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Review

An Overview of Remote Sensing Data Applications in Peatland Research Based on Works from the Period 2010–2021

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Abstract: In the 21st century, remote sensing (RS) has become increasingly employed in many environmental studies. This paper constitutes an overview of works utilising RS methods in studies on peatlands and investigates publications from the period 2010–2021. Based on fifty-nine case studies from different climatic zones (from subarctic to subtropical), we can indicate an increase in the use of RS methods in peatland research during the last decade, which is likely a result of the greater availability of new remote sensing data sets (Sentinel 1 and 2; Landsat 8; SPOT 6 and 7) paired with the rapid development of open-source software (ESA SNAP; QGIS and SAGA GIS). In the studied works, satellite data analyses typically encompassed the following elements: land classification/identification of peatlands, changes in water conditions in peatlands, monitoring of peatland state, peatland vegetation mapping, Gross Primary Productivity (GPP), and the estimation of carbon resources in peatlands. The most frequently employed research methods, on the other hand, included: vegetation indices, soil moisture indices, water indices, supervised classification and machine learning. Remote sensing data combined with field research is deemed helpful for peatland monitoring and multi-proxy studies, and they may offer new perspectives on research at a regional level.

Keywords: Landsat; open-source GIS software; peatlands; remote sensing; Sentinel; SPOT

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1. Introduction

Joosten and Clarke (2002) [1] define peatland as an area with or without vegetation, featuring a naturally accumulated peat layer at the surface and peat as a sedentarily accumulated material consisting of at least 30% (dry mass) of dead organic material. In order to protect peatlands, it is necessary to identify their range and explore their hydrological and geological conditions, including carbon reserves. The quantity and quality of peatlands are not globally uniform. Their global reach is estimated to be between 1 and 4.6 million km^2 (0.7–3.0% of the world's total land), and estimations of peatland carbon reserves range from 113 to 612 billion tons [2,3]. Previous studies on the global surface of peatlands were based on Global Land Cover (GLC) databases [3,4]. Examples of widely used GLC datasets include ISLSCP II [5] MODIS500 [6] and UMD [7].

The research capacity for detecting and characterising peatland ecosystems, and monitoring their dynamics, is often hindered by limited access to the site, risk of disruption of sensitive habitats and species, and a high surface complexity due to varied topography, hydrological properties and vegetation [8–10]. Remote sensing (RS) offers the benefit of capturing extensive research areas featuring the same state of plant phenology or flooding and a greater repeatability of data collection compared to field studies [11–14]. Furthermore, the high spectral sensitivity of sensors enables the observation of detailed changes in the composition of the peatland surface. However, the overall practical utility of remote sensing-based peatland assessments depends on image interpretation and feature extraction accuracy; thus, achieving a high accuracy in peatland analyses may be challenging [2,14].

RS data can help create accurate peatland maps and identify regions with the highest risks, priorities and drivers of change. These works can also be used in climate models to assess the sensitivity and response to future climate change [2]. Therefore, peatland research and monitoring should be improved to provide better mapping and rapid assessment tools for supporting protection-oriented endeavours and multi-stakeholder engagement [15]. RS methods are increasingly indicated as useful in the analysis of individual elements of peatlands, e.g., biology and mapping of peatland vegetation [16–22], peatlands water conditions [23–26], and greenhouse gas (GHG) emissions [27–29].

In our work, we analyse publications illustrating the use of remote sensing methods in the study of peatlands. The analysis performed earlier by Dronova [14], whose study encompassed the period 2000–2014, indicated that, after 2010, there was a significant increase in the use of remote sensing methods regarding studies on wetlands. This paper constitutes an overview of studies that incorporated such methods in the analyses of peatlands in the years 2010–2021 (fifty-nine case studies from different climate zones in the World, Table S1). In the review, we aimed to investigate which RS methods were most prevalent in peatland studies and the external factors that may impact their application development. For the purposes of our study, we analysed the articles available in the Web of Science and Scopus databases for the period 2010–2021. All articles used were published in English and related to RS methods and peatland areas. The review focuses predominantly on peatlands and investigates the study aim, applied GIS methods, and the type of data and remote sensing platform used by the authors. As mentioned above, Dronova [14] studied the application of RS methods in wetlands research. However, we elected to focus on peatlands due to their importance for carbon storage in the environment.

2. Remote Sensing in Peatland Research

2.1. Temporal and Spatial Pattern of Using RS in Peatland Studies

The development of remote sensing methods and a greater accessibility, quantity and quality of remote sensing images made using these materials in the analyses of peatlands more common after 2000 [2,30]. Dronova (2015) [14], based on studied works from 2002 to 2015, pointed out that the application of an object-based image analysis (OBIA) used for wetlands study has increased significantly since 2010. Dronva concluded that OBIA could be employed in tasks ranging from the detection, classification and delineation of wetland bodies to comprehensive analyses of within-wetland cover types and their changes [14,31].

Similar to wetlands, the state and condition of peatlands depend on water resources (moisture); furthermore, this is related to an occurrence/succession of peat-forming plants. Both can be monitored using remote sensing tools [22,32].

Methods for obtaining data through remote sensing can be categorised as follows:

- Satellite remote sensing (long-range)—the detail level and data availability depend on the selected Earth observation system. In generally available systems, the spatial resolution varies between 10 and 100 m. Their cyclicality also distinguishes the most popular satellite remote sensing systems (Landsat and Sentinel) because every land area on the Earth's surface is monitored at regular intervals (3–16 days);
- Medium-range (Airborne) and close-range remote sensing (UAV— unmanned aerial vehicle, such as a drone). The intensive development and accessibility of unmanned aerial vehicles (UAV) allows for their widespread use in monitoring the natural environment. These images feature a very high spatial resolution (1–10 cm) and enable a high repeatability;

Due to the accessibility of data and the regularity of measurements, peatland research most often uses satellite images from passive multispectral remote sensing systems Landsat 5–8 and Sentinel-2 (Supplementary Material, Figure S1), and from the active (radar) remote sensing system Sentinel-1. There are two main approaches to assessing the condition of the peatland environment: evaluation of peatland vegetation and evaluation of surface water resources (moisture).

Detailed information related to the studied papers is provided in Supplementary Material, Table S1. The 59 studied works analysed peatlands located in different climatic regions (Table 1); however, many of the works (17) concerned subtropical and tropical peatlands. Our analysis shows a noticeable increase in the use of remote sensing methods in the study of peatlands approximately 1–2 years after the open data became available (Figure 1, Supplementary Material Table S1). The rapid increase in the use of this data occurred after 2016, i.e., two years after the launch of the Sentinel-1A system and one year after the launch of the Sentinel-2A system (a detailed description of remote sensing data development is provided in Supplementary Materials). The development of the use of GIS data and remote sensing data in research on peatlands was also influenced by the rapid development and availability of applications that allowed the use of these data, such as QGIS (formerly Quantum GIS) and SAGA GIS (intensive development since 2008) as well as the remote sensing data analysis application provided by the European Space Agency—SNAP (Sentinel Application Platform)—from 2014.

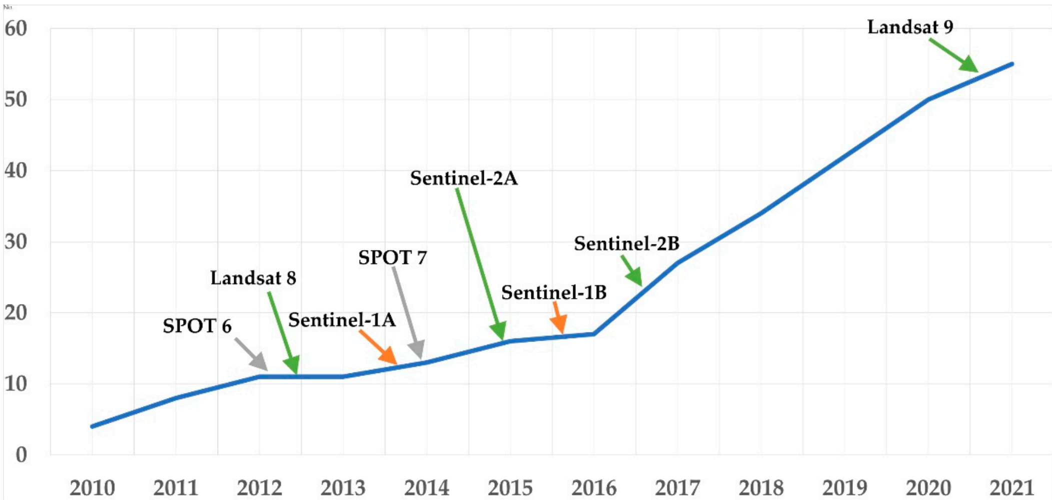

Figure 1. Cumulative number of reviewed studies during 2010–2021 and dates of launching selected satellite remote sensing systems (prepared based on works provided in Supplementary Material, Table S1).

Table 1. Geographic characteristics of reviewed studies (prepared based on works provided in the Supplementary Material, Table S2).

Climate Regions	Number of Studies	Locations	References
Subarctic, boreal	13	Sweden (1), Arctic circle (1), Canada (3), Finland (6), Alaska (USA) (1), others (1)	[17,21,22,25,28,29,31,33–38]
Cool temperature	10	Northern Hemisphere (2), Canada (7), Northern America and Scandinavia (1)	[20,24,27,39–45]
Oceanic temperate	12	Ireland (3), England (4), Wales (1), Argentina (1), Bolivia (2), Chile (1)	[23,26,46–55]
Temperate	7	Poland (2), Germany (2), Russia (2), France (1)	[18,56–61]
Subtropical, tropical	17	Florida (USA) (1), Indonesia (11), Malesia (4), Ghana (1), Ecuador (1)	[62–78]

It is also visible that the analysis of multispectral data prevails among the used methods (Figure 2). As many as forty-seven analysed articles employed data from multi- and hyperspectral analyses, and only seventeen publications made use of passive remote sensing data (Figure 2A). The largest part of the analysed studies used readily available data from the Landsat and Sentinel-2 systems and the SPOT, MODIS, and ASTER systems (Figure 2B). The intensive development and availability of data from UAVs was also reflected in more recent research on peatland areas [33,34,46].

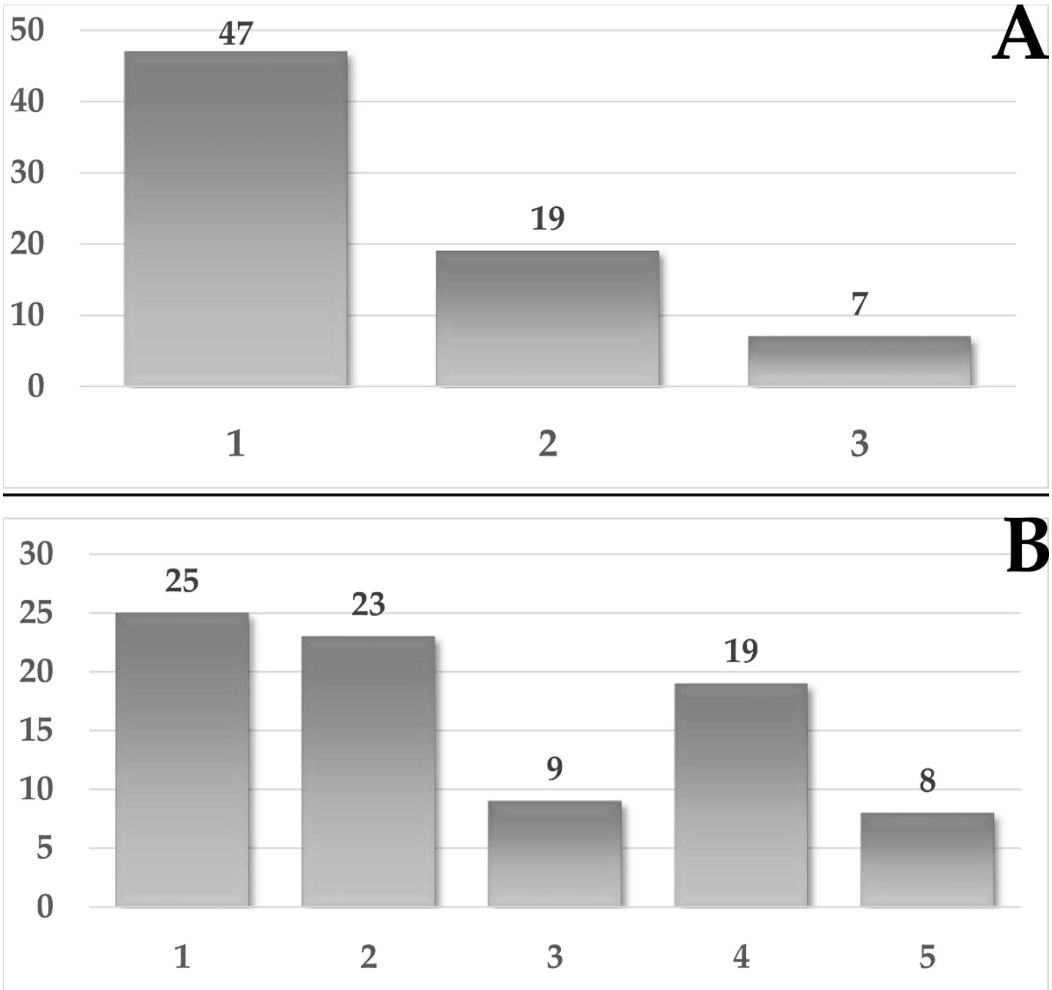

Figure 2. (**A**)—Type of remote sensing data: 1—Multispectral/hyperspectral, 2—Radar, 3—Both; (**B**)—Remote sensing platform: 1—Landsat (5–8)/Sentinel-2, 2—SPOT/MODIS/ASTER, 3—Other Multispectral/hyperspectral platforms, 4—Sentinel-1 and other radars, 5—Airborne and UAV data; (prepared based on works provided in Supplementary Material, Table S2).

2.2. RS Analytical Methods Used in Peatland Research

When analysing remote sensing research methods in peatland studies, the most common approaches include analyses related to area classification and complex methods of terrain cover analysis employing machine learning (Figure 3A). However, many studies tend to use popular vegetation indices and soil moisture indices. The use of these remote sensing analysis methods is correlated with major research topics, such as land classification/identification of peatlands, changes in water conditions, the monitoring of soil moisture in peatlands and peatland vegetation mapping (Figure 3B).

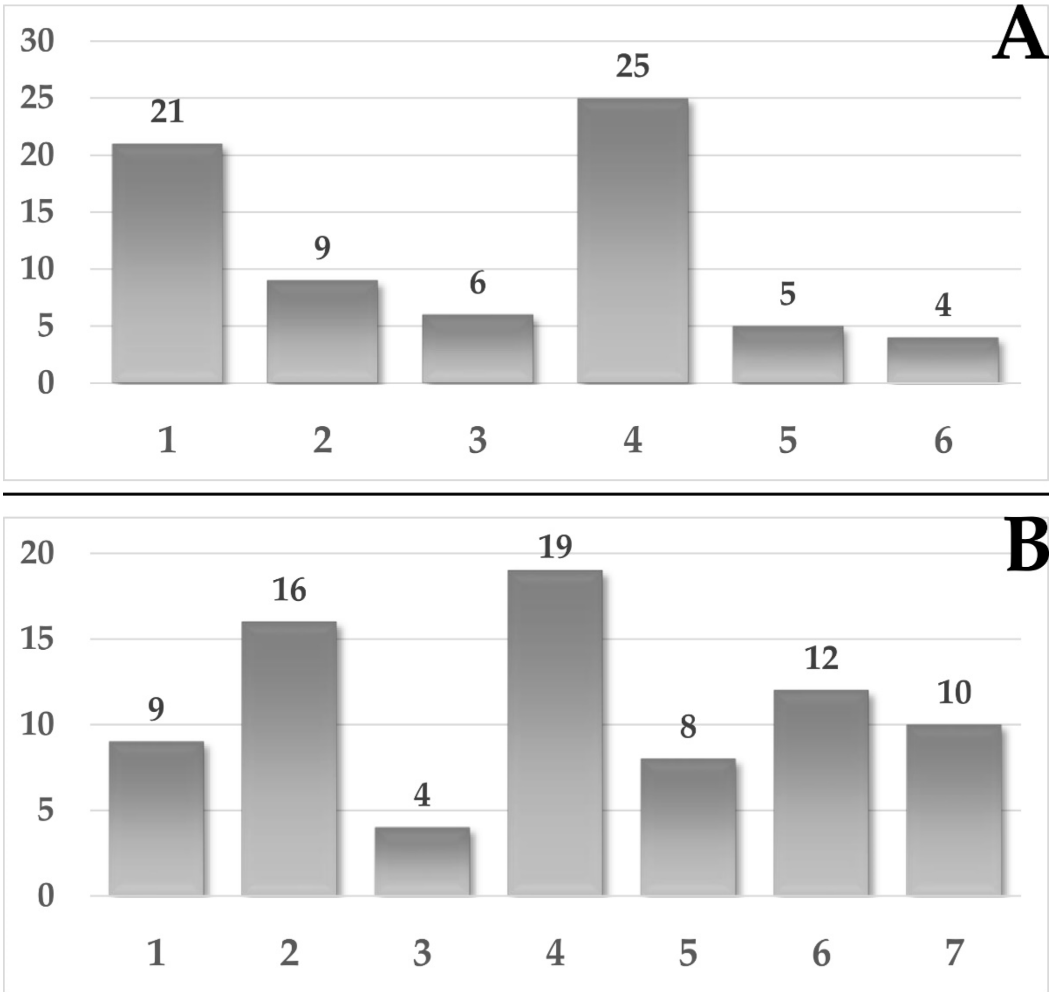

Figure 3. (**A**)—Used research methods: 1—Vegetation indices, 2—Soil moisture indices and Groundwater table, 3—Water indices and Water table depth, 4—Supervised classification and Machine learning land cover classification, 5—Gross Primary Productivity, 6—Ground deformation; (**B**)—The main focus of the research: 1—Monitoring of peatlands state, 2—Changes in water conditions in the peatland and monitoring soil moisture in peatlands, 3—Estimating balance of greenhouse gases, 4—Land classification/identification of peatlands, 5—Estimating carbon resources in peatlands, 6—Peatland vegetation mapping, 7—Monitoring of peatland state, based on Table 1.

The analysis of the surface vegetation state in peatlands uses multispectral images (spectral resolution 400–2400 nm Supplementary Material, Figure S1). A key element of multispectral analysis is image acquisition time (or revisit capability), which proves to be of utmost importance in the context of employing remote sensing in the analysis of vegetation ecosystems [79,80]. This procedure allows for the selection of appropriate satellite systems and bands for detailed analyses. A commonly used indicator based on multispectral imaging is the Normalised Difference Vegetation Index (NDVI) for a normalised (values from -1 to 1) evaluation of vegetation state [22,81,82]. NDVI is calculated based on red and near-infrared spectrum ranges (RED-NIR 620-875 nm (Supplementary Material, Figure S1)). For recurring time intervals, NDVI allows for the monitoring of plant growth in the vegetation period and their degradation caused by disasters, such as fires [83]. Changes in vegetation enable the intermediate evaluation of changes in hydrological conditions, as well as microclimate and CO_2 fluxes in a peatland and its surroundings [83]. A significant limitation regarding access to data from multispectral satellite sensors is connected to cloud cover, since electromagnetic radiation emitted by the sun does not penetrate through clouds within the spectrum range used for calculating the index. Another indicator used widely in the analyses of peatland vegetation is the chlorophyll index (CI) [80], designed to detect changes in chlorophyll in peatlands. The indicator implies general disappearance of chlorophyll as the peatland vegetation begins to dry out.

Remote sensing analyses concerning vegetation conditions are also primarily based on measuring the amount of water in plants. Therefore, another indicator frequently applied in studies on peatland vegetation is the Moisture Stress Index (MSI) [80,84]. MSI is primarily used to study the effects of water stress on plant health, following the assumption that a plant is under stress when its surface temperature is higher than the air temperature [85]. One of the basic indicators analysing the amount of water in plants is the Water Index (WI). Water Index (WI) is used for the estimation of plant water concentration (PWC) in ground-based reflectance measurements [86]. This indicator is currently used and modified in studies of peatlands (e.g., floating water band index (fWBI)) [80,81].

Multispectral images are also used for analysing soil moisture, including the surface zone of peatlands. Here, the normalised difference water index (NDWI) [87] is most often used to monitor a peatland's surface water content. Currently, a number of indices were designed and improved for performing analyses of soil moisture levels [88–90]; compared with NDVI, all of them have a higher spectral resolution, usually in the short-wave infrared range (SWIR 1400–2400 nm). This method is ineffective in peatland studies because the areas in question tend to be covered with dense vegetation.

Soil moisture in peatlands and their surrounding environments are also measured using a synthetic aperture radar (SAR, e.g., Sentinel-1) in the C band at a 5.6 cm wavelength, which partly penetrates through the vegetation and soil but is reflected off the water surface [26,35,39,58,65,91]. Primarily, multispectral sensors can recognise treetops and land cover spectral features, while SAR microwaves are sensitive to vegetation structure, surface roughness, and moisture content. In addition, SAR can partially pass through the treetops depending on the crown's wavelength and characteristics. This ability is important in wetlands where stagnant water often occurs beneath the vegetation cover. As backscattered microwave radiation is sensitive to the dielectric permeability of the first centimetres of the soil, radar data constitute a promising tool for acquiring spatial information on soil moisture and groundwater table depths (WTD) [35,38,39,58,65,92–94]. Asmuß et al. (2019) [58] used data from a Sentinel-1 synthetic aperture radar to determine a temporal Spearman correlation coefficient between WTD and backscatter ($\sigma^0{}_\theta$ (VV) constant, all orbits), which was calculated as 0.45 ($\pm$0.17). The authors observed a significantly decreased correlation between groundwater table depths and backscatter during increased vegetation activity in summer and decreases due to haymaking and grazing [58].

In addition to satellite data, peatland studies certainly benefit from the development and availability of close-range remote sensing technologies (drone, UAV) [33,34,46,95]. UAV technology allows for creating Digital Elevation Models (DEM), which are widely used in monitoring the environment, including peatlands [2,96]. Digital elevation models can be created from overlapping aerial photographs taken at different viewing angles by an unmanned aerial vehicle (UAV) at a low altitude [97]. Fonstad et al. (2013) [96] used UAV measurements to analyse the effects of fire on 5.2 hectares of peatland in Indonesia. A point cloud from UAV images for DTM (Digital Terrain Model) before and after the fire allowed the changes in the elevation of the peatland's surface and the thickness of the burnt layer of peat to be determined

Lovitt et al. (2017) [98] concluded that a photogrammetric UAV data-enabled accurate estimation of terrain elevation (in the range of 14–42 cm, which was related to the image resolution), depending on the plant cover and terrain complexity. Close-range photogrammetric methods could also be used to obtain very detailed orthophoto maps, which proved useful in delimitating and monitoring peatland habitats [30,99,100]. Lopatin et al. (2019) [101] indicated that integration of environmental knowledge with remote sensing applications holds an immense potential to improve final mapping accuracy but is also likely to contribute to the knowledge of peatlands ecosystem functioning.

3. Discussion

In terms of their ecosystem functions, peatlands are a valuable element of the natural environment, so it seems essential that they are preserved in their natural, non-degraded form. Peatlands are responsible for retaining carbon, generating biomass, and storing water, and constitute extremely valuable natural habitats of flora and fauna [1,102–105]. Thus, it is important to continuously examine the state of the peatland environment repeatedly and systematically, which is facilitated by, inter alia, the application of RS methods.

Trends in the development of existing peatlands cannot be forecast without investigating their history and determining their transformation rate. The evolution of peatlands can result from climate change and the natural 'ageing' of these ecological accumulation systems [106–108], as well as increasing anthropopressure [108–112]. Palaeoecological research on peatland and lake sediments increasingly uses a multi-proxy approach [105,110,113–119]. A comparison of results from multiple analyses (e.g., palynological, macrofossil, testate amoebae analysis, ^{14}C and ^{210}Pb dating) provides a broader view of events in the history of the ecosystem [114,116,118,120,121]. In studies on the past and the life cycle of peatlands, the authors used palaeobotanical, palaeozoological and chronometric methods to learn about the history of the area and its past climatic state. In order to be able to conduct such research, it is necessary to identify the location and borders of peatland, which are facilitated by the application of RS methods. In their study, Chambers et al. (2012) [122] emphasise the importance of peatland research in terms of analysing the climatic past. However, the authors do not seem to acknowledge the applicability of remote sensing methods in the analysis of peatlands.

The rapid acceleration of climate warming in recent decades necessitates the implementation of the systematic and global monitoring of peatlands, which function as a carbon storage system. Gross primary productivity and greenhouse gas emissions significantly influence climate change [27–29,46,66]. As demonstrated in our analysis, an increasing number of studies successfully employ remote sensing and advocate for the efficiency of this method in estimating carbon resources and CO_2 emissions in peatlands [27–29,40,46,62,66,74].

In the case of peatland areas, the settling of peat correlates with peat thickness as peatlands dry up and are supplied with water [123,124]. Estimates found in the available literature regarding the rate of CO_2 release caused by peat settling tend to vary considerably: 20 Mg CO_2 ha^{-1} year^{-1} [125], 58.4–74.5 Mg CO_2 ha^{-1} year^{-1} [126], 72.7 Mg CO_2 ha^{-1} year^{-1} [127], and up to 100 Mg CO_2 ha^{-1} year^{-1} [128]. In their study, Khasanah and van Noordwijk (2018) [129] noted that, in the case of subtropical peatlands, the rate of peat settling amounting to 4.7 cm year^{-1} generated up to 121 Mg CO_2 ha^{-1} year^{-1}. Hence, it seems that using remote sensing to gather repeated measurements of peatlands elevation [38,39,72,75] may be a viable method for observing the degradation of these environments and, by extension, the monitoring of potential hazards related to the emission of greenhouse gasses from peatlands into the atmosphere.

Minasny et al. (2019) [2] noted that the current global knowledge and mapping of peatlands is poor. Peatlands are fragmented, occupying a relatively small area (around 3% worldwide), and are often overlooked by large-scale soil surveys. This means that the results obtained using RS methods can be important in studying climate and GHG emissions.

In the past, the basic methods for delimitating the spatial distribution of peatlands and temporal changes in the surface features of peatlands included analysing topographic maps.

These maps provide information on land use forms, water networks and relief [3,4]. The disadvantage of this method involves the lack of up-to-date information in the case of standard cartographic materials. In contrast, RS data can be collected repeatedly over time, ensuring a much better accuracy.

Geography and related hydrological, hydroclimatic and land-use conditions, along with the changes therein, determine the condition and dynamics of wetlands and their ecosystem services. As noted by Ghajarnia et al. (2019) [4], the impact of these dependencies is not limited to the local scale of individual wetlands but extends to larger landscape areas that integrate multiple wetlands and their entire hydrological catchment area—the wetland landscape. As an essential element of all wetlands, peatlands are an essential element of the water cycle in the environment. Therefore, the use of RS methods in analysing changes in water resources is more and more prevalent [23–26,45,58,72].

Radar data proved invaluable for mapping peatlands in areas where cloud cover is persistent throughout the year [2]. Imaging radars equipped with a C-band are generally not hindered by atmospheric effects and are capable of imaging through tropical clouds and rain showers. Sentinel-1 radar data use a nominal frequency range from a 3.75 to 7.5 cm wavelength within the electromagnetic spectrum's microwave (radar) portion. Their penetration capability with regard to vegetation canopies or soils is limited and restricted to the top layers [91]. Our analysis indicates a considerable interest in the use of radar data after the launch of the Sentinel-1B mission in 2016 (Figure 1; Supplementary Material, Table S2). The stated data were used, for example, in studies concerning the identification of peatlands, estimating carbon resources in peatlands, the monitoring of peatland state, monitoring soil moisture in peatlands, and changes in water conditions in peatlands [26,37,38,58,70,77]. In their study, Asmuß et al. (2019) [58] analysed the impact of the depth of the groundwater level in areas characterised by a high proportion of organic soils. In an analysis of the water table depth (WTD), the authors noted: deep WTD has a low radar wave backscatter, shallow WTD has a high radar wave backscatter, and inundation features have a very low radar wave backscatter. Their analyses of radar remote sensing images show a partial correlation with the results of field measurements [58]. The authors of that study observed the highest correlations at sites with a mean annual WTD of approximately −0.40 m. A distinct decrease in correlation was found at sites with a mean annual WTD deeper than approximately −0.60 m or shallower than approximately −0.20 m. These results may indicate the efficacy of this method in the analysis of the biologically active surface of peatlands.

4. Summary and Conclusions

The presented review of research works published within the last ten years indicates a gradual increase in the number of studies on peatlands that employ remote sensing data. RS was applied for monitoring present-day peatland transformations (including their individual components) and the analysis of the historical development of peatlands associated with temporal changes in environmental factors (both natural and anthropogenic).

The data are predominantly used in studies involving land classification/identification of peatlands or changes in peatland water conditions, as well as for monitoring soil moisture in peatlands. The most frequently employed methods include supervised classification and land cover classification predicated in machine learning, as well as vegetation indices. Because remote sensing data have become readily available and free of charge, the number of studies on peatlands featuring such data has increased. Research in this field was also positively impacted by the rapid development of open-source applications.

Remote sensing data combined with field research information can improve the accuracy of results obtained in peatland studies. This, in turn, may support the preservation of peatlands and their environmental functions. The development of indices related to several features of peatlands, calculated based on available free-of-charge remote data, provides an opportunity to conduct studies on peatlands at a local and regional level. Therefore, these methods may be useful for studying, monitoring and supporting the management of peatlands both as stand-alone areas and as an element of the hydrological and environmental network. Bearing in mind that peatland studies call for, and benefit from, a multiproxy approach, remote sensing may prove to be a highly efficient method of choice, as it not only enables detection of peatlands, but facilitates the monitoring of their function in the environment.

Observed limitations related to the application of RS methods in studies on peatlands are connected with the spatial resolution of satellite imagery; cloud interference in the case of passive remote sensing data; restrictions to the surface layer of the peatlands; the considerable impact of high vegetation (trees, shrubs) on the results of analyses; differences in the interpretation of data results; and a lack of standardised data.

Accurate information regarding the distribution and extent of peatlands is deemed essential in the context of the sustainable management of these areas. Therefore, we recommend the further development of RS methods and their implementation with peatland analyses in mind, especially in comprehensive and multiproxy studies. Radar data (provided by, for example, the Sentinel-1 system) seem particularly noteworthy due to their availability (open access), high repeatability over time and independence from weather conditions.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land11010024/s1, Table S1: Characteristics of selected remote sensing data developed in the years 2000–2021; Figure S1: Multispectral range of Landsat 7–8 and Sentinel-2 satellite systems; Table S2: Characteristics of reviewed studies

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