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ABSTRACT

Most Orchards throughout the Mediterranean basin rely heavily on irrigation, a dependency increasing due to climate changes. Assessing the water requirement (*WR*) is crucial and depends on different factors, including orchard age, tree density per field, inter-row management. This study proposes new methods to evaluate these characteristics with remote sensing (RS). Various remote sensors providing high and very high spatial resolution images are investigated and their accuracy is assessed. The final objective is to assess *WR* using variables derived from remote sensing compared to data provided by water managers and from the FAO method. A typical Mediterranean watershed was selected in South-Eastern France, with orchards having various agricultural practices. Original methods were developed with Sentinel 2 (S2) data (2016–2023), 1 Pleiades image (2022) and the extraction of Google-satellite-hybrid images (GSH, 2017), and assessed using a large ground observation dataset (information on water use collected on 366 fields). Five orchards were monitored by capacitive sensors to assess the water balance. Irrigation durations ranged from 3–300 hours/year, with decision influenced by tree density and plot age. To identify young orchards, a thresholding approach on S2 derived NDVI effectively identified young orchards achieving a 98% accuracy rate. Grassed and non-grassed orchards were mapped using two methods, with a random forest classification using three spectral bands with 72% accuracy and a supervised approach yielding 81% accuracy for GSH and 57% for Pleiades. The performance depends on the acquisition date of images. A pattern detection algorithm applied to GSH and Pleiades determined tree density, showing a high correlation (r^2=0.9) with observed data. These RS derived variables allowed to compute orchard water requirements at the watershed scale, ranging from 70 to 550 mm annually depending on management practices. The proposed methods can be extrapolated to other territories and are implemented using open access softwares.

1. Introduction

Within the Mediterranean region, there is an increasing reliance on the use of irrigation in agriculture (Molle and Sanchis-Ibor, 2019). With climate change and more frequent (and extended) drought periods, crop water requirements are proving more difficult to meet, leading to the potential for increased water resource conflicts (Cramer et al., 2020). The year 2022 represented an extreme in this sense, as the drought period lasted from spring to early September in France. Temperatures have exceeded 30°C, much longer than the seasonal norms, with 25% rain deficit in the year (60% in May) and leading to irrigation restrictions being imposed across many regions (Meteo-France, 2022). Indeed, the water stocks are not subsequently yet completely renewed even in the winter period (Labbe et al., 2023). To maintain a sustainable and diversified agricultural sector and ensure more secure food and livestock production, an effective and adaptable water resource management is required (Grujard, 2003). Possible adaptation actions include changes in conventional agricultural practices to move towards an agroecological transition. Among these actions, a better irrigation management, new crop types (better suitable for high temperatures), or different practices for the sowing dates can be proposed (Basche and Edelson, 2017; Ruiz-Martinez et al., 2015; Thomas and Kevan, 1993). In the Mediterranean zone, integrated water resource management has become a major issue, both in terms of quantities needed and quality of

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water to be preserved. The degradation of the quality of a large number of rivers, groundwater and recent droughts have been reported by Guyomard et al., (2017).

1.1. Orchard water consumption

Orchards are one of the emblematic crops of the Mediterranean region, but have high water requirements that are rising due to increasingly hot summers. Although using a relatively enhanced form of irrigation delivery via drippers in the south-east of France, orchards can still consume large amounts of water, e.g. 526 mm/year for apricot trees, 738 mm for olive trees or 540 mm for cherry trees (CABRL, 2019). These water requirements are usually assessed using the Food and Agricultural Organization (FAO) method (Allen et al., 1998) because of its low data and calculation requirements. That approach is based on an estimate of a reference evapotranspiration. The computation uses data from a standard weather station (Penman, 1948), along with a correction coefficient (Kc) that can be defined for each crop type (Allen et al., 1998). Kc calibrations have been carried out for a large number of regions, crop types, and soil and climatic conditions, with a large body of results assessed against in situ measurements using lysimeters or the Bowen ratio measurements or eddy correlation flows (Pereira et al., 2015). Improvements have been proposed to consider the soil properties, which impact the evapotranspiration (ET) processes (Guerra et al., 2016). Numerous papers have shown that it is also important to account for physical and socio-economic factors (such as the irrigation material and the cost, the farm size, the man-power and market demand…), which may add some constraints in irrigation practices (Harmanny and Malek, 2019; Fernandez-Cirelli et al., 2009; Poussin et al., 2008). Importantly, the FAO method does not account for variations related to "on-farm" practices that might be implemented for dry and wet years, impacting the amount of water available to the plant (Allen et al., 2005; Djaman et al., 2016). Orchard irrigation techniques can be quite variable, including drip irrigation in the north-western Mediterranean, flooding mainly in North Africa regions, and microsprinklers as reported by (Monney, 2011). Depending on the techniques used, the delivered quantities significantly differ in time and space. One issue remains to assess this spatial and temporal variability at watershed scale.

In order to optimize the water quantities delivered on-farm, it is necessary to know the actual crop needs, which depend on phenology and the leaf development during the season, the soil water stock, and the farming practices (Stanhill, 1957), varying also in space and time. Farming practices, such as the choices of the variety (early, late, or seasonal), the plant density per hectare, tree age, pruning during the season, inter-row management (grassed or bare soil), are all relevant factors to be considered when estimating the water consumption of orchards (Allen and Pereira, 2009). If orchards present grass in their inter-rows, grass requires also water for its development. Competition can then appear with the trees (Ruiz-Colmenero et al. (2011). Not surprisingly, water deficits can lead to significant yield losses in crops. Up to now, there is no method delivering maps on the grassing of orchards.

1.2. Methods to assess the water needs

Related to this, one of the major problems for water managers at the catchment scale (ASA[1] for example), is to estimate sufficiently early in the year the water needs for agriculture across the whole territory, in order to be able to equitably distribute the water supplies for irrigation, particularly during shortage periods (Hajkowicz and Collins, 2007; Iglesias et al., 2007)

Various types of decision support systems (DSS) have been developed, although mainly applied at the field scale and for cereals (Zwart and Bastiaanssen, 2004). Most of these are based on the use of crop models such as STICS (Brisson et al., 2003), DSSAT (Jones et al., 2003), Optirrig (Richard et al., 2022) or Aquacrop (Rallo et al., 2012), which are used to simulate the water consumption of plants. Once calibrated, the models can then be employed to analyse different irrigation scenarios and assess the impact of climatic changes on production (Bregaglio et al., 2017). However, the spatialization of these models over an entire territory can be problematic due to the many parameters that required, and which are rarely well known (Faivre et al., 2004).

Other approaches for crop and resource management have relied on the use of remote sensing to characterize the surface variability (Courault et al., 2021, 2019) or to manage natural resources (Kasischke et al., 2014; Kennedy et al., 2009; Wang and Weng, 2013). With the launch of the Sentinel mission in 2015, the availability of high spatial (10 m pixel) and temporal (every 3 to 5 days, depending on satellites A/B) resolution images has advanced the options for monitoring cultivated areas (Bazzi et al., 2022; Behera et al., 2018; Veloso et al., 2017). In a similar vein, land use maps based on deep learning methods are increasingly available for the identification of crop types (Abubakar et al., 2022; Jafarzadeh and Attarchi, 2023). Likewise, operational products such as surface moisture maps derived from the Sentinel 1 and 2 combination are provided by the THEIA platform[2] over various regions at fine resolution (10 m every 6 days) (Bazzi et al., 2019; El Hajj et al., 2019).

1.3. Research issues

However, despite this abundance of satellite images and derived products, crops such as vineyards and orchards remain poorly characterized due to their structural heterogeneity (including inter-rows and trees). Recently, El Hajj et al., (2023) evaluated the potentialities of radar Sentinel 1 data to map the water uptake rate across a very high-density olive orchard in the hot and arid desert climate of Saudi Arabia. The proposed method gives satisfactory results but is restricted to evergreen orchards whose canopy volume does not change significantly. Orchard characterization is often addressed using very high resolution images such as drones (Dong et al., 2020; Özdarici-OK and Ok, 2023; Park et al., 2015) or sensors such as RapidEye, Quickbird, or Skysat (Houborg and McCabe, 2015). In recent work, Johansen et al., (2018) showed that routine collection of UAV images can provide useful information on agricultural practices, such as pruning effects on tree structure. Dian et al., (2023) combined UAV and Lidar to assess vertical structure of three citrus cultivars, while Teina (2009), used Ikonos images (pixel 1–4 m) to classify the different plant types of coconuts with high performances. Summarizing much of the recent progress in this area, Zhang et al. (2021) focused their review on studies using UAVs for orchard management. While very fine information can be extracted from UAV data, these sensors remain applicable to limited areas and periods and can often be costly. From a satellite-based perspective, remote sensing applications in orchards are very diversified on resource efficiency, production, geometric traits and diseases (Panda et al., 2010). In terms of orchard species, relatively few studies have been carried out on cherry trees and apricots, with most tending to focus on olive (Cammalleri et al., 2013; Elfarkh et al., 2023; Sepulcre-Cantó et al., 2006) and citrus orchards (Dian et al., 2023; Er-Raki et al., 2009; Glenn and Tabb, 2018; Xu et al., 2023).

In general, there are no operational methods easily applied at the watershed scale to derive key variables involved in the water consumption and in the monitoring of agricultural practices impacting water resources.

1.4. Objectives

In this sense, the main objective of this study is to develop methods to

[1] ASA: Association Syndicale Autorisée, association management the water distribution at regional scale in France

[2] https://www.theia-land.fr/)

estimate orchard characteristics at plot scale impacting water consumption, and then to estimate the water requirements of orchards at watershed scale. In terms of orchards characteristics, we particularly focused on examining: I) inter-row management, in order to detect grassed and non-grassed plots; II) discrimination between young (planted less than 5 years ago) and old orchards, since the water requirements are quite different for these two categories; and III) the tree density per plot. As the study scope is conducted at both plot and watershed scales (water management scale by ASA), various image sources were analysed having different spatial resolutions. Particular attention was paid for developing generalizable methods, easy to implement. One of the objectives was to assess the accuracy of the three variables (mentioned above) according to the used sensors. The final objective was to evaluate the water requirements computed from these variables derived from remote sensing to data provided by water managers (ASA) and from the FAO method. A large dataset of ground observations was used to evaluate the proposed methods.

2. Data and methodology

2.1. Study site and grounds observations

A typical Mediterranean area, the Ouvèze-Ventoux watershed (located in the South-Eastern France, centred 44°13.050' N, 5°8.579'E) was selected for this study (see Fig. 1). The catchment covers 100 km^2 and has an average annual temperature of around 15.5°C (1993–2023 average Carpentras weather station), with an annual rainfall amounts of around 650 mm (mainly concentrated in autumn-winter). The altitudes range from 209 m above sea level (a.s.l) on the plateau area to 1558 m a.s.l at Mont Ventoux, the higher peak of the region. Most agricultural areas are located on the plateau, between 250 and 400 m a.s.l on a silt-loam soil (~22% silt, 43% sand 35% loam) covered by vineyards (35% of the total cultivated areas), and orchards (28% with 631 ha). Most orchards and table grapes are irrigated. The water for irrigation is primarily sourced from the Ouvèze river and distributed through a network of pressurized pipelines managed by the Ouvèze-Ventoux ASA. The water for irrigation is available only from April to October.

Among orchards (1425 fields, 631 ha), cherry trees are the most numerous in the region. The field size is small, on average 0.4 ha). The development period starts in spring from March up to June. Around 80% of cherry orchards are irrigated by drip, with one or two pipes per row, while 10% have micro-sprinklers located 1 m above the ground between two trees, with the remainder by sprinkler and very few (< 2%) by flooding (see Fig. 1). According to the ASA information, the average of water quantity consumed per year per plot is around 350 mm (It is important to mention that there is large variability between farms and the trend is an increase of irrigation due to more frequent droughts and heat waves).

For several years (since 2017 up to 2023), observations and surveys were conducted by the French Institute of National Research in Agronomy and Environment (INRAE) across this area to collect information on the main agricultural practices. These surveys compiled ground references from 648 plots, with 359 plots occupied by orchards, whose main characteristics are summarized in Table 1. The average plot size on the whole basin is 0.4 ha with 265 tree/ha.

These agricultural surveys have demonstrated a wide variability of irrigation practices across the region. Most of the farmers start irrigation of cherry orchards after flowering, at the fruit set phenological stage. The leaves appear after flowering. The available water reserve is most of the time enough at the beginning of the year. Generally this water stock depends on winter rainfall. This stock can vary according to climatic years. ASA delivers water for irrigation from April. In this region, the day of the start of irrigation corresponds to the phenological stage of fruit-set. This day can vary according to the selected cultivars, covering the period from the end of March to the end of April. Generally, different varieties are found on a same plot in order to stagger the harvest dates, and better respond to the diversification of commercial demand. For instance, in cherry trees, the most common varieties are “Prime-giant” (earlier), “Belge”, “Burlat” (late), and “Folfer” (season) and the rootstock “Sainte-Lucie”. Apart phenological stage, a wide variability in irrigation practices was observed: for instance, in 2021, the applied dose for cherry trees can vary from to 57 mm to 525 mm/year. With drip irrigation, some farmers choose to bring water for 1 hour per day in April, then increase up to 2 or 3 hours every two days from May to August, and then decrease application after the harvest, again to 1 hour in September. Others prefer to bring water every week, but for longer periods (4 or 6 hours). This variability could be explained by their irrigation equipment (dripper type, spacing between drippers…), the inter-row management, the cultivar, tree age, the soil type and the available manpower. A soil map for the whole Vaucluse department was made by the SCP[3] (Société du canal de Provence) at 1/50000 and the soil water reserve map at France scale (at 90 m spatial resolution, downloaded at Agroenvgeo[4]) was used to have the main soil characteristics of the studied areas. It appeared as expected that farmers bring more water on sandy soils than on silty loamy soils. Apart from olives, the majority of orchards have grass with variable inter-row distances according to the orchards type and age (Table 1). The largest distances for the inter-rows are 9 m for young plum trees, and the lowest around 3.5 m for old apricot orchards. For grass inter-row orchards in the spring/summer, the soil vegetation can be in competition with the tree for the water requirements. Some farmers cut the grass anywhere between one to three times per year in order to minimise this competition, while other let it cover the soil, turning yellow in summer after the harvest (for cherry, apricots, plums) when irrigation decreases (Vilà and Sardans, 1999). A spatial cadastral database of the region fields is used from the following web link: https://cadastre.data.gouv.fr/map?style=ortho. The LPIS (European Land Parcel Identification System[5]) provides additional spatial information (in a shapefile) to identify each field of the study area at a finer spatial resolution. This LPIS file informs only on the fields declared by farms to receive subsidies (on our study area, only 40% of fields were declared). Additional ground observations were consequently done to complete these data by the notation of each crop type (orchard, vineyard or other crops) in each unknown plots and defined the boundaries of each new plot (finally there are 3548 agricultural fields, including 1415 orchards).

2.2. Remote sensing data

Given the different spatial resolutions that were explored, various remote sensing sources were used to extract key variables related to the orchard structure and to monitor their seasonal evolution (see Table 2). These included:

- **Sentinel 2**: images acquired over the study site (tile T31TFJ) were corrected for atmospheric effects corresponding to level 2 A according to methods described by Hagolle et al. (2008). The main characteristics of images are presented in supplementary material part 1. Data were downloaded each week automatically by Python programs from the THEIA platform[6] for the period between 2016 and 2022. The time frequency varies between 3 and 6 days, but some dates can present clouds and must be removed. The different spectral bands (green, red and near-infrared) are combined to compute the

[3] SCP: https://canaldeprovence.com/
[4] https://agroenvgeo.data.inra.fr/geonetwork/srv/api/records/393d8106-4400-51cd-9767-e8bbef2f73a6
[5] https://www.data.gouv.fr/fr/datasets/registre-parcellaire-graphique-rpg-contours-des-parcelles-et-ilots-culturaux-et-leur-groupe-de-cultures-majoritaire/
[6] THEIA: platform delivering products from remote Sensing https://www.theia-land.fr/en/homepage-en/

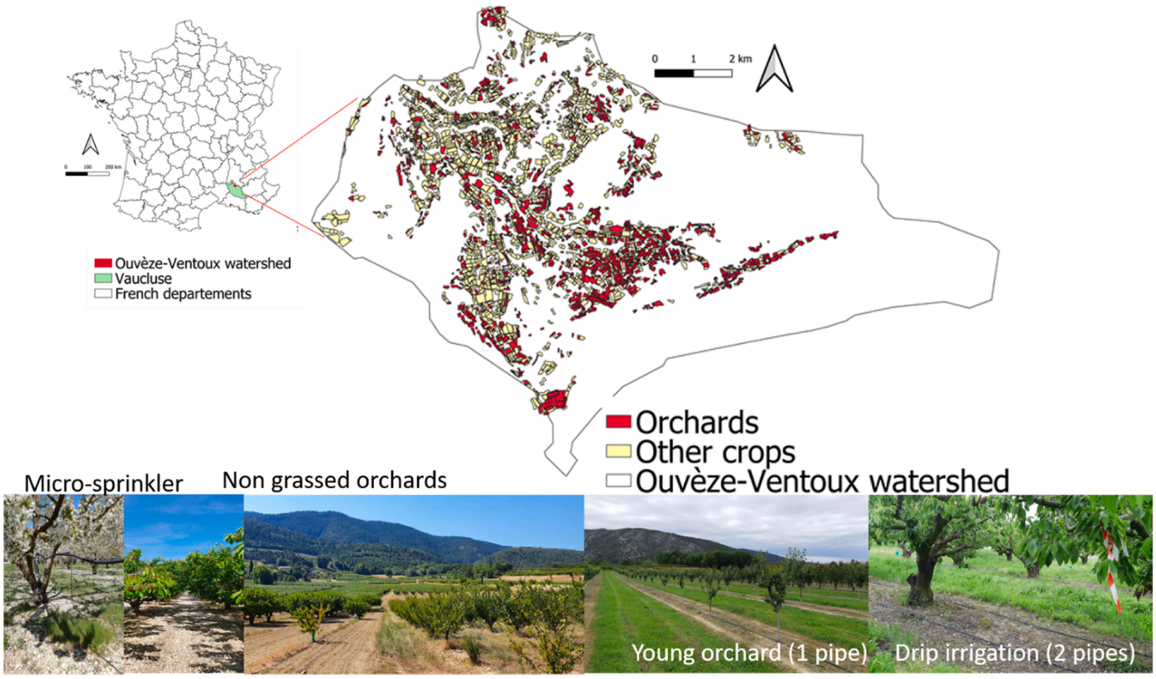

Fig. 1. Cartography of location of the Ouvèze-Ventoux watershed in the Vaucluse department in Southeastern France, and photos illustrating the diversity of orchards.

Table 1
Main characteristics of observed orchards (data obtained from farm surveys) on the studied area.

Known orchards	Plot number	surface (ha) Min -mean-max (ha)	Inter-row (IR) and Inter-tree (IT) distances min - mean - max (meter)
Cherry tree	106	0.02 - 0.7 – 4.57	**IR**: 5 – 6.9 – 9 **IT**: 4.5 – 5.9 – 9
Apricot tree	76	0.05 – 0.54 – 3.56	**IR**: 3.5 – 4.5 – 5 **IT**: 1.2 – 3.7 – 4.5
Olive tree	89	0.02 – 0.3 – 3.2	**IR**: 5 – 5 – 5 **IT**: 5 – 5 – 5 (1 observation)
Plum tree	40	0.06 – 0.52 – 2.74	**IR**: 4 – 5.2 – 7 **IT**: 4 – 4.4 – 5.5
Truffe oak tree	41	0.04 – 0.54 – 3.18	No observations
grenadier	7	0.14 – 0.49 – 1.26	**IR**: 5 – 5.2 – 6 **IT**: 3 – 3.1 – 3.5

bands and NDVI. There is no spatial interpolation, all pixels are considered and averaged at field scale.

- **Pleiades:** data were acquired through the Dinamis platform[7] operated by CNES and Airbus. A specific request has been made on the Ouvèze area for the summer. On the web site of dinamis, only a period can be defined, and not an accurate date can be chosen. Pleiades serves various services of territory monitoring (eg if floodings or landslides appear, priorities are managed by Airbus).The acquired date depends therefore on different factors among them the cloud occurrence, and emergency priorities for monitoring some other sites (see https://www.theia-land.fr/en/product/pleiades/ to have more details). The main characteristics (spectral bands and spatial resolution for the different modes, added in supplementary material table S1 and S2) of this space Earth Observation system is described in Lebègue et al. (2012). One image was available over our study area for the summer 2022. The covered area included the entire Ouvèze basin (see Fig. 1). The images have a pixel resolution

Table 2
Characteristics of the different image dataset (MS: multi-spectral, B: Blue, G: Green, R: Red, NIR: Near-Infrared), Google Satellite Hybrid images (GSH).

	Downloaded data	Spatial resolution	Time revisit	Spectral characteristics
Sentinel 2	2016-2017-2018-2019-2020-2021-2022	10 m (Bands:2-3-4-8), 20 m (B11-12), 60 m (B5)	3-5days from 2017	10 bands (visible-infrared)
Pleiades	25/7/2022 on the entire basin	in Panchro mode:50 cm Multispectral:2 m	Punctual by programmation	panchro:470-830 nm, MS:4 bands: B,G,R,PIR
Drone images	1 image 29/7/2021 on two small areas	8 mm	Punctual by programmation	4 bands: B,V,R,PIR
Extraction from GSH	30/4/2017	50 cm	/	RGB images

most common vegetation index (NDVI) for each acquisition date (Cantini et al., 2023). As some periods present no data due to cloudy dates, temporal interpolation is done using the "WhittakerFilt" function in R (Vuolo et al., 2011) to get daily values for each spectral

of 50 cm at nadir for the panchromatic spectral mode and 2.8 m for the multispectral mode (4 spectral bands: blue, green, red near-infrared). These last multispectral images were resampled using the fusion algorithm of Liu (2023) to derive a spatial resolution of 50 cm.

[7] https://dinamis.data-terra.org/

- **Unmanned Aerial Vehicles:** Images were acquired using an RGB camera for two areas of the basin at a height of 50 m above the surface. 1415 images were taken with an overlap of 80%. The georeferencing is done using reference disks located on the ground at different places marked with a precision GPS. Automatic algorithms (developed by the INRAE team) are then used to make the image fusion. The images were processed by the commercial enterprise Hiphen,[8] which provided an orthorectified mosaic with a spatial resolution of 10 mm (calibration coefficients were given in supplementary material table S3). Pixel aggregation to 20 cm was performed to optimize the computational time and reduce the data storage. In this study, the UAV imagery were used as reference data to validate our method to compute tree number per orchard.
- **Google satellite hybrid images (GSH)** have been used combining both QGIS software to extract the full image from the google source and R functions to characterise the plot scale image with the different RGB bands (Crop functions and zonalstat functions were used in R). This data was downloaded from Tile+ pluggin used with qgis (http://bit.ly/3inbiMt). This tool offers the possibilities to add various open access layers, provided by different operators, among them the google satellite hydrid image[9]. This image was the result of merging different images taken in April 2017 over our area, from various sensors operating at fine resolution (SPOT 7-Pleiades). The final spatial resolution was 50 cm using a resampling function based on a bilinear method. All the images cover various years with different resolutions. Ground observations were done from 2017 to 2023 on the agricultural practices and landuse. It can happen that some landuse modifications appear between years. We have taken into account the changes for some fields in this case. The images from the different sensors were overlaid on the vector spatial database containing all the plot boundaries using R functions to generate as many thumbnails in raster format as parcels (Fig. 2).

2.3. Remote sensing analysis

Fig. 2 presents the general approach that was applied to the different remote sensing data sources, including the UAV, GSH, Pleiades, and Sentinel 2 platforms, and covering resolutions from 8 mm to 10 m. More detail is given for each method in the following sections. Of course, each of these sources has its own constraints. For instance, Sentinel 2 is open access but comes with a relatively large pixel size, while Pleiades has improved resolution but is far less frequent in time (i.e. imagery must be tasked). Similarly, GSH offers fine resolution, but with no choice of acquisition date, while the UAV data provides enhanced resolution, but can be expensive and has a comparatively small sampling footprint. In this figure, the main inputs (at left) and outputs (at right) are outlined. For determining the orchard age, a thresholding is applied on Sentinel-2 NDVI during the summer season to distinguish young and old plantations. Regarding inter-row grassiness, two methods were experimented: one involved a random forest statistical classification applied to Sentinel 2 images to map grassy and non-grassy plots, while the second method applied on GSH and Pleaides data relied on classifications based on thresholding the blue band to isolate three components within a plot: tree, grass, and bare soil. Lastly, tree density was estimated using a pattern detection algorithm applied to GSH, Pleiades, and UAV images. The results were compared and validated from ground observations. By incorporating these three orchard characteristics, the water requirements are estimated to better characterize water needs at the watershed scale.

2.3.1. Sentinel 2 Data for classify the orchards (young/old and grassed or non-grassed)

Two different methods were developped to extract the aimed orchard characteristics from Sentinel 2 data

First, to separate old and young orchards (the right part of Fig. 3), mean values of NDVI, reflecting the ratio between the difference between near infra-red (Band 8) and the red (Band 4) reflectance bands and the sum of these bands (Rouse et al., 1974), were computed for all available Sentinel 2 dates across each orchard. Then, temporal profiles of average values obtained at plot scale were analysed for all orchards where ground observations were available (i.e. old or young orchards (orchard age information was given from farmer survey). From the analysis of the temporal profiles of NDVI for all cherry trees, it can be observed that young orchards (<5 years) always presented low NDVI values in summer (see light grey line in Fig. 7a). Therefore, a NDVI threshold of 0.4, based on field data was proposed in the period between DOY 220 (8/8) and 250 (7/9) for the studied years (2016–2022) to classify the whole watershed and map young orchards at watershed scale.

Then in order to identify the plots with grass and non-grass on the inter-rows, a supervised classification was applied to a Sentinel 2 image with the green (G), red (R), and near-infrared (NIR) spectral bands as predictive variables (left part of Fig. 3). The database of ground observations (with information of grassed and non- grassed fields: 307 plots) was divided into two parts: one for the training (50 plots) and the other for the validation (257). The target variables are the fields classified into two classes: inter-row with grass or without grass. A cloudless date acquired in the beginning of spring (early March, when trees have no leaves) was chosen to ensure clear separation between orchards with green grass in the inter-rows from orchards with bare soils. The random forest (RF) algorithm was applied, considering the learning dataset extracted from ground observation that included 50 randomly selected orchards, and with the hyper-tuning parameters fixed at follows: 10 for the number of trees, min power set size: 2 and max power set size:7, and 5000 for the number of training samples (values very commonly used for similar supervised classifications). The remaining 257 plots not used in the training stage were used for validation. Validation consists in comparing if each plot is well classified, either grassed or not. Accuracy is computed by counting the well classified fields compared to the total number of plots of the validation database.

2.3.2. Assessment of grassed and non-grassed orchards from Pleiades and GSH images

Fig. 4 summarizes the different steps to classify grassed or non-grassed orchards using GSH and Pleaides data. We chose to develop a method easier to implement on images having less spectral bands and with less acquisition dates than Sentinel 2, and easier to understand compared to more complex statistical approaches. A hierarchical approach is proposed in two main stages. Among the different spectral bands, first the blue band is selected because it presents more contrasts to separate trees from the background. Walter, (2004) has mentioned that the best discrimination between landuse classes using the variance can be seen in blue band. Then a classification is done using a threshold (T1) based on the averaged value in blue band of the trees extracted from the calibration dataset (for GSH T1=0.6, for Pleiades T1=0.85). Then, a second classification was performed on the last classified images defining a second threshold (T2) to separate grassed from bare soil pixels of inter-rows (for GSH, T2=0.10, Pleiades=0.95. T2 correspond to the mean values of interrow grass computed from the calibration dataset). The next step consisted of computing at the plot scale the number of non-grassed pixels. If 65% of pixels were classified in bare soils then the field was classified as non-grassed field. The last stage is the validation of the obtained maps comparing ground observations to the classified plots. Similarely, to classical supervised classification, a database for the calibration is necessary and also an independent validation dataset. The advantage of the method here is that it requires a small database for the

[8] www.hiphen-plant.com
[9] https://qms.nextgis.com/geoservices/1135/

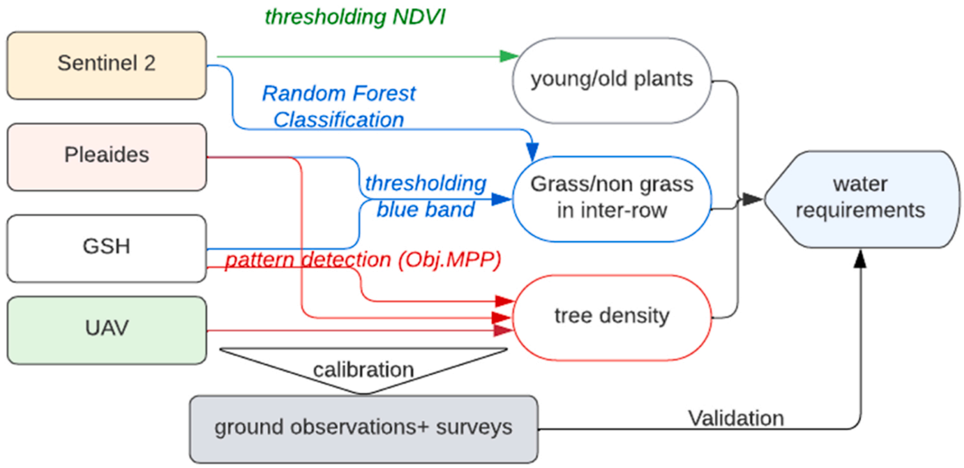

Fig. 2. General diagram of the methods applied for different satellite sources to obtain local information about orchards to characterise water requirements.

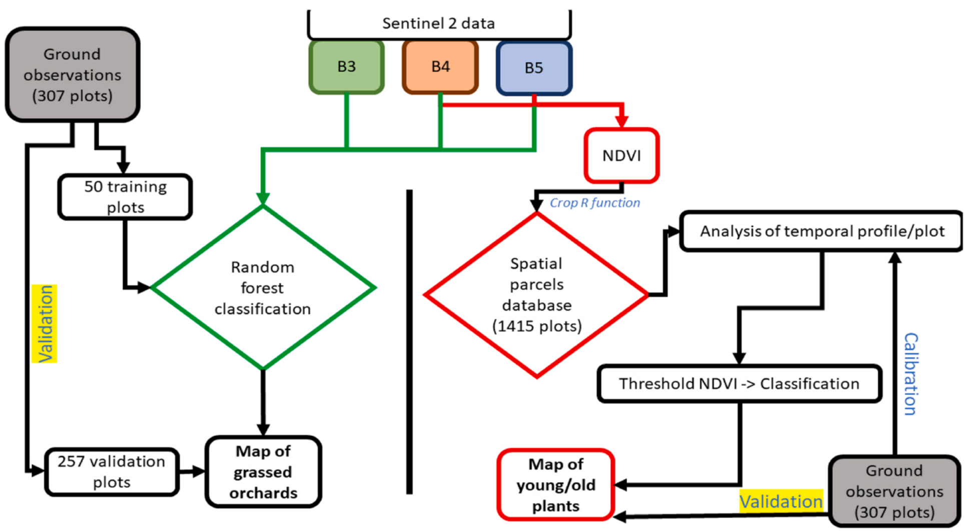

Fig. 3. Flowchart describing the method to detect grassed or non-grassed orchards; young orchard plants from Sentinel 2 images.

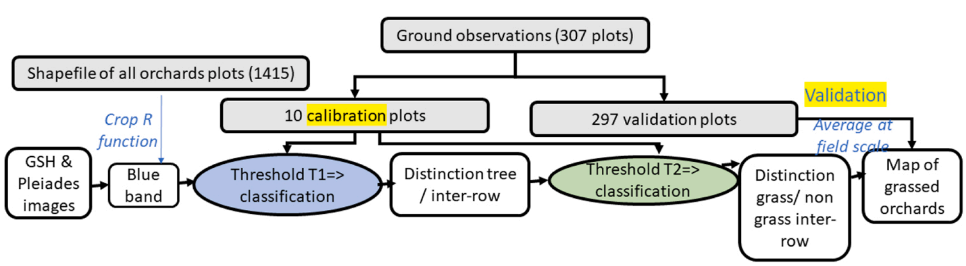

Fig. 4. The main steps to classify grassed and non-grassed orchards from GSH and Pleiades images. .

calibration (here only 10 plots were selected). All the processings were developed using R functions, easily accessible and operational to be applied on other sites with PLEIADES or GHS images. The problem of using thresholds is that they are data dependent. Different factors can influence the reflectance at a given date. An expert knowledge is often required for most methods to choose the most representative dataset for training. This point will be more argued in the discussion part.

An accuracy assessment was done comparing results obtained with ground observations of 195 plots not used for calibration. The results will be discussed in the part 3.

2.3.3. *Assessment of the number of trees*

We applied an algorithm based on Marked Point Process (Obj.MPP, open access at https://gitlab.inria.fr/edebreuv/Obj.MPP and written in python) for the detection of parametric objects (or patterns) in a signal (De Graeve et al., 2019). The objects are defined by a finite set of parameters (see supplementary material table S5 and S6 part6) 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). The number of iterations must be fixed with a quality indicator to stop the process. An accurate description of this algorithm applied to various studies can be found in De Graeve et al., (2019) and Eldin et al., (2012).

Each geometrical parameter needs to be calibrated according to the spatial resolution of the analysed images and the studied object dimension. These parameters can be affected by the contrast in images and consequently are dependent on whether or not there is grass between the rows. This first step to define the main parameters was done from a reference dataset of known representative orchards. The reference dataset is composed of 5 selected plots with different tree densities, for which it was easy to identify the actual tree number from GSH images. Table S6-S7 given in supplementary material provide these different input parameters according to the sensors, and to the state of the grass between the tree rows. Among the outputs, a tabular file gives (for each plot) the tree number and for each tree, its size (radius) and the centroid location.

2.4. Assessment of water consumption

A micrometeorological station was installed in May 2022 in the center of a large cherry orchard to measure relative humidity and air temperature, net radiation, rainfall, surface temperature, soil and heat fluxes at a 15 minutes time step (see in supplementary material part 2 the description of the sensors). For previous years, data were taken from the weather station of Carpentras[10] (located 15 km SE of the study area). An example of micrometeorological measurements obtained for the year 2022 is presented in Fig S1a in supplementary material. Comparisons between stations for common periods have been done to evaluate the differences for the main variables (see Fig S1b in the supplementary materials). The results showed significant correlations for the main climatic variables (rain and temperature) between the two stations (see supplementary material Fig S1 a-b). A systematic bias for the air temperature was observed, in the order of 1°C (temperatures are higher at Carpentras than on the Ouvèze area), which is easily explained by both the altitude impact (Carpentras altitude is 95 m a.s.l, Ouvèze station is at 200 m a.s.l), and the fact that the weather station in the Ouvèze watershed is located in the middle of an irrigated cherry orchard (with higher evapotranspiration cooling the environment air), and the Carpentras station is on open grassland. On five orchards showing different irrigation managements, soil moisture content was monitored with capacitive probes (Teros 10, Meter) down to 30–50 cm, both in the row and the inter-row. Data are recorded since 2021 each 30 minute with a data logger (CR1000X, Campbell Sci.). Soil samples were also collected on the same fields to estimate the available water content (AWC) for the 0–50 cm layer (AWC given in the supplementary material Fig S3a, Table S4). On the largest field monitored, sap flow meters were also set up and monitored by Kaust team. All these last measurements are currently analysed according to methods described in El Hajj et al., (2023). In parallel, tree phenological stages were noted and hemispherical photos were taken once a month on 13 various orchards to characterize the leaf development all along the year according to protocols described in (Courault et al., 2022, Lopez-Lozano et al., 2022). Biophysical variables characterizing the orchard structure such as LAI, FCOVER and FAPAR are evaluated from these photos following methods detailed in (Demarez et al., 2008). All these measurements allowed to have reference observations on the water uptake rate from the trees for the monitored fields (details are given in the supplementary material part 3 for the formulations used to compute water budget at plot scale).

Seven years of data were analysed from 2016 to 2022, which were characterised by the annual Martonne Aridity Index (Botzan et al., 1998; De Martonne, 1920) described in the supplementary material (Fig S2) to classify wet and dry years. The results of this index show that 2018 appears as the wettest years and 2017 the driest.

Three methods were examined to analyse the annual water amounts used for irrigation at regional scale:

1) The maximal water consumption for each crop (ETm) was computed from the FAO 56 method (Allen et al., 1998) using the potential evapotranspiration (ETp) derived from the weather station measurements and crop coefficients (Kc) for each crop found in tables adapted for the region (CABRL, 2019)[11]. These ETm values were then combined with cumulative rainfall to estimate water requirements (WR) for each crop class following Eq. 1 (see Fig S1a in supplementary material). The values were then aggregated at farm scale for each year.

$$WR = (kc \ x \ ETp) - Rainfall \ [mm] \quad (1)$$

2) Using data provided by the ASA (Association Syndicale Autorisée)[12] at the farm scale for each year which are recorded from the irrigation terminal. These values (here named WASA), can be affected by water losses in the network. The various equipments are also old and not checked regularly by farmers, and ASA does not have the resources or staff to improve this point. The accuracy of the DATA provided by ASA is thus estimated to be around 30%.
3) Determining the water amount brought to each field from the information given by the surveyed farms (Eqs. 2–3). In Eq. 3, we see that orchard characteristics such as the number of trees, inter-row distances, field size are required, as too is information regarding the irrigation equipment (i.e. number of pipes per row, number of drips/m and flow in L/h). The row number is computed for 1 Ha from the inter-row distance, then the pipe length is derived per field according to the field size and the row number.

$$WF_{drip} = (Ltot/Ld) \ x \ Qd \ x \ t \ / \ Surf \ [mm] \quad (2)$$

$$WF_{microsprinkler} = Td \ x \ Ns \ x \ Surf \ x \ Flow \ x \ t \ / \ Surf \ [mm] \quad (3)$$

Where, *Ltot:* total *pipe length, Ld:* space between 2 drippers*, t:* irrigation duration per year*, Surf: field surface, Qd: dripper flow, Td: tree density, Ns: number of micro-sprinkler per tree, Flow: sprinkler flow.*

Fig. 5 shows the distributions of the different variables used to compute Eqs. 2 and 3. The row number per field varied from 3 to 34 with a median around 10, showing a majority of small fields. We observed a large variability in dripper flow rate from 2 L/h for the majority to 8 L/ha (Fig. 5a 5b). The duration of drip irrigation varied from 0 to 300 hours per year with two groups around 50 and 250 hours (Fig. 5e). The space between two drippers also varied a lot from 0.33 to 2.5 m. There was no observed correlation between the flow and the irrigation duration. On the irrigation amount brought per field per year, the distribution is bimodal with a median at 154 mm and maximum up to 919 mm. Different factors can explain these variabilities such as the soil type, the orchard age and the slope. Additional parameters, including the number of trees par field, row number can be found in supplementary materials (part 3 Fig S4).

3. Results

3.1. Monitoring of orchard development and identification of young orchards from Sentinel 2

The analysis of the temporal NDVI profiles was mainly focused on cherry trees, which were more numerous in the Ouvèze area and for which we have more observations for validation. Fig. 6 shows the typical temporal profiles obtained in various orchards with different agricultural management (i.e. grassed (Fig. 6b/not-grassed Fig. 6a). The

[10] https://donneespubliques.meteofrance.fr/metadonnees_publiques/fiches/fiche_84031001.pdf

[11] https://www.brl.fr/fr/memento-irrigation-agricole

[12] association management the water distribution at regional scale in France

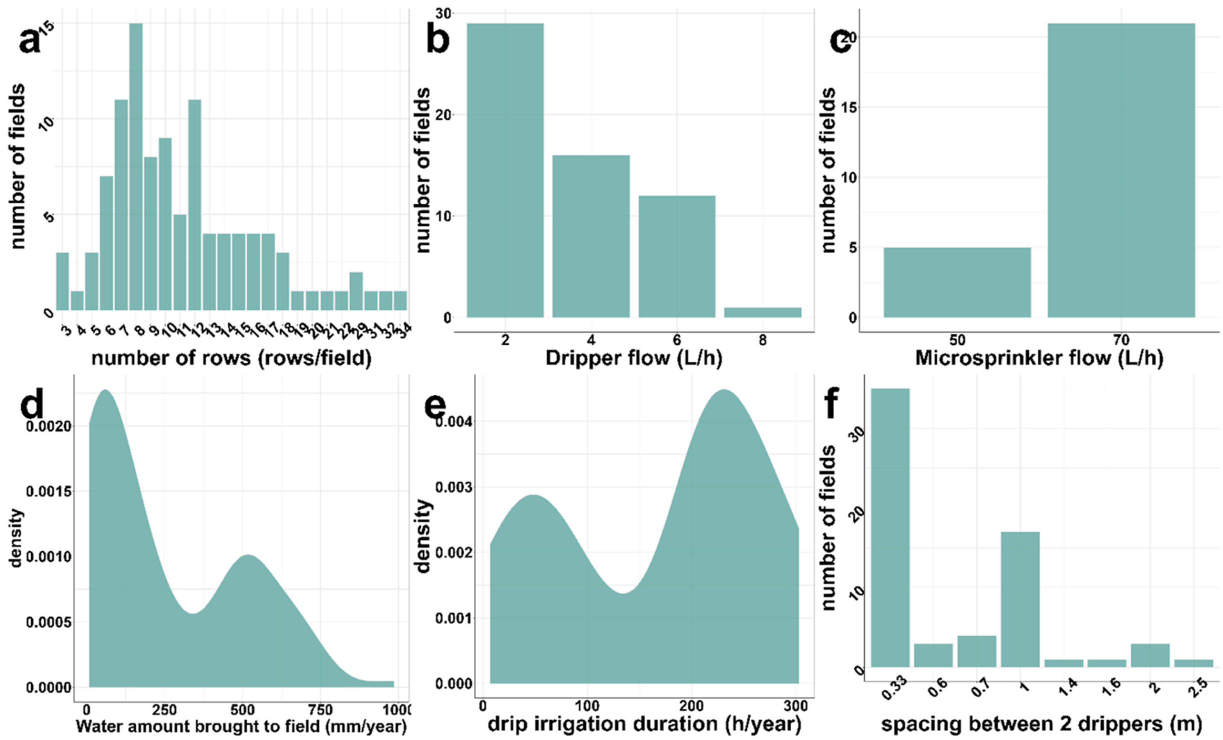

Fig. 5. Distributions of the main variables used to calculate the water brought to each field from information given by farmers.

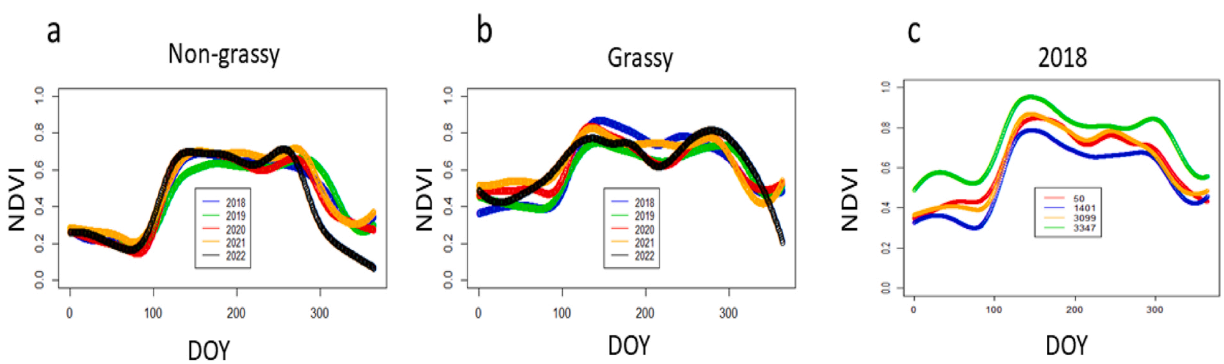

Fig. 6. Comparison of different NDVI temporal profiles of two fields (a) without grass and b) with grass) for different years and c) for the year 2018, comparison between 4 different cherry orchards.

profiles show an increase from spring (end of March) when the first leaves appear, then from day of year (DOY) 150 (mid-June) the NDVI was maximum corresponding to the peak leaf development. In July (around DOY 200) a slight decrease was observed. This decrease was due both to the decrease of irrigation after the harvest, the leaves are rolled up in the middle of the day, and leaf inclination varied. At the pixel scale, there is also an impact of the inter-row on NDVI. In summer, the grass in the inter-row of orchards becomes yellow. An increase in NDVI was observed following the arrival of autumn rainfall, allowing the inter-rows to again become green. This inter-row impact is more pronounced during the 2022 year (which was exceptionally dry and hot) compared to other years (2018 was at the opposite: a remarkably wet year, see statistics in table S4 in supplementary material). Fig. 6c shows the distinction between the NDVI development during the year 2018 for four grassed orchards having different water management. Here, two fields (50 and 3099) were irrigated by drip irrigation, one (3347) was irrigated by micro-sprinkler and the last (1401) was non-irrigated. The micro-sprinkler irrigation gives the highest values of NDVI. This field received also more water than the others. As expected, the non- irrigated field presented the lowest NDVI values, especially during summer.

The resulting number of young orchards obtained from the method described in Section 2.3.1 and in Fig. 3 (expressed in % to the total number of orchards) is presented in Table 3.

Table 3 shows a large heterogeneity of the proportion of young orchards, varying from 11 to 30% between years. It is worth noting that young orchards can range from being recently planted (first year) or have 5 years and be almost ready to produce. As such, an orchard that is 5 years old in one year, will not be counted in the following year, which may explain some of the observed variability in Table 3. Ground surveys have confirmed around 20–25% of land use changes over the watershed, which also appears in the interval obtained. Some farmers test new orchard varieties (more profitable), other decide to replace old orchards becoming less productive. As can be seen, the highest proportion of young orchards was observed for 2017, while the lowest was seen in 2018. However, the 2018 value is too low compared to the other years and when compared against ground references. In this case, the inaccurate identification for 2018 appear to be related to the fact that 2018 was a very rainy year (according to the aridity index of de Martonne).

Table 3
Percentages of young cherry orchards classified according to a threshold defined at 0.4 in summer period for the seven studied years and corrected threshold for 2018 at 0.5. cherry.

Young Orchard	2016	2017	2018	2018c	2019	2020	2021	2022
Cherry	26	30	11	32	23	27	22	25

The NDVI in summer was considerably higher than in other years, with green grass still visible in the inter-rows for some orchards (see Fig. 7b). Consequently, the threshold for wet years (when the Martonne index is higher than 30) was modified and set at 0.5 during the same period between DOY 220 and 250 to separate young and old orchards (Fig. 7b). The corrected values for 2018 are also shown in Table 3, which is more in accordance with ground observations. Indeed, the performance of this classifications (based on simple thresholding) achieved 98% for the classification of young cherry orchards in the studied area. Globally we can consider that the method gave quite satisfactory results.

3.2. *Maps of grassed or non-grassed plots*

Fig. 8 presents the map of grassed (in red) and non-grassed (in green) orchards at the watershed scale obtained from Sentinel 2. The overall accuracy (computed from confusion matrix) was 79% of well classified fields meaning that fields classified in grassed orchard was always a grassed orchard according to our ground observations. 21% were misclassified. The analysis of these misclassified plots has shown that they corresponded to very heterogeneous plots in grass state and are often covered with a lot of stones at the surface, shifting their classification to non-grassed fields rather than their correct classification as grassed fields. Despite this, we can consider this first results as satisfactory and difficult to improve given the fact that the Sentinel 2 pixel integrates a mix of row and tree and that the field size is relatively small (compared to the pixel size) in the study area. It is for this reason that we have explored data acquired at a finer spatial resolution, which is detailed in the following section.

Table 4 shows the results obtained from GSH and Pleiades images to discriminate grassed and non-grassed orchards using the method described in Section 2.4.2 for the whole watershed, compared to the ground observations. 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. Overall accuracy was 88% of correct identification with GSH for the detection of grassed orchards, 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 show 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 in Pleiades classifications as shown in Fig. 9 and consequently the inter-row is less visible.

3.3. *Assessment of tree number per field from UAV, GHS and Pleiades images*

Fig. 10 shows the results of the tree delineation algorithm (from Obj. MPP) for identifying circular patterns within the UAV image of the western part of the largest orchard of the watershed. On the entire parcel, the algorithm detects 1073 trees (overestimation 3%) from the UAV, 918 are detected using GSH images (underestimation 14%) and 956 trees from Pleiades images (underestimation 11%). The algorithm detects both small and large trees with high precision.

The algorithm was applied to all orchards within the watershed. Validation was done from a random sample of 50 fields. Fig. 11 shows the correlations obtained with the GHS images (Fig. 11 a) and the Pleiades images (Fig. 11b). The correlation coefficients are high for both cases. The largest field with more than 1000 trees impacts the statistics. If this last field is removed, the performances are lower with (r^2=0.75 with GSH images, r^2=0.72 with Pleiades, see graphs in supplementary material Fig S5-S6). Some underestimation in the number of trees is observed for several fields when using the GSH images. Analysis of those fields revealed that the orchards were very heterogeneous. The detection worked poorly for a particular apricot orchard, where it estimated only 75 trees, compared to 331 observed trees. This parcel was very heterogeneous, with young and old trees and with a large soil moisture variability visible at the surface (with dark and light areas). Projected shadows and various contrasts in the background likely distorted the analysis and the number of trees counted, explaining the deficient results obtained for this field. The acquisition date of images used for delineation of trees is important to consider. If the canopy is well developed, a problem can also appear with the tree overlap for some fields leading to an underestimation of the number of trees.

From these results, the tree density can be assessed for all orchards of the Ouvèze area. The median was in the order of 75 trees/orchard (median value from GSH) and 69 from Pleiades. The median of the tree density was in the order of 267 trees/ha (from GSH) and 242 from

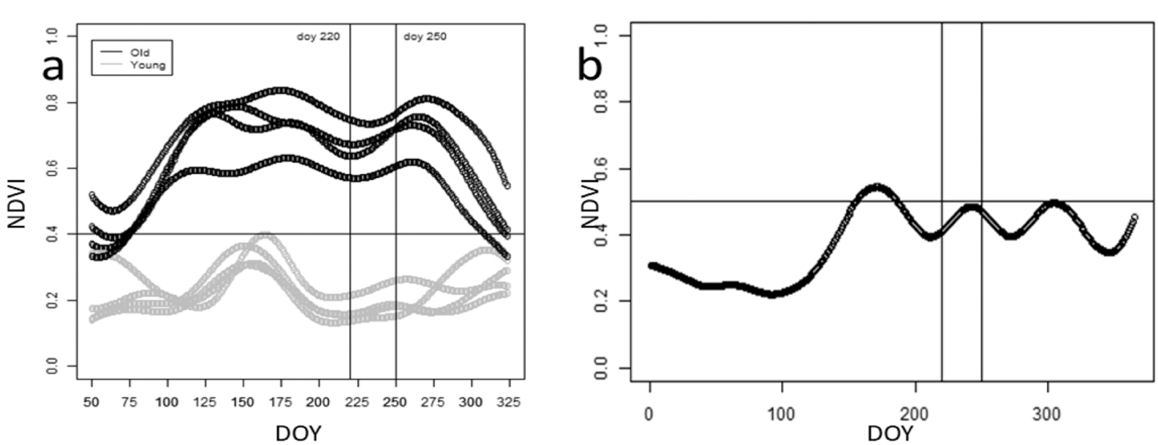

Fig. 7. a) Comparison of NDVI temporal profiles computed in 2017 between old (black) and young (grey) cherry orchards (age <5 years), b) NDVI of a young orchard in 2018, the threshold was fixed higher than the other years.

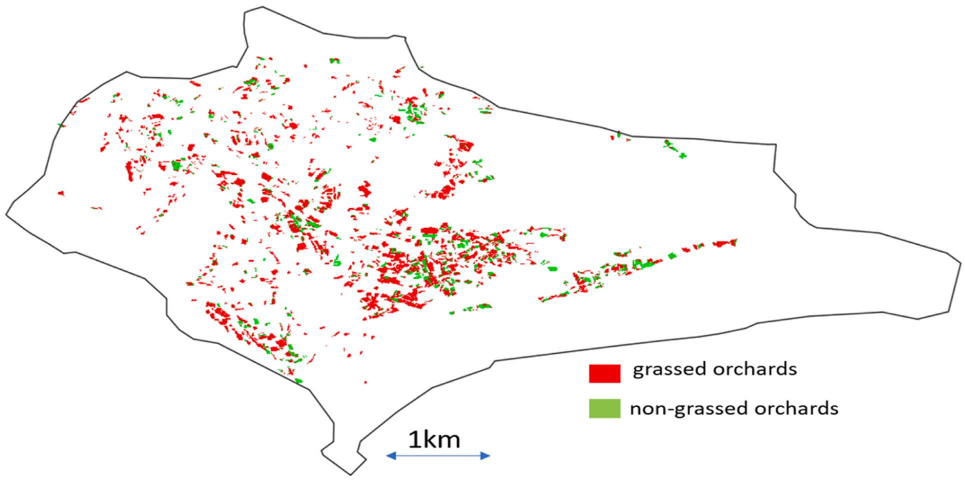

Fig. 8. Classification obtained to separate grassed or not orchards,.

Table 4
Results of the identification of the grass cover of orchards on Ouvèze-Ventoux area, using GSH and Pleiades images.

	GSH	Pleiades (25/7/2022)
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%)

Pleiades. As expected, larger plots have greater number of trees. However, we observed a slight difference according to the species as displayed in Fig. 12. Olive trees are generally less spaced than apricot and cherry trees, with a mean density of 304 trees/ha against 222 for cherry trees and 244 for apricot (according to the results with GSH).

The previous assessment of plot variables computed from remote sensing (i.e., number of trees per field) was used to estimate water consumption of orchards according to Eqs. 2 and 3 (described in Section 2.4). Accurate information on the irrigation equipment, flow and irrigation duration from farmers were also needed. This technical information was available from farmer surveys representative of the variability of agricultural practices encountered in the watershed. Values obtained for water consumption varied from 8 to 910 mm with an average in the order of magnitude of 244 mm. For example, at field scale, from field survey with water sensors (see Fig. S3a, Table S2), a water balance neglecting drainage, indicates 200 to 300 mm of water added as irrigation from May to September depending on the year. At the farm scale, comparisons have been performed between three farms (representative of the diversity of the agricultural practices, two used drip irrigation with different schedules, the third use micro-sprinkler). Fig. 13 shows the results obtained for the different irrigation water volumes estimated by the three methods (described in Eq. 1 (*WR* considered as the reference according to regional guidelines (Kc method), Eq. 2 (WF from surveys and remote sensing data) and WASA) for three farmers and three contrasted years (2016: normal, 2017: dry and 2018 classified as wet, see table S4 in supplementary material). There are uncertainties at different levels. The ASA data are associated with approximately 30% uncertainty due to network losses and misrepresentations, which is accounted for by including an error bar (blue box). Furthermore, for the calculation of WF, some farmers have given us very accurate information on their irrigation practices and strategies according to the wet or dry years (they generally bring less water for wet year), while others were more inaccurate indicating only a standard practice, without changes according to the year climate. When information was available, error bars were added to irrigation water volumes computed from surveys (WF, green boxes).

In addition to uncertainties according to the climatic years, other uncertainties can be due to the other factors occurring in Eq. 3, among them the number of trees par plot. In order to quantify the impact of this uncertainty on the assessment of water brought by the farmer, we have computed the water dose for one field considering in the first case 75

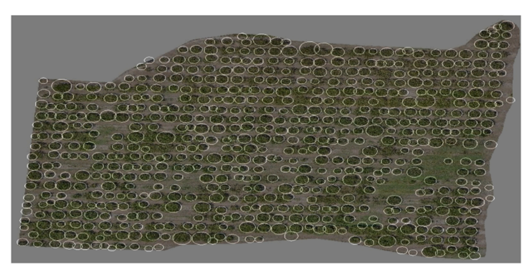

Fig. 10. Application of the algorithm to delineate trees at the plot scale using a UAV image (western part of the largest cherry tree of the study area).

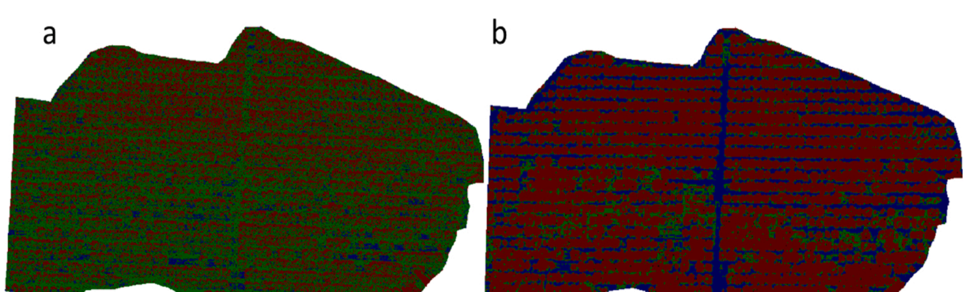

Fig. 9. Results of the classifications applied to the largest orchard to separate the grass (green), trees (red) and bare soil (blue) a) from the GSH and b) Pleiades.

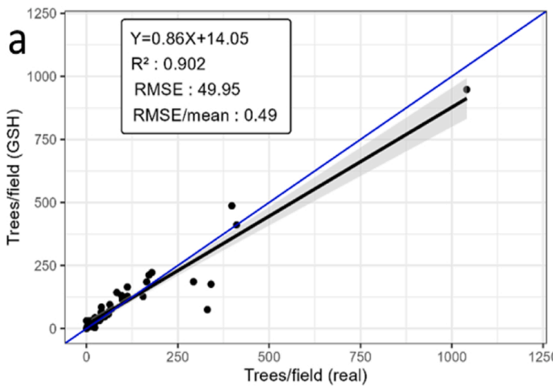

Fig. 11. Validation of the identification of the number of fields with a) GSH images (mean manual counting: 102 trees) and b) Pleiades images (mean manual counting: 108 trees, the date is not the same than GSH) on 50 fields.

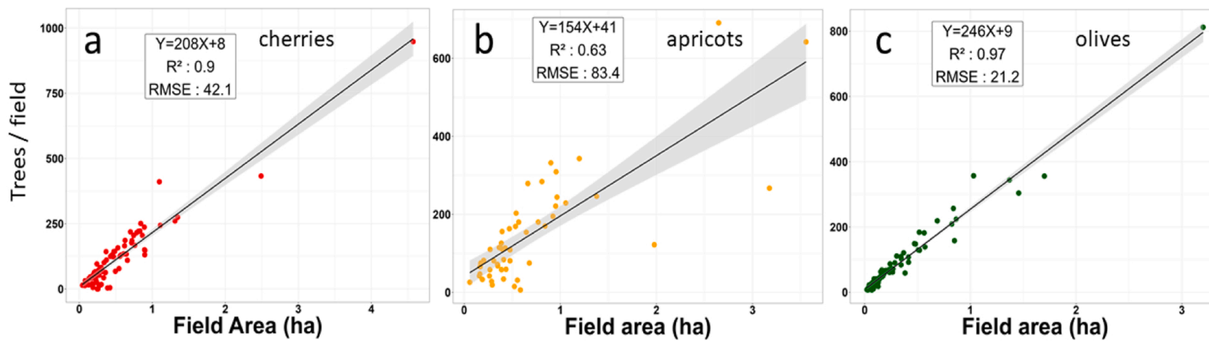

Fig. 12. Comparison between the number of trees estimated from GSH images and the area of fields for a) cherry trees, b) apricot trees and c) olive trees.

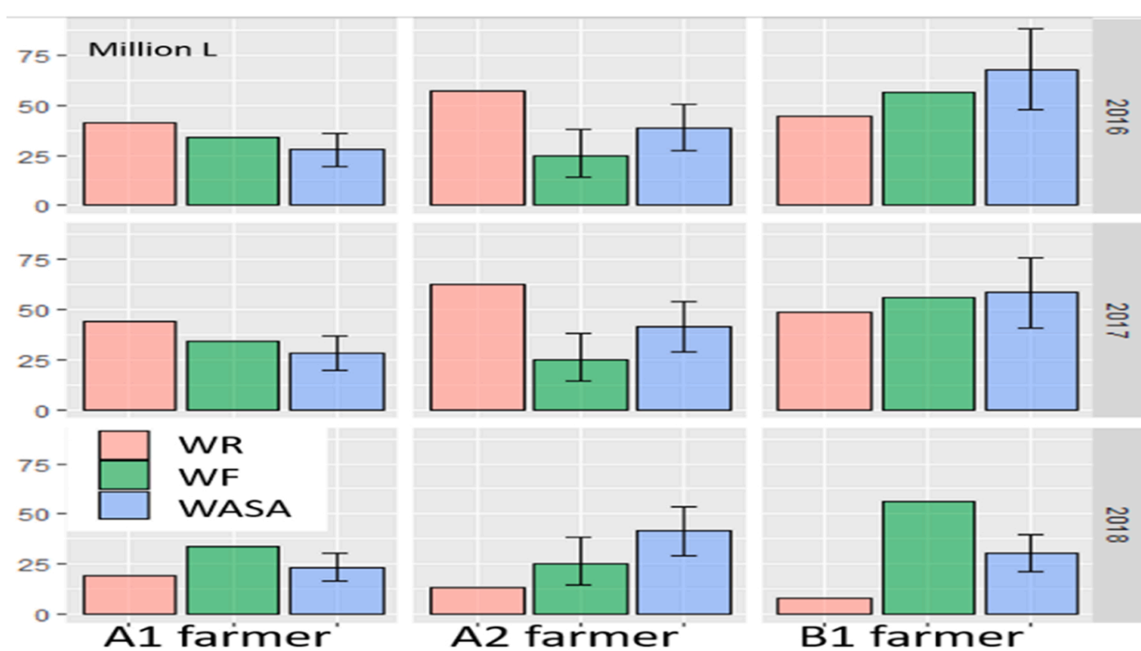

Fig. 13. Comparisons between water requirements (WR), water consumed from ASA (WASA) and water used for irrigation computed from farm surveys and variables derived from remote sensing.

trees (estimated from GSH images) and 69 trees from Pleiades. The hourly intake when deploying micro-sprinklers (flow at 70 L/h and with 1 micro sprinkler per tree) 5250 litres per hour for GSH and 4830 litres per hour with Pleiades. This difference can be significant at the farm scale having an average of more than twenty irrigated plots.

The analysis of the results shows that for the A1 farmer, the three methods do not vary between normal and dry years. For the A2 farmer, values from surveys (WF) are always lower than the two other methods except for the wet year. On the other hand, the B1 farmer consumes more than the two other farms and above the crop needs (expressed in red). Overall, we can identify three clear behaviours: one that is more water-efficient (A2), one that is more water intensive (B1), and the last (A1) which seems to follow recommendations.

4. Discussion

- Monitoring orchard development and mapping young orchards from Sentinel 2

Although the spatial resolution of Sentinel 2 is 10 m, it allowed to identify the young plantations of fruit trees at regional scale. A simplified approach based on a thresholding of NDVI gave accurate maps (98% global accuracy) of young orchards for the 7 studied years. Nageswara Rao et al., (2004) have shown spectral NDVI profiles of different crops and also observed that young mango (planted less than 5 years) has relatively low profile throughout indicating that the amount of green cover is low. The leaf development and the senescence can be easily detected from Sentinel 2 times series. A typical pattern was observed for orchards, with a first increase from March to June then a plateau more and less deepened in summer according to the stress and then at the end from October a slight decrease of NDVI. Similar profiles were observed by Zhu et al., (2020) on apple and cherry trees in China. The effect of water stress is less marked in this study case due to the climate.

- Water needs and contribution of remote sensing data

The simplified FAO method based only on crop coefficient and evapotranspiration presents many computational limits. Among them, the limited attention given to soil characteristics that can have a strong influence on the available water for the crop. Many papers have proposed various approaches using remote sensing to derive Kc, with several including the addition of a stress coefficient to improve this simplified approach (Pereira et al., 2020; Pôças et al., 2020; Simonneaux et al., 2008). However, Pôças et al. (2020), consider that for an improved estimation of crop water requirements, these methods should be used in combination with soil water balance models.

The surface characteristics such as grassed or not, together with inter-row management, are then useful parameters that can improve the information about water competition. In this study, we have compared different methods to identify grassed orchards from non-grassed, comparing range of remote sensing platforms. An accuracy of 79% of orchards with a correct identification of the inter-row (grassed or non-grassed) was obtained from Sentinel 2. This accuracy increases with the use of finer resolution images (freely accessible, GSH 81%) but the performances are also highly dependent on the date of image acquisition. The choice for the method to apply depends on the image availability. The main advantage of using Sentinel 2 data is that there are often numerous acquisitions all along the year, so it is easier to choose the best period to identify inter-row, but the final accuracy is limited because of the spatial resolution. With finer images such as PLEIADES or GSH data, the acquisition date is difficult to choose. It is the reason why we have proposed another method easier to implement and requiring a limited calibration dataset (fairly intuitive method which does not require knowledge on random forest methods). One drawback of this last method is the determination of threshods which is data dependent. Using a simple thresholding approach for separating herbaceous and tree layers on a satellite image rather than a statistical approach can be preferable in certain situations for several reasons: −1) Simplicity and ease of implementation: Simple thresholding is often easier to implement and understand compared to more complex statistical approaches. This can be advantageous, especially if the time or resource are constraints; 2) Robustness to local variations: In some regions, a statistical approach may be sensitive to local variations or changing environmental conditions. Simple thresholding can be more robust in such situations as it does not rely as much on statistical assumptions about the data; 3) Less data requirements: Statistical approaches may require a significant amount of data to properly calibrate models. In contrast, simple thresholding can often be done with less data, which can be useful in regions where data are limited; and at finally, 4) Interpretability: Simple thresholding can be easier to interpret as it often produces more intuitive results. This can be important when communicating results to a non-specialized audience. However, it is essential to note that the choice between simple thresholding and a statistical approach will depend on the specific objectives of the study, the complexity of the data, and the requirements for accuracy. Generally for each classification, an expert knowledge is required either to choose a representative dataset for calibration or to evaluate the accuracy of the classification.

Other approaches based on the analysis of times series of Sentinel 2 data have been applied to detect inter-row of vineyards by (Abubakar et al., 2023; Palazzi et al., 2023). Abubakar et al., (2023) have identified a background signal which they subtracted to the Sentinel 2 LAI time series to classify the grassed and non-grassed plots. This method seems difficult to implement to orchards because the background signal presents different spectral signatures (fruit trees are bigger than vineyard plants and the signal can be confused for young plantations). Ronchetti et al., (2020) have compared five classification algorithms to monitor crop variability from UAV data. If the performances are high for their various studied crops, they showed that for pear orchards, the detection methods were the noisiest, because of the presence of weeds, the effect of shadows depending of the acquisition date and time. Moreover, the use of UAV is limited and often expensive to be applied at larger regional scale.

The soil characteristics of orchards are also important to consider. For the moment, only soil maps that have variable accuracy at small scales are available to be used. Some approaches have proposed digital soil map combining remote sensing (Gomez et al., 2019; Lagacherie, 2008), but these methods are difficult to implement for orchards and require large areas of bare soils.

- Assessment of irrigation volumes

The assessment of irrigation water volumes from surveys (WF) requires accurate data on irrigation material and on the irrigation time. It is still difficult to get this information for all the farms of the watershed. The assumption is to consider a statistical representative sample of farm surveys including various practices. More ground surveys must be done to acquire more data to build relationships on the water volume brought to young orchards compared to old plots.

While the number of trees can be estimated with satisfactory performance from high resolution data (GSH, Pleaides), the accuracy depends on the sensor type and on the acquisition image date. Some over- and under-estimation has been observed for young orchards or very heterogenous fields, with misclassification and poor delineation occasionally resulting. Higher accuracy (>90% of correct estimations) are obtained on the number of trees using UAV images at finer spatial resolution on various orchard types by Dong et al. (2020) or Johansen et al. (2018), but UAV can be expensive (time and for data processing) and has a small sampling footprint compared to Pleiades or GSH. The proposed simplified method applied to Pleaides or GSH images makes it possible to estimate the number of trees for all the orchards in a catchment area. (Ozdarici-ok and Ok, (2023) have reviewed various techniques and sensors types to identify orchard trees. No cherry trees studies are reported. Most of the references cited used methods based on deep learning algorithms requiring a large dataset for training the networks, or classifications.

The acquisition dates of images at high resolution also have an impact on the results, particularly for tree discrimination. According to the homogeneity of the surface (inter-row and tree), the detection method can miss some trees, especially if there is a mixture of young and old trees within the field. The date of acquisition is an important consideration for the retrieval of certain parameters and can influence the quality of detection of trees (i.e. the development of the tree canopy or grass cover is dependent on timing). To improve the robustness of the results, it is recommended to collect some imagery in winter or earlier spring to better identify if there is grass in the inter-rows from Sentinel 2 and other finer resolution platforms. Antecedent conditions can also affect retrieval results. For example, the choice of Pleiades acquisition tasking should avoid periods after heavy rain, since large surface soil heterogeneities can confound the classification of orchard plots. While the use of GSH offers advantages in terms of resolution, there is little control regarding the timing of collection. Despite these constraints, the use of free data that can be easily accessed from various online resources makes the proposed methods more operational and less costly than using UAV or commercial satellite data, or making collecting laborious ground- based observations.

Alternative remote sensing methods are also available to be explored to improve the assessment of the number of trees e.g. LIDAR sensors (Dian et al., 2023; Tsoulias et al., 2020). An ambitious program[13] co-ordinated by IGN (Institut national de l'Information Géographique) aims to map all the France territory by LIDAR at very fine resolution. With these new data, we can expect to have tree level information that is more accurate which can complement existing methods. Likewise, while the use of radar and thermal sensors was not addressed in this study, they also offer directions to be explored to have complementary information of the soil moisture and irrigation practices (Courault et al., 2022; McCabe et al., 2019). For the moment operational satellites which have thermal bands do not have a sufficient spatial or temporal resolution for tracking agricultural practices on small fields (such as those within the Ouvèze watershed). The future TRISHNA missions[14] which should be launched in 2025 (Lagouarde et al., 2019; Rama et al., 2023) should improve these last points.

5. Conclusion

Here we evaluated a range of approaches to characterize agro-informatic variables typical of Mediterranean orchards using a variety of remote-sensing based platforms. With increasing drought periods due to climate changes and water restrictions occurring in many regions, it is crucial to have an accurate assessment of the real water requirements at the landscape and river basin scale to improve water resource management. Sentinel 2 images with high spatial and temporal resolution allow for the monitoring of leaf development and inter-row management with satisfactory results. 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. The performances of the resulting maps of inter-row cover depends on the date of acquisition images. One way of improving this point may be to use a combination of different sensors to maximise the image number acquired in the optimal period at the end of winter or at the beginning of spring. The number of trees can be quantified using a simple algorithm based on circle detection. Recent advances in Lidar technology will certainly provide new insights to improve the performances on this point. All of these remote sensing derived variables are useful to consider the spatial variability encountered at the watershed scale and can be integrate to better model the functioning of orchards and their management in future investigations. Despite this, ground observations will still be needed to validate the estimations and to obtain information on irrigation techniques at large scales.

[13] https://www.ign.fr/institut/lidar-hd-vers-une-nouvelle-cartographie-3d-du-territoire)

[14] https://earthobservation.magellium.com/project/trishna/)

CRediT authorship contribution statement

Guillaume Pouget: Software, Resources, Methodology, Data curation. **Claude Doussan:** Writing – review & editing, Writing – original draft, Resources, Investigation, Formal analysis. **Dominique Courault:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Fabrice Flamain:** Validation, Resources, Data curation. **Marta Debolini:** Writing – original draft, Methodology, Investigation, Formal analysis. **Raul Lopez-Lozano:** Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Matthew McCabe:** Writing – original draft, Resources, Methodology. **Pierre Rouault:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis.

Declaration of Competing Interest

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Data availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2024.108763.

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