendations using causal inference

Our approach

Model the farm system using a causal graph, and identify the effect of sowing on a recommended day on the yield the farmer observed.

Unit Field

Treatment (T) The field was sown on a recommended day

Outcome (Y) Yield observed at the end of season

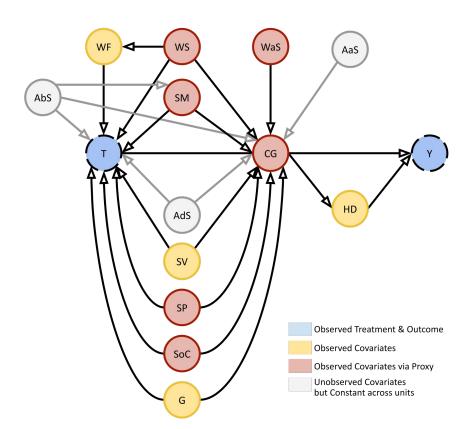
$$ATE = \mathbb{E}[Y|do(T=1)] - \mathbb{E}[Y|do(T=0)]$$

Our end goal is to account for exactly the variables that will allow us to identify the Average Treatment Effect (ATE) of the treatment on outcome

Unobserved confounding, selection bias, counterfactual yield not observed

of the cooperative's modus operandi and harness agricultural knowledge

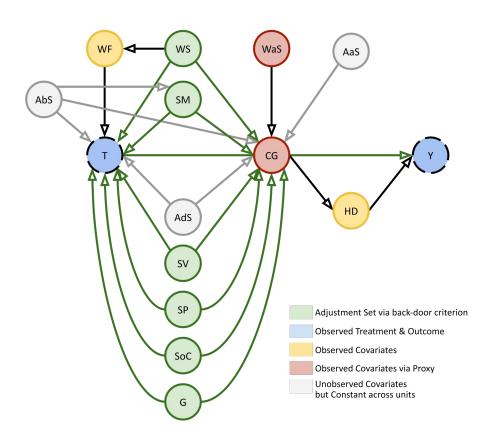
Graph Building



Id	Variable Description	Source			
Т	Treatment	Recommendation System			
WF	Weather forecast	GFS, WRF			
WS	Weather on sowing day	Nearest weather station			
WaS	Weather after sowing	Nearest weather station			
CG	Crop Growth	NDVI via Sentinel-2			
SM	Soil Moisture on sowing	NDWI via Sentinel-2			
SP	Topsoil physical properties	Map by ESDAC			
SoC	Topsoil organic carbon	Map by ESDAC			
SV	Seed Variety	Farmers' Cooperative			
G	Geometry of field	Farmers' Cooperative			
AdS	Practices during sowing	Farmers' Cooperative			
AbS	Practices before sowing	Farmers' Cooperative			
AaS	Practices after sowing	Farmers' Cooperative			
HD	Harvest Date	Farmers' Cooperative			
Y	Outcome (Yield)	Farmers' Cooperative			

In collaboration with domain experts and by making clear assumptions, we establish a causal graph of the farm system

Effect Identification

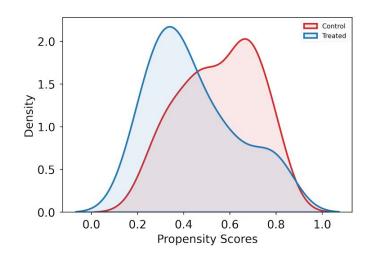


Id	Variable Description	Source			
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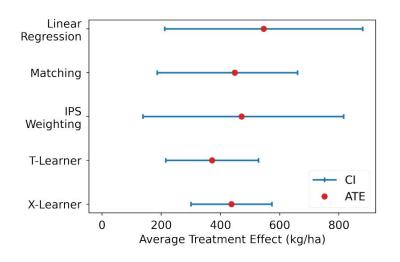
Applying the back-door criterion, the following set of variables was found to be sufficient for effect identification:

$$Z = \{ ws_{min, max}, soc, sm, g, \\ sp_{silt, clay, sand}, abs, ads, sv_{1-13} \}$$

Effect Estimation



Propensity score P(T=1|Z)
distribution and overlap for
treatment and control groups



Point ATE estimates and 95% confidence intervals

Results & Refutations

Causal Effect Estimation]	Refutations	S			
			Placebo		RCC		UCC	RRS		
Method	ATE	CI	p-value	Effect*	p-value	Effect*	p-value	Effect*	Effect*	p-value
Linear Regression	546	(211, 880)	0.0015	-25.74	0.39	546	0.49	85	543	0.45
Matching	448	(186, 760)	0.0060	50.82	0.39	432	0.40	116	438	0.48
IPS weighting	471	(138, 816)	0.0010	38.82	0.40	470	0.40	113	462	0.45
T-Learner (RF)	372	(215, 528)	0.0240	9.26	0.49	373	0.46	-	353	0.42
X-Learner (RF)	437	(300, 574)	0.0050	5.10	0.50	430	0.37	-	409	0.36

All methods indicate a significant, positive ATE of the treatment on yield

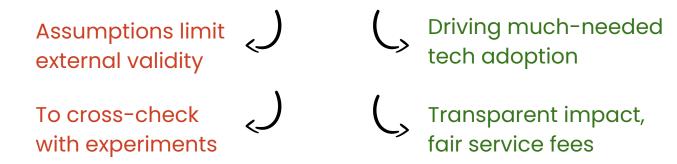
Methods successfully passed 4 refutation tests, indicating robust estimates



Sowing on a recommended day drove a yield increase ranging from 372 to 546 cotton kg/ha (12%-17% relative to mean yield)

Conclusions & Next Steps

Evaluating Digital Tools for Sustainable Agriculture using Causal Inference



Examine other forms of effect identification, fit Structural Causal Models for counterfactual analysis, learn Conditional ATEs with Machine Learning

New pilot applications will allow us to practically test the external validity of our results across different seasons, crops and locations.



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