Can we use open data to track grazing intensity?

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This communication is part of the project TED2021-129315B-C22, financed by MCIN/AEI/10.13039/501100011033 and the European Union NextGenerationEU/PRTR

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Introduction

Two key concepts for rangeland management

- For continuous grazing, **spatial distribution** of livestock is the main issue to pay attention.

- **Stocking rate** is the most powerful tool for rangers to adequate the management strategy to the carrying capacity of pastures.

- Generally, spatial distribution and stocking rates are studied separately, however, the effects of **grazing intensity** are the result of both combined.

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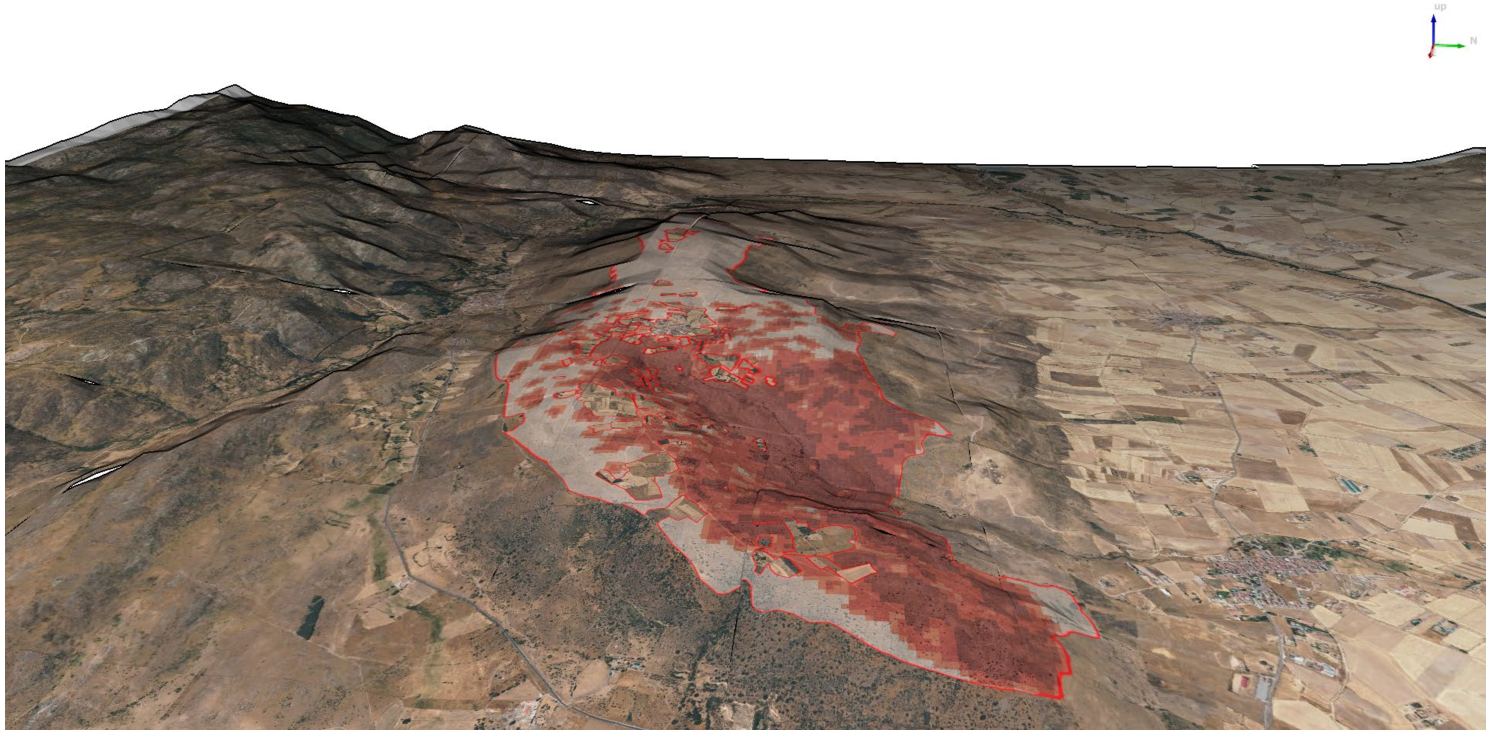
The unevenness of spatial distribution

- How should we approach the evaluation of the effects of unevenness of distribution?

  a. **Key area**: portion of the pasture which serve as an indicator of the condition of the entire system (SRM, 1998)

  b. **Sacrifice area**: preferred areas overused by livestock even under light stocking rates (Holecheck et. al, 1998)



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Impacts of a poor management

- Soil degradation
- Losses of pastures quality and quantity
- Negative impacts to biodiversity (both plants and wildlife)
- If combined with high stocking rates, the effects can be irreversible, especially in arid/semiarid conditions
- It all depends on the grazing system, climatic conditions, type of animal, etc…

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The question to answer

- Can the vegetation measured by remote sensing serve as a predictor of grazing intensity?

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Materials and Methods

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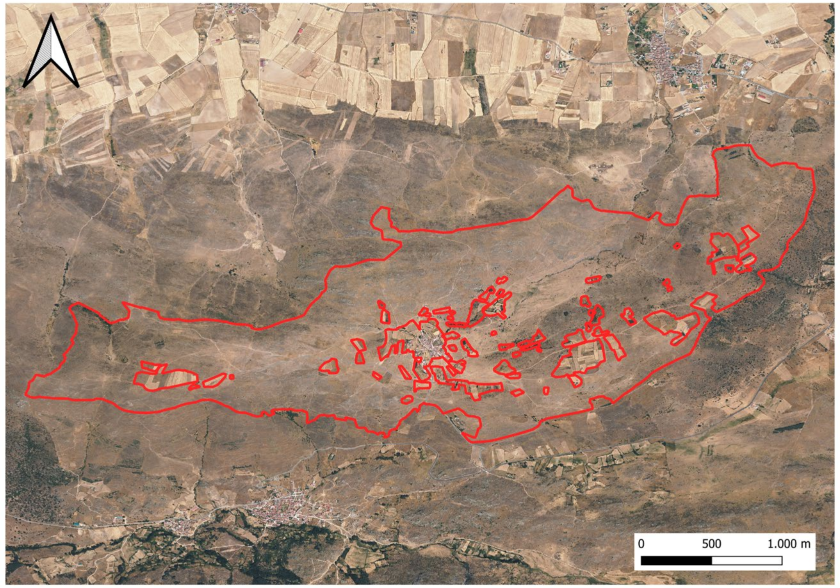
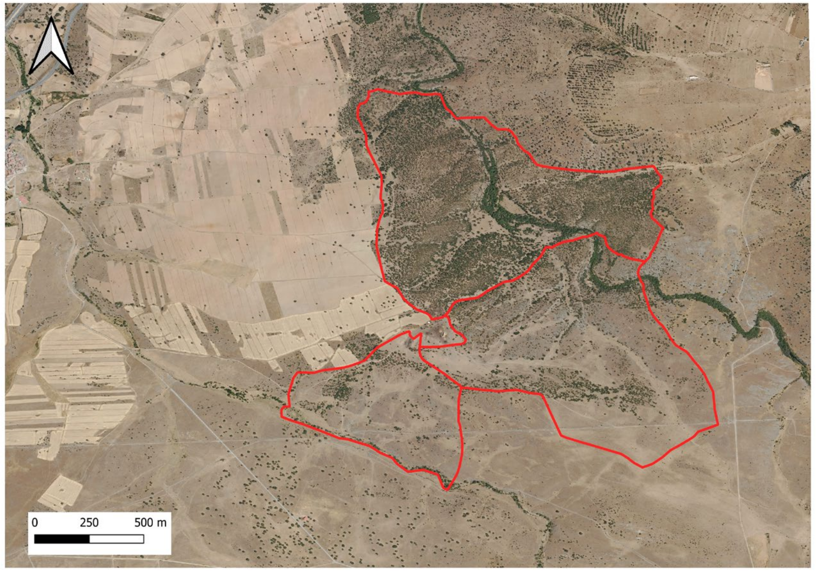
Farm A

- A common land of 630 ha with a herd of 230 cattle cows.
- Almost half of the area (46%) has steep slopes (>20%).



Farm B

- Commercial farm of 250 ha divided in 3 paddocks (43 to 108 ha) with a stock of 85 cattle cows.
- Slopes were between 10 and 20%.



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Animal tracking

- 200 commercial GNSS tracking collars (Digitanimal Ltd., Madrid, Spain)
- Time resolution of 30 minutes.
- Studied period was between 2017 and 2022.

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Data preprocessing

- Removal of gross errors of the GNSS collars.
- Remove not installed collars
- Remove days with less than 12 positions
- Resampling of trajectories for:
  a. Standardize the amount of data per day and collar
  b. Standardize the interval between signals to exactly 30 minutes
- Classifying between non-active and grazing behavior based on Hassan-Vázquez et. al, 2022.

Grazing intensity

- Kernel Density Estimation (KDE) values per month were calculated from GNSS collar data and standardized as:

$$\textbf{Grazing intensity}\ (\mathrm{AU} * \mathrm{day}) = KDE * \frac{AU * \frac{day}{month}}{\sum \frac{KDE}{month}}$$

- KDE values were computed separately for all collected data and grazing behavior.

- KDE pixel resolution used was 60x60 meters to match with Sentinel 2 grid.

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Spectral indexes

Index	Type of index	Index calculation	Satellite
NDVI	Vegetation	$\frac{(B08-B04)}{(B08+B04)}$	Sentinel 2
GNDVI	Vegetation	$\frac{(B08-B03)}{(B08+B03)}$	Sentinel 2
GRVI	Vegetation	$\frac{(B08-B02)}{(B08+B02)}$	Sentinel 2
RGBVI	Vegetation	$\frac{B03-(B04*B02)}{(B03*B03)+(B04+B02)}$	Sentinel 2
AVI	Vegetation	$\sqrt[3]{(B08*(1-B04)*(B08-B04)}$	Sentinel 2
SAVI	Vegetation	$\left(\frac{B08-B04}{B08+B04+0{,}428}\right)*(1{,}428)$	Sentinel 2
EVI	Vegetation	$\left(\frac{(B08-B04)}{\left((B08+6)+\left(B04-(7{,}500*B02)\right)\right)+1}\right)*2{,}500$	Sentinel 2
GCI	Vegetation	$\left(\frac{B09}{B03}\right)-1$	Sentinel 2
BSI	Soil	$\left(\frac{(B11+B04)-(B08+B2)}{(B11+B04)+(B08+B02)}\right)$	Sentinel 2
MSI	Water	$\left(\frac{B11}{B08}\right)$	Sentinel 2
NDMI	Water	$\frac{(B08-B11)}{(B08+B11)}$	Sentinel 2
NDWI	Water	$\frac{(B03-B08)}{(B03+B08)}$	Sentinel 2

Monthly average of indexes and differences between the first and last week of each month were calculated. Raw band data also was analyzed.

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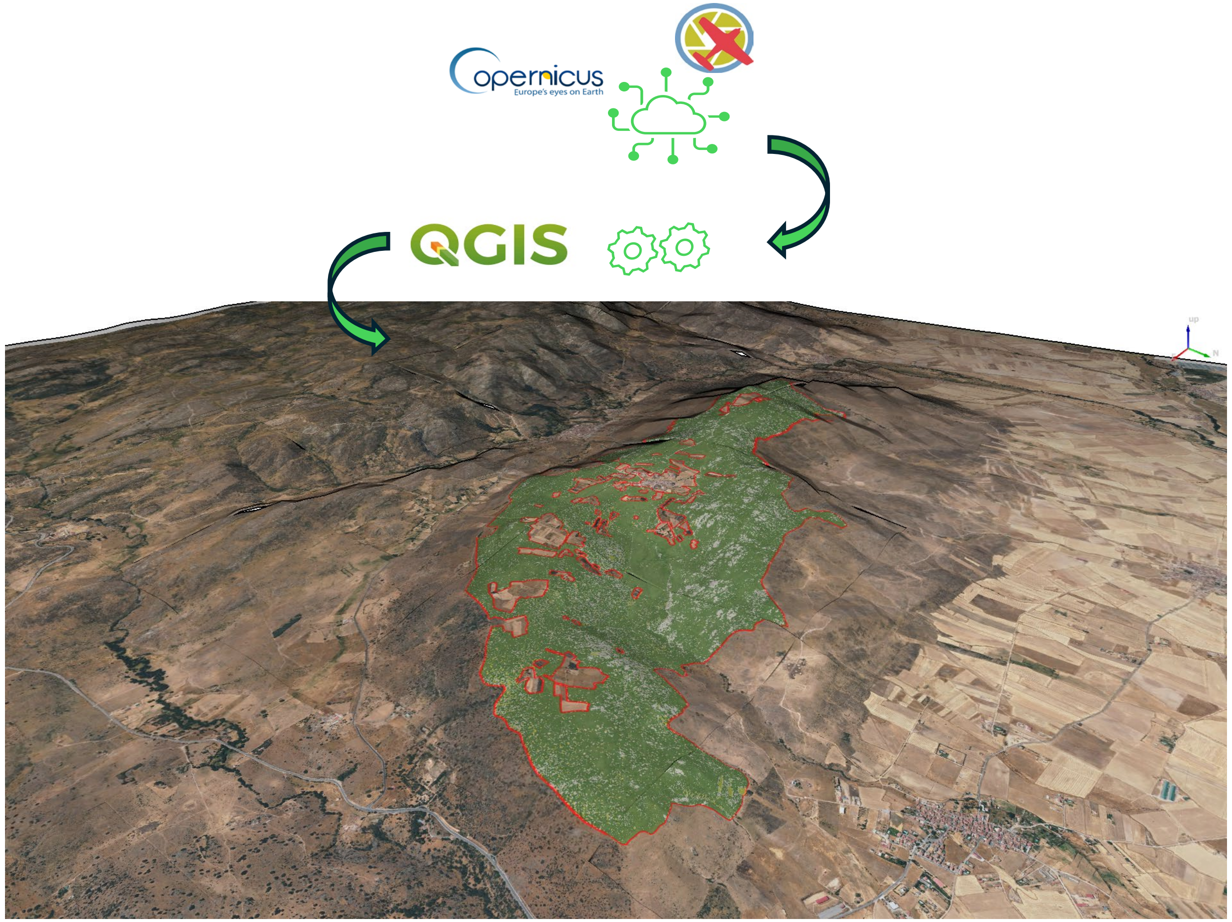
Vegetation type

- RGB orthoimages from PNOA with 0,25 meters resolution were used to vegetation classification by using a semi-automated classification algorithm (i.e Minimum distance) included in SCP QGIS plugin.
- After the classification, PNOA pixels were merged with 60-meter Sentinel 2 pixels.
- Percentage of grass area of each merged pixel was calculated. Pixels below 75% were removed from the analysis.



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Statistical processing

- Pearsons correlations between the S2 bands and spectral indexes (monthly averages and differences) and the grazing intensity (KDE standardized).

- Normalization of the bands and spectral indexes (SI) values.

- Spatial autorregresive (SAR) models were computed to predict grazing intensity from satellite data.

- External validation in both spatial and temporal domains:
    a. Spatial: Farm A served as training set and Farm B as testing set
    b. Temporal: Year 2022 was used as testing set

Results

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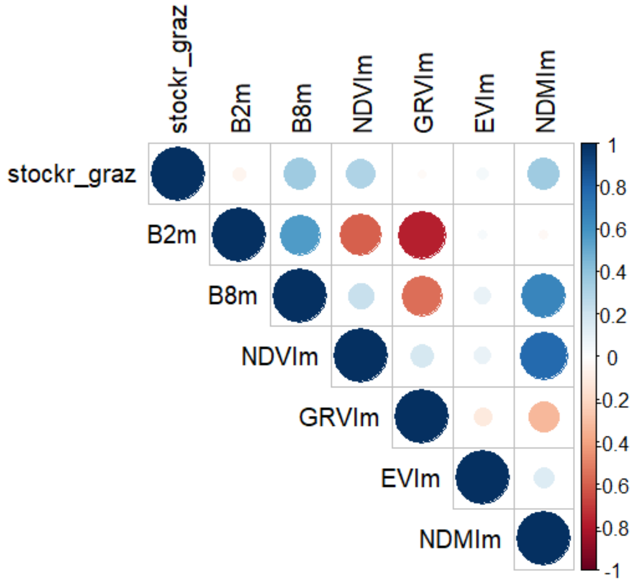
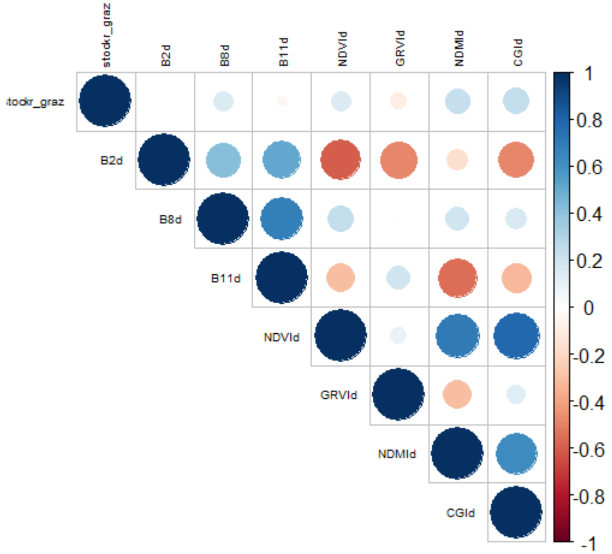
Correlations of grazing intensity and spectral indexes

- Correlated spectral indexes (r >0,8) were removed to avoid collinearity.
- Best results appeared when we use the adjusted KDE for grazing behavior.





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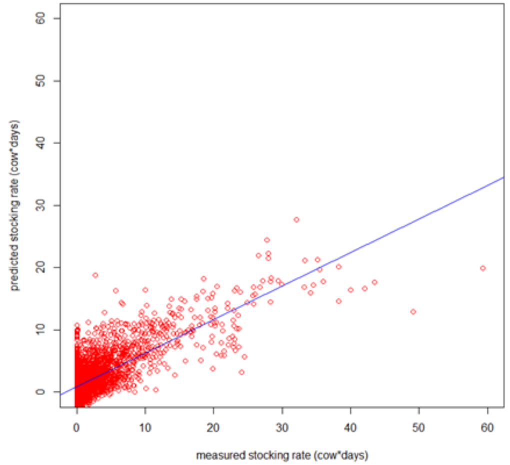
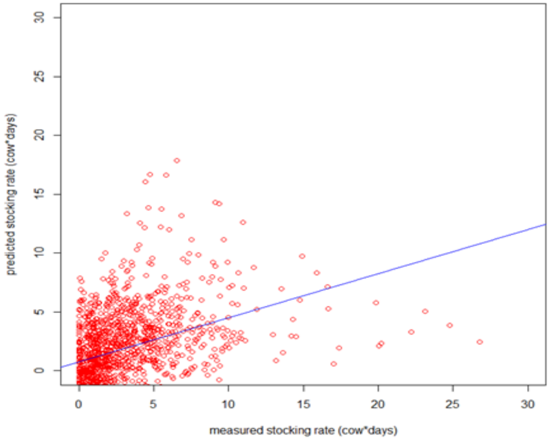
SAR models

AU * day ~ B2m + B8m + NDVIm + EVIm + B2d + B8d + B11d + NDVId + GRVId + NDMId + CGId + factor(season)

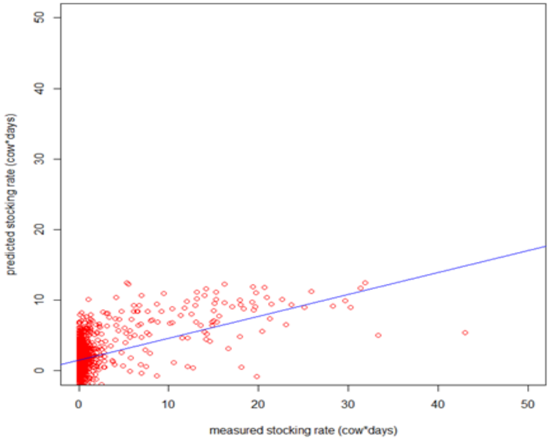
Fitted model



Spatial validation



Time validation



Type of model	AIC
SAR	22688
Lm	23463

$$Y=\rho WY+X\beta+\epsilon$$

Monthly average of NDVI and EVI, apparently, do not explain any variance of grazing intensity (p>0,05). The monthly difference of those indexes, however, can explain part of the variance of grazing intensity (p<0,000).

Conclusions

- Include spatial component in the model improves the predictive capacity of the model.

- Classification model for discriminate grazed and non-grazed pixels could improve the performance of the SAR model.

- Remote sensing data can be useful to track the grazing intensity of livestock but has limitations.

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Grazie per la vostra attenzione!!

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