GRASS COVER, TREE DENSITY, AND LEAF DEVELOPMENT OF MEDITERRANEAN ORCHARDS FROM HIGH RESOLUTION DATA

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ABSTRACT

The study focused on Mediterranean orchards and aimed to explore different remote sensing data (Sentinel 2 data (2016–2023), 1 Pleiades image (2022) and the extraction of Google-satellite-hybrid images (GSH,2017)) to compute key variables affecting water requirements such as tree age and density per plot, leaf development, the inter-row management. Surveys were conducted on 22 farms where accurate information on agricultural practices was collected. The results have shown that a thresholding on the NDVI Sentinel 2 in the summer period allowed the identification of young orchards with an accuracy of 98%. The analysis of temporal profiles of FAPAR allowed the identification of key phenological stages such as flowering and fruit set. Supervised classification was employed to separate grassed and non-grassed plots using three spectral bands of Sentinel 2. Classifications performed from GSH images gave more accurate results (81% well classified) compared with Sentinel 2 (79%) and Pleiades (57%) when identifying grassed plots. The methods presented in this study propose methods easily accessible based on free-to-download data, making them applicable in diverse orchard contexts.

1. INTRODUCTION

Orchards represent one of the emblematic crops of the Mediterranean region. They have high water requirements increasing significantly due to climatic changes (Ramos et al., 2023). The water consumption of orchards depends on various factors, among them, soil and climate, and temporal variations of leaf development and farming practices (Ahumada-Orellana et al., 2019; Dian et al., 2023). Many approaches have proposed to use remote sensing (RS) to characterize the crop and surface variability (Abubakar et al., 2022; Courault et al., 2021). With the arrival of new data at increasingly fine spatial and temporal resolutions such as the Sentinel missions from Copernicus program or Pleiades and SkySat images, it becomes possible to monitor crops systems with more and more accuracy (Jafarzadeh and Attarchi, 2023). Thus (Abubakar et al., 2023) have shown that orchards can be well classified from Sentinel 2 data using deep learning methods. The combination of both, high temporal and spatial resolution of Sentinel 2 images (pixel 10m and time revisit 3-5 days), enables to monitor in-season vegetation phenology through the analysis of time-series. Recent studies from (Meroni et al., 2021) have demonstrated the potential of Sentinel data to derive phenological dates of herbaceous crops through the analysis of vegetation indices time-series. In tree orchards, by contrast, the presence of grass in the soil background joint with differences in management practices (e.g. weed control, mowing frequency, type of irrigation, pruning…) can introduce large uncertainties in the interpretation of satellite time-series. The presence of grass in the inter-row can also impact the water consumption of heterogenous crops (Ruiz-Colmenero et al., 2011). In period of water shortage, there can be competition for water between trees and grass which can lead to significant yield losses. The major challenge for irrigation is to deliver water to the crops at the right time according to their requirements. Different tools have been proposed in literature to help farmers for water management based on various crop models (Battude et al., 2017; Richard et al., 2022). (Le Page et al., 2012) have proposed a decision tool based on the combined use of remote sensing data and model to help irrigation strategies. Recent papers have shown that irrigation events can be assessed from Sentinel 1 and Sentinel 2 data and soil moisture products derived from RS (Bazzi et al., 2021; Hamze et al., 2023). If these last studies showed good performances on cereals, these methods do not apply yet to vineyards or orchards because of the complex structure of these crops. A lot of bibliography has explored RS acquired at very high resolutions from drones (UAV) to detect pruning for example (Johansen et al., 2018) or count trees (Dong et al., 2020), or information on orchard structure from Quickbird satellites (Panda et al., 2010) and LIDAR (Dian et al., 2023). Various models have been developed to assess evapotranspiration of orchards (Elfarkh et al., 2023; Nieto et al., 2019; Ramos et al., 2023). Some of them such as Qualitree model (Miras-Avalos et al., 2013) can take into account a lot of processes and can simulate the fruit quality. However, most models require a lot of parameters for their calibration, from in situ sensors to characterise the microclimatic and/or soil conditions. They are consequently difficult to spatialize at larger scale.

The objective of our study was to propose an approach based on RS data to estimate unique orchard characteristics impacting water consumption. The following variables are focused:

- the leaf development,

- the inter-row management: the main output was the detection of grassed and non- grassed plots,
- the separation of young (< 5 years) and old orchards,
- and the tree density per plot.

2. DATA AND METHODS

2.1 The Ouvèze watershed and ground observations

A typical Mediterranean watershed was chosen in Southeastern France, where various observations were conducted on orchards (the Ouvèze-Ventoux watershed, 880 km², centered 44° 13.050' N, 5° 8.579'E). The altitudes vary between 209 and 1558m (Figure 1). The climate is Mediterranean with cold and moist winters and dry and hot summers (yearly rainfall 650mm; mean temperature 15° from the Carpentras weather station).

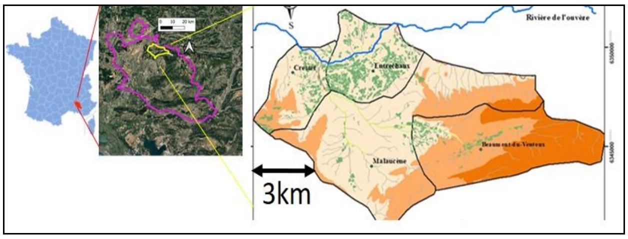

Figure.1. Location of the Ouvèze basin.

Orchards cover 307 ha (1430 small plots, mean size <2ha). Most are drip irrigated, less than 10% are irrigated by sprinklers or micro-sprinklers. A wide variety of cultivars can be found: earlier, seasonal and late cherry or apricot trees, and plume trees. Various surveys were conducted by the INRAE team to better understand the farming practices besides different farmers (22 farms, 749 fields).
From these surveys, it appeared that irrigation started after the flowering stage at the end of March for the earliest varieties, then decreased generally after the harvest (at the end of June), and lasted for varying durations (3-300 hours/year). The applied doses for cherry trees could vary from to 57 mm to 525mm/year (for the year 2021). The largest distances for the inter-rows were 9 m for young plum trees, and the lowest up to 3.5m most (often observed for old apricot orchards).

I*n situ* annotations of tree phenology were performed as well between budburst and fruit growth stages in a set of 13 plots for 3 years (2021-2022-2023) including cherry trees with different ages, cultivars, tree density and management practices (bare soil and grass as background). Observations were done at the tree scale on two opposite branches, and for 3 trees per plot. Hemispherical photos were taken at the same locations, both towards the ground aiming the surface in the interrow, and towards the sky aiming the tree canopy (Figure 2). All photos were processed with the Can-eye software (www6.paca.inrae.fr/can-eye/) to derive the main biophysical variables (Baret et al., 2007): FAPAR (Fraction of Absorbed Photosynthetically Active radiation) and FCOVER (Fraction of vegetation cover).

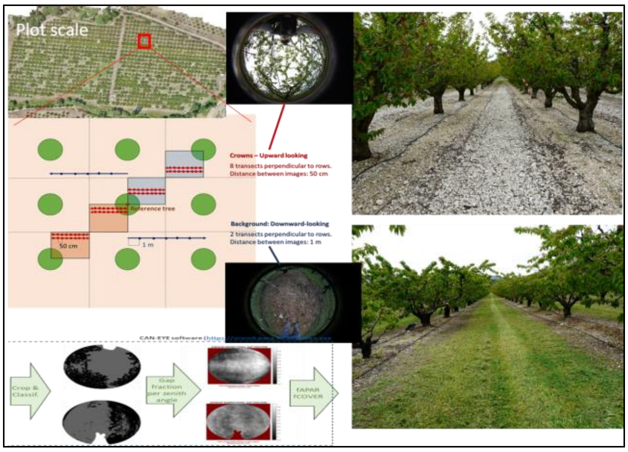

Figure 2. Protocol used to monitor leaf development from hemispherical photos taken on different orchards with grass or without grass in the inter-row. All photos were processed using classifications separating green parts from the background based on deep learning methods and an algorithm developed by EMMAH Team.

2.2 Image dataset and processings

Images from various sensors (Sentinel 2, Pleiades, UAV and Google Satellite hybrid (GSH)) were acquired on the study area (Table 1). **Sentinel 2** data (tile T31TFJ at level 2, corrected from atmospheric effects according method described in (Hagolle et al., 2008), were downloaded each week automatically from the THEIA platform (https://catalogue.theia-land.fr/) and the same biophysical variables than described in section 2.1 (LAI, FCOVER and FAPAR) were computed from the BVNET model described in (Lacaze et al., 2015; Weiss et al., 2002). Additionally, spectral indices such as NDVI were computed for each date. R functions have been developed to extract for each monitored field, the mean values of all indices for each date.

Table 1 Characteristics of the used remote sensing data (B: Blue, G: Green, R: Red; NIR: Near-InfraRed)

	Downloaded data	Spatial resolution	Time revisit	spectral characteristics
Sentinel 2 (A-B)	2016-2017-2018-2019-2020-2021-2022	10m (B3-4-8), 20m (B11-12), 60m (B5)	3-5 days from 2017-	10 bands: (visible-infrared)
Pleiades	25/7/2022 from Dinamis platform	Panchro mode:50cm Multispectral : 2m	Punctual by programming	panchro:470-830nm, 4 bands: B,G,R, NIR
UAV	1image 29/7/2021 on two small areas	8mm	Punctual by programming	4 bands: B, G, R, NIR
GSH	30/4/2017 From Google Earth	20 cm	/	RGB bands

Figure 3 summarises the use of each sensor and the main aimed outputs.

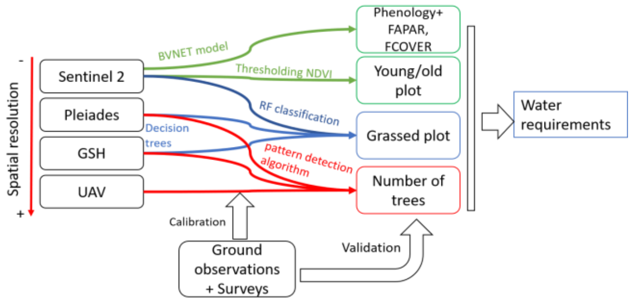

Figure 3. Main sensors and outputs

Sentinel 2 temporal profiles were analysed for all orchards where ground observations were available (on plantation age, inter-row and irrigation management). The method to separate young and old orchards was based on defining a threshold on NDVI during the summer period. Then, a supervised classification was applied to a Sentinel 2 colour composite considering the green (G), red (R) and near-infrared (NIR) spectral bands, for a date acquired in March, when trees have no leaves because it is easier to separate orchards with green grass in the inter-rows from orchards with bare soils. A random forest (RF) algorithm was then applied, considering a learning dataset extracted from ground observation, including 50 randomly selected orchards for the training and 250 plots for validation. At a finer resolution, with GSH and Pleaides data, a hierarchical approach was proposed with two main steps to map grassed plots. A first threshold based on the color intensity of the pixel (T1) was manually determined for each sensor type and date from the analysis of various samples of known plots (representative of the variability encountered in the basin) to classify the trees from the background (for GSH T1=60, for Pleiades T1=85). A second classification was performed from a new threshold (T2) defined to separate grassed from bare soil pixels of inter-rows (for GSH, T2=100, Pleiades=95) (Table 2). The accuracy assessment was done comparing results obtained with ground observations of 195 plots not used for calibration.

Table 2. Thresholds fixed to separate grassed and non-grassed plots from GSH and Pleaides images (in blue band)

Thresholds to separate :	Background and trees	In the background: grass / bare soil
GSH images	Trees <60	Bare soils >100
Pléiades images	Trees <85	Bare soils >95

At least, in order to have an assessment of the number of trees per plot, an algorithm (Objj.MPP) based on Marked Point Process (MPP) was used for the detection of parametric objects (De Graeve et al., 2019). The objects are defined by a finite set of parameters (Table 3) according to their shape (circle, rectangle, triangle…). In this case, for detecting trees, we selected a disk described by the radius (min and max lengths in the studied samples), and the overlap tolerance (expressed in pixel number). An accurate description of this algorithm applied for various studies can be found in (De Graeve et al., 2019; Eldin et al., 2012).

Table 3. Main parameters fixed for detecting the number of trees per plot using the Objj.MPP algorithm.

Data source	Grass	Radius_rng	Overlap_tolerance	Min_quality
GSH	Grassed	(18, 28, 0.8)	30	22
GSH	Non-grassed	(17, 25, 0.8)	20	35
Pleiades	Grassed	(6, 8, 0.8)	10	15
Pleiades	Non-grassed	(6, 8, 0.8)	30	22

Validation was done considering plots randomely drawn from ground observations.

3. RESULTS

3.1 Monitoring of the vegetation development

The different spectral indices and biophysical variables computed from Sentinel 2 are correlated and allowed to monitor the leaf development of the orchards. Figure 4a shows the temporal profiles of NDVI for few cherry trees.

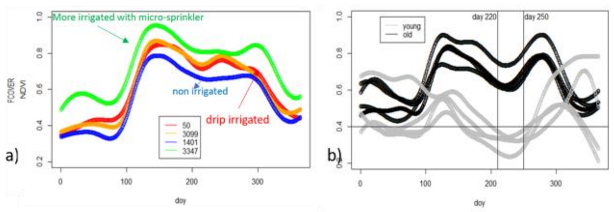

Figure 4. Temporal profiles for different cherry trees

We can observe a characteristic pattern with an increase of NDVI in spring up to June (canopy greening starts at the end of March, with a rapid increase immediately after the full flowering (corresponding to the phenological stage BBCH65)). In mid-May, fruit starts to grow (BBCH69) once full leaf area expansion has taken place. Then in summer a slight decrease is observed due to a decrease in irrigation, that yields to a yellowing of the grass in the inter-row. From September, rain comes back and participates to greening again the inter-row and the signal increases. The last stage is the senescence in autumn where the leaves fall. These typical patterns can present variability according to the farming practices. The grass background in many of the plots have a strong impact in the canopy-level. A field having received more water by irrigation displays generally higher NDVI or FCOVER, FAPAR, and at the opposite, non-irrigated orchards or orchards with bare soils in the inter-rows have lower values particularly in summer (Figure 4a).

3.2 Identification of young orchards

Young orchards (<5 years) are easy to detect because of their low development (Figure 4b). An NDVI threshold of 0.4 was implemented in the period between DOY 220 (8/8) and 250 (7/9) for dry and standard years, and 0.5 for wet years to separate young orchards. This classification was applied to the whole watershed. The results shows 25% of young orchards on the whole basin. This value is in accordance with observations. The classification accuracy is in the order of 98% of well classified plots.

3.3 Identification of phenological stages

To remove the influence of grass, we propose to normalize the biophysical variables (fAPAR and FCOVER) per season, using as a reference the value (min) at day 70 (before flowering) and another value (max) at the seasonal maximum period (after leaf expansion). By this normalization, BBCH65 stage (full flowering stage) can be well identified with a normalized fAPAR of 0.2 in most of the plots, whereas BBCH69 stages coincides with a normalized fAPAR of 1.0 (Figure 5). Such simple approach permits to infer two essential phenological stage in cherry-tree orchards with a relatively small influence of the background.

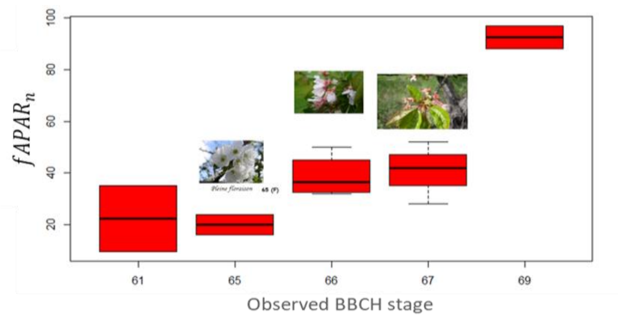

Figure 5. Normalized fAPAR according phenological stages observed from 13 cherry trees.

3.4 Identification of grassed orchards

Figure 6 presents the map of grassed (in red) and non-grassed (in green) orchards at the watershed scale obtained from Sentinel 2. The global accuracy was 79%. Some fields which were very heterogeneous with stony inter-rows or presenting patches of vegetation and bare soils, are often classified as non-grassed plots although they are grassed. The spatial resolution of Sentinel 2 (pixel 10m) does not allow to improve this detection because the reflectance results of mixing inter-row and trees which cannot detect such surface heterogeneities. It is the reason why we have explored finer images (Pleiades and GSH). The results obtained from these last data are presented in Table 4. The performance was improved for GSH images relative to the Pleiades images acquired in summer, which is expected since GSH has a highest spatial resolution. Satisfactory results were obtained for the detection of grassed orchards, which returned up to 88% with GSH. A slightly lower performance was obtained for non-grassed fields (61%). An explanation is due the acquisition period for GSH images: in April, inter-rows can have grass regrowth or are not yet moved. For Pleiades, the lower score can be explained by the acquisition period in July. At this period, the grass in the inter-row is often very dry and yellow and then the fields can be classified as non-grassed orchards. The crown development of the tree is also larger than on GSH classification.

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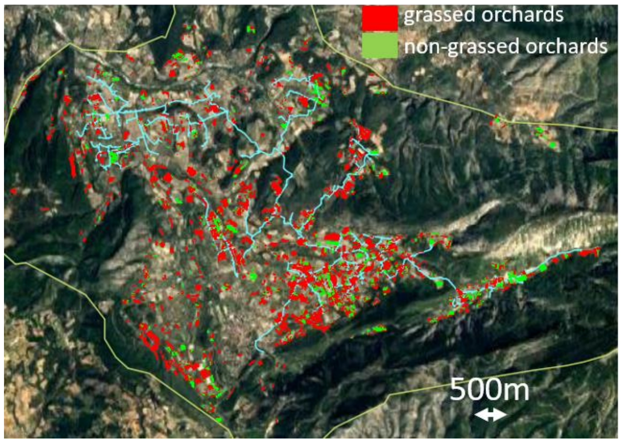

Figure 6. Map of grassed and non-grassed orchards obtained from the classification of Sentinel 2 image acquired on 2022-03 -03 on the Ouvèze basin.

Table 4. Performances obtained with GSH and Pleiades images to separate grassed and non-grassed plots.

	GSH	Pleiades
Correct identification	177/219 (81%)	124/218 (57%)
Correct identification (grassed)	140/159 (88%)	66/159 (42%)
Correct identification (non-grassed)	37/60 (61%)	58/59 (98%)

3.5 Assessment of the number of trees per field

A first step was to evaluate the application of the pattern algorithm (Objj.MPP) at plot scale on the largest field of the watershed (Figure 7). 1073 cherry trees were detected with an overestimation of only 3% corresponding most of the time to areas where some trees were uprooted with regrowth of tall grasses. The results obtained using GSH and PLEAIDES images have shown high correlations compared with ground observations (r^2=0.9). Some fields present underestimations of number of trees, because they mixt young and old trees and have different soil types impacting the background as displayed in Figure 8.

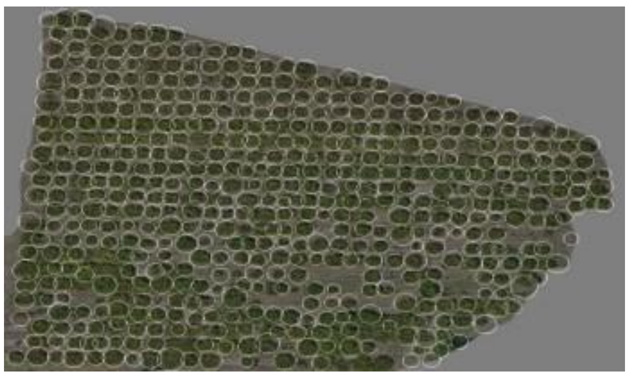

Figure 7. Detection of the number of a cherry tree from the UAV image acquired on 2021-07-29.

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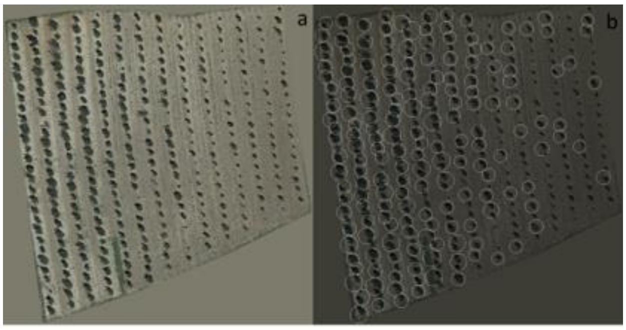

Figure 8. Example of heterogenous orchard with young and old trees where the pattern algorithm underestimates the number of trees.

The median value over the whole basin was in the order of 75 trees per field. The density considering the surface of the fields was in the order of 267 trees/ha. As expected, larger plots have greater number of trees. A linear relationship can be proposed to derive tree number from field area for the main species:

Tree number=208 (field surface (ha)) +8, for cherry trees
Tree number=154 (field surface (ha)) +41, for apricot trees
Tree number=246 (field surface (ha)) +9, for olive trees.

Olive trees are generally less spaced than apricot and cherry trees, with a mean density of 305 trees/ha against 217 for cherry trees and 244 for apricot.

4. DISCUSSION-CONCLUSION

The different variables derived from remote sensing data are useful to estimate the water consumption at the watershed scale and to analyse the spatial variability according to the agricultural practices. Surveys performed on 22 farms have revealed that the water quantities provided to each field are highly correlated to the orchard age, the tree number per field and soil type. Most of farmers start irrigation at the fruit set stage. The results have shown that the high frequency of Sentinel 2 data allowed to detect the orchard development and to identify key phenological stages such as the flowering and fruit set stages which determine the start of irrigation. Irrigated and non-irrigated plots can be distinguished from the analysis of temporal profiles of biophysical variables. A simple thresholding applied on the NDVI temporal profiles computed for each orchard allowed for the classification of young from old plantations, which require different irrigation strategies, reasonably well. The use of images with finer spatial resolutions such as Pleaides data or GSH improved the assessment of grassed from non-grassed orchards and allowed the quantification of the number of trees per field using a pattern detection approach. Normalising fAPAR and fCOVER presents the advantage to mitigate the influence of soil background and to better identify some crucial phenological stages such as the flowering stage.

The methods proposed here, have the advantages to use data easier to download and free for access. These methods can be applied in various contexts and orchard types. Next steps will focus on the addition of radar data from Sentinel 1 to inform on the water status of the soil.

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