Sunflower Crop Rotation's Biophysical Impact on Agricultural Fields

Subjects: Environmental Sciences
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Crop rotation is an important determining factor of crop productivity. Sustainable agriculture requires correct rules of crop rotation. Failure to comply with these rules can lead to deterioration of soil biochemical characteristics and land degradation.

Keywords: sustainable agriculture ; vegetation indices ; sunflower monocropping

1. Introduction

Crop rotation is a necessary practice for sustainable food production. In many countries, crop rotation rules are regulated at the state level. This is especially important now, when Europe is moving toward the implementation of Green Deal practices to mitigate anthropogenic influences on climate change. The main task of agricultural management is to preserve the original composition and productivity of soils. The physical and chemical parameters of soils directly affect the condition of plants [1]. At the same time, noncompliance with recognized positive agricultural practices leads to the deterioration of soil fertility and soil quality due to the imbalance of nutrients and the disappearance of beneficial microflora in soils and the biodiversity that supports important processes in soils.

2. Crop Rotation Violation Impact on the Agricultural Productivity

Crop rotation violation leads to a significant change in the carbon content of soils. Currently, studies of the impact of agricultural management and of changes in plant species on agricultural lands is focused on soil quality. Interesting research in this area was made by Zuber et al. in 2018 [1]—the scholars evaluate the effect of long-term crop rotation and tillage on the quantity of carbon and nitrogen stored in the soil organic matter. Itwas conducted for the state of Illinois in the United States on the basis of in situ measurements on the test sites. It shows that some crop rotation schemes, such as corn-soybean-wheat, can increase the soil organic carbon (SOC) stocks in the soil, whereas crop rotation schemes such as soybean-soybean-soybean reduce SOC and total nitrogen content. Another research project was done for the Anhui province, China [2]. The high accuracy of the estimation of organic carbon in the topsoil based on a combination of vegetation variables with crop rotation types. It showed the importance of crop rotation information and the effectiveness of its use to assess the change and state of organic carbon.

3. Land Degradation Monitoring with Use of Satellite Data

The main purpose of modern agricultural practices is to achieve high crop productivity with a neutral level of land degradation. The implementation of these practices would allow farmers to use the full potential of agrarian lands without harming the environment and thus to overcome hunger and to ensure food security in the future.

In practice, land productivity indicators can be assessed with remote sensing imagery. In this case, integrated approaches are used to take into account the carbon content in the soil, trends in vegetation indices, and changes in land cover. All these indicators are interrelated—land use changes lead to a significant change in the carbon content of soils. This methodology is used to assess the sustainable development goals (SDGs) indicator 15.3.1, "Proportion of land that is degraded over total land area" [3]. In this case, the maps of changes in land cover are used as a separate sub-indicator that reflects the positive, neutral, or negative human impact on the land surface and as a means to assess changes in carbon content in the soil. The biophysical parameters of land productivity can be obtained from satellite images. Land productivity indicators estimated by remote sensing vegetation indices (VIs) are generally accepted for mapping and assessing land degradation and desertification [4]. They are widely used for countries in Europe [5] as well as in Asia [6] and Africa [7]. Different combinations of vegetation indices, which are studied as time series, are used and reflect the dynamics of vegetation and its biophysical indicators. The most popular indicator is the normalized difference vegetation index (NDVI), which is used for land productivity mapping for indicator 15.3.1 and for supporting the calculation of indicator 2.4.1, "Proportion of agricultural area under productive and sustainable agriculture" in a 2020 study by Kussul et al. [8]. The most common collection of satellite NDVI for land productivity maps is the MODIS data collection (MOD13Q1-coll6). However, today's satellite data processing methods and available satellite missions provide information on land productivity from higher spatial resolution NDVI.

Another vegetation index, the enhanced vegetation index (EVI), is more sensitive in areas with dense vegetation. Similar to NDVI, it can be used to quantify vegetation greenness. In addition to VIs, biophysical variables could be extracted from satellite data, including the leaf area index (LAI) and the fraction of absorbed photosynthetically active radiation (FAPAR). LAI is extracted from satellite data using complex biophysical models and better conveys the biophysical characteristics of the plant [9]. This index describes the amount of biomass on the earth's surface and its condition, and it makes it possible to qualitatively assess the crop yield and deliver land productivity maps [10]. Another biophysical variable, FAPAR, makes it possible to assess photosynthesis in plants and the absorption of solar energy. This biophysical characteristic directly indicates the primary productivity of photosynthesis. One more interesting vegetation index is the land surface water index (LSWI), which is commonly used for drought monitoring and reflects the total amount of water in vegetation and its soil background. The response of LSWI to rainfall indicates the usability of this index for water state monitoring for agricultural crops, especially in the critical time of the crops' development stages in the early part of the season [11].

4. Crop Classification in Agricultural Monitoring

Most developed countries provide crop mapping based on satellite data on a regular basis or are working on the operationalization of crop mapping technologies. Accurate crop maps are in themselves a valuable product of data processing, and the availability of such products for one area for different years provides great opportunities for the qualitative analysis of land use practices. A good example of a large collection of historical crop maps is the United States' Cropland Data Layer, which has been making crop maps publicly available annually since 1997 [12]. The availability of long-term crop classification maps gives the possibility to get a better understanding of agricultural patterns for different territories and conduct very accurate forecasts. The research by Johnson D. et al. [13] shows that historical crop classification maps can be a valuable source of information for the pre-season or in-season crop classification. So, the pre-season crop classification map for the Corn Belt in the Unites States that was built with use of only previous classification maps can achieve 70% accuracy. In European countries that use the Land Parcel Identification System [14] as part of the Common Agriculture Policy, almost all crop information for agricultural parcels is provided by farmers; even in these cases, there is still a need to deliver such maps to analyze and validate the collected information. For this aim in Europe, there are systems that provide the automatic processing of satellite data and land cover and building of crop type maps, such as Sen-2-agri and Sen-4-CAP [15]. Thus, remote sensing data of the Copernicus program and machine learning land cover and crop type classification models are already having a lot of application in European Union for supporting CAP [16]. In 2021, the first European continental scale crop classification map based on Sentinel-1 data was published by the European Commission team [17]. The next steps will be the operationalization of continental scale crop classification technologies and the creation of crop maps for other years.

5. Sunflower Crop Rotation's Biophysical Impact on Agricultural Fields

The five-year monocropping model with the binary representation of sunflower planting confirms the negative effect of frequent planting of sunflowers. It shows the strong relationship between the number of years of sunflower plantings in the crop rotation and a decline in the vegetation indices. Additionally, it demonstrates that this effect is more significant for small intervals between sunflower plantings. This analysis also showed that planting sunflowers once per seven years according to the crop rotation rules in Ukraine is rational because of the high positive influence on the vegetation indices. However, starting from the sunflower planting interval equal to three years, the negative effect from sunflower planting is not observed. Thus, planting sunflowers once every four years would be infrequent enough to avoid negative consequences and land degradation. Analysis of crop rotations of all major crops over three years shows that different crop rotations with and without violations have different effects on sunflower productivity. All crop rotations with previously planted sunflowers had the highest negative effect on the vegetation indices. The worst crop rotation with the highest negative effect for most crop types and biophysical characteristics is crop rotation violations for sunflowers. In addition, there is a tendency to use more sustainable crop rotation schemes for long-term crop rotation strategy and common violations of rules and use of unsustainable crop rotations for the short-term strategies.

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