Citrus Orchards Monitoring based on Remote Sensing and Artificial Intelligence Techniques: A Review of the Literature

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Abstract: In recent years, with the emergence of new technologies, in particular artificial intelligence techniques and remote sensing data, agriculture has become intelligent. These technologies have helped us to improve the quality and quantity of yield, and to facilitate many difficult tasks for farmers. In this paper, we will present an extensive review of the techniques and themes used in the field of agriculture in general, and citrus crop in particular, through the realization of a bibliometric and bibliographic study based on several published articles over the last years. Through an in-depth analysis of several works, we have found that there are several factors that are very interesting in this field. In fact, we have many parameters related to trees such as detection and counting; canopy or crown size; tree location; detection of individual trees and missing trees, etc. We have also the effect of vegetation indices such as normalized difference vegetation index(NDVI),normalized difference red edge index(NDRE),modified chlorophyll absorption ratio index(MCARI), etc. Which are strongly correlated with fruit production. In addition, monitoring tree health and water stress is very interesting. All these factors and more can be obtained from high-resolution spectral images, using machine learning algorithms, remote sensing techniques, and image processing. The purpose of this study is to explain how we can control the situation of orchards to have better yield.

1 INTRODUCTION

In recent years, most scientific researchers in several fields use artificial intelligence techniques in their projects to get good results and to develop new approaches based on data. In fact, the field of agriculture presents a lot of data every season. These data can be external such as climatic or internal such as soil analysis and tree monitoring. Thus, many of these data can be extracted from spectral images in several bands, which makes it possible to provide information on vegetation, water stress, etc. In the electromagnetic spectrum, we find several electromagnetic waves with frequencies of different levels. In the field of remote sensing, there is the visible part which contains the RGB bands. These bands are the normal images that we can see with the naked eye. Apart from this part, there is the SWIR(Short-wave infrared) part and the LWIR(long wavelength infrared) part, which present other spectral bands like multispectral images with 8 bands in the SWIR and 6 bands in the LWIR in addition to the RGB and panchromatic bands. There are also the hyperspectral images that contain hundreds of bands and the ultraspectral images with thousands of bands. The presence of several bands allows us to have more information and get several factors to improve the field of agriculture, especially the citrus crop which we are interested in. Since multispectral or hyperspectral images provide interesting datasets, whether imagery or digital, the presence of artificial intelligence, especially machine learning algorithms can help us predict the factors that will improve and facilitate the agriculture monitoring.

The goal of this paper is to present a global vision about the exploitation of spectral images as input data for machine learning algorithms to extract and predict several factors which are very important to obtain good yield and to facilitate several tasks for farmers.

The remaining of this article is structured as follows: section II gives an overview about the use of the scientific mapping method to select the most useful papers, and get an idea of the keywords most correlated with our goals. Section III present a global synthesis with comparisons on the factors and the works which deal with the problematic of citrus tree monitoring based on remote sensing and/or artificial intelligence. Finally, the conclusion is drawn in section IV.

2 SCIENCE MAPPING

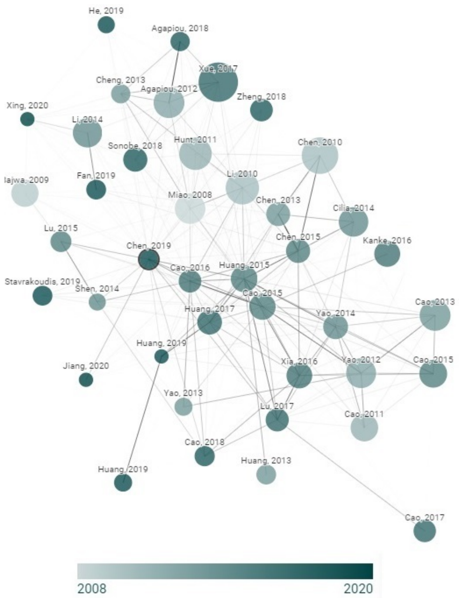

Figure 1: connected papers.

The goal of science mapping is to obtain a lot of information and to select the best papers based on citation, keywords, abstracts,etc. There are several open source softwares used for scientific mapping. In our case, we used SciMAT software (Cobo et al., 2012)(open-source software tool developed to perform a science mapping analysis under a longitudinal framework) to obtain several graphs based on list of keywords with document number by each keyword, papers citation and h-index. In our case, after obtaining and analyzing these graphs, we get a clear vision of the papers which are strongly correlated to our problem and which have a good quality. We also get a good idea about the trends of artificial intelligence techniques and remote sensing in agriculture, especially the citrus cultivation. We also used another software to obtain more documents correlated to our problem. This software called connectedpapers(LLC,). It gives a graph composed of circles with several links between them. The size of circles signify the number of citations. The thickness of lines measures the correlation between the papers based on keywords and abstracts. Finally, the visibility of the circles' color indicates the age of the paper. The graph in figure 1 is an example of graphs provided by connectedpapers software. The used keywords are: "smart agriculture, remote sensing, satellite images, UAV images, spectral images, tree segmentation, tree detection, tree canopy, tree crown, citrus orchard monitoring, image processing, vegetation index, water stress index, artificial intelligence, machine learning and deep learning". The figure 1 shows that we obtained a reasonable number of papers that are correlated to the input paper and we can select the best ones based on the citation, the correlation, and the age.

3 CITRUS ORCHARD MONITORING

The Citrus orchards need specific monitoring to give good yield. In fact, this monitoring starts at the beginning of the agricultural year and continues until the harvest period, and concerns several parameters that are very important to obtain good quality and quantity of fruits. this monitoring also depends on the phenological cycle of citrus as shown in figure 2 (Pons et al., 2012). In fact, all citrus species start with the initiation phase when the small branch begins to develop, the flowering period with two phases from the beginning of flowers until full, after that we have the fruit period with 4 phases: start with the initiation of fruits, fruit development, coloration, and the maturation phase when the fruits are ready to be harvested. Finally, after the harvest period, we have a winter phase when the trees need rest. So, each citrus orchard requires specific monitoring at each phase.

we have clear and well-known factors such as irrigation and nutrition. So we all agree that without these two parameters, we cannot get yield. The cultivation of citrus fruits requires fertilization which contains the product necessary for each soil, and it also needs good irrigation with then appropriate dosing and at the best moment. Other important factors must be under control as well. One of these latter is the phytosanitary treatment against diseases that attack citrus. Another important factor is the pruning operation which is very important in each citrus orchard to remove dead and broken branches to keep the best size of trees. In addition, we have many very interesting factors in each citrus orchard such as the climate (temperature, humidity, light ...), flowering, and also the canopy and the size of the trees. So all these factors and others can be extracted from multispectral and hyperspectral images. Through the use of artificial intelligence techniques that exploit this data, we can obtain an important follow-up of citrus orchards during the agricultural year. In the next, we will give more details about each factors.

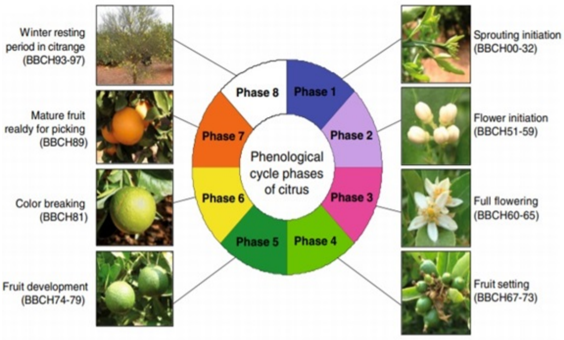

Figure 2: phenological cycle of citrus.

3.1 Irrigation and Nutrition

At the beginning of each crop year, citrus orchards need a soil and tree test. These analyzes cover several factors such as phosphorus which is very important for the transfer of energy and the transport of the product of photosynthesis, potassium for the regulation of osmotic pressure, nitrogen for tree growth, magnesium for fruit ripening and calcium which is also important for the strength of the branches. All these chemical elements are very important, and through to laboratory analysis, we can control them at each period of time to maximize or minimize the phytosanitary dose required(Obreza and Morgan, 2008). Along with nutrition, there is irrigation, which is one of the most important factors for producing good yield of quality citrus. In fact, good irrigation consists of knowing the quantity of water depending on different areas in an orchard. Therefore, irrigation has a direct impact on the health of trees as well as on the yield, size and quality of fruits(Zarco-Tejada et al., 2012). Thomas A. and al (Obreza and Morgan, 2008) conducted several tests over different months on orange trees and their soil in Florida. They discovered that during the agricultural year, there are chemical compositions decrease such as potassium, magnesium, and nitrogen, and others increase like calcium. So it is necessary to add other products or do whatever is necessary to balance these main factors. Also in their work, they presented a recommendation on the quantity of each chemical composition needed by the soil and trees.

Salvatore Meli and al (Meli et al., 2002), say that the period of good irrigation in the Mediterranean region begins in May and after a month the soil shows an increase in microbial parameters.

However, soil and plants analysis in the laboratory is expensive and cannot be done several times a year. There are other methods for determining water stress and nutritional status based on imagery. For example, multispectral and hyperspectral images provided by satellites or drones can give several signs to vegetation and water stress which are very important for analyzing the condition of the parcels and for adding the necessary irrigation or nutrition. Currently, there are several projects for monitoring vegetation and water stress in orchards based on imagery and they are giving good results. Indeed, in (Zhang et al., 2019) authors. It used multispectral images collected by an UAV to mapping water stress for maize. In the last work, authors calculate a crop water stress index (CWSI) by extracting several vegetation indices such as normalized difference vegetation index (NDVI))(Rouse Jr, 1974) , renormalized difference vegetation index (RDVI)(Zarco-Tejada et al., 2013), soil-adjusted vegetation index (SAVI)(Jackson et al., 1981) , optimization of soil-adjusted vegetation index (OSAVI)(Haboudane et al., 2002) , and transformed chlorophyll absorption in reflectance index (TCARI)(Haboudane et al., 2002).An example of a mapping CWSI, is given in figure 3. It shows distribution of water stress; hence, he/she can decide the accurate needed dosing water of each zone. Actually, the CWSI can be calculated based on weather conditions, but authors of (Zhang et al., 2019) demonstrate that the CWSI extracted from multispectral images is more efficient and cheaper.

The formula of CWSI is:

$$CWSI = \frac{T(canopy) - T(wet)}{T(dry) - T(wet)} \tag{1}$$

where T(canopy) is the surface temperature of the canopy, and T(wet) and T(dry) are reference surfaces that are completely wet or dry to simulate maximum and minimal leaf transpiration under the exposed environmental conditions.

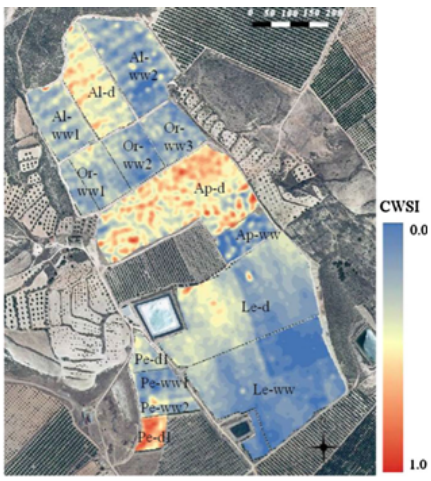

Figure 3: Water stress index map

Another very important work (Gonzalez-Dugo et al., 2013) explores the UAV thermal imagery to assess the variability in the water status. The results of this work is illustrated in figure 3 which consists of a map that shows the distribution of CWSI by color. Thus, this map helps us to define the regions that need water easily.

3.2 Phytosanitary Treatment

Citrus diseases are fatal for some species. However, there are useful treatments for these diseases. In the normal case, there is a follow-up by periodic visits to the orchards in order to monitor the health of trees and to initiate the necessary treatment at the beginning of the disease. Nonetheless, if there are large parcels, it is difficult to be controlled by humans, and sometimes there is a delay in the detection of the diseases, which negatively influences the fruits. For this reason, the use of remote sensing images to detect a disease or its limitations is very interesting. Actually, the use of remote sensing images in agriculture is not a new field in the sense that many projects have been conducted by it. In the next, we will give some examples:

Several spectroscopes and imaging techniques have been studied to detect diseases such: (Bravo et al., 2004; Moshou et al., 2004; Chaerle et al., 2007) that are based on fluorescence imaging technique,(Sevick-Muraca and Paithankar, 1999; Shafri and Hamdan, 2009; Qin et al., 2009) used spectral imaging.while (Spinelli et al., 2004) and (Purcell et al., 2009) use infrared spectroscop, and (Yang et al., 2007; Delalieux et al., 2007; Chen et al., 2007) use the visible/multiband spectroscopy.

The idea of remote sensing is to provide images with several bands with frequencies that exceed the visible spectrum and is able to find some differences in the structure of plants and trees in order to decide if there are changes by diseases. Sometimes these changes occur in the vegetation. through the experience of researchers in this field, it has appeared that there are specific changes in certain bands such as near-infrared and infrared because of diseases. Authors of(Hahn, 2009) says that the Sensors for disease detection and food quality will evolve over the next years with the help of nanotechnology. In fact, fluorescence and vision sensors can detect the quality of fruit and predict diseases more accurately than our eyes. The spectral range of the sensor is wider than the spectral response of the naked eye and the sensors are capable of detecting polarized light. Nanotechnology is able to capture gases in bubbles creating internal reactions without affecting the quality of fruits or vegetables. Thus, with these technologies, we manage and minimize the use of phytosanitary products, and with artificial intelligence algorithms, we can collect historical data to predict and control the disease before it occurs.

3.3 Vegetation and Canopy

Among the very interesting factors in the monitoring of citrus orchards, there is the condition of the vegetation. This vegetation helps the farmer to know every place or every tree that needs more care. In fact, the vegetation index can be extracted from RGB images, multispectral images, and hyperspectral images, but the precision will be different. in fact, hyperspectral images contain hundreds of bands which can get more information, and if we have a good spatial resolution, we can extract a vegetation index from each tree or from each part of the orchard.

In table 1 we present some vegetation indexes.

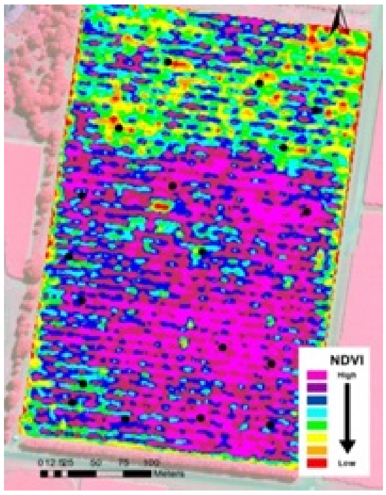

Figure 4: Exemple of NDVI classification map.

As we can see in figure 4, authors of (Robson et al., 2017) control the situation of orchard by extracting several vegetation indexes from worldview-3 multispectral images, and select the most important index based on PCA(principal component analysis)(Wold et al., 1987) approach to map the vegetation of yield in each part of orchard.

In addition, the detection, segmentation, and counting of trees are very important in the monitoring of each orchard. These factors can be produced using deep learning and machine learning algorithms (Koirala et al., 2019; Zou et al., 2019).

Actually with data science approaches, especially deep learning architectures like U-net, RCNN, faster RCNN, Yolo, retinanet.etc, the scientific researchers improve the result of object segmentation. With these

Table 1: Vegetation indexes by formula.

Vegetation Index	Formula
Normalized Difference Rededge/Red (NDVI rededge)(Gobron et al., 2000)	(RE - R) / (RE + R)
Transformed Chlorophyll Absorption in Reflectance Index (TCARI)(Haboudane et al., 2002)	3 × ((RE - R) - 0.2 x (RE - G) × (RE/R))
Structure Insensitive Pigment Index (SIPI)(Penuelas et al., 1995)	(NIR1 - B) / (NIR1 + R)
Coastal Blue Structure Insensitive Pigment Index (CB SIPI)(Penuelas et al., 1995)	(NIR1 - CB) / (NIR1 + CB)
Normalized difference Red/Red-edge index (R / RENDVI(Gitelson et al., 1996b)	(NIR1 - R) / (NIR1 + RE)
Normalized difference Red/NIR2 index (R / N2NDVI)(Robson et al., 2014)	(NIR1 - R) / (NIR1 + NIR2)
Green normalized difference vegetation index (GNDVI)(Gitelson et al., 1996a)	(NIR1 - G) / (NIR1 + G)
Modified Simple Ratio (MSR)(Chen, 1996)	(NIR1/R - 1)/(SQRT((NIR1 / R) + 1))
Ratio Vegetation Index (RVI)(Jordan, 1969)	NIR1/R
Normalized Difference Vegetation Index (N1NDVI)(Rouse Jr et al., 1974)	(NIR1 - R) / (NIR1 + R)
Normalized Difference Vegetation Index (N2NDVI)(Rouse Jr et al., 1974)	(NIR2 - R) / (NIR2 + R)
Normalized difference red edge index 1 (RENDVI1)(Fitzgerald et al., 2010)	(NIR1 - RE) / (NIR1 + RE)
Normalized difference red edge index 2 (RENDVI2)(Fitzgerald et al., 2010)	(NIR2 - RE) / (NIR2 + RE)
Transformed difference vegetation index (TDVI)(Bannari et al., 2002)	1.5 x ((NIR1 - R) / (SQRT(NIR1^2 + R + 0.5))
Transformed difference vegetation index 2 (TDVI2)(Bannari et al., 2002)	1.5 x ((NIR2 - R)/(SQRT(NIR2^2 + R + 0.5))

[1]R: red band(631–689 nm), RE: red edge band(703–742 nm), G : green band(516–578 nm), B : blue band(407–448 nm), CB: coastal blue (407–448 nm), NIR1: near infra-red 1 band(774–874 nm), NIR2: near infra-red 2 band(869–958 nm).

new technologies, We achieved a control of the tree state or each small part in the orchard. In this case, we have a lot of challenges to do some segmentation of trees.

Three types of trees can be distinguished:(1) the orchards that are not condensed and we can see the space between the trees and between the parcels. (2) is the case where we have a very condensed rows of trees which cannot be separated, but we can see the space between the rows. Therefore, we can do some segmentation based on these rows. In the last type (3) orchards are overcrowded; we cannot separate the trees or the rows. In this case, we can make a segmentation by defining a fixed area, and detecting the spaces in orchards. Figure 5 give an example of the overcrowded orchards.

Figure 5: Overcrowding of trees.

Many examples of projects use the crown or canopy of the tree to control the state of trees, parcels or orchards. Authors of(Zortea et al., 2018) collect large data that contain citrus trees images with a good resolution using a drone. Then they classify each part of 32 * 32 pixels to know whether it is a tree or not. In fact, their model with 17 layers and trained to 56000 images gave a good result with 94% in accuracy.
Table II presents a list of works with results that use trees segmentation. and as we can see, the deep learning approaches such as CNN and Mask R-CNN gives a good score compared to the other methods. In addition, the image data provided by UAV with good resolution, help the model to be perfect.

Table 2: Trees segmentation approaches and results

Approach	Results	Data
CNN(Zortea et al., 2018)	94(accuracy)	UAV
VF(Gougeon, 1995)	81(accuracy)	Aerial image
LMF(Nelson et al., 2005)	13.67 (Z-score)	Satellite images
WS(Wang et al., 2004)	75.6(percentage)	Aerial imagery
LM(Santoro et al., 2013)	0.8(RMSE)	Satellite images
OBD(Ardila et al., 2012)	0.8(R^2)	Satellite images
PBP(Ok and Ozdarici-Ok, 2018)	91(accuracy)	Satellite images
U-Net(Zhao et al., 2018)	61.2 (accuracy)	UAV
MRCNN(Zhao et al., 2018)	98.5(accuracy)	UAV

[2]CNN: convolutional neural network,
VF: Valley following,
LMF : Local maximum filtering,
WS : Watershed segmentation,
OBD: Object-based detection,
PBP: Pixel-based performance,
U-NET: Convolutional Networks for Biomedical Image Segmentation,
MRCNN: mask Region-based Convolutional Neural Networks.

4 CONCLUSION

The Citrus crop requires special monitoring to obtain good performance in terms of quality and quantity. In fact, several parameters are responsible for it, such as climate, nutrition, irrigation, drop of flowers and fruits, rootstock operation, and the size of the tree canopy, etc. In this case, the spectral images provide a lot of historical data about all these parameters and other. Indeed, with remote sensing techniques, we can control vegetation, water stress, and diseases in citrus orchards at any time of the year. Also, with data science approaches, in particular deep learning, we use spectral images to make several segmentation's of trees or rows and to do several classifications by size, by vegetation and also by water stress. In this sense, several works have given a good score greater than 98% in precision. But these works are based on UAV images that have a very high resolution and in orchards that contain non-condensed trees. Moreover, the spectral images provided by satellite they don't have a very high resolution (the highest resolution is 0.31m in worldview3), so when we have an overcrowded orchard, it is difficult to get a good result. In addition, the deep learning algorithms need big data in training to give good precision. In fact, if we compare drone and satellite images we can say that the satellite offers historical images with a good resolution, but to produce very high resolution images, we need to use the drone every year and wait a few years to collect them. Also to make predictions about yield and disease, machine learning algorithms need the maximum amount of data. In this case, smart agriculture needs an information system capable to follow-up the orchards and collecting data at any time. Finally, With all these technologies, we can get several factors which are very important to facilitate several tasks for the farmers and to develop the yield.

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