Optical sensors for precision agriculture: a new look

ABSTRACT

The increasing human population added to the rural exodus has aggravated the pressure in the agricultural sector for greater production. Faced with this problem, research has increased to develop optical sensors for agriculture with the purpose of minimizing the effects of rural exodus, obtaining rapid information and promoting the rational use of natural resources. Optical sensors have a differential consisting of the ability to use the spectral signature of an attribute or part of it to gain information, often not obvious. This review provides recent advances in optical sensors as well as future challenges. The studies have shown the wide range of applicability of optical sensors in agriculture, from detection of weeds to identification of soil fertility, which favors management in different areas of agriculture. The main limitation of optical sensors used in agriculture in most of the world has been the cost of purchasing the devices, especially in poor countries, so one of the future challenges is the reduction of final prices paid by consumers.

1. INTRODUCTION

The growth of the world population implies an increase in food demand. With natural resources, such as limited freshwater and fertilizers, the implementation of initiatives aimed at incrementing a productive and efficient use of natural resources is needed. In this context, several scientific efforts have been made to multiply agricultural production. The sensor-based information system is one of these efforts, being one of the bases of precision agriculture and of fundamental applicability for agricultural monitoring and decision making oriented towards greater production and efficiency [1].

For precision farming, knowledge about soil attributes, the health of developing plants and the quality of fruits and grains harvested are extremely important. In view of this, several types of sensors have been researched and developed, either to monitor soil attributes such as moisture, salinity, conductivity and fertility; monitor environmental conditions such as precipitation, solar radiation and relative humidity; or monitor plant attributes such as chlorophyll content, nitrogen requirement, water stress, among others [2].

Among the different types of sensors, optical sensors have a differential aspect compared to others, which is the ability to use the spectral signature of an attribute or part of it. To do this, every optical sensor has the ability to measure reflectance or use the reflectance property for information. This ability to differentiate, for example, the state of a normal plant from one with some problem, be it water deficit or lack of some nutrient, such as nitrogen [3].

36 Thus, to carry out the present study, we undertook a bibliographic review aiming at to seek
37 for the uses of optical sensors in precision agriculture, presenting future advances and
38 challenges.

39 **2. MATERIAL AND METHODS**
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41 The method proposed for this study was based on the review of publications related to the
42 applicability of optical sensors in precision agriculture, presenting future advances and
43 challenges in the exploration of agricultural activity in a global way. According to the
44 objective of the study, the review comprised five stages: i) establishment of the theme and
45 selection of the research question; ii) establishment of inclusion and exclusion criteria; iii)
46 definition of the information to be extracted from the selected articles; iv) analysis and
47 interpretation of results and v) presentation of knowledge review and synthesis. Considering
48 the specificity of the topic, the methodology used and the main results were used as
49 parameters for the definition of the information to be extracted from the selected
50 publications.

51 The inclusion criteria of the papers used were: publications between 2003 and 2018, which
52 portrayed the subject matter of global use in agriculture; and that addressed the key words
53 and expressions like smartphone, weed control, water stress, pathogen detection and soil
54 fertility.

55 For the analysis of the data, a thorough reading of the selected papers was carried out, in
56 order to verify the adherence and consistency to the focus of this research. The ideas were
57 grouped by similarity so as to compose a narrative synthesis of the results and discussion of
58 the information related to the study.

59 **3. RESULTS AND DISCUSSION**
60
61 **Applicability of optical sensors in agriculture**

62 **Irrigation**

63 The scarcity of water in various areas of the world and the increase in the cost of use leads
64 to the need for proper use of this. Therefore, knowing the right moment to irrigate and
65 quantity is grounded for rational use.

66 The use of optical sensors such as thermographic, multispectral and hyperspectral cameras
67 is being studied by many researchers to monitor the canopy, identify water stress of plants
68 and estimate the stomatal conduct to assist in irrigation planning.

69 The use of thermal imaging obtained by thermographic camera, was evaluated by [4] as a
70 potential for irrigation management by serving as a water stress indicator for a commercial
71 42ha orchard located in Murcia, Spain. The results showed that thermal imaging is a
72 valuable tool for decision making regarding the timing of orchard irrigation.

73 In this perspective, [5] evaluated the use of thermal imagery to assess water stress in
74 soybean and cotton crops in Texas, USA. [6] studied the use of thermographic camera for
75 the detection of water stress in citrus and persimmon trees in Valencia, Spain. [7] evaluated
76 the use of a thermal camera to determine water stress in vines in the town of Lleda, Spain.
77 [8] studied the use of VANT to detect water stress in orange and tangerine cultivars using
78 hyperspectral and thermal images in Seville, Spain. Theses mentioned papers have allowed

79　to draw the conclusion that the use of thermal imaging is an efficient tool to identify the water
80　stress of crops and guide the management of irrigation

81　Multispectral cameras and thermal cameras on board unmanned aerial vehicles (UAV) were
82　used by [9] in the cultivation of apple trees for the detection of water stress in the trees.
83　Captured images allowed water stress to be detected at the individual tree level in order to
84　allow localized management of irrigation.

85　All the researches show great applicability of multispectral, thermographic and hyperspectral
86　cameras to identify plants in water stress. To achieve this result, complex image processing
87　was developed and good performance computers were required.

88　These studies must be improved so that they can get into the hands of producers, since the
89　results are still dependent on the laboratory environment.

90　**Management of nitrogen fertilization**

91　The chlorophyll is the most important pigment of the leaf and some of the most important of
92　the plant, since it is through the manages to capture the sunlight and to use it as energy
93　source. In order to quantify the amount of chlorophyll in the leaf, it is possible to estimate the
94　lack of sufficient amount of nitrogen in the plant, indicating the need for nitrogen fertilization
95　or not [10].

96　Nitrogen is one of the most influential nutrients in plant development, being a limiting
97　element of production. Due to this characteristic, it is intensively used in productive crops,
98　aiming the crop to reach its maximum potential [11]. However, if used in excess of the cost
99　of production also leads to contamination of water resources due to leaching and
100　evaporation [10].

101　Commercial optical sensors such as the GreenSeeker and Minolta SPAD-502 are based on
102　NIR and SPAD Analysis of Soil Plants. With the NDVI, as measured by GreenSeeker, it is
103　possible to estimate the nitrogen fertilization for the crop according to the desired
104　productivity, with the SPAD as measured by the Minolta SPAD-502, the amount of
105　chlorophyll in the plant is estimated and thus it is possible to identify the state of health, as
106　well as to recommend nitrogen fertilization.

107　Yara N-Sensor is another sensor also used for nitrogen fertilization. It is based on spectral
108　reflection in specific bands related to the chlorophyll and biomass content of the cultures.

109　The CropCircle optical sensor makes readings of up to 6 spectral bands covering blue,
110　green, red, near-red and near-infrared. With the combination of these bands it is possible to
111　estimate different vegetation indices, among them NDVI [12].

112　[11] have constructed to prototype optical sensor to measure NDVI aiming at low production
113　cost. They set up an experiment with corn and wheat to verify the calibration and
114　performance of the prototype with the GreenSeeker commercial sensor. Their results
115　showed that prototype is a useful sensor to measure NDVI and by means of this estimate of
116　nitrogen fertilization. The performance and accuracy are lower than the GreenSeeker, due to
117　the low cost of the prototype, but it does not disturb the farmer who uses it.

118　[13] and [14] have developed very similar surveys with commercial geraniums. They verified
119　the performance of the GreenSeeker and Minolta SPAD-502 sensors in the identification of
120　nitrogen concentration in two geranium cultivars. NDVI and SPAD measures are possible to

121 identify changes in the nitrogen concentration state, but they point out that research must
122 correlate these variations with the necessary dose of nitrogen to be applied in the
123 geraniums.

124 [15] used the CropCircle sensor to measure the Meris Terrestrial chlorophyll index (MTCI) of
125 corn crops in Brazil submitted to different treatments of nitrogen fertilization. With the MTCI
126 data and the correlation with the nitrogen dose used in each treatment, they created an
127 algorithm to estimate the application rate of nitrogen in corn.

128 [16] evaluated the performance of the NDVI sensor prototype developed by [11] and the
129 SPAD-502 sensor in the identification of the nitrogen concentration in Gaillardia. The results
130 indicate that both sensors can be used to identify the nitrogen concentration of this flower,
131 as long as the sampling time is not short. [16] point out that in order to develop fertilization
132 guidelines it is necessary to investigate further the different production practices and
133 additional cultivars with the measured NDVI and SPAD values.

134 The studies indicate that there is a field of research to develop algorithms that estimate the
135 nitrogen dose to be applied in different commercial cultivars according to the value of SPAD
136 or NDVI measured, or other index. GreenSeeker, for example, uses algorithm that
137 recommends only dose to be applied to grains. Therefore, there are a variety of agricultural
138 species still to be studied.

139 **Chemical properties of soil**

140 Studies show that the number of ions in the soil and organic matter affect the reflectance,
141 absorption or transmittance of electromagnetic waves by the soil. This fact may be
142 interesting for the use of optical sensors as a measure of soil chemical properties [17].

143 [18] used a mobile NIR spectrophotometer to map the surface layer of organic farms and to
144 study the correlation among the spectral data with the results of the laboratory analysis for
145 P, K, Mg, soil organic matter (OM), N and pH. For the local calibrations, the best results
146 were pH, N-total, MO, K-total and Mg-total, with r 2: 0.71, 0.69, 0.61, 0.55, 0.53 ,
147 respectively; therefore, showing correlation between NIR spectral data of the soil with the
148 chemical properties of this soil. However, they concluded that the correlation between the
149 spectra and the parameters was location dependent, and this would make it difficult to
150 develop general calibration models.

151 [19] developed a prototype using NIR spectrophotometer to map soil reflectance and
152 correlate with chemical parameters. The results of an initial study indicated that the locally
153 weighted regression analysis was able to predict moisture, C-total, N-total and pH, with R2:
154 0.82, 0.87, 0.86 and 0.72, respectively. The experimental unit produced data with a high
155 level of repeatability, thus showing soil patterns related to NIR spectral reflectance.

156 **Detection of pathogens in plants**

157 Studies in the literature show that plants after being attacked by pathogens suffer damage
158 that causes changes in the rate of transpiration and flow of water throughout the plant or in
159 organs. This leads to increased temperature in localized parts of the plant, such as leaves
160 [20, 21].

161 [22] studied the applicability of the multispectral camera and thermographic camera for the
162 detection of Huanglongbing disease in citrus trees. The experiment was carried out in the
163 experimental field of citrus of the University of Florida, USA. Their results conclude that

164   using the band of the visible and thermal infrared as input characteristics, the overall
165   average classification accuracy of 87%, with 89% specificity and 85% sensitivity, could be
166   achieved to classify trees with leaves infected by Huanglongbing. The support vector
167   machine model was used for identification.

168   [23] used a multispectral camera coupled to UAV to diagnose citrus trees affected by
169   Greening's disease, based on spectroscopy. For this, the data generated from the
170   processing of six spectral bands and seven vegetation indices derived from these bands,
171   among them the NIR / R (near infrared / red), were used in the classification algorithm.
172   Among the indexes analyzed, NIR / R showed a better significant difference between
173   healthy trees and infected plants. The authors concluded that the processing of multispectral
174   images taken at low altitudes is reliable in the detection of Greening disease (the
175   classification reached an accuracy of 85%), being a tool that could reduce the production
176   costs of the citrus crop due to the rapid identification of the disease.

177   **Apps for smartphone**

178   Smartphones are a device that in addition to presenting a fast processing system also a
179   camera feature, being an interesting platform for image processing. In light of this, work has
180   been developed using the images captured by the RGB camera to create applications for
181   precision agriculture.

182   [10] created an application called SmartSPAD responsible for estimating the SPAD of corn
183   plants by means of contact image obtained by the camera of smartphones. Its application is
184   based on two models of SPAD prediction from the corn leaf image: neural network model,
185   and the multivariate linear model. For the validation of SmartSPAD, the SPAD values
186   measured by it were compared with the SPAD values measured by the Minolta SPAD-502
187   device, used as standard. The validation r^2 values were 0.88 and 0.72 and the mean square
188   error was 4.03 and 5.96 for neural network and linear model, respectively. The application
189   proved to be a good estimator of SPAD values at a low cost.

190   [24] have created a ground classification sensor based on smartphone application. The
191   sensor is formed by external optical support and a smartphone application. The support is
192   formed of two external lenses and a shading cover, since the classification application is
193   based on the linear discriminant analysis model. The Munsell color card was used as the soil
194   classification standard. The results reached by the authors show that the sensor had hits
195   above 90% for all soil samples evaluated.

196   A similar research to the work of [24] was also developed by [25]. The latter authors also
197   applied an application for Android smartphones with the aim of classifying solo in relation to
198   Munsell color card through RGB images. Their results were obtained in controlled lighting
199   environments and showed that the ratings by the application were good and acceptable in a
200   controlled lighting environment.

201   **Future Challenges Regarding Optical Sensors**

202   The maximum nitrogen fixation by plants, in the traditional form of fertilization, is around
203   50%, with the world average being 33%. This is due to several factors, either by leaching,
204   evaporation and / or plant losses [11] Thus, of all the nitrogen fertilization used in the world
205   for agricultural production, an average of 67% is wasted.

206   The use of commercial optical sensors with GreenSeeker, Yara N-Sensor, CropCircle and
207   SPAD-502 promotes improved fixation rate, but these sensors are expensive and not very

208 accessible to many farmers, especially in developing countries. These countries correspond
209 to about 70% of the nitrogen consumption for fertilization in the world [11].

210 According to [26], it is realistic to expect crops on the farms of the future to be managed
211 plant by plant. This approach will require the collection and analysis of massive data on a
212 scale not considered today and the need for stationary or mobile sensors that can measure
213 individual plant characteristics in real time.

214 Real-time point-to-point sampling is possible today but at a very high cost. And due to cost,
215 sampling in a productive area is done with few points, which decreases the accuracy of the
216 final result, and inefficient becomes the whole set.

217 The acquisition cost of a thermographic, multispectral and hyperspectal camera is high,
218 especially in countries not benefited by the local currency. This makes it difficult for many
219 research centers around the world to reduce research development in many areas that could
220 leverage technology to improve their research and make new discoveries [21].

221 Given the current context, it will be future challenges to develop low-cost optical sensors and
222 make them as accessible as possible to the producer and the research centers. That these
223 sensors promote the improvement of the nitrogen fixation in different agricultural crops and
224 that they can monitor in real time the plant or the homogeneous set of these, facilitating the
225 management at the varied rate.

226 Another challenge will be to develop optical sensors that all steps of image capture,
227 processing and final result take place on the same equipment. This will facilitate the
228 immersion of this technology in the field.

229 Table 1 presents a summary table of the most studied research fields with emphasis on the
230 use of optical sensors for the monitoring of agricultural crops and agricultural processes.

231 **Table 1. More developed research to study the use of optical sensors for the**
232 **monitoring of crops and agricultural processes**

Country	Product	Optical sensor feature	Reference
Spain	Water stress in almond, apricot, peach, lemon and orange	Thermal	[4]
USA	Water stress in cotton	Thermal	[5]
Spain	Water stress on persimmon and citrus trees	Thermal	[6]
Spain	Water stress in the vine	Thermal	[7]
Spain	Water stress in orange and tangerine feet	Hyper-Spectral and thermal	[8]
France	Water stress in apple trees	Thermal	[9]
USA	SPAD reading application	CCD	[10]

USA/ Mexico	Management of nitrogen fertilization in maize	NDVI reader	[11]
Brazil	Management of nitrogen fertilization in maize	MTCI Reader	[15]
USA	Management of nitrogen fertilization in Gaillardia	NDVI/SPAD Reader	[16]
USA	Chemical properties of soil	Multispectral NIR	[18]
USA	Chemical properties of soil	Multispectral NIR	[19]
USA	Huanglongbing on citrus trees	Thermal	[22]
USA	Huanglongbing on citrus trees	Multispectral	[23]
China	Application to sort soil	CCD/lenses	[24]
Spain	Application to sort soil	CCD	[25]
Greece	Identification of *Silybum marianum*	Multispectral	[27]
Spain	Identification of *Sorghum halepense*	Multispectral and RGB	[28]

233

234 In analyzing Table 1, as well as the various literature cited in this study, it is noteworthy that
235 the USA followed by Spain is the country that presents the most published study on the use
236 of optical sensors in various areas of agriculture, from identification of the soil chemical
237 properties, as well as classification, identification of diseases.

238 Regarding the period of publication, of the total of works analyzed, one was published in
239 2003, two in 2011, two in 2012, six in 2013, one in 2014, two in 2015, three in 2016 and one
240 in 2017. In 33.3% were thermal, 5.6% hyperspectral, 16.7% charge-coupled device (CCD),
241 27.8% multispectral and 16.7% studied reading sensors of vegetation indices. The year and
242 type of publication are shown in Figure 1.
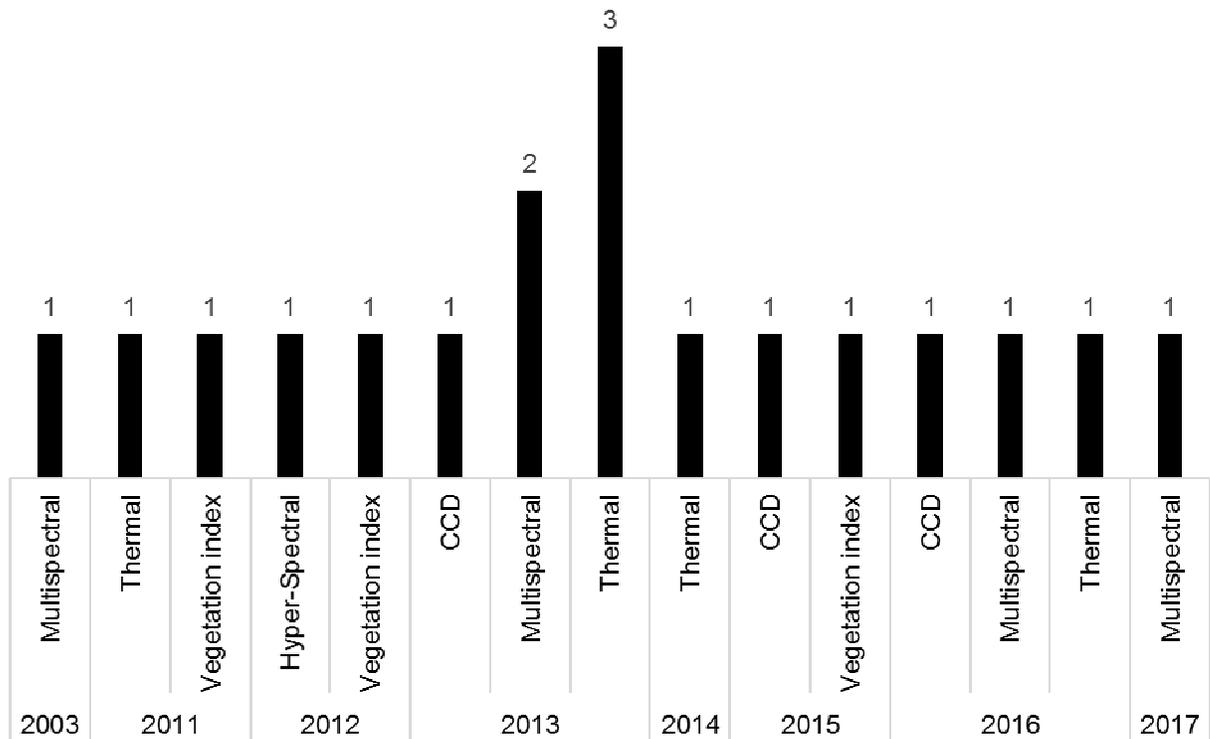
Fig. 1. Number of publications by type and year.

4. CONCLUSION

The studies developed and presented show the great applicability of optical sensors as a precision agriculture tool from identification of water stress and weeds to nitrogen fertilization management in crops.

The main limitation of an optical sensor used in agriculture in most parts of the world is the cost of purchasing the devices, especially in poor countries where agriculture is the basis of the economy. therefore, a future challenge will be to develop efficient sensors with low acquisition cost.

Image processing for precision farming is a very effective information method, however, the results are not immediate and you need a computer that performs well to get them. smartphones have combined processor and camera into one device. due to this feature, the smartphone has proven to be very useful for digital image processing. the trend is for processing to become better, given that every day better smartphones, in terms of processor and camera are launched with cost-effectiveness.

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