Understanding the drivers of changes in agro-ecosystems

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Outline

- Introduction
- Preliminary Ecosystem Services assessment
- Assessing Impacts
- Achievements
- The way forward and next steps

Introduction Concept and Objectives



Common Agricultural Policy (CAP)

- National and farm-level flexibility in choices of greening measures resulted in the horizontal implementation of management rules (lack of spatial targeting of environmental measures)
- The **increase of production efficiency** has lead to landscape homogenization.
- Criticized for their **cost** and environmental **effectiveness**^{1,2}
- The **post 2020 CAP** brings to the table key elements for the environment and climate, aiming to increase efficiency

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¹ European Court of Auditors, Special Report n°21/2017

² Evaluation of the CAP Greening measures, European Economic Interest Grouping



Introduction - Agroecosystem resilience





Introduction - Ecosystem Services (ES) Concept

The Cascade Model





Ecosystems' Projects





Ecological memory



Encoding of past environmental conditions in the current ecosystem state that affects its future trajectory





Preliminary ES assessment Multi-functionality, ecosystem resilience



Agricultural landscapes

Increased demand led to **agricultural intensification** and **homogeneous landscapes**, causing **loss of biodiversity** and **degradation of ecological processes**











Methodology - ES quantification

| Ecosystem services | Indicators | Method | Related literature |
|--------------------------|--------------------------------|--|--|
| Nutrition biomass | Nutrition value of crops | Quantification of per hectare caloric value for different crop types using harvest yield and nutritive factors | Haase et al. (2012); Kroll et al. (2012); Maes et al. (2016) |
| Erosion control | Actual soil erosion prevention | Assessment of the provision of soil erosion prevention using the RUSLE model | Guerra et al. (2016) |
| Climate regulation | Carbon sequestration | Calculation of the difference of annual net primary production using the CASA model | Braun et al. (2018); Raich et al. (2002) |
| Lifecycle maintenance | Functional diversity | Measuring Rao's Q (quadratic entropy) diversity index using remotely sensed vegetation indices as a biodiversity proxy | Rocchini et al. (2017; 2018; 2019) |
| Pollination | Relative pollination potential | ESTIMAP Pollination model | Lonsdorf et al. (2009); Stange et al. (2017); Zulian et al. (2013) |



Methodology - Agricultural management practices

Crop Abundance (7 variables)

• Forage, Fruit, Maize, Potato, Sugarbeet, Tuber_Roots, Winter Wheat

Crop Transition (6 variables)

- Maize to Potato, Maize to Winter Wheat
- Potato to Maize, Potato to Winter Wheat
- Sugarbeet to Winter Wheat
- Winter Wheat to Maize

Spatial Diversification

• Shannon's diversity index









Methodology - Geographical Random Forest

library(GWmodel)

Define bandwidth value

bw.a <- bw.gwr(ES[^]Forage + Fruit + Maize + Potato + Sugarbeet + Tuber_Roots + Winter_Wheat + Maize_to_Potato + Maize_to_Winter Wheat + Potato_to_Maize + Potato_to_Winter_Wheat + Sugarbeet_to_Winter_Wheat + Winter_Wheat_to_Maize + DIVERSIF, data=rf.trainset, approach = "AICc", kernel = "gaussian", adaptive = TRUE)

library(SpatialML)
Coords <- rf.trainset@data[,2:3]</pre>

run model

grf.model <- grf(formula, dataframe, bandwidth=bw.a, kernel, cords=Coords, ntree=ntree, mtry=mtry, importance=TRUE, forests = TRUE) # *formula = ES[~]all_features

predict

pred.grf <- predict.grf(grf.model , test.df, x.var.name="X", y.var.name="Y")





Output of geographical random forest model

| Locations | a numeric matrix or data frame of two columns giving the X,Y coordinates of the observations |
|---------------------|--|
| Local.Pc.IncMSE | a numeric data frame with the local feature importance (IncMSE) for each predictor in each local random forest model |
| Local.IncNodePurity | a numeric data frame with the local IncNodePurity for each predictor in each local random forest model |
| LGofFit | a numeric data frame with residuals and local goodness of fit statistics (training and OOB). |
| Forests | all local forests. |
| 1ModelSummary | Local Model Summary and goodness of fit statistics (training and OOB). |



Results - ES distribution





Results - ES synergies and trade-offs

Table 1. Pairwise correlations between ES and potential agricultural management practices through time; all listed correlations are significant with p-value < 0.05.

| | 2016 | 2017 | 2018 | 2019 |
|-------------------------------|--------|--------|--------|--------|
| Among ES (all possible pairs) | | | | |
| NB - EP | 0.000 | 0.280 | 0.280 | 0.150 |
| NB - CR | -0.100 | -0.270 | -0.270 | -0.160 |
| NB - PL | -0.424 | -0.361 | -0.346 | -0.350 |
| NB - LM | 0.050 | 0.260 | 0.310 | 0.300 |
| EP - CR | -0.580 | -0.603 | -0.733 | -0.711 |
| EP - PL | -0.170 | -0.370 | -0.390 | -0.330 |
| EP - LM | 0.631 | 0.419 | 0.592 | 0.528 |
| CR - LM | -0.476 | -0.393 | -0.584 | -0.543 |
| CR - PL | 0.340 | 0.497 | 0.524 | 0.472 |
| LM - PL | -0.200 | -0.220 | -0.310 | -0.330 |

Between ES and explanatory variables (selected pairs)

| NB - Grassland | -0.240 | -0.200 | -0.190 | -0.150 |
|----------------|--------|--------|--------|--------|
| EP - Grassland | -0.230 | -0.330 | -0.330 | -0.369 |
| CR - Grassland | 0.280 | 0.290 | 0.310 | 0.330 |
| PL - Grassland | 0.270 | 0.300 | 0.290 | 0.290 |
| NB - Maize | 0.586 | 0.571 | 0.577 | 0.575 |
| EP - Maize | -0.240 | 0.351 | 0.280 | 0.140 |
| PL - Maize | -0.386 | -0.260 | -0.290 | -0.280 |
| NB - Potato | 0.324 | 0.320 | 0.330 | 0.310 |
| NB - Wheat | 0.320 | 0.351 | 0.384 | 0.466 |
| NB - Diversity | 0.450 | 0.459 | 0.430 | 0.515 |
| PL - Diversity | -0.348 | -0.240 | -0.230 | -0.240 |
| LM - Diversity | 0.320 | 0.360 | 0.357 | 0.389 |

Among explanatory variables (selected pairs)

| Barley - Wheat to Barley | 0.792 | 0.795 | 0.764 | 0.736 |
|----------------------------------|-------|-------|-------|-------|
| Maize - Diversity | 0.422 | 0.420 | 0.430 | 0.439 |
| Potato - Diversity | 0.391 | 0.386 | 0.381 | 0.385 |
| Wheat - Diversity | 0.400 | 0.370 | 0.370 | 0.385 |
| Potato - Maize to Potato | 0.752 | 0.718 | 0.725 | 0.738 |
| Potato - Wheat to Potato | 0.400 | 0.401 | 0.370 | 0.354 |
| Wheat - Maize to Wheat | 0.733 | 0.701 | 0.703 | 0.723 |
| Wheat - Potato to Wheat | 0.468 | 0.506 | 0.515 | 0.504 |
| Wheat - Sugar beet to Wheat | 0.336 | 0.390 | 0.387 | 0.366 |
| Sugar beet - Wheat to Sugar beet | 0.654 | 0.651 | 0.620 | 0.620 |





Results - Local-specific contributions



High Forage and Maize High crop types' diversity Fruit abundance Maize, potato, roots

1000 2000 3000

MeanDecreaseGini



The plan

Identification of **multifunctional areas** to support **resilient** and **healthy ecosystems** while ensuring societal and economic (human) well-being



Assessing Impacts CAP, Sustainability & Land Suitability



The big picture

Understanding the **local impact** of agricultural practices on agroecosystems

e.g. crop diversification, grassland maintenance

OR CLIMATE CHANG Local specific contribution of management practices to agricultural resilience Identification of suitable areas for sustainable agriculture

> Climate change adaptation and mitigation



Causal Machine Learning: Overview

A family of machine learning methods specialized for causal inference



Use historical large scale data to learn the impact of interventions



What is the effect of a new drug on blood pressure?

Highly relevant to decision making, policy evaluation, personalization



Causal Machine Learning: Personalization

What is the average impact of an intervention on the whole population?

(Non-personalized insight, aka "Average treatment effect")

What is the impact of an intervention for a unit with particular characteristics?

(Personalized insight, aka "Heterogeneous treatment effect")





The new common agricultural policy: 2023-27

The new common agricultural policy will be key to securing the future of agriculture and forestry, as well as achieving the objectives of the European Green Deal.



On 2 December, 2021, the agreement on reform of the common agricultural policy (CAP) was formally adopted. The new legislation, which is due to begin in 2023, paves the way for a fairer, greener and more performance-based CAP.

It will seek to ensure a sustainable future for European farmers, provide more targeted support to smaller farms, and allow greater flexibility for EU countries to adapt measures to local conditions.



َ ﴾َ Flexibility to adapt measures to local conditions

-> Geospatial "personalization"



The new CAP: a personalization problem

What is the impact of an intervention for a unit with particular characteristics?



The estimated practice impact is proposed as a land suitability score



Crop rotation Crop diversity...



Ecosystem Services Yield Soil Organic Carbon Net Primary Productivity...



Proof of Concept (Flanders, Belgium, 2010-2020)





Estimated impact for "crop rotation" practice*



*Impact on ecosystem Net Primary Productivity (MODIS NPP)



Environmental conditions favoring practices



*Environmental conditions driving impact of crop rotations



Data-informed agro-ecological rules



*Environmental conditions driving impact of crop rotations



Towards climate smart agriculture



*In a warmer planet, crop rotation might be more beneficial for productivity

*Using future climate projections, how do impact results change?

Achievements Paper Writing, Visibility & Network



Paper Writing



- Targeted workshop for AI4EO community
- In its 3rd year, frequently featuring top names and institutions
- Carries the CVPR seal (main track IF : 45)
- "Emerging applications in Remote Sensing" (IEEE Xplore, presenting June 19th) 31



Visibility

| May 3, 2022 – May 3, 2022 | ENVIRONMENTAL RESEARCH | |
|--|---|--|
| Community Workshop on Microsoft's Causal Tools | LETTERS | |
| Location: Virtual Workshop | LETTER | |
| Microsoft Research | Satellite data to assess the benefits of crop rotations on yields Dan M Kluger ^{1,*} , Art B Owen ¹ , and David B Lobell ² ¹ Department of Statistics, Stanford University, Stanford, CA, 94305, United States of America ² Department of Earth System Science and Center on Food Security and the Environment, Stanford University, Stanford, CA, 94305, United States of America [*] Author to whom any correspondence should be addressed. E-mail: kluger@stanford.edu | |

- Presented our work in a community workshop organized by Microsoft Research
- Correspondence and feedback from Stanford researchers



Network ESP Ecosystem Services Partnership

Thematic Working Groups: TWG 3 – ES Indicators

Lead Team & Members

- · Roxanne Lorilla, National Observatory of Athens (NOA), Greece
- · Ute Schwaibold, University of the Witwatersrand, South Africa
- Lyndre Nel, Hungarian University of Agricultural & Life Sciences, Hungary
- Alexander van Oudenhoven, Leiden University, The Netherlands

Session Co-hosts in the upcoming ESP Europe Conference 2022

T3a - The operationalization of ecosystem services indicators: a matter of scale, data, purpose and end-users <u>https://www.espconference.org/europe22/wiki/754946/s</u> <u>ession-overview</u>



150 leading international experts, over 50 countries around the world are contributing to the Nexus assessment.



The way forward Next steps & Conclusions



European Commission

Joint Research Centre

The operationalization of Ecosystem Services

Biodiversity Observation Network

The journey to monitoring ecosystem services

- 1. Identify key ES indicators
- 2. Combining observations and data across scales
- 3. Monitor teleconnections among ES
- oss scales

Ecosystem Services Partnership

- 4. Identifying essential social metrics of ES and improve socio-ecological link
- 5. Interdisciplinary collaboration to guide applications



Science and Policy

for People and Nature



Outlook



Agricultural policy making as a geospatial **impact assessment** problem

Data-hungry methods meet ever-increasing volumes of EO data

Other exciting directions have yet to be pursued (discovery of causal drivers in ecosystems, natural experiments)

Modern, not "black-box" science inherently explainable and transparent

Hard to evaluate: more domain knowledge & robustness checks needed



Thanks! Questions?