

An overview of remote sensing data applications in peatland research based on works from the period 2010–2021

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The development of satellite remote sensing commenced in 1972, i.e. with the launch of the ERTS-1 (Earth Resources Technology Satellite) system by NASA – now Landsat 1 [1]. However, the use of satellite remote sensing data did not gain momentum until the beginning of the 21st century, which may be attributed to the commissioning of systems capable of providing higher spatial resolution, such as IKONOS-2 and Landsat 7 [2]. The USGS announced the free-and-open data policy on 21 April 2008, rendering Landsat images free to the public [3]. As far as studies on peatland areas are concerned, the applicability of remote sensing data greatly improved with the launch of Landsat 8 in 2013, Sentinel-1A in 2014 and Sentinel-2A in 2015. In the following years, the European Space Agency launched twin satellites of the Sentinel 1 and 2 system, effectively reducing their revisit capability by half. Another multispectral satellite of the Landsat system was launched in September 2021 (Landsat 9 – currently undergoing tests) [4]. The European Space Agency plans to launch another 4 satellites operating in the Sentinel 1 and 2 system in the coming years, which is aimed at further enhancing the revisit capability [5,6]. Table S1 presents the characteristics of selected remote sensing data developed in 21st century, and Figure S1 demonstrates the multispectral range of Landsat 7-8 and Sentinel-2 satellite systems. Table S2 includes detailed information pertaining to the works analyzed in this study.

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Table S1. Characteristics of selected remote sensing data developed in the years 2000–2021.

Platform	Type of data	Launch data	Revisit capability
SPOT 5 [7]	<u>Multispectral</u>	4 May 2002	5 days with two-satellite constellation (SPOT 4 and SPOT 5)
	High Resolution Geometric (HRG)		
	High Resolution Stereoscopic (HRS)		
	Vegetation-2		
	Doppler Orbitography and Radiopositioning Integrated by Satellite (DORIS)		
SPOT 6 [8]	<u>Multispectral</u>	9 September 2012	between 1 and 3 days with only one satellite
	New AstroSat Optical Modular Instrument (NAOMI)		
Landsat 8 [1]	<u>Multispectral</u>	11 February 2013	15 days
	Operational Land Imager (OLI)		
Sentinel-1A [5]	<u>Radar</u>	3 April 2014	- 12 days - 3 days at the equator
	Synthetic Aperture Radar (SAR)		
Sentinel-2A [6]	<u>Multispectral</u>	23 June 2015	10 days
	MultiSpectral Instrument (MSI)		
SPOT 7 (Azersky) [9]	<u>Multispectral</u>	30 June 2014	- 1 day with SPOT 6 and SPOT 7 operating simultaneously - between 1 and 3 days with only one satellite
	New AstroSat Optical Modular Instrument (NAOMI)		
Sentinel-1B [5]	<u>Radar</u>	25 April 2016	- 10 days - 6 days out of phase with Senti-nel-1A - < 1 days at high latitudes out of phase with Senti-nel-1A
	Synthetic Aperture Radar (SAR)		
Sentinel-2B [6]	<u>Multispectral</u>	7 March 2017	- 10 days - 6 days out of phase with Sentinel-2A
	MultiSpectral Instrument (MSI)		
Landsat 9 [4]	<u>Multispectral</u>	27 September 2021	- 15 days - 8 days out of phase with Landsat-8
	Operational Land Imager 2 (OLI-2)		
	Thermal Infrared Sensor 2 (TIRS-2)		

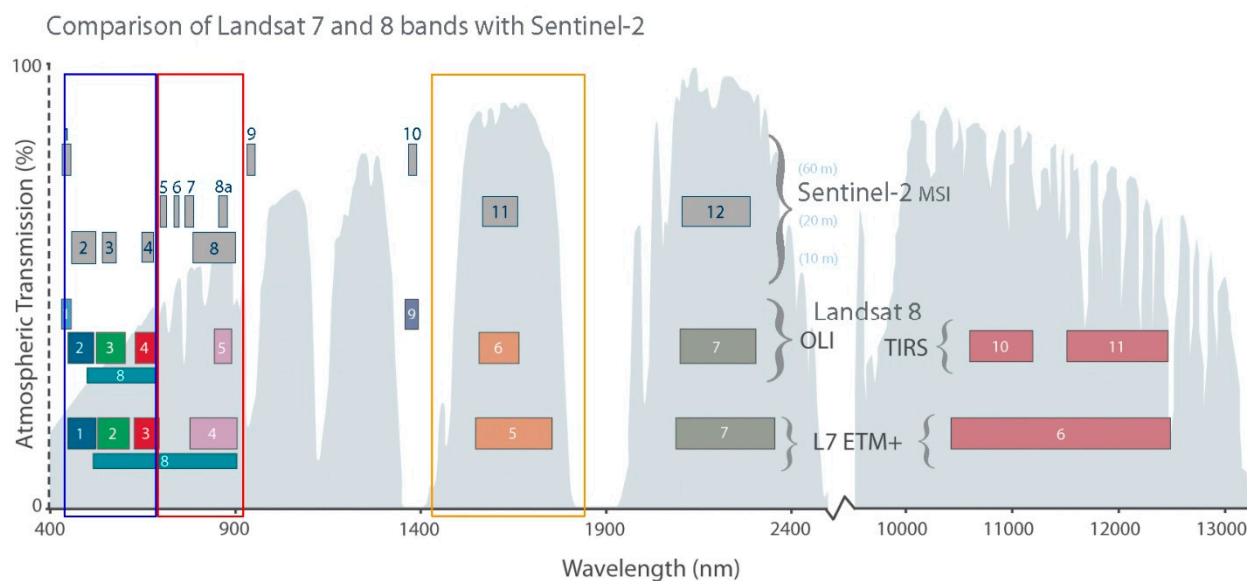


Figure S1. Multispectral range of Landsat 7-8 and Sentinel-2 satellite systems [10].

Table S2. Characteristics of reviewed studies.

Authors	Year	Location	Region	Used research methods	Platform	Type of data	The main focus of the research
Anderson et al. [11]	2010	Cumbria (UK)	oceanic temperate	Supervised classification	IKONOS	Multispectral	land classification / identification of peatlands changes in water conditions in the peatland
Miettinen and Liew [12]	2010	Indonesia	tropical	Vegetation indices Soil moisture indices	Landsat 5 SPOT	Multispectral	monitoring of peatland state
Neta et al. [13]	2010	Canada	boreal/northern	Water indices Vegetation indices	Airborne data	Hyperspectral	peatland vegetation mapping changes in water conditions in the peatland
Wijaya et al. [14]	2010	Borneo	tropical	Supervised classification	TerraSAR X Landsat	Multispectral Radar	land classification / identification of peatlands
Connolly et al. [15]	2011	Ireland	oceanic temperate	Vegetation indices	MODIS	Multispectral	monitoring of peatland state
Frick et al. [16]	2011	German	temperate	Vegetation indices Soil moisture indices	QuickBird WorldView I SPOT 2	Multispectral	peatland vegetation mapping changes in water conditions in the peatland
Harris and Dash [17]	2011	Canada	temperate/northern	Gross Primary Productivity	MODIS	Hyperspectral	estimating CO ₂ balance

							Gross Primary Productivity
Jaenicke et al. [18]	2011	Indonesia	tropical	Soil moisture indices	ASAR PALSAR	Radar	changes in water conditions in the peatland
Middleton et al. [19]	2012	Finland	boreal/northern	Soil moisture indices Machine learning land cover classification	Airborne data	Hyperspectral	peatlands classification
Miettinen et al. [20]	2012	Indonesia	tropical	Supervised classification	SPOT Landsat	Multispectral	estimating carbon resources in peatlands
Torbick et al. [21]	2012	Sweden	arctic	Water table depth (WTD) Supervised classification	PALSAR	Radar	land classification / identification of peatlands changes in water conditions in the peatland
Akumu and McLaughlin [22]	2014	Canada	temperate/northern	Supervised classification	SPOT 5	Multispectral	estimating carbon resources in peatlands
O'Connell et al. [23]	2014	Ireland	oceanic temperate	Vegetation indices	ASTER Landsat SPOT Ikonos QuickBird	Multispectral	peatland vegetation mapping
Watts et al. [24]	2014	Arctic circle	arctic	Gross Primary Productivity	MODIS	Hyperspectral	estimating CO2 balance Gross Primary Productivity
Cabezas et al. [25]	2015	Chile	temperate/oceanic	Vegetation indices Gross Primary Productivity	Landsat 8 Pleiades 1B	Multispectral	estimating carbon resources in peatlands
Crichton et al. [26]	2015	Cumbria (UK)	oceanic temperate	Supervised classification	Landsat Ikonos	Multispectral	estimating carbon resources in peatlands
Harris et al. [27]	2015	Wales (UK)	oceanic temperate	Vegetation indices	Airborne data	Hyperspectral	peatland vegetation mapping
Lehmann et al. [28]	2016	South Patagonia (Argentina)	temperate/oceanic	Supervised classification	UAV (drone)	Multispectral	estimating carbon resources in peatlands
Bourgeau-Chavez et al. [29]	2017	Canada	boreal/northern	Supervised classification Machine learning land cover classification	Landsat 5 PALSAR	Multispectral Radar	peatlands classification

Connolly and Holden [30]	2017	Ireland	oceanic temperate	Supervised classification	QuickBird MODIS	Multispectral	land classification / identification of peatlands changes in water conditions in the peatland
Dissanska et al. [31]	2017	Canada	temperate/northern	Supervised classification	QuickBird	Multispectral	land classification / identification of peatlands
Erudel et al. [32]	2017	France	temperate	Vegetation indices	-	Hyperspectral	peatland vegetation mapping
Gatis et al. [33]	2017	Southwest England	oceanic temperate	Vegetation indices Supervised classification	MODIS	Multispectral	estimating carbon resources in peatlands peatland vegetation mapping
Gumbrecht et al. [34]	2017	-	tropical	Water indices Soil moisture indices	MODIS	Multispectral	land classification / identification of peatlands
Hribljan et al. [35]	2017	Ecuador	tropical	Supervised classification	Landsat PALSAR RADARSAT	Multispectral Radar	land classification / identification of peatlands estimating carbon resources in peatlands
Medvedeva et al. [36]	2017	Russia	temperate	Supervised classification	SPOT 5 SPOT 6 Landsat 7	Multispectral	monitoring of peatland state changes in water conditions in the peatland
Merchant et al. [37]	2017	Canada	boreal/northern	Supervised classification Machine learning land cover classification	RADARSAT-2	Radar	land classification / identification of peatlands
Novresiandi and Nagasawa [38]	2017	Malesia	tropical	Supervised classification	PALSAR Landsat 5	Multispectral Radar	land classification / identification of peatlands
White et al. [39]	2017	Canada	temperate/northern	Supervised classification	RADARSAT-2	Radar	land classification / identification of peatlands
Alshammari et al. [40]	2018	Northern Scotland (UK)	boreal/northern	InSAR ground deformation	Sentinel-1 ERS	Radar	monitoring of peatland state
Arroyo-Mora et al. [41]	2018	Canada	temperate/northern	Vegetation indices	Sentinel-2	Multispectral	peatland vegetation mapping
Kalacska et al. [42]	2018	Canada	temperate/northern	Water indices	Landsat 5 Landsat 8 Sentinel-2	Multispectral	changes in water conditions in the peatland

Marshall et al. [43]	2018	Malesia	tropical	InSAR ground deformation	Sentinel-1	Radar	monitoring of peatland state
Millard et al. [44]	2018	Canada	temperate/northern	Vegetation indices	MODIS	Radar	monitoring soil moisture in peatlands
Sencaki et al. [45]	2018	Sumatra	tropical	Machine learning land cover classification	Landsat 8 MODIS ASTER	Multispectral Radar	land classification / identification of peatlands
Torabi Haghighi et al. [46]	2018	Finland	boreal/northern	Vegetation indices	SPOT Landsat	Multispectral	changes in water conditions in the peatland
Asmuss et al. [47]	2019	German	temperate	Water table depth (WTD)	Sentinel-1	Radar	changes in water conditions in the peatland
Bandopadhyay et al. [48]	2019	Poland	temperate	Vegetation indices	Airborne data	Multispectral	peatland vegetation mapping
Karlson et al. [49]	2019	Finland	boreal/northern	ArcticDEM ground deformation	Sentinel-1	Radar	land classification / identification of peatlands
McPartland et al. [50]	2019	Alaska (USA) Minnesota (USA)	boreal/northern temperate	Vegetation indices	-	Multispectral	peatland vegetation mapping changes in water conditions in the peatland
Räsänen et al. [51]	2019	Finland	boreal/northern	Vegetation indices	UAV (drone) Airborne data WorldView-2	Multispectral	peatland vegetation mapping
Widyatmanti et al. [52]	2019	Indonesia	tropical	Vegetation indices Soil moisture indices	Landsat 8 Sentinel-2	Multispectral	monitoring soil moisture in peatlands land classification
Yager et al. [53]	2019	Bolivia	temperate/oceanic	Supervised classification	Landsat 5 Landsat 8	Multispectral	monitoring of peatland state
Zhou et al. [54]	2019	Indonesia	tropical	InSAR ground deformation	ALOS	Radar	monitoring of peatland state
Bechtold et al. [55]	2020	Northern Hemisphere	-	Groundwater table (GWT) Soil moisture indices	SMOS	Radar	land classification / identification of peatlands changes in water conditions in the peatland
Burdun et al. [56]	2020	USA Canada Finland Sweden Estonia	temperate/northern	Soil moisture indices	Landsat MODIS	Multispectral	changes in water conditions in the peatland
Lees et al. [57]	2021	-	-	Vegetation indices Gross Primary	MODIS	Multispectral Radar	estimating carbon resources in peatlands

				Productivity			
Park et al. [58]	2020	Indonesia	tropical	Groundwater table (GWT) Soil moisture indices	MODIS	Hyperspectral	estimating carbon resources in peatlands
Räsänen et al. [59]	2020	Finland	boreal/northern	Leaf-area index and biomass	UAV (drone)	Hyperspectral	determination of biomass resources
Sencaki et al. [60]	2020	Sumatra	tropical	Machine learning land cover classification	Landsat 8 MODIS	Multispectral	land classification / identification of peatlands
Sirin et al. [61]	2020	Moscow Region (Russia)	temperate	Supervised classification	SPOT Landsat Sentinel	Multispectral	monitoring of peatland state
Sutikno et al. [62]	2020	Indonesia	tropical	Supervised classification	Landsat 8	Multispectral	peatlands degradation
Zhang et al. [63]	2020	Florida (USA)	subtropical	Machine learning land cover classification	Landsat 8	Multispectral	estimating methane balance
Amoakoh et al. [64]	2021	Ghana	tropical	Vegetation indices Texture features (moisture, roughness and shape) Machine learning land cover classification	Sentinel-2 Sentinel-1	Multispectral Radar	land classification / identification of peatlands
Anda et al. [65]	2021	Indonesia	tropical	Supervised classification	SPOT Landsat	Multispectral	land classification / identification of peatlands
Anderson et al. [66]	2021	Bolivia Peru Argentina Chile	temperate/oceanic	Vegetation indices	Landsat	Multispectral	monitoring of peatland state
Bandopadhyay et al. [67]	2021	Poland	temperate	Vegetation indices	Airborne data	Multispectral	peatland vegetation mapping
Junttila et al. [68]	2021	Sweden Finland	boreal/northern	Vegetation indices	Sentinel-2 MODIS	Multispectral	estimating CO2 balance Gross Primary Productivity

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