A multispectral UAV imaging for optimizing cover crop management in viticulture : application of a multivariate multi-block modelling approach

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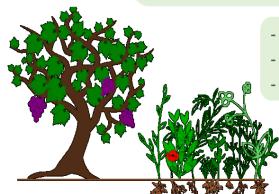
Context - Managing service crops to avoid dysservices

• The management of service crops in viticulture appears to be a key lever to reach trade-offs between ecosystem services and disservices (Garcia et al. 2018, Winter et al. 2018, Giffard et al. 2022)



- Yield
- Berry quality
- Fodder production

- Soil biodiversity and biological activity
- Microclimate regulation
- Fungal disease regulation
- Weed control



- Biodiversity conversation
- Aesthetic landscapes
- Tourism
 - H₂O and nutrient competition
 - Yield losses
 - Hosts and pests

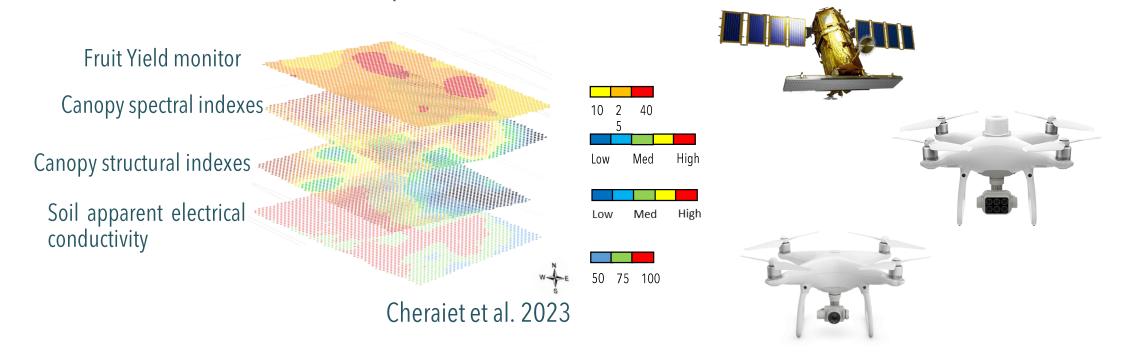
To minimize disservices and achieve the targeted services :

- -Choice of species
- -Seeding density, period
- -Service crop duration
- -Destruction tool
- -Residue management

- Soil fertility
- Erosion control
- Water pollution control
- Carbon sequestration
- Climate change mitigation

Context - Contribution of sensing technologies

- High-resolution spatio-temporal data are increasingly available in viticulture
- These data enable the study of agroecosystems at scales difficult to achieve through conventional experimentation, and facilitate on-farm experimentation



When and what types of agricultural data are needed to optimize service crops management in viticulture?

Strategy & Objectives

Strategy: data fusion analysis using multi-block methods to extract more relevant information from UAV data sources (Surowiec et al. 2019)

Objectives:

- Explore the applicability of a multi-block modelling approach (SO-PLS) to a multivariate data structure (spatio-temporal) to predict two variables of interest: Yield and Pruning weight
- **Identify relevant, data types and timings** for predicting these two variables



Experimental set up

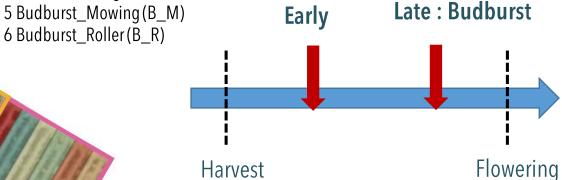
One year: **2022**

Site: Domaine du Chapitre (Villeneuve-lès-Maguelone)



3 plots - 6 treatments

Two termination periods:



Harvest Three termination methods:



Treatment

1 Early_Tillage (E_T)

3 Early_Roller (E_R)

2 Early_Mowing (E_M)

4 Budburst_Tillage (B_T)

6 Budburst_Roller(B_R)

Plot

Plot 1

Plot 2

Plot 3





Roller



Aerial photos of Syrah block (1 ha)

(Garcia et al. 2024, poster 192)



Data collection

Crop data

For each treatment, two types of data were collected on 10 individual vines per

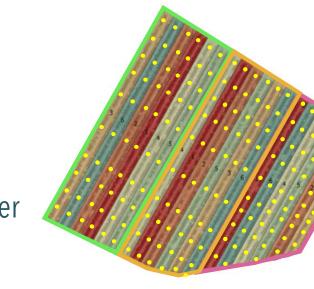
treatment and block (total 180):

• **Yield** (kg/vine stock)



Pruning weight (kg/vine stock)







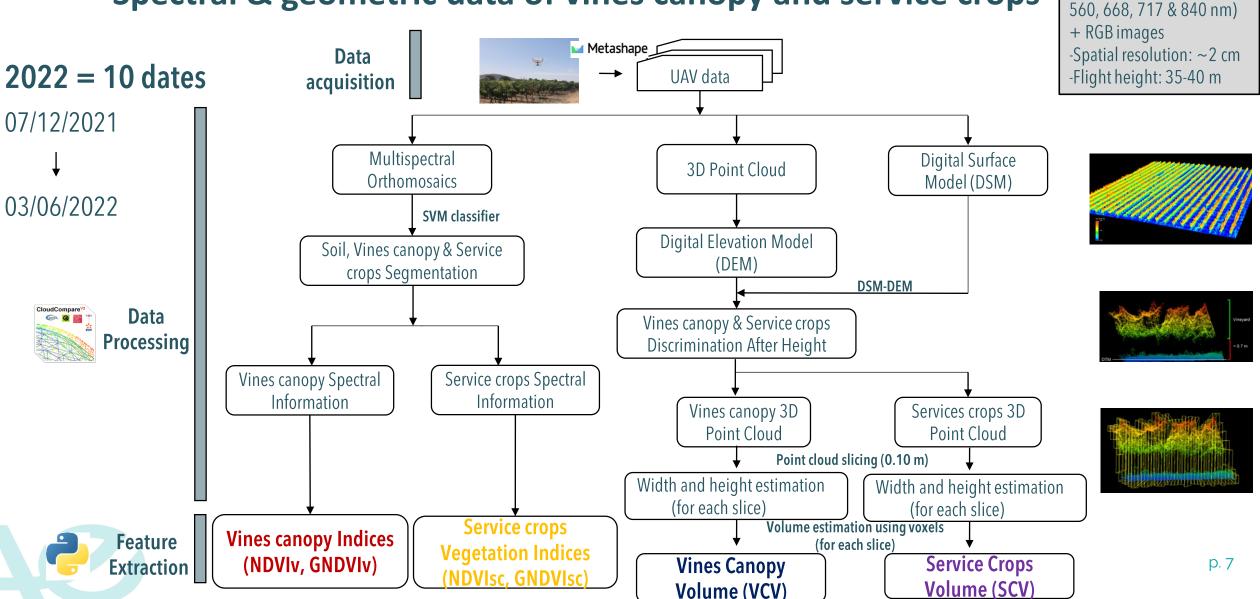
Data collection

Spectral & geometric data of vines canopy and service crops

Phantom 4

- Multispectral + ProV2

- 5 narrow bands (475,



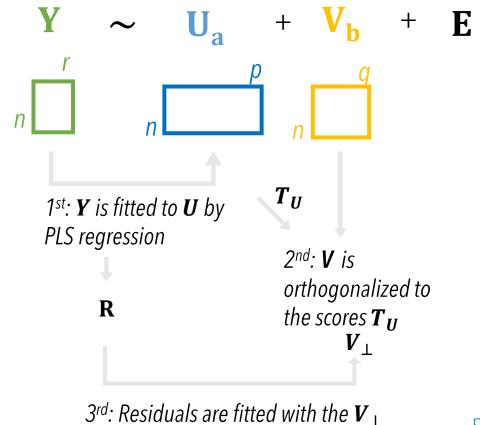
Theory - Multi-bloc method

Sequential and Orthogonalized Partial Least Squares: SO-PLS (Naes et al. 2013)

How it works: example with 2 predictor blocks

- * Y is the response variable
- * **U** and **V** are the predictor blocks
- * **a** and **b** are the regression coefficients
- * E is the residual matrix.

Advantage: blocks of different sizes to be combined

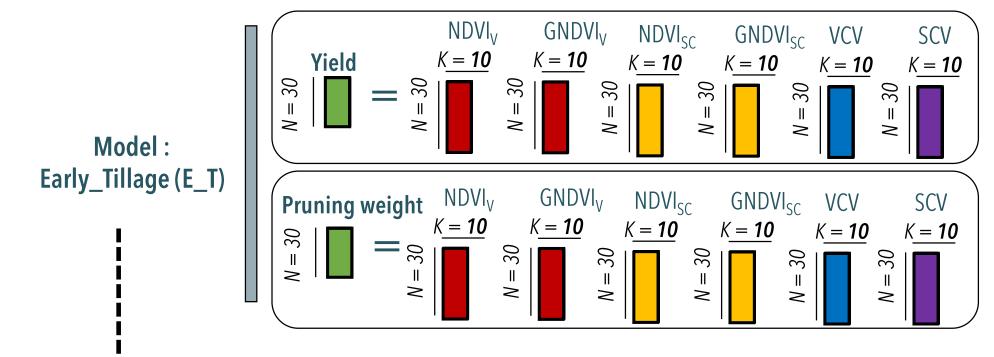




Application - Multi-bloc analysis

2022 - 1 model per treatment (aggregation of data from 3 blocks) - combination of 8 predictor blocks (2 Vines Canopy indices + 2 Services Crops vegetation indices + 1 Vine Canopy volume + 1 Service Crops volume)

N = individual vines & K = Dates



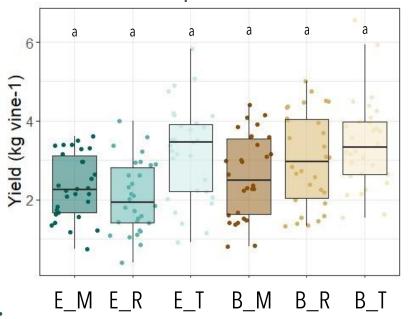
calibration data set (N = 20) - validation data set (N = 10)

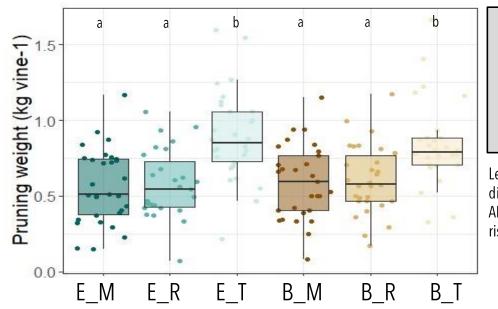




Results - Data visualisation: Variables of interest

Distributions of response variables in 2022





Early_Tillage (E_T)
Early_Mowing (E_M)
Early_Roller (E_R)
Budburst_Tillage (B_T)
Budburst_Mowing (B_M)
Budburst_Roller (B_R)

Letters represent significantly different classes obtained by ANOVA and a Bonferroni test with a risk of $\alpha = 0.05$.

- Yield:
- The destruction tool and the presence of cover crops do not seem to be prejudicial to yields
- Yields can be ordered by destruction tool: Tilled > Rolled > Mowed
- Great variability in measurements according to vine stock (0.68 kg/vine stock to 5.9 kg/vine stock)
- Pruning weight:
- The destruction tool has a significant effect on pruning weights, with Tilled modalities > Mowed and Rolled modalities

Results - Cross-validation results

N = 20

Independently select the number of latent variables for each block

Treatment	Variable	$nRMSE_{cv}$	R ² cv	Latent variables per block					
				NDVIv	GNDVIv	NDVIsc	GNDVIsc	VCV	SCV
E_T	Yield	6.9	0.77	2	1	1	1	1	0
	Pruning weight	8.7	0.69	1	1	0	1	2	1
E_M	Yield	9.6	0.74	2	1	0	1	1	1
	Pruning weight	11.1	0.67	1	2	0	1	1	1
E_R	Yield	7.1	0.71	2	0	1	1	1	1
	Pruning weight	9.4	0.68	1	2	1	0	1	0
B_T	Yield	5.8	0.73	2	1	0	2	1	0
	Pruning weight	12.2	0.64	1	2	0	1	2	0
B_M	Yield	7.8	0.75	2	1	1	0	1	1
	Pruning weight	9.1	0.61	1	2	0	1	1	1
B_R	Yield	5.9	0.72	2	1	0	1	1	1
	Pruning weight	10.1	0.65	1	2	0	1	1	1

- Regardless of the treatment, the quality and robustness of the models remain satisfactory
- Depending on the response variable considered, the **contribution of the 6 predictor blocks is not the same**
- Geometry indices (VCV & SCV) appears to provide additional information to spectral data

Results - Validation results

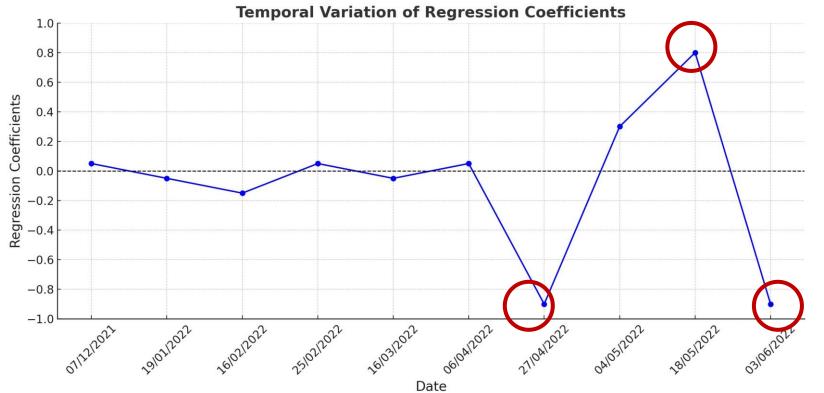
Performance evaluation of multivariate prediction models for each response variables

Treatment	Variable	nRMSEp	R ² _{1:1}
	Yield	10.9	0.78
E_T	Pruning weight	13.0	0.69
г м	Yield	9.1	0.75
E_M	Pruning weight	13.5	0.67
	Yield	9.8	0.76
E_R	Pruning weight	12.3	0.69
	Yield	10.1	0.74
B_T	Pruning weight	14.2	0.65
D. M.	Yield	11.1	0.76
B_M	Pruning weight	13.4	0.66
	Yield	10.2	0.77
B_R	Pruning weight	13.1	0.69

N = 10

 The performance of the prediction models was satisfactory for each treatments tested, despite the significant variability seen in productivity and vigor

Results - Interpretation tool: Regression coefficient of models indicating optimal detection dates Example: Regression coefficients derived from the E_T yield prediction model with the NDVIv predictor block



Identify the canopy detection dates that are relevant for predicting harvest & vigor variables, in order to provide clear information to winegrowers

Take Home Message

• Experimental validation:

Field experiments showed that destruction tools and residue management appear to influence vine yield and pruning weight (see Garcia et al. 2024, poster 192)

Application of SO-PLS modeling:

SO-PLS approach, which combines spectral & geometric blocks of data obtained on vine canopy and service crops:

- Can create synergies to improve the prediction performance of these 2 key variables
- Can improve information on the optimal timing of detection, and supports more informed and adaptive strategic decision-making for vineyard management

Next steps

- Assess robustness in other years and vineyards
- Refine predictive models by including additional variables (from other data sources) to improve the accuracy and robustness of predictions



UAV imagery could be used as a decision-support tool for the management of service crops

References

Cheraiet, A., Gobrech, A., Naud, O., & Taylor, JA., 2023. Digital Tools Revolutionizing On-Farm Experimentation: Empowering Agro-Ecological Transitions, OFE2023 – 5th – 7th December - Second International Conference on Farmer-centric On-Farm Experimentation.

Garcia, L., Celette, F., Gary, C., Ripoche, A., Valdés-Gómez, H., Metay, A., 2018. Management of service crops for the provision of ecosystem services in vineyards: A review. Agric. Ecosyst. Environ. 251, 158–170. https://doi.org/10.1016/j.agee.2017.09.030

Garcia, L., Krafft, G., Enard, C., Bouisson, Y., Metay, A., 2024. Adapting service crop termination strategy in viticulture to increase soil ecosystem. functions and limit competition with grapevine. Eur. J. Agron. 156, 127161. https://doi.org/10.1016/j.eja.2024.127161

Giffard, B., Winter, S., Guidoni, S., Nicolai, A., Castaldini, M., Cluzeau, D., Coll, P., Cortet, J., Le Cadre, E., d'Errico, G., et al., 2022. Vineyard Management and Its Impacts on Soil Biodiversity, Functions, and Ecosystem Services. Front. Ecol. Evol. 10, 850272.

Naes, T., Tomic, O., Afseth, N.K., Segtnan, V., & Måge, I., 2013. Multi-block regression based on combinations of orthogonalisation, PLSregression and canonical correlation analysis. Chemometrics and Intelligent Laboratory Systems, 124, 32-42.

Surowiec, I., Skotare, T., Sjögren, R., Gouveia-Figueira, S., Orikiiriza, J., Bergström, S., et al. 2019. Joint and unique multiblock analysis of biological data-multiomics malaria study. Faraday Discussions, 218, 268-283.

Winter, S., Bauer, T., Strauss, P., Kratschmer, S., Paredes, D., Popescu, D., Landa, B., Guzmán, G., Gómez, J.A., Guernion, M., Zaller, J.G., Batáry, P., 2018. Effects of vegetation management intensity on biodiversity and ecosystem services in vineyards: A meta-analysis. J. Appl. Ecol. https://doi.org/10.1111/1365-2664.13124

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