

Optical sensors for precision agriculture: an outlook

Lucas de Arruda Viana^{1*}, Deborah Campos Tomaz², Rodrigo Nogueira Martins³, Jorge Tadeu Fim Rosas⁴, Fernando Ferreira Lima dos Santos⁵, Marcelo Fagundes Portes⁶

ABSTRACT

The growing human population added to the rural exodus has aggravated the pressure in the agricultural sector for greater production. Faced with this problem, research has developed optical sensors for more productive 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 to the use of optical sensors in agriculture in most parts 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.

Keywords: Smartphone; weed; hydric stress; pathogen detection; soil fertility.

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 augment 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].

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

40 **2. MATERIAL AND METHODS**

41

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

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

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

60 **3. RESULTS AND DISCUSSION**

61

62 **3.1. Applicability of optical sensors in agriculture**

63 **3.1.1. Irrigation**

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

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

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

74 In this perspective, O'shaughnessy et al. [5] evaluated the use of thermal imagery to assess
75 water stress in soybean and cotton crops in Texas in USA. Ballester et al. [6] studied the use
76 of thermographic camera for the detection of water stress in citrus and persimmon trees in
77 Valencia in Spain. Bellvert et al. [7] evaluated the use of a thermal camera to determine
78 water stress in vines in the town of Lleda in Spain. Zarco-Tejada et al. [8] studied the use of
79 VANT to detect water stress in orange and tangerine cultivars using hyperspectral and
80 thermal images in Seville in Spain. These above-mentioned papers have allowed to draw

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

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

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

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

92 **3.1.2. Management of nitrogen fertilization**

93 The chlorophyll is the most important pigment of the leaf and one of the most important of
94 the plant, since it is through it that plants manages to capture sunlight and to use it as
95 energy source. By means of sensors it is possible to estimate the amount of chlorophyll in
96 the leaf, and thus to be able to evaluate the deficiency of nitrogen in the plant, indicating the
97 necessity of nitrogen fertilization or not. [10].

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

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

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

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

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

121 Wang et al. [13] and Wang et al. [14] have developed very similar surveys with commercial
122 geraniums. They verified the performance of the GreenSeeker and Minolta SPAD-502

123 sensors in the identification of nitrogen concentration in two geranium cultivars. NDVI and
124 SPAD measures are possible to identify changes in the nitrogen concentration state, but
125 they pointed out that research must correlate these variations with the necessary dose of
126 nitrogen to be applied in the geraniums.

127 **Shiratsuch et al.** [15] has used the CropCircle sensor to measure the Meris Terrestrial
128 chlorophyll index (MTCI) of corn crops in Brazil submitted to different treatments of nitrogen
129 fertilization. With the MTCI data and the correlation with the nitrogen dose used in each
130 treatment, they have created an algorithm to estimate the application rate of nitrogen in corn.
131 **Dunn et al.** [16] has evaluated the performance of the NDVI sensor prototype developed by
132 **Crain et al.** [11] and the SPAD-502 sensor in the identification of the nitrogen concentration
133 in Gaillardia. The results indicate that both sensors can be used to identify the nitrogen
134 concentration of this flower, as long as the sampling time is not short. **Dunn et al.** [16]
135 pointed out that in order to develop fertilization guidelines it is necessary to further
136 investigate the different production practices and additional cultivars with the NDVI and
137 SPAD measured values.

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

143 **3.1.3. Chemical properties of soil**

144 Studies **have** shown that the number of ions in the soil and organic matter affect the
145 reflectance, absorption or transmittance of electromagnetic waves by the soil. This fact may
146 be interesting for the use of optical sensors as a measure of soil chemical properties [17].

147 **Schirrmann et al.** [18] has used a mobile NIR spectrophotometer to map the surface layer of
148 organic farms and to study the correlation among the spectral data with the results of the
149 laboratory analysis for P, K, Mg, soil organic matter (OM), N and pH. For the local
150 calibrations, the best results were pH, N-total, MO, K-total and Mg-total, with **r^2 representing**
151 0.71, 0.69, 0.61, 0.55, 0.53, respectively; therefore, showing correlation between NIR
152 spectral data of the soil with the chemical properties of this soil. However, they concluded
153 that the correlation between the spectra and the parameters was location dependent, and
154 this would make it difficult to develop general calibration models.

155 **Christy et al.** [19] **has** developed a prototype using NIR spectrophotometer to map soil
156 reflectance and correlate with chemical parameters. The results of an initial study indicated
157 that the locally weighted regression analysis was able to predict moisture, C-total, N-total
158 and pH, with **r^2 representing** 0.82, 0.87, 0.86 and 0.72, respectively. The experimental unit
159 produced data with a high level of repeatability, thus showing soil patterns related to NIR
160 spectral reflectance.

161 **3.1.4. Detection of pathogens in plants**

162 Studies in the literature show that plants after being attacked by pathogens suffer damage
163 that causes changes in the rate of transpiration and flow of water throughout the plant or in
164 organs. This leads to increased temperature in localized parts of the plant, such as leaves
165 [20, 21].

166 **Sankaran et al.** [22] have studied the applicability of the multispectral camera and
167 thermographic camera for the detection of Huanglongbing disease in citrus trees. The

168 | experiment was carried out in the experimental field of citrus of the University of Florida in,
169 USA. Their results concluded that using the band of the visible and thermal infrared as input
170 characteristics, the overall average classification accuracy of 87%, with 89% specificity and
171 85% sensitivity, could be achieved to classify trees with leaves infected by Huanglongbing.
172 The support vector machine model was used for identification.

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

182 **3.1.4. Apps for smartphone**

183 Smartphones are devices that in addition to presenting a fast processing system also have a
184 camera feature, being an interesting platform for image capture and possible processing. In
185 view of this, the work was developed using images captured by the RGB camera to create
186 applications for precision agriculture.

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

195 **Han et al.** [24] have created a ground classification sensor based on smartphone
196 application. The sensor is formed by external optical support and a smartphone application.
197 The support is formed of two external lenses and a shading cover, since the classification
198 application is based on the linear discriminant analysis model. The Munsell color card was
199 used as the soil classification standard. The results reached by the authors showed that the
200 sensor had hits above 90% for all soil samples evaluated.

201 A similar research to the work of **Han et al.** [24] was also developed by **Mulla** [25]. The latter
202 authors also applied an application for Android smartphones with the aim of classifying soil
203 in relation to Munsell color card through RGB images. Their results were obtained in
204 controlled lighting environments and showed that the ratings by the application were good
205 and acceptable in a controlled lighting environment.

206 **3.2. Future challenges regarding optical sensors**

207 The maximum nitrogen fixation by plants, in the traditional form of fertilization, is around
208 50%, with the world average being 33%. This is due to several factors, either by leaching,
209 evaporation and / or plant losses [11]. Thus, of all the nitrogen fertilization used in the world
210 for agricultural production, an average of 67% is wasted.

211 The use of commercial optical sensors with GreenSeeker, Yara N-Sensor, CropCircle and
 212 SPAD-502 promotes improved fixation rate, but these sensors are expensive and not very
 213 accessible to many farmers, especially in developing countries. These countries correspond
 214 to about 70% of the nitrogen consumption for fertilization in the world [11].

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

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

222 The acquisition cost of a thermographic, multispectral and hyperspectral camera is high,
 223 especially in countries not benefited by the local currency. This makes it difficult for many
 224 research centers around the world to carry out research and development in many areas
 225 that could leverage technology to improve their research and make new discoveries [21].

226 Table 1 presents summarizes most studied research fields with emphasis on the use of
 227 optical sensors for the monitoring of agricultural crops and agricultural processes.

228 **Table 1. More developed research on the use of optical sensors for the monitoring of**
 229 **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	NDVI/SPAD Reader	[16]

	fertilization in <i>Gaillardia</i>		
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 <i>Silybum marianum</i>	Multispectral	[27]
Spain	Identification of <i>Sorghum halepense</i>	Multispectral and RGB	[28]

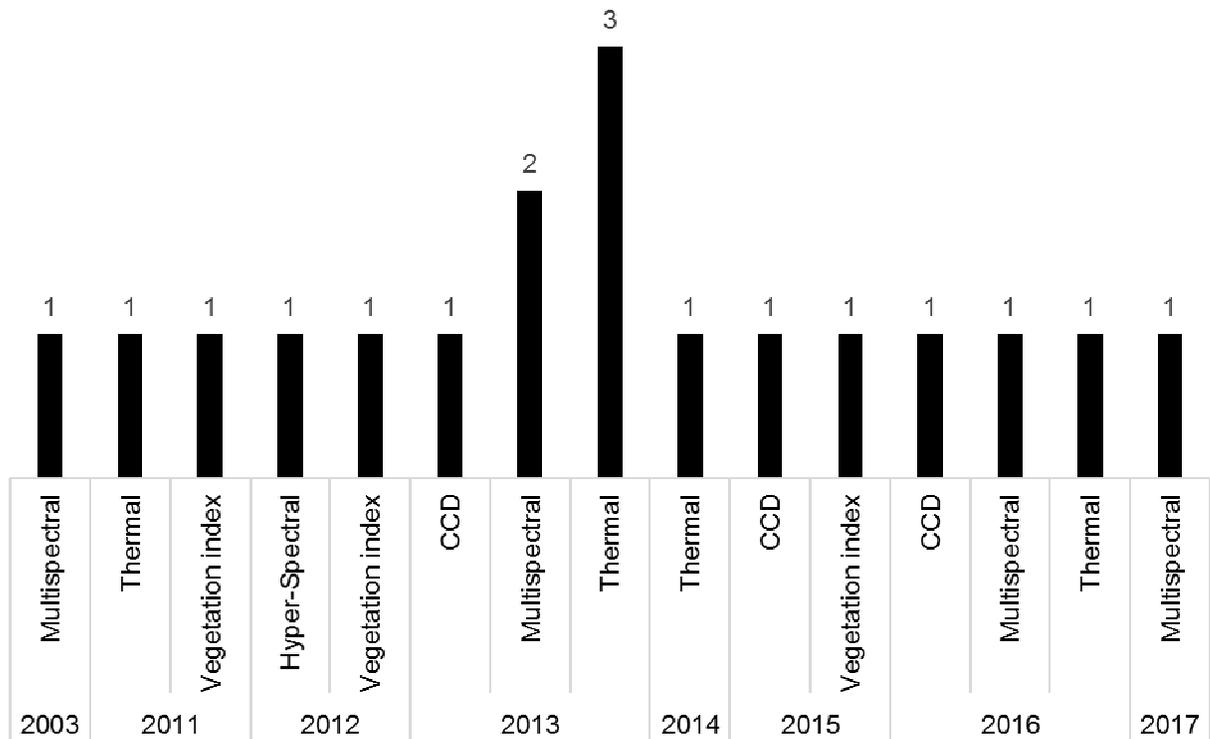
230

231 In analyzing Table 1 as well as the various literature cited in this study, it is noteworthy that
 232 the USA followed by Spain are the countries that present the most published study on the
 233 use of optical sensors in various areas of agriculture, including the identification of the soil
 234 chemical properties, as well as the classification and identification of diseases.

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

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

243 The total of 18 works published from 2003 to 2017 including one in 2003, two in 2011, two in
 244 2012, six in 2013, one in 2014, two in 2015, three in 2016, and one in 2017. About 33.3%
 245 were thermal, 5.6% hyperspectral, 16.7% charge-coupled device (CCD), 27.8%
 246 multispectral and 16.7% studied reading sensors of vegetation indices. The year and type of
 247 publication are shown in Figure 1.



248

249 **Fig. 1. Number of publications by type and year.**

250 **4. CONCLUSION**

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

254 The main limitation **to the use** of an optical sensor in agriculture in most parts of the world is
 255 the cost of purchasing the devices, especially in poor countries where agriculture is the basis
 256 of the economy. **Therefore, the** challenge **is the production of cost-effective** sensors.

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

263 **ACKNOWLEDGEMENTS**

264 The authors are grateful to the Federal University of Viçosa - UFV for the academic support
 265 and availability of laboratories and the National Council for Scientific and Technological
 266 Development-CNPq for the financial support.

267 **REFERENCES**

268

269 1. Rehman AU, Abbasi AZ, Islam N, Shaikh ZA A review of wireless sensors and networks'
270 applications in agriculture. *Computer Standards & Interfaces*, 2014;36(2): 263-270. DOI:
271 <https://doi.org/10.1016/j.csi.2011.03.004>

272 2. OJHA T, MISRA S, RAGHUWANSHI NS, Wireless sensor networks for agriculture: The
273 state-of-the-art in practice and future challenges. *Computers and Electronics in Agriculture*,
274 2015; 118: 66-84. DOI: <https://doi.org/10.1016/j.compag.2015.08.011>

275 3. LING C, LIU H, JU H, ZHANG H, YOU J, LI W. A Study on Spectral Signature Analysis of
276 Wetland Vegetation Based on Ground Imaging Spectrum Data. *Journal of Physics:*
277 *Conference Series*, 2017; 910, 8p. DOI: <https://doi.org/10.1088/1742-6596/910/1/012045>

278 4. GONZÁLEZ-DUGO V, ZARCO-TEJADA PJ, NICOLÁS E, NORTES PA, ALARCÓN JJ,
279 INTRIGLIOLO DS, FERERES E. Using high resolution UAV thermal imagery to assess the
280 variability in the water status of five fruit tree species within a commercial orchard. *Precision*
281 *Agriculture*, 2013; 14(6): 660-678. DOI: <https://doi.org/10.1007/s11119-013-9322-9>

282 5. O'SHAUGHNESSY SA, EVETT SR, COLAIZZI PD, HOWELL TA. Using radiation
283 thermography and thermometry to evaluate crop water stress in soybean and cotton.
284 *Agricultural Water Management*, 2011; 98(10): 1523-1535. DOI:
285 <https://doi.org/10.1016/j.agwat.2011.05.005>

286 6. BALLESTER C, JIMÉNEZ-BELLO MA, CASTEL JR, INTRIGLIOLO DS, Usefulness of
287 thermography for plant water stress detection in citrus and persimmon trees. *Agricultural and*
288 *Forest Meteorology*, 2013; 168:120-129. DOI:
289 <https://doi.org/10.1016/j.agrformet.2012.08.005>

290 7. BELLVERT J, ZARCO-TEJADA J, GIRONA J, FERERES J. Mapping crop water stress
291 index in a 'Pinot-noir' vineyard: comparing ground measurements with thermal remote
292 sensing imagery from an unmanned aerial vehicle. *Precision Agriculture*, 2014;15(4): 361-
293 376. DOI: <https://doi.org/10.1007/s11119-013-9334-5>

294 8. ZARCO-TEJADA PJ, GONZÁLEZ-DUGO V, BERNI JAJ. Fluorescence, temperature and
295 narrow-band indices acquired from a UAV platform for water stress detection using a micro-
296 hyperspectral imager and a thermal camera. *Remote Sensing of Environment*, 2012; 117:
297 322-337. DOI: <https://doi.org/10.1016/j.rse.2011.10.007>

298 9. GÓMEZ-CANDÓN D, VIRLET N, LABBÉ S, JOLIVOT A, REGNARD J. Field phenotyping
299 of water stress at tree scale by UAV-sensed imagery: new insights for thermal acquisition
300 and calibration. *Precision Agriculture*, 2016; 17(6): 786-80. DOI:
301 <https://doi.org/10.1007/s11119-016-9449-6>

302 10. VESALI F, OMID M, KALEITA A, MOBLI H. Development of an android app to estimate
303 chlorophyll content of corn leaves based on contact imaging. *Computers and Electronics in*
304 *Agriculture*, 2015; 116: 211-220. DOI: <https://doi.org/10.1016/j.compag.2015.06.012>

305 11. CRAIN, J.; ORTIZ-MONASTERIO, I.; RAUN, B. Evaluation of a Reduced Cost Active
306 NDVI Sensor for Crop Nutrient Management. *Journal of Sensors*, 2010; 2012, ID 582028, 10
307 pages. DOI: <http://dx.doi.org/10.1155/2012/582028>

- 308 12. CAO Q, MIAO Y, WANG H, SHANYUHUANG S, SHANSHANCHENG S, KHOSLA R,
309 JIANG R. Non-destructive estimation of rice plant nitrogen status with Crop Circle
310 multispectral active canopy sensor. *Field Crops Research*, 2013; 154: 133-144. DOI:
311 <https://doi.org/10.1016/j.fcr.2013.08.005>
- 312 13. WANG Y, DUNN BL, ARNALL DB, Assessing nitrogen status in potted geranium through
313 discriminant analysis of ground-based spectral reflectance data. *HortScience*, 2012a; 47:
314 343-348.
- 315 14. WANG Y, DUNN BL, ARNALL DB, MAO P. Use of an active canopy sensor and SPAD
316 chlorophyll meter to quantify geranium nitrogen status. *HortScience*, 2012b; 47: 45-50.
- 317 15. SHIRATSUCHI LS, VILELA MF, FERGUSON RB, SHANAHAN JF, ADAMCHUK VI,
318 RESENDE AV, HURTADO SC, CORAZZA EJ. Desenvolvimento de um algoritmo baseado
319 em sensores ativos de dossel para recomendação da adubação nitrogenada em taxas
320 variáveis. In: INAMASU RY, NAIME JM, RESENDE AV, BASSOI LH, BERNARDI ACC.
321 *Agricultura de precisão: um novo olhar*. São Carlos: Embrapa Instrumentação, 2011; 1: 184-
322 188.
- 323 16. DUNN BL, SHRESTHA A, GOAD C, KHODDAMZADEH AA. Use of optical sensors to
324 monitor *Gaillardia Foug.* nitrogen status. *Journal of Applied Horticulture*, 2015; 17(3): 181-
325 185.
- 326 17. ADAMCHUK VI, HUMMEL JW, MORGAN MT, UPADHYAYA SK. On-the-go soil sensors
327 for precision agriculture. *Computers and Electronics in Agriculture*, 2004; 44(1): 71-91. DOI:
328 <https://doi.org/10.1016/j.compag.2004.03.002>
- 329 18. SCHIRRMANN M, GEBBERS R, KRAMER E. Performance of Automated Near-Infrared
330 Reflectance Spectrometry for Continuous in Situ Mapping of Soil Fertility at Field Scale.
331 *Vadose Zone Journal*, 2013 ; 12(4): 14p. DOI: <https://doi.org/10.2136/vzj2012.0199>
- 332 19. CHRISTY CD, DRUMMOND P, LAIRD DA. An on-the-go spectral reflectance sensor for
333 soil. *ASAE Annual Meeting*, nº 031044, 2003.
- 334 20. MAHLEIN AK. Plant Disease Detection by Imaging Sensors - Parallels and Specific
335 Demands for Precision Agriculture and Plant Phenotyping. *APS Journals*, 2016; 100(2): 241-
336 251.
- 337 21. VIANA LA, ZAMBOLIM L, SOUSA TV, TOMAZ BC. Potential use of thermal camera
338 coupled in UAV for culture monitoring. *Brazilian Journal of Biosystems Engineering*, 2018;
339 12(3): 286-298. DOI: <http://dx.doi.org/10.18011/bioeng2018v12n3p286-298>
- 340 22. SANKARAN S, MAJA JM, BUCHANON S, EHSANI R. Detecção de Huanglongbing
341 (Citrus Greening) usando técnicas visíveis, Near Infrared e Thermal Imaging. *Sensors*,
342 2013; 13(2): 2117-2130. DOI: <https://doi.org/10.3390/s130202117>
- 343 23. GARCIA-RUIZ F, SANKARAN S, MAJA JM, LEE WS, RASMUSSEN J, EHSANI R.
344 Comparison of two aerial imaging platforms for identification of Huanglongbing-infected
345 citrus trees. *Computers and Electronics in Agriculture*, 2013; 91: 106-115. DOI:
346 <https://doi.org/10.1016/j.compag.2012.12.002>

- 347 24. HAN P, DONG D, ZHAO X, JIAO L, LANG Y. A smartphone-based soil color sensor: For
348 soil type classification. *Computers and Electronics in Agriculture*, 2016; 123: 232-241. DOI:
349 <https://doi.org/10.1016/j.compag.2016.02.024>
- 350 25. GÓMEZ-ROBLEDO L, LÓPEZ-RUIZ N, MELGOSA M, PALMA AJ, CAPITÁN-VALLVEY;
351 JF, SÁNCHEZ-MARAÑÓN M. Using the mobile phone as Munsell soil-colour sensor: An
352 experiment under controlled illumination conditions. *Computers and Electronics in*
353 *Agriculture*, 2013; 99: 200-208. DOI: <https://doi.org/10.1016/j.compag.2013.10.002>
- 354 26. MULLA DJ. Twenty-five years of remote sensing in precision agriculture: Key advances
355 and remaining knowledge gaps. *Biosystems Engineering*, 2013; 114(4): 358-371. DOI:
356 <https://doi.org/10.1094/PDIS-03-15-0340-FE>
- 357 27. PANTAZI XE, TAMOURIDOU AA, ALEXANDRIDIS TK, LAGOPODI AL, KASHEFI J,
358 MOSHOU D. Evaluation of hierarchical self-organising maps for weed mapping using UAS
359 multispectral imagery. *Computers and Electronics in Agriculture*, 2017; 139: 224-230. DOI:
360 <https://doi.org/10.1016/j.compag.2017.05.026>
- 361 28. LÓPEZ-GRANADOS F, TORRES-SÁNCHEZ J, CASTRO AI, SERRANO-PÉREZ A,
362 MESAS-CARRASCOSA FJ, PEÑA JM. Object-based early monitoring of a grass weed in a
363 grass crop using high resolution UAV imagery. *Agronomy for Sustainable Development*,
364 2016; 12 pages. DOI: <https://doi.org/10.1007/s13593-016-0405-7>