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Trends in Remote Sensing Technologies in Olive Cultivation

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ABSTRACT

Various Remote Sensing (RS) technologies and platforms have been widely used in olive cultivation studies over the last 16 years. These technologies and platforms have been applied throughout the olive cultivation cycle, providing significant insights into olive growth and productivity. The goal of this review was to determine the importance of RS technologies and platforms in specific agronomic focus areas in order to determine the equipment and platform requirements in olive cultivation studies. For this reason, frequency and correspondence studies were carried out. Unmanned aerial vehicles, multispectral sensors, and vigour assessment found to be important in olive cultivation studies. Additionally, each agronomic focus area in an olive cultivation study presents different needs in equipment, proximity of sensing, and coverage area, indicating that this must be taken into account during field experiments with RS. Further technological improvements will permit the use of other RS technologies and platforms during future studies. Finally, future studies are expected to focus more on RS data processing as well as on the use of unmanned aerial and ground vehicles in swarms for data collection and performance of actions.

1. Introduction

Olive (*Olea europaea* L.) is one of the oldest cultivations in the world and is mainly cultivated in the Mediterranean countries [1]. However, the future of this cultivation is in peril due to climate change [2] as well as other reasons such as olive crop diseases (e.g. *Xylella fastidiosa*) [3]. Thus, there is a need to acquire and process a high volume and quantity of information related to the olive crop for taking immediate actions that will allow sustainable and perpetual production of high yield and quality.

The collection of information about items or locations without having direct interaction is referred to as Remote Sensing (RS) [4]. RS has transformed the way of acquiring and processing information about agricultural environments. RS collects data in a fast and cost efficient way compared to other methods and, consequently, has proven to be a game-changer in agriculture [5]. This was carried out as a result of technological advancements in the sectors of electronics and computing such as 3D printing, robot utilization, smart production systems, and artificial intelligence, which allowed for increased production efficiency of such technology and, as a result, lower sensor and electronics production costs [6–10]. All of the aforementioned factors have expanded the use of all types of sensors, including RS sensors, in a variety of industries, including agriculture.

Currently, a significant number of sensors are utilized in agriculture to map the spatial and temporal variability of various parameters and assist producers in making crop management decisions [11]. RGB [12,13], multispectral [14,15], hyperspectral [16,17], and thermal cameras [18,19], as well as other sensors like Light Detection and Ranging (LiDAR) [20,21], Radio Detection and Ranging (RADAR) [22,23] and electromagnetic induction (EMI) [24,25], are used alone or in combination to estimate critical agricultural characteristics like crop vigour, water stress, pest and disease severity, and soil conditions in a non-destructive manner. After being suitably analysed (e.g., using spectral vegetation indices in the case of optical sensors), this information can lead to the identification of management zones and the administration of variable rate inputs such as fertilizers, water, and plant protection products [11].

Furthermore, the platforms that are employed with the sensors are equally essential. According to the platform on which the sensors are installed, RS can be categorized as satellite, aerial, or ground/proximal RS. The satellite RS has the advantage of being able to cover wide areas quickly, but its main drawback is the collection of medium resolution data (meter resolution) [5]. Although aerial RS employing Unmanned Aerial Vehicles (UAV) or manned flights can provide high resolution

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data (cm resolution), it cannot cover as big an area as satellite RS in the same amount of time [26]. Finally, proximal RS, which can be performed using Unmanned Ground Vehicles (UGV), vehicles with an operator, or on foot, can retrieve high-resolution data (mm resolution), but requires long and heavy effort [5,27,28].

Thus, the goal of this study was to i) map the use of various RS technologies in relation to the information that they provide in various agronomic focus areas of olive cultivation (e.g. crop status, delineation of management zones, and variable rate application of crop inputs) and the type of research that was used for (survey, method presentation, and system/subsystem development); and ii) identify trends and gaps in the use of RS technologies in order for them to be easily adopted by olive crop stakeholders.

2. Materials and Methods

2.1. Search of Scientific Studies

Scopus (www.scopus.com) and Web of Science (www.webofscience.com) were used to develop a systematic search strategy. Table 1 shows the queries that were utilized by each search engine.

2.2. Results Filtering

To focus on contemporary research publications, the research articles for this study were collected from the period of January 2001 to December 2021.

The previously described queries yielded 119 research studies jointly. For this systematic review, the PRISMA framework was used [29]. Thus, the first results were filtered to exclude publications that were not related to the study's aim based on the title and abstract, were duplicates, or were published in a language other than English. In total, 52 of these articles satisfied the aforementioned criteria and were thus eliminated. With just 67 scientific publications accessible, the manual selection of articles was extended in one more round to remove studies that were unable to be completely read and those that were beyond the focus of our study according to the entire text (n=11). Finally, for the study, 56 research studies (articles and conference papers) were considered (Figure 1).

Table 1
Search engines and queries that were used for the scope of this study.

Search Engine	Website	Query
Scopus	www.scopus.com	TITLE-ABS-KEY ("remote sensing" OR "proximal sensing" OR "sensing" OR "smart farming" OR "smart agriculture" OR "precision agriculture" OR "precision farming") AND TITLE-ABS-KEY ("aerial" OR "ground" OR "satellite" OR "drone*" OR "UAV*" OR "UGV*" OR "robot*") AND TITLE-ABS-KEY ("multispectral" OR "hyperspectral" OR "thermal" OR "LIDAR" OR "RADAR" OR "sensor*" OR "EMI" OR "electromagnetic induction" OR "sound sensor" OR "ultrasonic") AND TITLE-ABS ("olive*" OR "olive orchards" OR "olive groves" OR "olive tree*") AND PUBYEAR > 2001
Web of Science	www.webofscience.com	(TS=(remote sensing) OR TS=(proximal sensing) OR TS=(sensing) OR TS=(smart farming) OR TS=(smart agriculture) or TS=(precision farming)) AND (TS=(aerial) OR TS=(ground) OR TS=(satellite) OR TS=(drone*) OR TS=(UAV*) OR TS=(UGV*) OR TS=(robot*)) AND (TS=(multispectral) OR TS=(hyperspectral) OR TS=(thermal) OR TS=(LIDAR) OR TS=(RADAR) OR TS=(sensor*) OR TS=(EMI) OR TS=(electromagnetic induction) or TS=(sound sensor) OR TS=(ultrasonic)) AND (TS=(olive*) OR TS=(olive orchards) OR TS=(olive groves) OR TS=(olive tree*))

2.3. Scientific Studies Classification

The selected papers were categorized into four classes that were related to the review's goal. The initial topic was the categorization of sensors according to their type. Then, a second categorization took place according to the study's agronomic focus area, while a third process was to categorize the research studies based on the utilized platform type. The fourth topic focused on the classification of articles as surveys, methodological presentations, and the introduction of a new system/subsystem, or software for use in olive groves. The study's categorization topics are listed in Table 2.

The platform and sensor types were classified by merging existing reviews on themes related to RS applications in agriculture [30–39]. The classification of the agronomic focus areas covered by the use of RS in olive cultivation was based on the olive practices that are followed from planting to harvest [40], as well as on the use of precision agriculture methods (e.g., spectral vegetation indices for crop growth monitoring) and was retrieved during the scientific literature screening. Finally, the research articles were divided into three categories: i) methods, when the authors presented new methods for analyzing data in order to provide information about oliviculture; ii) systems, when the authors presented systems/subsystems or software for use in olive crop surveys; and iii) surveys, when the authors presented RS in field surveys.

2.4. Statistical Analysis

The statistical analysis of the publications comprised the number of research articles produced annually and by type. In addition, analyses were undertaken by platform type, sensor type, and agronomic focus area for each year during the last two decades. The contribution of each platform type and sensor type was also assessed in each agronomic focus area. Finally, a basic tabular correspondence analysis was performed between the agronomic focus area, platform types, and sensor types using the statistical software Statgraphics 19 (StatPoint Technologies Inc., Warrenton, VA, USA).

3. Results and Discussion

3.1. Classification of research studies

In Table 3, the results of the classification for each of the 56 research studies are presented according to country, research type, agronomic focus area, platform type, and sensor type.

3.2. Cumulative number of research articles

According to the results, the first studies with the use of RS technologies in olive cultivation were conducted in 2006, as it shown in Figure 1. Additionally, the results analysis showed that the use of RS technologies has expanded significantly during the last three years when compared to the previous period. It is indicative that half the research studies occurred during that period. Consequently, it can be assumed that the adoption rate of RS technologies in olive crop studies is increasing. This is in accordance with other review papers on the use of RS in agriculture [11,97]. Also, it is worth noticing that the number of studies decreased in 2021 when compared to 2019 and 2020. This can be possibly explained by the impact of the COVID-19 pandemic on non-COVID-19 related research studies, which has resulted in a lower number of publications compared to COVID-19 related studies. This is in agreement with the findings of Gao et al. [98], who imply that there will be long-lasting negative effects on research studies (e.g. lower number of publications and funded research projects) that are related to non-COVID-19 fields if there are no appropriate measures taken.

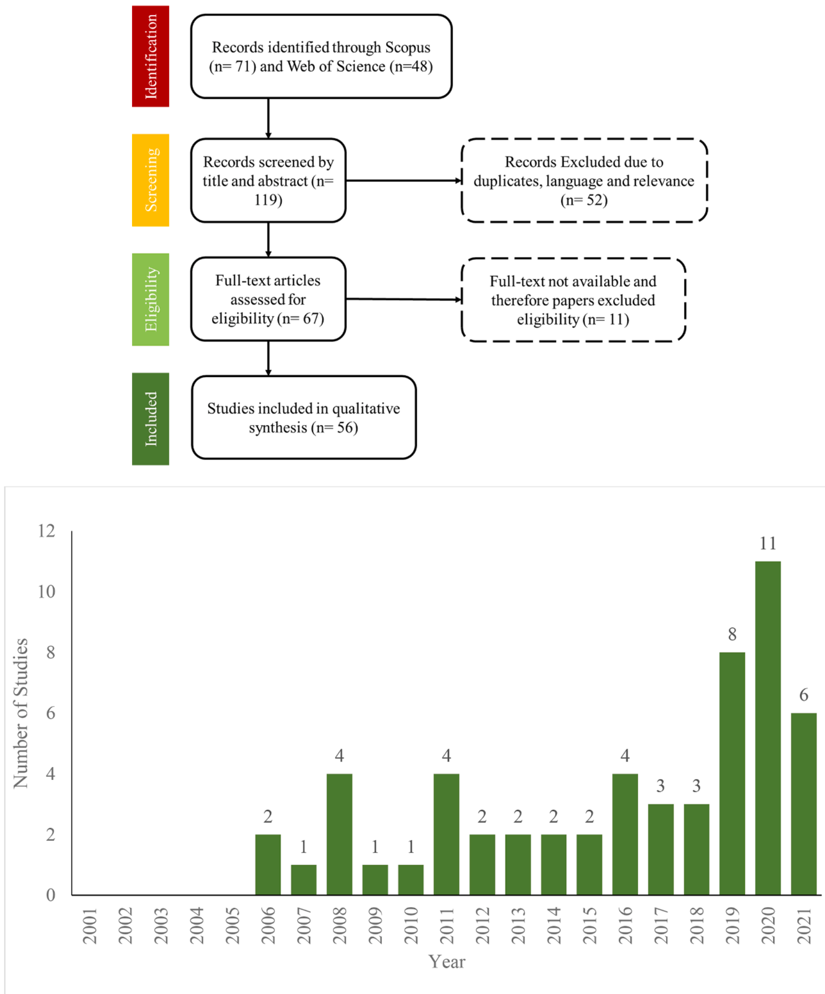

Figure 1. The PRISMA workflow diagram of the literature review search for this study. Number of research studies on RS technologies in olive cultivation for the period 2001-2021.

Table 2
Classification types of the research articles under the different topics of this paper.

Class	Subclass type
Sensor Type	RGB, Multispectral, Hyperspectral, Thermal, LIDAR, RADAR, EMI
Agronomic Focus Area	Planting, Biomass, Structural Parameters, Row/Tree identification, Variety/Phenology, Vigor, Fertilization, Irrigation, Pests, Diseases, Weeds, Yield, Spraying, Management Zones, Soil Parameters
Platform Type	Satellite, UAV, Manned Flight Measurements, UGV, Manned Ground Measurements
Research Type	Method, Survey, System

3.3. Geographical distribution of research studies

According to the results, most of the studies (approximately 93%) took place in the Mediterranean region. Specifically, the most of them were held in Spain (26), followed by Italy (11) and Greece (5). The other countries of the Mediterranean region in which RS-related studies were conducted are Portugal* (3), Tunisia (3), Morocco (3), and Turkey (1). Chile (3) and Argentina (1) are the only two countries outside the Mediterranean region that held RS-related studies in olive cultivation without being in the Mediterranean region (Figure 2). These findings are in accordance with Fraga et al. [2], who refer to the long history of olive production in the Mediterranean basin, in which most of the olive producing countries are found. Additionally, the existence of studies in the southern hemisphere confirms the continuous growth of olive production globally. Specifically, Torres et al. [99] refer to the expansion of olive cultivation to other areas beyond the Mediterranean region such as Argentina, Chile, Perú, and Australia to cover the increasing global demand for olive products (oil and table olives). Thereafter, future studies are expected to cover more countries.

3.4. Use of Sensors in Olive Cultivation

According to the analysis of the results, most of the studies (42%) used multispectral sensors in olive cultivation, with thermal sensors ranking second (23%). Hyperspectral sensors were the third most popular sensor type, being used in 13 % of the total number of studies. Regarding the other sensor types, RGB was used in 11% of the research studies, while LIDAR, RADAR, and EMI were the least used sensor types (5%, 5%, and 1% of the total research studies, respectively). The temporal analysis of sensors' use shows that multispectral sensors were not present in research studies for only two years (2007 and 2018), while thermal sensors were not present for four years (2015, 2014, 2012, 2011 and 2010). The rest of the sensors were not as frequently present in

* While not having a coastline in the Mediterranean, Portugal is often included in the list of Mediterranean countries due to its climate and flora common/specific for with the Mediterranean countries.

Table 3
Classification of research studies per country, research type, agronomic focus area, platform type and sensor type.

Research Study	Country	Research Type	Agronomic Focus Area	Platform Type	Sensor Type
[41]	Spain	Method	• Irrigation	• Satellite	• Multispectral • Thermal
[42]	Greece	System	• Diseases • Row/Tree identification • Vigor	• UAV	• Multispectral
[43]	Spain	Survey	• Vigor • Fertilization	• UAV	• Multispectral
[44]	Tunisia	Method	• Irrigation	• Satellite	• Multispectral • Thermal
[45]	Spain	Survey	• Structural Parameters	• UAV	• RGB
[46]	Portugal	Survey	• Vigor • Fertilization	• UAV	• Multispectral
[47]	Italy	Method	• Row/Tree identification	• Satellite • Manned Flight Measurements	• Multispectral
[48]	Portugal	Survey	• Variety/Phenology	• Manned Ground Measurements	• Hyperspectral
[49]	Italy	Survey	• Diseases	• Satellite • Manned Flight	• Multispectral • Hyperspectral
[50]	Greece	Survey	• Vigor	• Satellite	• Multispectral
[51]	Spain	Method	• Vigor • Structural Parameters • Row/Tree identification	• UAV	• RGB • Multispectral
[52]	Portugal	Survey	• Vigor • Irrigation	• UAV	• Thermal
[53]	Italy	Method	• Vigor • Row/Tree identification	• UAV	• Multispectral
[54]	Italy	Method	• Vigor • Row/Tree identification • Diseases	• UAV	• RGB • Multispectral
[55]	Spain	Survey	• Irrigation	• UAV	• RGB • Hyperspectral
[56]	Spain	Method	• Row/Tree identification	• UAV	• Multispectral
[57]	Greece	Method	• Yield • Vigor	• UAV	• Multispectral
[58]	Turkey	Method	• Variety/Phenology	• Satellite	• Multispectral • RADAR
[59]	Italy	Survey	• Variety/Phenology	• UAV	• Multispectral
[60]	Spain	Method	• Structural Parameters • Row/Tree identification	• UAV	• RGB
[61]	Spain	Survey	• Irrigation • Vigor	• UAV	• Multispectral
[62]	Greece	Survey	• Vigor • Diseases	• Satellite	• Multispectral
[63]	Italy	System	• Diseases • Vigor • Structural Parameters	• UGV	• RGB • Multispectral • Hyperspectral • Thermal • LIDAR
[64]	Spain	Method	• Row/Tree identification	• UAV	• RGB
[65]	Italy	Method	• Vigor • Row/Tree identification	• Satellite	• RGB
[66]	Italy	Method	• Management Zones • Soil Parameters	• Manned Ground Measurements	• RADAR • EMI
[67]	Spain	Method	• Vigor	• UAV	• Thermal
[68]	Italy	Survey	• Vigor • Row/Tree identification • Diseases	• Manned Flight Measurements	• Hyperspectral • Thermal
[69]	Spain	Survey	• Vigor • Irrigation	• UAV	• Thermal
[70]	Chile	Survey	• Vigor • Irrigation	• UAV	• Multispectral • Thermal
[71]	Spain	Method	• Vigor • Irrigation	• Satellite • Manned Flight	• Thermal
[72]	Italy	Method	• Vigor • Irrigation	• Satellite	• Multispectral
[73]	Greece	Survey	• Vigor • Diseases	• UAV • Satellite	• Multispectral
[74]	Chile	System	• Irrigation	• Satellite	• Thermal
[75]	Chile	Survey	• Vigor • Irrigation	• UAV	• Multispectral • Thermal
[76]	Spain	Survey	• Vigor • Variety/Phenology • Row/Tree identification • Structural Parameters	• UAV	• Multispectral
[77]	Spain	Survey	• Biomass	• Manned Flight Measurements	• LIDAR

(continued on next page)

Table 3 (*continued*)

Research Study	Country	Research Type	Agronomic Focus Area	Platform Type	Sensor Type
[78]	Tunisia	Method	• Structural Parameters • Vigor • Irrigation	• Satellite	• Multispectral
[79]	Spain	Method	• Soil Parameters	• UAV	• Multispectral
[80]	Spain	Survey	• Vigor • Diseases	• UAV	• Multispectral • Hyperspectral • Thermal
[81]	Spain	Method	• Vigor • Irrigation	• Satellite	• Multispectral
[82]	Spain	Method	• Planting	• Manned Flight Measurements	• Multispectral
[83]	Tunisia	Method	• Row/Tree identification • Soil Parameters	• Satellite	• Multispectral • RADAR
[84]	Argentina	System	• Planting • Row/Tree identification	• UGV	• RGB • LIDAR
[85]	Spain	Survey	• Structural Parameters • Row/Tree identification • Vigor	• Satellite • Manned Flight Measurements	• Multispectral • Hyperspectral
[86]	Spain	Method	• Soil Parameters • Structural Parameters	• Satellite • Manned Ground Measurements	• RGB • RADAR
[87]	Spain	Method	• Structural Parameters	• Manned Ground Measurements	• LIDAR
[88]	Spain	Survey	• Variety/Phenology • Vigor	• Manned Ground Measurements	• Multispectral
[89]	Spain	Survey	• Row/Tree identification • Vigor • Irrigation	• UAV • Manned Ground Measurements	• Multispectral • Hyperspectral • Thermal
[90]	Morocco	Survey	• Vigor • Irrigation	• Satellite	• Multispectral
[91]	Morocco	Method	• Irrigation	• Satellite	• Thermal
[92]	Spain	System	• Management Zones • Yield • Vigor • Structural Parameters • Planting	• Satellite • Manned Flight Measurements	• Multispectral
[93]	Morocco	Method	• Irrigation	• Satellite	• Thermal
[94]	Spain	Survey	• Irrigation	• Manned Ground Measurements • Manned Flight Measurements	• Thermal
[95]	Italy	Survey	• Structural Parameters • Vigor • Irrigation	• Satellite • Manned Flight Measurements	• Multispectral • Hyperspectral • Thermal
[96]	Spain	Method	• Vigor • Irrigation • Row/Tree identification	• Manned Flight Measurements	• Hyperspectral • Thermal

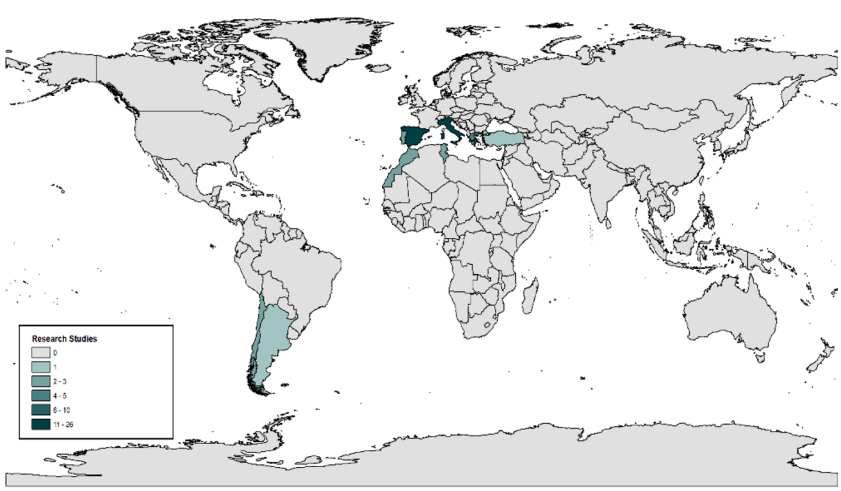

Figure 2. Geographical distribution of research studies on RS technologies in olive cultivation.

research studies as the aforementioned, with the EMI sensor type having the least presence (Figure 3).

In detail, while both multispectral and hyperspectral sensors can provide the same type of information, in terms of reflectance, through the calculation of spectral vegetation indices their main difference is the number of bands they use. Multispectral sensors have a limited number of bands, and therefore they produce a limited number of spectral vegetation indices. On the contrary, hyperspectral sensors collect data from hundreds of bands of the electromagnetic spectrum and, consequently, can produce a larger number of spectral vegetation indices and even produce a spectral signature of an object. Because of the aforementioned, hyperspectral sensing has a high demand for data processing

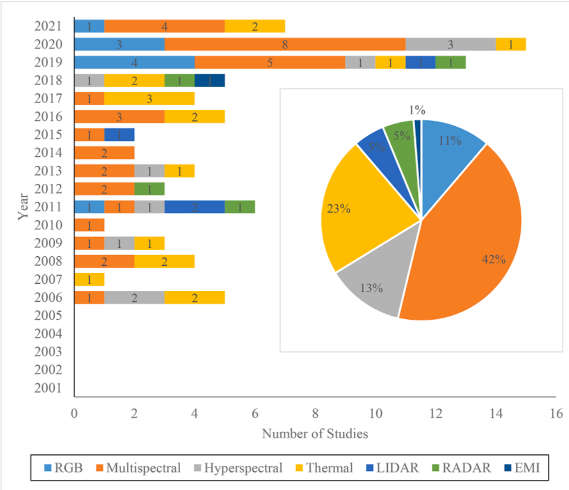

Figure 3. Use of sensors in olive cultivation per type and year.

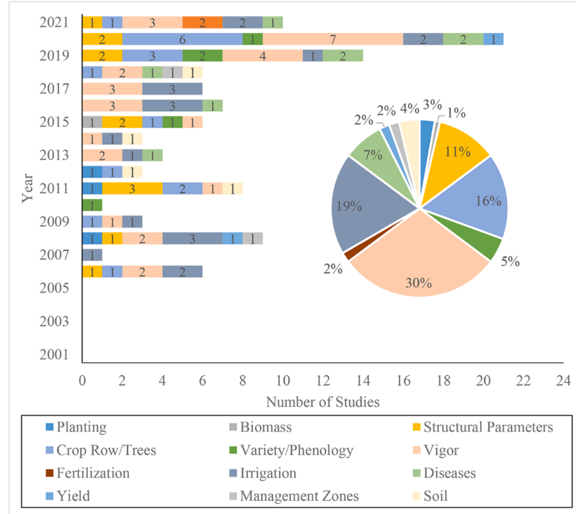

Figure 4. Agronomic focus areas of RS studies in olive cultivation per type and year.

resources, which has been identified as a major barrier to its adoption in agricultural studies when compared to multispectral sensing [100]. Regarding thermal sensing, it measures object emissivity instead of reflectance, as multispectral and hyperspectral sensing do. Based on this, thermal sensing is used to assess structural components of leaves (e.g., cell wall) and leaf water content, which occur in the thermal infrared domains and indirectly provide information related to irrigation, disease and pest infestation, yield and other factors [101]. Thus, the use of thermal sensors can provide additional information to the researchers, and in this way, the high adoption rate of this sensor type is justified on RS related studies in olive cultivation, since water and crop diseases are limited factors in olive yield. The limited use of the rest of the sensors (RGB, RADAR, LIDAR, and EMI) can be explained by the limited information that they offer compared to the multispectral, thermal, and hyperspectral sensors. Specifically, RGB sensors lack the ability to provide adequate information on crop vigor because plant leaf components (e.g. chlorophyll and carotenoid) typically display higher reflectance and transmittance in other spectra [102]. RADAR sensing is a challenging process in which scattering mechanisms should be considered for retrieving accurate information such as volumetric water content and crop growth monitoring when compared to other types of RS sensors [103]. Accordingly, LIDAR can only provide information related to geometric characteristics of crops (e.g., height, volume) by measuring distance and indirectly assessing crop vigor, water and nutrient needs [104]. Regarding EMI sensors, they are used for measuring important soil parameters such as apparent soil electrical conductivity, which is correlated to soil properties (soil water content, silt percentage, cation exchange capacity) that affect crop growth [105].

It is worth mentioning that more than one type of RS sensor was used in 19 research studies (34%), indicating the importance of multisensory research in olive cultivation for addressing the drawbacks from the use of only one sensor mentioned above.

3.5. Agronomic Focus Areas of RS related research in Olive Cultivation

As it is presented in Figure 4, olive vigor assessment is the most frequent agronomic focus area that is monitored with the use of RS technologies (30%). Vigor assessment is followed by irrigation (19%), Crop Row/Tree identification (16%), and structural parameter monitoring (11%). The remaining agronomic focus areas, namely diseases (7%), variety/phenology (5%), soil (4%), planting (3%), yield (2%), fertilization (2%), biomass (2%) and management zones (1%) definition, have been conducted in 26% of the total number of studies. Vigor related studies are present in all but three years (2007, 2010 and 2012), while irrigation-related studies were not published in the years 2010, 2011, 2012, and 2018. Accordingly, the least published agronomic focus area is related to management zones (published only in 2018).

It is worth mentioning that RS research studies have covered most of the farming practices that occur in an olive grove. Only spraying, pruning, and weeding have not yet been covered, as well as pest and weed detection studies in RS related olive research. Also, the aforementioned findings indicate the high correlation of vigor assessment with important parameters of olive, such as yield, structural parameters, nutrient and water consumption, and crop diseases [106–109]. Furthermore, crop row/tree identification is an important agronomic focus area due to the various planting systems in which olives are being cultivated and, as a result, have different needs in crop inputs in order to be more productive [110].

3.6. Use of Platforms in Olive Cultivation

UAVs (43%) and satellites (39%) represented the largest and second largest groups of platforms employed in RS-related studies in olive farming, respectively. The manned flight measurements (20%) were the third-largest group, while the manned ground measurements were the fourth-largest group (13%). UGV studies accounted for the least percentage of platform-related research publications (4%). Except for 2010, all studies used aerial (UAV or manned flight measurements) or satellite RS (Figure 5).

Based on the above mentioned results, it is obvious that the UAV is the most well-known platform in RS related olive crop research, with satellites set second. Numerous scientists have shown the advantages of UAV, which are the quick area scanning and the very high resolution of collected data when compared with different platforms. Satellites have the main benefit of covering large areas and being able to collect data at high revisit times, albeit sometimes the presence of clouds can influence the quality of the collected information [111]. One more benefit of satellites is the wealth of unreservedly accessible information from public and worldwide missions (for example Copernicus and Landsat satellite missions [112,113]) that allows observation of olive plantations in high temporal resolution. Subsequently, there is a drop in the utilization of monitored trips in olive research studies because of the great danger and cost of study. Manned ground measurements (by foot or vehicle) comprise the third largest sort of platform utilized in olive crop studies related to RS. This is justified by the very high resolution data that these sorts of platforms are capable of collecting when contrasted with aerial and satellite platforms [114]. In any case, this is an exceptionally time consuming and tedious way of covering large agricultural

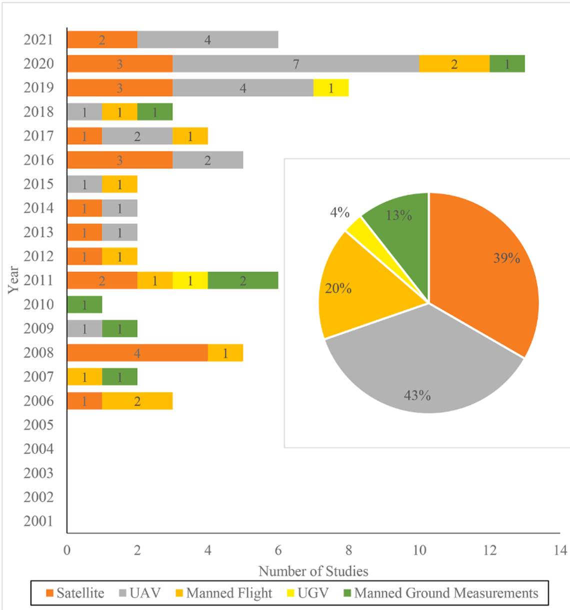

Figure 5. Use of platforms in olive cultivation per type and year.

areas. For manned ground measurements, the utilization of UGVs has recently started to receive more attention, in spite of the fact that there is a need to tackle a few issues, for example, restricted run time (e.g. of electric UGVs) and the availability of various vehicle types [115].

3.7. Type of RS related studies in Olive Cultivation

According to the findings, RS technologies are most commonly used in methodological research publications (51%). Field surveys were the second largest group of RS-related studies (45%), and RS was employed in this context to examine nondestructively olive vigor, diseases, irrigation, structural factors, and biomass. Finally, RS studies that presented the creation of systems and/or subsystems for non-destructive measures in olive cultivation accounted forthe smallest number of research papers, accounting for only 9% of all research articles (Figure 6). The increased number of methods can be justified by the advances in data science, which allowed the introduction of new data processing methods (e.g. artificial intelligence, machine learning, data fusion, geostatistics) for various data formats [116–119]. Accordingly, system related studies began to emerge due to advancements in electronics science in the agricultural domain that led to the introduction of new sensors and systems such as robotics and sensors for non-destructive estimation of key parameters [39,100,120–122].

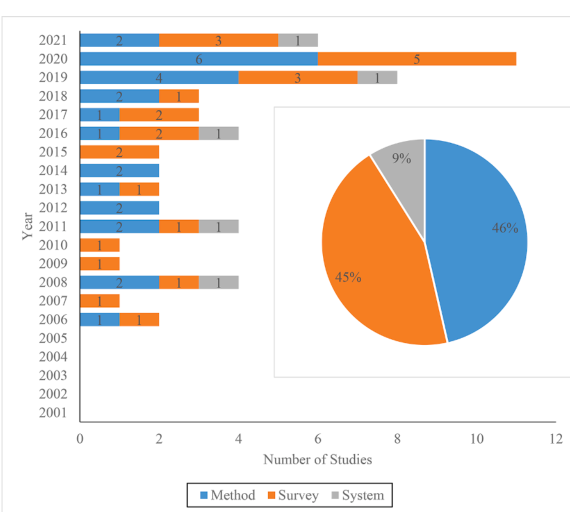

Figure 6. RS studies in olive cultivation per type and year.

3.8. Sensors per agronomic focus area in RS studies in olive cultivation

In Figure 7, the correspondence analysis between the sensors and the agronomic focus areas is presented. The two dimensions of the analysis contribute to more than 77% of the variance, indicating that a small portion of the insights are missing from the two-dimensional plot. Regarding the agronomic focus areas, there is similarity among the sensors (RGB, multispectral, hyperspectral, and thermal sensors) used in structural parameters, crop row/tree identification, vigor, variety/phenology fertilization, irrigation, disease detection, and yield estimation. The similarity between RGB, multispectral, and hyperspectral sensors can be explained by the fact that the abovementioned sensors share the same principle. Specifically, they measure reflectance at different bands of the electromagnetic spectrum, which is then processed into spectral vegetation indices that are highly correlated to valuable crop related parameters (e.g., leaf area index, chlorophyll content, etc.) and indirectly to nutrient and water consumption, pests and diseases, and yield [100]. Accordingly, thermal sensors have been used to measure the thermal emissivity of plants, which is connected with vibrations of various compounds present in plant leaves that occur at molecular level and therefore help indirectly get information on irrigation, vigor, crop row/tree identification, crop diseases, and yield [101]. RADAR type sensors presented strong similarities for use in soil parameter assessment. This can be justified by the fact that these types of sensors can penetrate into soil and assess important parameters such as soil moisture and clay content [103,123]. The other sensor types did not show any similarity with the rest of the agronomic focus areas. The limited number of studies in which LIDAR and EMI were used, did not allow the strong similarity of these sensors with agronomic focus areas. This can be explained by the constraints that the use of this type of sensor exhibits, such as complicated data processing, limited value of information, and increased time for data collection (for EMI sensors), when compared to the other sensor types [124].

3.9. Platforms per agronomic focus area in RS studies in olive cultivation

In Figure 8, the correspondence analysis among the platforms and the agronomic focus areas is presented. The two dimensions of the analysis contribute to more than 78% of the variance, suggesting that only a small portion of the insights are missing from the two-dimensional plot. In detail, there is similarity between structural

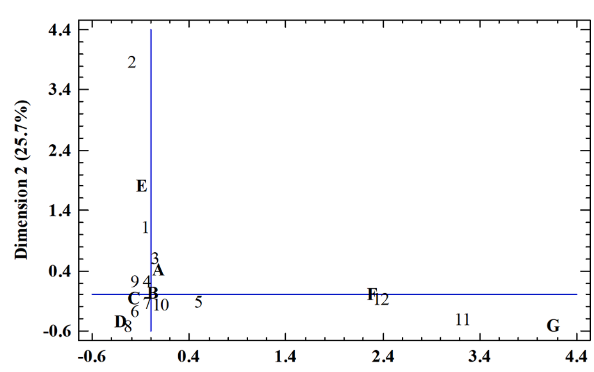

Figure 7. Correspondence plot between sensors and agronomic focus areas of olive crop. (where 1: Planting; 2: Biomass; 3: Structural Parameters; 4: Crop Row/Trees identification; 5: Variety/Phenology; 6: Vigor; 7: Fertilization; 8: Irrigation; 9: Disease Detection; 10: Yield Estimation; 11: Management Zones Delineation; 12: Soil Parameters; A: RGB; B: Multispectral; C: Hyperspectral; D: Thermal; E: LIDAR; F: RADAR; G: EMI)

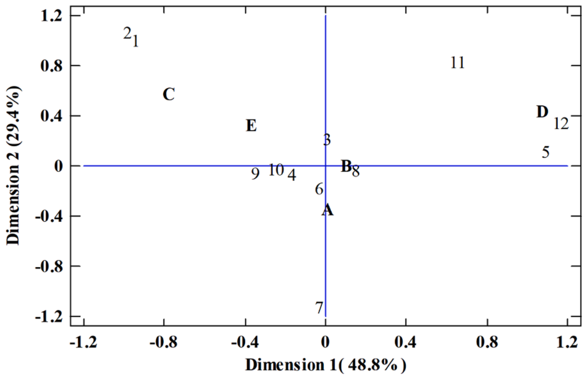

Figure 8. Correspondence plot between platforms and agronomic focus areas of olive crop. (where 1: Planting; 2: Biomass; 3: Structural Parameters; 4: Crop Row/Trees identification; 5: Variety/Phenology; 6: Crop Status; 7: Fertilization; 8: Irrigation; 9: Disease Detection; 10: Yield Estimation; 11: Management Zones Delineation; 12: Soil Parameters; A: UAV; B: Satellite; C: UGV; D: Manned Ground Measurements; E: Manned Flight Measurements)

parameters, crop row/tree identification, crop status, irrigation, disease detection, and yield estimation, with UAV, satellite, and manned flight measurements. The aforementioned finding indicates the need for covering continuous areas in order to obtain reliable data for assessment of the related agronomic focus areas in olive crops since the use of sparse data points through interpolation methods may present unreliable results due to no error assessment, unclear physical meaning of trends, subjective delineation of areas and classes, and high expertise in data processing in geostatistics [125]. Accordingly, manned ground measurements presented similarity with variety/phenology and soil parameter focus areas. Similarity with variety/phenology can be explained by the need for very high resolution sparse data due to unhomogenized crop parameters [125], while similarity with soil parameters can be explained by the use of certain sensors (e.g. EMI or ground penetration radar) which perform measurements with high proximity to the soil [105,123]. Finally, UGV did not present significant similarity with agronomic focus areas due to the limited number of research studies in which this platform was used. This platform is expected to be widely used in future studies in olive cultivation when problems such as limited run time in the case of electric UGVs and the availability of a variety of vehicle types will be solved [115].

4. Conclusion

RS technologies have been used in olive cultivation research studies for the past 16 years. Technological developments, as well as new regulations and initiatives, made it possible for this type of equipment to be quickly adopted in olive cultivation-related studies. This will lead to even wider use of RS in olive cultivation in the coming years by olive stakeholders.

Because of the advantages they bring to researchers, UAVs and satellites are the most commonly used platforms in olive research. This means that most studies must cover a broad area in a short amount of time in order to provide reliable and accurate data. Ground measurements are likely to be carried out due to the advantages of very high resolution, which allows for more precise data as well as ground validation of data gathered from aerial or satellite platforms. As a result, due to the benefits that UGVs provide, such as automated field surveys, the usage of UGVs in field research is projected to rise in the coming years. Furthermore, the employment of swarms of UAVs and UGVs in future olive-related studies is likely to be researched further in order to capture more data in less time.

In olive studies, multispectral sensors were the most commonly utilized type of sensor. Other types of cameras (e.g., RGB, hyperspectral, and thermal) are widely used, indicating that this data can be easily interpreted by researchers as compared to other sorts of sensors, and hence is preferred. Proximal canopy sensors are crucial because they provide very high spatial resolution ground data. Other sensors that have already been introduced (e.g., RADAR, EMI) in a limited number of research studies will be further investigated to determine the benefits that they may provide not only in research but also in the market as well.

Vigor assessment of olive cultivation is of high importance because it provides the appropriate information for taking decisions and optimizing application of all farm practices and, for this reason, was the most frequent agronomic focus area. Studies related to olive operations are expected to expand and cover missing agronomic focus areas such as spraying application, pruning, and detection of pests. Specifically, future RS-related olive studies are expected to study further precision application of farm inputs through the coupled use of RS technology and variable rate equipment under different settings (e.g. through prescription maps and an “on-the-go” approach). Furthermore, important focus will be given to the processing of data from various sensors to provide more accurate insights. Technologies such as AI and data fusion are expected to act as catalysts for this reason.

Author Contributions

EA: Conceptualization, Methodology, Investigation, Data analysis, Visualization, Writing – original draft preparation; **AB:** Methodology, Investigation, Supervision, Writing – review and editing; **SF:** Supervision, Conceptualization, Methodology, Writing – review and editing.

Data availability Not included, available upon request.

Conflicts of Interest

The authors declare no conflict of interest.

Informed Consent

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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