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Reviews

REVIEW OF THE APPLICATIONS OF SATELLITE REMOTE SENSING IN ORGANIC FARMING – PART II

Milen Chanev, Lachezar Filchev

Space Research and Technology Institute – Bulgarian Academy of Sciences
e-mail: mchanev@space.bas.bg, lachezarhf@space.bas.bg

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Abstract

The use of remote sensing methods for monitoring, managing, and decision support in agriculture is increasingly intensifying. With the advancement of technologies, they become more accessible, while the quality and security of the obtained data are improving. Striving to improve the quality of the environment and its preservation, expanding the areas occupied by organic farming will allow us to achieve these goals. At the same time, this type of agriculture provides healthy and safe food. For this reason, it is of great importance to start applying satellite data in organic farming as quickly as possible. In Part II of the "Review of the applications of satellite remote sensing in organic farming," we examine the various areas of satellite data application in organic farming. Five different areas of satellite data application in organic farming have been identified, including satellite remote sensing monitoring of weeds, remote sensing of crop stress and irrigation needs, yield forecasting using remote sensing methods and remote sensing monitoring of plant nutrition. From the review conducted, we found that satellite data can significantly support and facilitate the transition to organic farming, adequate fertilization, application in phytosanitary monitoring of crops, and assessment of crop stress.

Introduction

In the first part of the "Review of the applications of satellite remote sensing in organic farming," published in issue 35, we examined the main applications of remote methods, the use of satellite data, and the potential of unmanned aerial vehicles (UAVs) platforms in agriculture, and their possible application in organic farming. We analyzed publications on the topic published in specialized databases. Our analysis revealed that the top 25 most cited publications, indexed in CrossRef and parsed by the Scite_ platform (https://scite.ai accessed on 06.02.2024), were published by Elsevier, followed by AAAS, Wiley, and MDPI. Further analysis of the literature on the issue showed that the most cited publications are from the years 2010, 2011, and 2013, indicating that the interest in satellite data applications in organic farming is relatively recent, dating back approximately 14 years. We also conducted an analysis using the open web tool WordItOut (https://worditout.com accessed on 06.02.2024). The word cloud mapped 141 words out of 301 unique words. Other commonly occurring words include "image," "plant," "vision," "resolution," "spectral," "surface," and "grain," which more or less reveal the main objectives of the studies in question.

Materials and methods

This study provides an overview and a comprehensive analysis of articles, reports and materials published on the Internet in the following scientific database Scopus, ResearchGate, and Google Scholar. A combination of keywords with logical queries was used when searching the scientific and specialized database for the period from the beginning of space remote sensing from the late 1980s to 2021. The main keywords that we used are: "organic farming" AND "remote sensing", "organic farming" AND "satellite data". The results obtained were categorized into five application categories of satellite data in organic farming. The separated application categories are: satellite remote sensing monitoring of weeds, remote sensing of crops stress and the need for irrigation, forecasting of yields using remote sensing methods and remote sensing monitoring of plant nutrition.

Results and discussion

Satellite remote sensing monitoring of weeds

Weed control on organic farms is one of the main problems facing organic farming. With the help of remote sensing monitoring systems, the problems caused by weeds, can be overcome. This can be achieved both by integrating drones carrying different sensors and with satellite images that include hyperspectral, multispectral, and RGB in combination with artificial intelligence guaranteeing the possibility of a better result in weed management [1].

Information on the distribution of weeds in the field is necessary for the compilation of an assessment map of crops to determine the achievement of their biological threshold of harmfulness. Perez et al. (2000) [2] propose two approaches to automatic weed monitoring:

- Rough identification of weeds in the observed areas by remote sensing.
- Fine identification using proximal methods, such as video imaging and image analysis, should confirm the location and allow the most appropriate local treatment of the crop to be selected.

A review of the potential of remote sensing techniques for crop protection suggests that one way to differentiate between weeds and crops is by studying temporal patterns of plant indices during the growing season [2, 3]. In addition, using remote sensing methods, only a few species of weeds in different phenophases can usually be distinguished. The spectral characteristics of weeds should be taken from populations in groups of weeds identified shortly before the detection process, as characteristics are highly variable and depend on the phenophase of weeds or weed associations [2, 4]. Two approaches are usually used for automatic weed monitoring. One is to establish geometric differences in leaf litter between crops and weeds [5–10]. The second approach is based on differences in spectral reflectivity. It is possible to look for differences in the location of the crop and the weeds in the crop [2, 11]. Guyer [5] explored the possibility of using leaf shape for plant identification. The team led by Franz [12] used local spectral characteristics of plant leaves to distinguish different weeds. Zhang and Chaisattapagon (1995) [13] use machine vision to identify weeds in wheat fields. They apply three approaches to distinguish them from cultivated plants: color analysis, shape analysis, and texture analysis. In the laboratory, they use black-and-white digital images with various color filters. They found that red and green filters were effective in detecting reddish stems in some weeds. Leaf-blade parameters are effective for distinguishing deciduous weeds from cereal leaves. Another way to differentiate between young crops and weeds is by analyzing the spectral reflectivity using specific wavelengths in the range of 200 to 2000 nm [14, 15]. We can say that the opportunities offered by RS are extremely important for weed management in organic farms, as the use of herbicides is prohibited there.

Remote sensing of crops' stress and the need for irrigation

The RS provides a good opportunity to assess stress, and these methods are also used to calculate different vegetation indices that serve to estimate different crop parameters [16-18]. Remote sensing methods in agriculture can be a powerful technique for visualizing, diagnosing, and quantifying the crop response to stress caused by abiotic, biotic factors, or improper management decisions. In most cases, stress leads to deviations in the pigmentation of plants, and this can be used to diagnose stress in crops using RS methods [19, 20]. The main problem facing both conventional and organic farming is the quantification of crop water consumption and the water stress they experience. The use of satellite-based images and the computational processing of satellite images is an opportunity to manage water stress on crops in organic farming [21, 22]. Sharma [23] propose that the problem of irrigation in organic farms be managed using RS and data processing using Support Vector Machine (SVM). Data is stored in computer software sent to SVM to determine the status of crops on organic farms. The information is sent to the user interface, where the farmer receives farm information using Google's mobile communication module. This method of image processing allows farmers to take preventive action to save crops. Solaiman and Salaheen [22] note that there has been an increase in interest in the use of satellite and RS for organic farming, with the main goal being to establish the health status of farms. Vroege [24] proposed that RS technologies be used to compile drought risk assessment maps based on satellite soil moisture data. These cards are used to limit financial risk for farmers affected by drought.

Forecasting of yields using remote sensing methods

Crop production is perhaps the most important information for crop management in precision agriculture. A big problem is that yield data are obtained after the season, while problems such as nutrient deficiencies, water stress or pest infestation must be managed during the growing season. Images from satellites or UAVs obtained during the growing season have the potential not only for post-season management but also for in-season management. In addition, yield maps composed of images obtained by DM can be used as an alternative when data from the yield monitor are not available [19, 25]. Because yield does not affect the reflectivity of the crop, it is derived indirectly from other biophysical parameters of the crop [25, 26]. It was ultimately found that this relationship can only be explained implicitly by biophysical and biochemical characteristics, despite the fact that it may suggest that determination of cereal yield directly from reflection spectra is statistically feasible [26–30]. From RS data, chlorophyll content (CHL) and leaf area index (LAI) may be accurately determined and linked to yield [26, 31-33]. In addition, soil mineral nitrogen naturally has a strong effect on plant development and thus on chlorophyll production and leaf area, so these parameters can be considered as indicators of nitrogen uptake in plants [34]. LAI is one of the most important parameters for describing plant conditions in agriculture. It can be used, for example, to obtain information on biomass, nutrient supply, growth stage, and yield assessment [35]. Many studies have been done on how LAI can be assessed using hyperspectral data from remote sensing [26]. According to [26], LAI and CHL forecasts from UAV-based hyperspectral data for yield forecasting are promising.

Remote sensing monitoring of plant nutrition

Efficient food production requires a balance between minimizing environmental damage and maximizing yields [36]. From the point of view of the agricultural producer, the most important economic parameter is the achieved yields. Generous application of nitrogen fertilizers, within the legal limits, leads to higher costs without added value in terms of additional yield. In addition, new concepts for monitoring these effects during vegetative growth allow the development of precision farming applications specifically designed for efficient N fertilization [37]. RS will support decision-making regarding plant nutrition in organic farming. By collecting and analyzing data, formulating specific management recommendations, and implementing management practices to correct factors that limit crop growth, productivity, and quality [37-41]. Sozzi [42] found that it is most cost-effective to use the vegetation index NDVI generated from satellite images with medium-resolution satellite data with good optical properties and high-resolution satellites with lower optical quality to determine the needs of H fertilization in the fields. Remote sensing methods in combination with GIS and using different vegetation indices such as NDVI make it possible to map different fertilization rates in the field [37, 43].

Conclusions

In conclusion, it should be said that remote sensing methods can greatly support and facilitate the transition to organic farming. RS can adequately manage fertilization in organic farming. RS can serve to timely signal the phytosanitary state and to assess crop stress on organic farms and in weed management. Using the capabilities of RS organic farmers can forecast yields, which helps them to better plan their costs and profits and thus increase the sustainability of their organic farm. With the help of RS, biodiversity in agriculture can be monitored. They provide a very good opportunity to remotely distinguish biological fields from conventional fields, which can serve state organizations and certification bodies to control organic farmers to comply with the rules and norms of organic farming.

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Conflicts of interest

The authors reported no potential conflicts of interest.

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ПРИЛОЖЕНИЕ НА СПЪТНИЦИТЕ В БИОЛОГИЧНОТО ЗЕМЕДЕЛИЕ (Част II)

М. Чанев, Л. Филчев

Резюме

Употребата на дистанционни методи за мониторинг, управление и подпомагане на вземането на решения в земеделието се засилва все повече. С развитието на технологиите те стават все по-достъпни, като същевременно се подобрява качеството и сигурността на получените данни. Стремейки се към подобряване на качеството на околната среда и нейното опазване разширяването на заетите площи с органично земеделие ще ни позволи да постигнем тези цел. Същевременно с това този тип земеделие предоставя здравословни и

безопасни храни. Именно поради тази причина е от голямо значение максимално бързо да се започне с прилагане на сателитни данни при органичното земеделие. В част II на „Review of the applications of satellite remote sensing in organic farming“ разглеждаме различните области на приложение на сателитните данни в органичното земеделие. Отделени са пет различни области на приложение на сателитните данни в органичното земеделие, които са: сателитен мониторинг на плевелите, дистанционно наблюдение на стреса на културите и необходимостта от напояване, прогнозиране на добивите с помощта на дистанционни методи, дистанционен мониторинг на храненето на растенията. От направения преглед установихме, че сателитните данни могат значително да подпомогнат и улеснят прехода към биологично земеделие, да се извършва адекватно торене, намира приложение при фитосанитарния мониторинг на посевите и оценка на стреса, който изпитват културите.