

## A Geospatial Farm Typology for the EU based on FADN data

Marc Müller, Hugo Scherer, Michael Wögerer Walter Rossi-Cervi, Tamás Krisztin, Felicity Addo

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## Project background

- BrightSpace:
  - Duration 2022-2027, 14 Partners
  - Definition and operationalization of a Safe and Just Operating Space for EU agriculture
  - Identification of quantifiable indicators
  - Projections until 2050
- LAMASUS:
  - Duration 2022-2026, 17 Partners
  - Ex post and ex ante impact assessment of European policies on land use and land management
  - Projections until 2050





## Research background

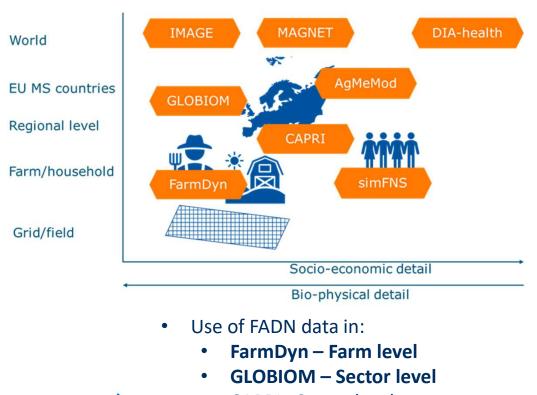
- Ex-ante policy analysis
  - Identification of innovative policy and governance measures in agriculture
  - Which farms are likely to get involved in agro-environmental measures?

- Ex-ante technology analysis
  - Identification of promising agricultural technologies
  - Which farms are likely to invest in GHG saving technologies?

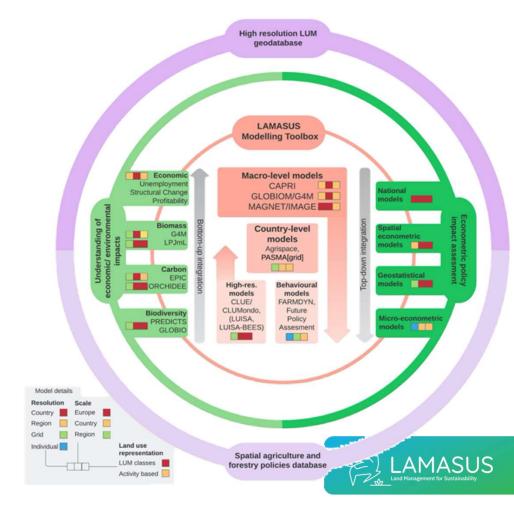




## BrightSpace and LAMASUS model toolboxes



- BRIGHT SPACE
- CAPRI– Sector level
- <sup>4</sup> MAGNET– Economy-wide



## How FADN is used in FarmDyn

- Optimization of farm production plan
- Very detailed representation of technology (inputs per activity, e.g. field operations, feed nutrient contents, manure application, yield responses to fertilization,...)
- Data from FADN:
  - Outputs (yields and levels of cropping and animal activities)
  - Endowments (areas, herds, labour)
- Additional data:
  - Input prices
  - Activity specific input levels (variable cost, machinery requirements)
  - Sources: Handbook data, dedicated databases (KTBL in DE, KWIN in NL)





## Illustrative farm level programming tableau & data sources



SPACE



## Typical vs individual farms

- Obstacles for modelling individual farms:
  - Technology coefficients
  - Environmental characteristics
  - Computation time (e.g. FarmDyn may take 90 sec for a single dairy farm)
- Two solutions:
  - Summarize non-observable costs in a farm-specific cost term (PMP approach)
    - JRC's IFM-CAP model does this!
  - Focus on few typical farms!
    - Farm types in FADN (TF14) are great, but require further split as e.g. dairy farms are one single group.





## How FADN is used in GLOBIOM

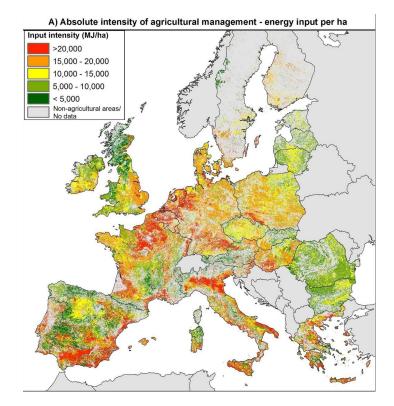
- Estimation of activity-specific variable cost
- Cost structure of technologies
- Upscaling of case studies





# Energy intensity as criterion for a farm typology

- Article:
  - Rega, C., Short, C., Pérez-Soba, M., & Paracchini, M. L. (2020). A classification of European agricultural land using an energybased intensity indicator and detailed crop description. Landscape and urban planning, 198, 103793.
- Main argument: anthropogenic energy intensity is relevant for design of policies aiming at GHG and nutrient emission reduction



## Selected FADN variables

- Standard output (SE005)
- Expenditures for:
  - Fertilizer (SE295)
  - Plant protection (SE300)
  - Seeds (SE285)
  - Energy (SE345)
- Share of grassland (SE028) in UAA (SE025)
- Livestock density per UAA





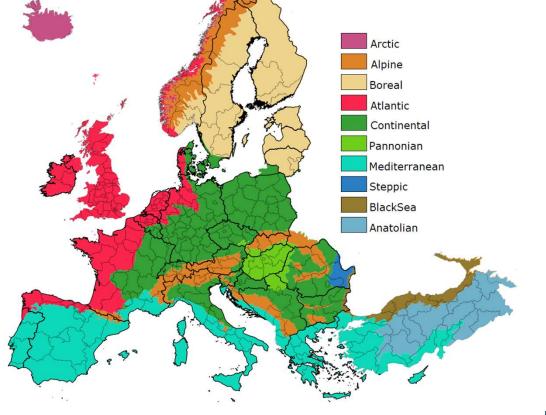
## Adding spatial data to FADN

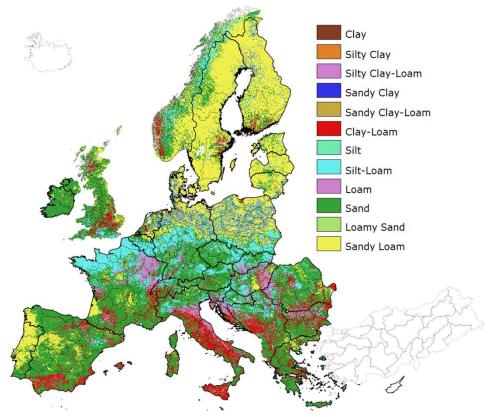
- We want to bring spatial data to FADN, not the other way around!
- Bio-geographic regions
- Soil texture
- Challenge: FADN provides only NUTS2 for location of farms
- Approach: Mask out non-agricultural areas to increase precision





## Bioregions and soil texture at NUTS2 level







#### **EEA Bio-geographic regions**

(httpsk∄/www.eea.europa.eu/en/analysis/maps-andcharts/biogeographical-regions-in-europe-2)

## JRC LUCAS Data (Texture classes based on USDA)

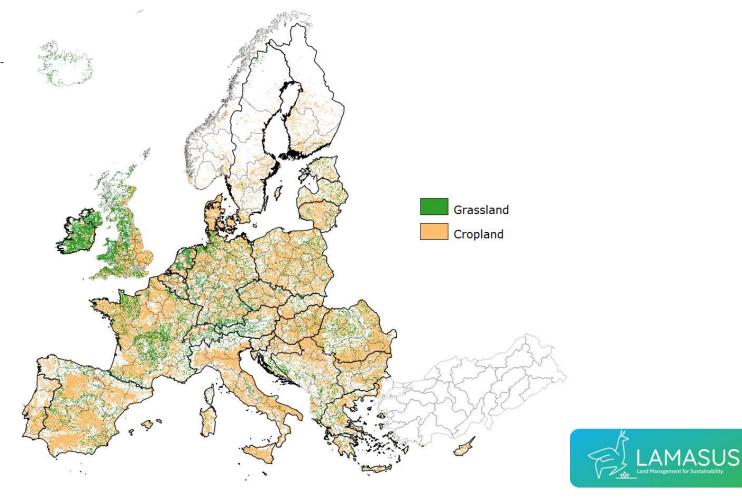
(https://esdac.jrc.ec.europa.eu/content/topsoil-physical-propertieseurope-based-lucas-topsoil-data)



### Input data: Land use maps

#### **Corine Land Cover Map**

https://land.copernicus.eu/en/products/corine-land-cover



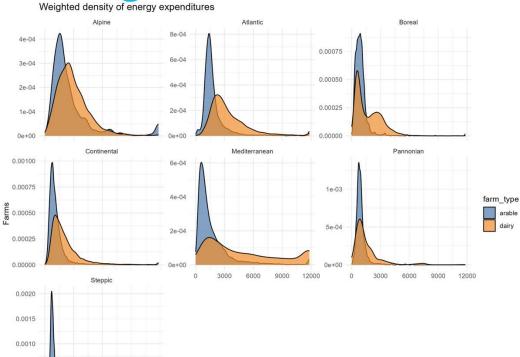


## Explorative analysis – farm type and biogeo regions

0.0

5

10



Energy Expenditures

0.0005

0

BRIGHT

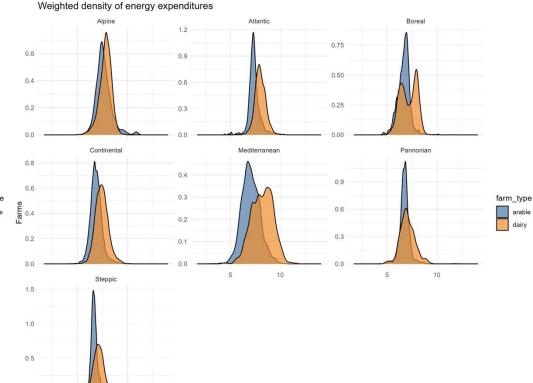
SPACE

3000

6000 • 9000

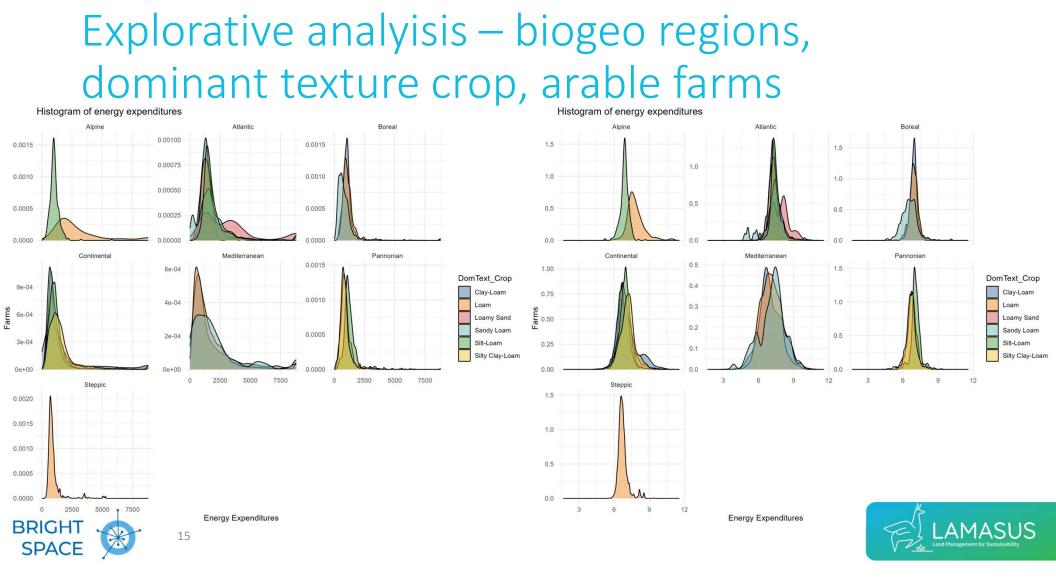
12000

14



Energy Expenditures





## Explorative data analysis - Summary

- No clear pattern visible
- Variables appear log-normal distributed
- Multiple modes only in few cases

• Solution: Cluster analysis





## **Clustering techniques**

- Permit the identification of similar groups within large number of variables
- Inclusion of categorical variables (e.g. bio-geo regions) using dummy variables (1-0)
- Based on minimization of distances to
  - a central point (e.g. k-means)
  - each other (e.g. hierarchical clustering)
- Number of clusters set by researcher (no specific rule)
- Stepwise reduction of cluster number

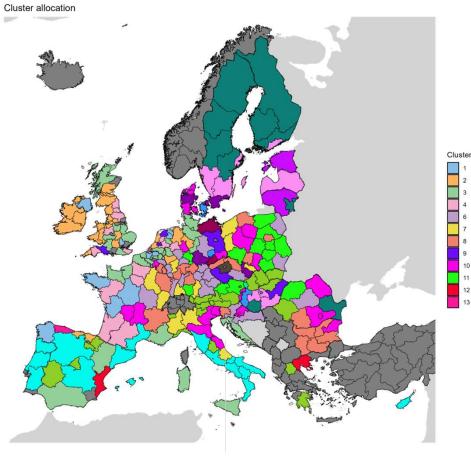




## Example clustering result

- Hierarchical clustering
- 27 possible clusters
- 22 dominant per NUTS2 region

18







## Example clusters 7 & 8

#### Cluster 7: Continental, all grassland

Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
BioReg_crop [character]	1. Continental	3281 (100.0%)		3281 (100.0%)	0 (0.0%)
ls_density [numeric]	Mean (sd) : 1.5 (0.9) min ≤ med ≤ max: 0.1 ≤ 1.4 ≤ 7.5 IQR (CV) : 0.9 (0.6)	3267 distinct values		3281 (100.0%)	0 (0.0%)
energy_expenditures [numeric]	Mean (sd) : 2046.9 (1292.9) min ≤ med ≤ max: 56 ≤ 1814 ≤ 11789.4 IQR (CV) : 1509.4 (0.6)	3281 distinct values		3281 (100.0%)	0 (0.0%)
SE005 [numeric]	Mean (sd) : 128.6 (108.1) min ≤ med ≤ max: 6.7 ≤ 99.1 ≤ 1085.8 IQR (CV) : 122 (0.8)	3245 distinct values		3281 (100.0%)	0 (0.0%)
grass [numeric]	Mean (sd) : 1 (0.1) min $\leq$ med $\leq$ max: 0.8 $\leq$ 1 $\leq$ 1 IQR (CV) : 0.1 (0.1)	1096 distinct values		3281 (100.0%)	0 (0.0%)
arable [numeric]	Mean (sd) : 0 (0.1) min $\leq$ med $\leq$ max: 0 $\leq$ 0 $\leq$ 0.2 IQR (CV) : 0.1 (1.5)	1079 distinct values		3281 (100.0%)	0 (0.0%)

#### Cluster 8: Continental, mixed grass and cropland

Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
BioReg_crop [character]	1. Continental	5450 (100.0%)		5450 (100.0%)	0 (0.0%)
ls_density [numeric]	Mean (sd) : 1.5 (0.9) min ≤ med ≤ max: 0.2 ≤ 1.4 ≤ 14.3 IQR (CV) : 0.8 (0.6)	5443 distinct values		5450 (100.0%)	0 (0.0%)
energy_expenditures [numeric]	Mean (sd) : 2211.8 (1385.2) min ≤ med ≤ max: 103.8 ≤ 1958.9 ≤ 16163.8 IQR (CV) : 1540 (0.6)	5450 distinct values		5450 (100.0%)	0 (0.0%)
SE005 [numeric]	Mean (sd) : 175.8 (138.2) min ≤ med ≤ max: 7.6 ≤ 135.9 ≤ 769.7 IQR (CV) : 194.6 (0.8)	5422 distinct values		5450 (100.0%)	0 (0.0%)
grass [numeric]	Mean (sd) : 0.7 (0.1) min $\leq$ med $\leq$ max: 0 $\leq$ 0.7 $\leq$ 0.9 IQR (CV) : 0.1 (0.1)	4427 distinct values		5450 (100.0%)	0 (0.0%)
arable [numeric]	Mean (sd) : 0.3 (0.1) min $\leq$ med $\leq$ max: 0 $\leq$ 0.3 $\leq$ 0.6 IQR (CV) : 0.1 (0.3)	4434 distinct values		5450 (100.0%)	0 (0.0%)

## Example cluster 20

#### Cluster 20: Several biogeo regions, dominantly alpine

Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
BioReg_crop [character]	1. Alpine 2. Mediterranean 3. Pannonian 4. Steppic	2199 (76.6%) 487 (17.0%) 115 ( 4.0%) 68 ( 2.4%)		2869 (100.0%)	0 (0.0%)
ls_density [numeric]	Mean (sd) : 1.6 (1.2) min ≤ med ≤ max: 0.1 ≤ 1.4 ≤ 8.7 IQR (CV) : 1.3 (0.8)	2864 distinct values		2869 (100.0%)	0 (0.0%)
energy_expenditures [numeric]	Mean (sd) : 2805.8 (2287.1) min ≤ med ≤ max: 52 ≤ 2321.9 ≤ 24375.8 IQR (CV) : 2594.6 (0.8)	2869 distinct values		2869 (100.0%)	0 (0.0%)
SE005 [numeric]	Mean (sd) : 128 (168.5) min ≤ med ≤ max: 7.8 ≤ 77.4 ≤ 1420.3 IQR (CV) : 90.2 (1.3)	2848 distinct values		2869 (100.0%)	0 (0.0%)
grass [numeric]	Mean (sd) : 0.9 (0.1) min ≤ med ≤ max: 0.3 ≤ 1 ≤ 1 IQR (CV) : 0.2 (0.2)	862 distinct values		2869 (100.0%)	0 (0.0%)
arable [numeric]	Mean (sd) : 0.1 (0.1) min $\leq$ med $\leq$ max: 0 $\leq$ 0 $\leq$ 0.7 IQR (CV) : 0.2 (1.6)	791 distinct values		2869 (100.0%)	0 (0.0%)

### Summary

- Need for a farm typology for EU beyond TF14 for modelling purposes
  - Analysis of policy and technology/management scenarios
- Spatial data were combined with FADN to derive a farm typology that takes farm location into account
  - Combination was done at NUTS2 level
  - Non-agricultural areas were excluded
- Hierarchical clustering with step-wise reduction of cluster numbers
- 22 Clusters for dairy farms in the EU were identified





### Next steps

- Refine clustering
- Apply method to arable farms
- Ensure that cluster farms can be recognizable by EU member states farming experts
- Add additional data (spatial, FADN variables)





## Remaining questions

- Are we selecting the right variables from FADN?
- Which additional spatial data should be included?
  - Rainfall? Average temperature?
  - Share of area equipped for irrigation?
- Why else would apparently similar farmers find different optimal cropping plans?









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