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Applications of satellite platforms and machine learning for mapping and monitoring grasslands and pastures: A systematic and comprehensive review

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ABSTRACT

Grasslands and pastures are critical ecosystems globally, essential for their agricultural and environmental roles. Extensive research from 2000 to 2022, comprising 504 articles, has explored the integration of remote sensing and statistical modelling for mapping and monitoring grassland and pasture ecosystems. These articles were sourced from the SCOPUS database and analysed using text mining and natural language processing techniques to investigate the evolution of publication trends over the past twenty-two years. The number of publications per year on this topic has grown consistently in the considered period, from 3 in 2000 to 93 in 2022, doubling their weight compared to the total number of Scopus publications. The quantitative analysis of satellite platform utilisation revealed the increasing importance of Sentinel-2, even though MODIS remained the most utilised satellite platform throughout the study period. The increasing availability of big data has helped spread the utilisation of machine learning algorithms, mostly in the last ten years. Among these, random forest appeared to be the most widespread for grassland and pasture studies. Researchers' primary interest in this field centres on the technologies and their applications. This is evidenced by cluster analysis, which reveals a dominant focus on terms related to the 'Instruments' (25.8 %) and 'Parameters' (24.9 %) categories. This analysis aims to outline the progression of research, offering insights that could be useful in forecasting future trends and facilitating stakeholder engagement in this sector.

1. Introduction

Grasslands are among the most critical and widespread ecosystems in the world. In 2020, they covered >3 million ha worldwide [1] and stored approximately 30 % of terrestrial biomass [2].

The role that these ecosystems play regarding climate-changing emissions is prominent [3]; pastures and grasslands can both stock and emit carbon dioxide (CO_2) [4] and other greenhouse gases, such as methane (CH_4) and nitrous oxide (N_2O) [5]. Several authors have investigated the role of grasslands as carbon sinks and highlighted their importance. Dass et al. [6] stated that in California, grasslands might be more resilient and reliable than forests as carbon sinks. Evidence from European grasslands shows that the soil C sequestration rate can reach 0.77 g C m-2 [7], while a Swiss study by Guillaume et al. [8] concluded that the first 50 cm of grassland topsoil contains approximately 7 kg C m-2 and that including temporary grassland in crop rotation may increase carbon storage in agricultural soils. Compared with croplands, grasslands and pastures have the potential to act as C and N sinks and mitigate GHG emissions in livestock systems, as C and N sequestration can offset GHG emissions [7,8]. Recent studies developed remote sensing tools based on Sentinel-2 and Sentinel-5p to track and quantify GHG emissions [9].

Furthermore, grasslands are the cradle of vast plant and animal biodiversity [10,11].

Despite their role in mitigating greenhouse gas emissions, these ecosystems face significant threats from climate change. This is particularly evident in issues like erosion [12] and reduced grass productivity [13].

From an agricultural point of view, using grasslands as pastures represents a vital resource. It is the least expensive way to produce

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fodder, providing nearly half the feed requirements for global livestock production [14] and covering 67 % of agricultural land worldwide [1]. The amount and quality of forage produced in pastures significantly impact animal welfare and final production [15,16]. Grasslands covering marginal areas in agricultural environments as riverbanks, also have potential as biomass supplier for anaerobic digestion plants [17]. Changes in the botanical composition, production, and quality of pastures can affect final production, which can have important socioeconomic consequences for rural areas. The different characteristics of pastoral activities can change their effect on the grassland environment, both in terms of productivity and biodiversity. Sartorello et al. [18] identified four main categories of pastoral activities: (*i*) traditional management, defined as extensive grazing; (*ii*) overgrazing, representing land overexploitation; (*iii*) Agri-Environmental Schemes (AESs), reducing overgrazing towards traditional extensive management to mimic and/or enhance biodiversity conservation; and (*iv*) land abandonment following previous pastoral activities.

During the last decades, mountainous regions have experienced profound socioeconomic transformations [19,20]. These changes encompass land abandonment, a decline in agricultural practices, an ageing farming population, and increased urbanization [21]. Consequently, pastoral systems have deteriorated, with unpalatable grasses taking over, shrubs encroaching, and reforestation occurring [22–24]. This degradation of pastoral landscapes highlights the need for sustainable management and restoration efforts to preserve these vital ecosystems [19,25].

To ensure accurate information about the state of grasslands, characterisation, monitoring, and management are necessary. Additionally, understanding the potential of nearby environments is crucial. Traditional ground-based methods are laborious and time-consuming [26], while remote sensing is efficient and fast and thus has the potential to provide large amounts of useful real-time data to improve pasture and grassland management at both large (regional) and small (farm) scales. The activity of researchers in this field has substantially increased in recent years, together with the tools and possibilities offered by remote sensing technologies [27]. Some of the most investigated topics include monitoring grassland degradation [28]; estimating vegetation-related parameters such as aboveground biomass [29–33], leaf area indices [34] or fractional vegetation cover [35]; and characterising grassland habitats [36]. Some of the most utilised satellite platforms include moderate-resolution imaging spectroradiometer (MODIS) (which is especially suitable for large-scale studies [37–39]), Landsat satellites from NASA [40,41], and the Sentinel constellation from the ESA [42–44]. Remote sensing multispectral and hyperspectral images and radar data can also be used to predict grassland taxonomic and functional plant diversity, as well as phenological traits [45–47]. Fauvel et al. [47] used a combination of optical data from Sentinel-2 and synthetic aperture radar from Sentinel-1 to compute several diversity indices, while Imran et al. [46] focused on the application of fine-scale hyperspectral imaging to estimate grasslands biodiversity.

Numerous studies have recently focused on integrating machine learning and deep learning techniques to extract valuable information about grassland vegetation from remote sensing data. Techniques such as random forest [48,49], regression models [50], neural networks [51], and clustering methods [52] have significantly enhanced the analysis and interpretation of complex datasets. These advancements have led to more accurate and comprehensive assessments of grassland ecosystems.

In recent years, several authors have reviewed the status of grassland observation methods and applications based on remote sensing data and machine learning applications, the advancements in technology and methodology for retrieving various grassland biophysical data and management traits and recognised the primary unmet needs and forthcoming trends for development [53–55].

The reviews included major advancements and trends from scientific researchers on the topic. However, a systematic quantitative review is missing. This review, similarly to other recent studies [56–59], would analyse trends and geographical and thematic clusters emerging from large quantities of scientific papers.

In this research, the scientific literature was analysed using a quantitative method based on text-mining techniques. In fact, due to the vastness of the specific topic, the framework of the literature review should follow the guidelines presented in the PRISMA statement [60]. The present analysis aims to provide a comprehensive state-of-the-art review of the literature concerning the use of remote sensing technologies for characterising and monitoring grasslands and pastures. The specific objectives of this review are to (*i*) describe the trend of the publications throughout the years, (*ii*) highlight the significant gaps in the research relating to the use of remote sensing in this field, both in terms of topics and geographical areas, with a focus on satellite platforms and machine learning algorithms, and (*iii*) categorise the interrelationships among the grassland and pasture monitoring and management activities and remote sensing-based tools, with a focus on satellite platforms, reported in the literature using cluster analysis.

2. Materials and methods

A systematic quantitative review was performed by extracting documents from the Scopus database. This approach relies on selecting explicit and reproducible survey methods [61], which allow a holistic view of the literature. It enables the presentation of a clear and complete picture of the state of the art. Additionally, it highlights key topics raised by the scientific community and facilitates cluster analysis.

The analytic methodology approach makes it possible to map the gaps, not only from a theoretical point of view but also from a methodological and geographic point of view.

The analysis was conducted through a text-mining approach. This involved examining the words present in the "title – abstract – keywords". The tools utilised included NumPy, Pandas, Matplotlib and Seaborn libraries in Python 3.0.11, Microsoft Excel and Gephi's (Gephi® Consortium, Compiegne, France) graphical representation tools, which are open-source network analysis software. Text mining involves extracting meaningful numerical indices from texts by scrutinising unstructured textual data. Analysing these indices statistically unlocks the understanding of the text, yielding substantial and quality insights [36,59,62].

2.1. Article selection

The analysis focused on the remote sensing technologies and techniques utilised to map and characterise grasslands and pastures. The article selection was based on the combination of the terms "grassland" and "pasture" with the general terms "remote sensing", "UAV", "drones", and "satellite" and with the specific satellite platform names "Landsat", "Sentinel", "RapidEye", "Planet", "Worldview", "Gaofen", "Modis", "Alos", "Spot", "Avhrr", "Hyperion", "Ikonos", "Radarsat", "Envisat", "Formosat", "Pleiades" and "Quickbird". Only documents published in journals and written in English were utilised, and the considered timespan ranged from 2000 to 2022. The query string utilised is reported in Table 1.

Table 1
Script for the extraction of research papers.

Query String	((TITLE (pasture*) OR TITLE (grassland*)) AND (TITLE (satellite*) OR TITLE (uav*) OR TITLE (drone*) OR TITLE (sentinel) OR TITLE (landsat) OR TITLE (rapideye) OR TITLE (planet) OR TITLE (gaofen) OR TITLE (worldview) OR TITLE (modis) OR TITLE (spot) OR TITLE (avhrr) OR TITLE (hyperion) OR TITLE (ikonos) OR TITLE (alos) OR TITLE (radarsat) OR TITLE (envisat) OR TITLE (formosat) OR TITLE (pleiades) OR TITLE (quickbird) OR TITLE (remote AND sens*))) AND (PUBYEAR > 1999 AND PUBYEAR < 2023) AND (LIMIT-TO (SRCTYPE,"j")) AND (LIMIT-TO (DOCTYPE,"ar") OR LIMIT-TO (DOCTYPE,"re")) AND (LIMIT-TO (LANGUAGE,"English"))

A total of 504 articles were selected and downloaded using the .csv extension. Data relating to the following key metadata fields were selected: 'Title', 'Authors', 'Year', 'Source title', 'Affiliation', 'Cited by', and 'Author Keywords'.

Due to the specific dataset and time period utilised, the study's limitations in terms of generalizability are clear. Even though these constraints are explicitly addressed, Scopus is a broad database, and several reviews are based on sole Scopus database [56,57,63]. According to Sampson et al. [64], "Searching additional databases with overlapping coverage but fewer precision-enhancing features may reintroduce irrelevant material that has already been eliminated from the retrieval in the database with the fullest feature set". By concentrating on a well-defined dataset, we aim to ensure the robustness of our findings while acknowledging the inherent limitations of this approach.

2.2. Trend analysis

The dataset downloaded from Scopus was imported using Python's panda's library, which is renowned for its powerful data manipulation capabilities and was instrumental in processing and analysing these data. Preliminary analysis involved descriptive statistical techniques to summarise publication trends over time and the geographical distribution of research contributions. Matplotlib and seaborn, Python's primary libraries for statistical graphics, facilitated the visualisation of these trends.

2.3. Quantitative analysis of satellite platforms and machine learning algorithms

This segment of the analysis focused on extracting specific information about satellite platforms and machine learning algorithms from the corpus of articles. The objective was to ascertain the prevalence and usage trends of various satellites and algorithms within the field. The search for the occurrence of satellite platforms and machine learning algorithms was exclusively conducted within the 'Abstract' section of each article in the dataset. This decision was based on the rationale that the abstracts provide a succinct and focused summary of the research, including key methodologies and technologies employed. The process involved the following detailed steps:

1. *Defining Keywords*: The first step was to compile comprehensive lists of keywords representing both satellite platforms and machine learning algorithms, as reported in Table 2.
2. *One-Time Count per Abstract*: To quantify the occurrence of these technologies, a distinct counting rule was applied: each term was counted only once per abstract, regardless of the number of times it appeared within that abstract.
3. *Frequency Tallying*: The Python script scanned each abstract for the presence of the predefined keywords, employing case-insensitive matching to ensure comprehensive detection. When a keyword was identified, it was counted for that abstract, and subsequent mentions within the same abstract were discarded.
4. *Data Aggregation and Interpretation*: The final tally provided insights into the prevalence of specific satellite platforms and machine learning algorithms within the field based on their utilisation in different studies.

Table 2
Lists of keywords employed for the quantitative analysis of satellite platforms and machine learning algorithms.

Topic	Keywords
Satellite Platforms	'Sentinel', 'Landsat', 'Modis', 'Spot', 'AVHRR', 'Worldview', 'RapidEye', 'Planet', 'Radarsat', 'Quickbird', 'Alos', 'Gaofen', 'Hyperion', 'Envisat', 'Formosat', 'Hyspiri', 'Ikonos', 'Prisma', 'Venus'
Machine Learning Algorithms	'Linear Regression', 'Logistic Regression', 'Partial Least Square Regression', 'Decision Tree', 'Random Forest', 'Support Vector Machine', 'Naïve Bayes', 'K-Nearest Neighbors', 'Artificial Neural Network', 'Gradient Boosting', 'Generalized Additive Model', 'Convolutional Neural Network', 'Recurrent Neural Network', 'Principal Component Analysis'

2.4. Natural language processing, clustering and network analysis

The textual content of titles, author keywords and abstracts underwent extensive natural language processing, implemented through several Python libraries:

1. *Text Cleaning and Normalization*: Utilising regular expressions (via Python's remodule), extraneous elements such as URLs, punctuation, and numerals were removed, and text normalization was achieved by converting all characters to lowercase.
2. *Tokenization and Stop Words Removal*: The nltk library (Natural Language Toolkit), a comprehensive suite for NLP in Python, facilitated the tokenization of text, splitting it into individual words and removing common stopwords.
3. *Stemming*: Nltk's PorterStemmer was applied to reduce word tokenisation of their root form, aiding in consolidating various morphological variants of words.
4. *Bigram Collocation* Analysis: Identification of frequently co-occurring word pairs (bigrams) was executed using nltk's BigramCollocationFinder.
5. *Word Frequency Counting*: The collection library's counter class was used to count the occurrence of each term within the corpus.

From the frequency distribution obtained by the analyses, we selected the 150 most common words. The CSV file was imported into Microsoft Excel for manual validation and clustering. The list of words was verified for synonyms and irrelevant words. The word list was ultimately limited to the 70 most important and recurring words. The definition of the clusters was based on an initial topic modelling analysis, which was then adapted by the authors in order to fit the relevant terms highlighted by the analysis.

The five identified clusters were 'Vegetation', 'Instruments', 'Environment', 'Parameters' and 'Management'; the words composing the five clusters are shown in Table 3.

The co-occurrence matrix was then constructed using these 70 terms. The matrix was a two-dimensional array in which both the rows and columns represented the selected words. For each document in the dataset, the script iterated through pairs of these top words, recording the instances where both words in a pair appeared together in the same document. The value in each cell of the matrix corresponded to the count of co-occurrences for the word pair it represented. This was achieved using Python's data manipulation capabilities, specifically with

Table 3
Cluster composition.

Cluster	Lemmas
Instruments	Model, Remote Sensing, Image, Satellite, Modis, Sentinel, R, Map, Landsat, Regression, Algorithm, Random Forest, UAV, Correlation, Hyperspectral, Multispectral
Parameters	Vegetation Index, Accuracy, Index, NDVI, AGB, Productivity, Spatial, Spectral, Time Series, Normalized Difference, LAI, GPP, Resolution, Temporal, Variability, Reflectance, Optical, Bands, Seasonal, EVI, RMSE
Vegetation	Grassland, Pasture, Biomass, Species, Phenology, Plant, Grass, Agricultural, Canopy, Forage
Environment	Soil, Ecosystem, Degradation, Water, Carbon, Ground, Drought, Land, Climate, Ecological, Precipitation, Fire, Steppe, Temperature, Alpine
Management	Estimation, Monitoring, Classification, Grazing, Mapping, Conservation, Livestock, N

pandas and collections. The final co-occurrence matrix provided a quantified representation of the relationships between key terms in the corpus. This matrix served as the foundation for constructing an edge list, in which each edge represented a pair of co-occurring terms, and the weight of the edge corresponded to their co-occurrence frequency.

The edge list was formatted for compatibility with Gephi, facilitating the visualisation of the term network and the exploration of thematic clusters within the research field. The concluding stage involved utilising Gephi (Gephi® Consortium, Compiegne, France), which is open-source software for visualising the relationships between terms. In Gephi's graphical representation, terms are depicted as interconnected nodes (possibly with assigned weights), and the vectors, which can be directed or undirected, represent the links between these terms. Fig. 1 depicts the conceptual flow of the analytical process.

3. Results

3.1. Analysis of trends

The first consideration concerns the number of articles published per year in the considered period (2000–2022) concerning remote sensing in the fields of Earth and planetary sciences and agricultural and biological sciences.

Fig. 2 compares them with the total number of publications published in Scopus during the same period. The number of total publications in Scopus has grown constantly, from 1182,106 in 2000 to 3971,310 in 2022. Even the number of publications concerning remote sensing in Earth and planetary sciences and agricultural and biological sciences has grown, going from 2446 in 2000 to 13,962 in 2022, but following a less constant trend. The upwards trend followed an up-and-down trajectory until 2017, when it grew steeply and constantly, with the only exception being 2021, when it reached its maximum in 2022.

In the second phase of the analysis, the focus moved from remote sensing applications to grassland and pasture monitoring and management topics and its ratio to the total number of publications in Scopus.

As shown in Fig. 3, the number of publications concerning our research topic has increased in the last 20 years, increasing from 3 publications in 2000 to 93 in 2022. Additionally, the percentage of publications on the use of remote sensing for the management and monitoring of grasslands out of the total number of publications in Scopus increased significantly in 2022 and was more than two times greater than that in 2000. The increase in the number of publications is related to the general increase in the number of scientific publications and the growing interest in utilising remote sensing technologies, especially when related to environmentally relevant topics such as land management and monitoring of grasslands and pastures.

Fig. 3 shows the number of publications on our research topic (blue histogram) and the ratio of the total number of publications in Scopus (red line plot). The trend over the years has increased, reaching its maximum for both the number of publications and the ratio in 2022.

Another quantitative approach that has been used concerns the distribution of scientific publications across major contributing countries. The most important contributing country is China, with 142 publications corresponding to 28.2 % of the total, followed by the United States with 77 (15.3 %) and Germany with 51 (10.1 %) publications. Table 4 lists the top 10 contributing countries in 2000–2022 and shows the evolution of the number of publications in each country.

To compare the temporal trends of individual countries, Fig. 4, highlighting the individual trend of the top 5 publishing countries, clearly shows how China has become the main protagonist actor over the last 20 years, passing from 0 publications in 2000–2004 to the absolute leader in recent years, quadrupling the number of publications of the second most important publishing country in 2022, with 36 publications versus 9 publications from the United States of America.

The journals that published the most papers on the topic were also analysed, and Table 5 reports the 10 most important journals by number of publications. The journal 'Remote Sensing' has a prominent role, as it published >20 % of the articles, followed by the International Journal of Remote Sensing with 7.3 % and Remote Sensing of Environment with 6.3 %. Even if the publications are distributed across 159 different journals, the first five account for >44 % of publications, showing that the topic is well identified and has a precise editorial placement.

3.2. Satellite platforms and machine learning quantitative analysis

Satellite platforms and machine learning algorithms have a prominent role in the application of remote sensing technologies to characterise and monitor grasslands and pastures [36,48,65].

A quantitative analysis was carried out to analyse and quantify the impact of individual satellite platforms and machine learning algorithms. UAVs are also important remote sensing data sources and were widely utilised in this review's research. The decision to focus on the analysis of satellite platforms was made after a preliminary quantitative analysis of the considered scientific articles. The number of articles

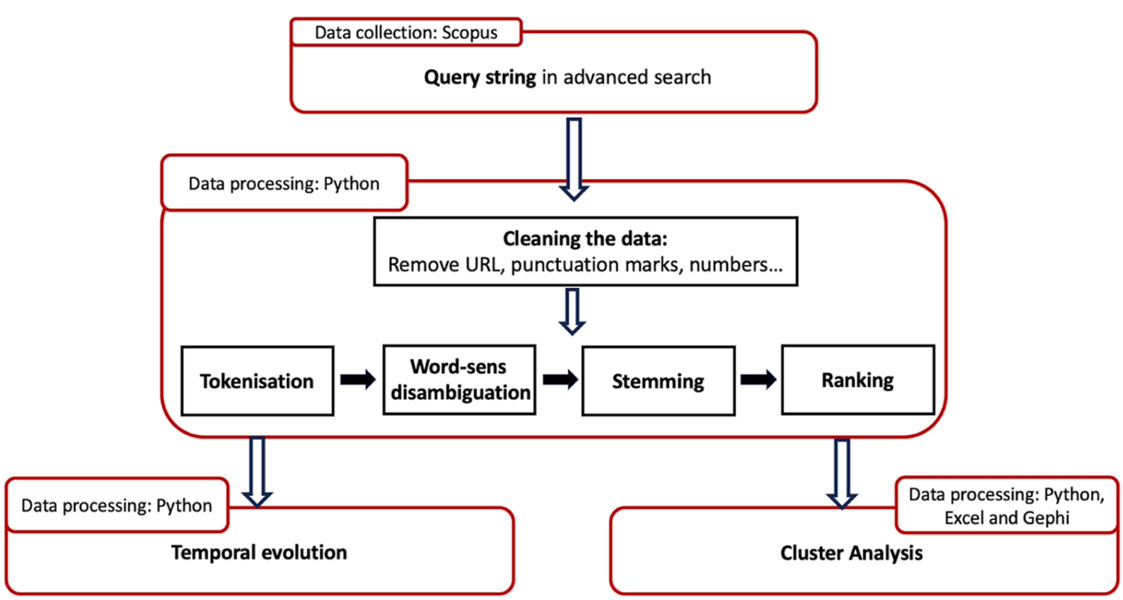

Fig. 1. The conceptual flux of the analysis: model and software used.

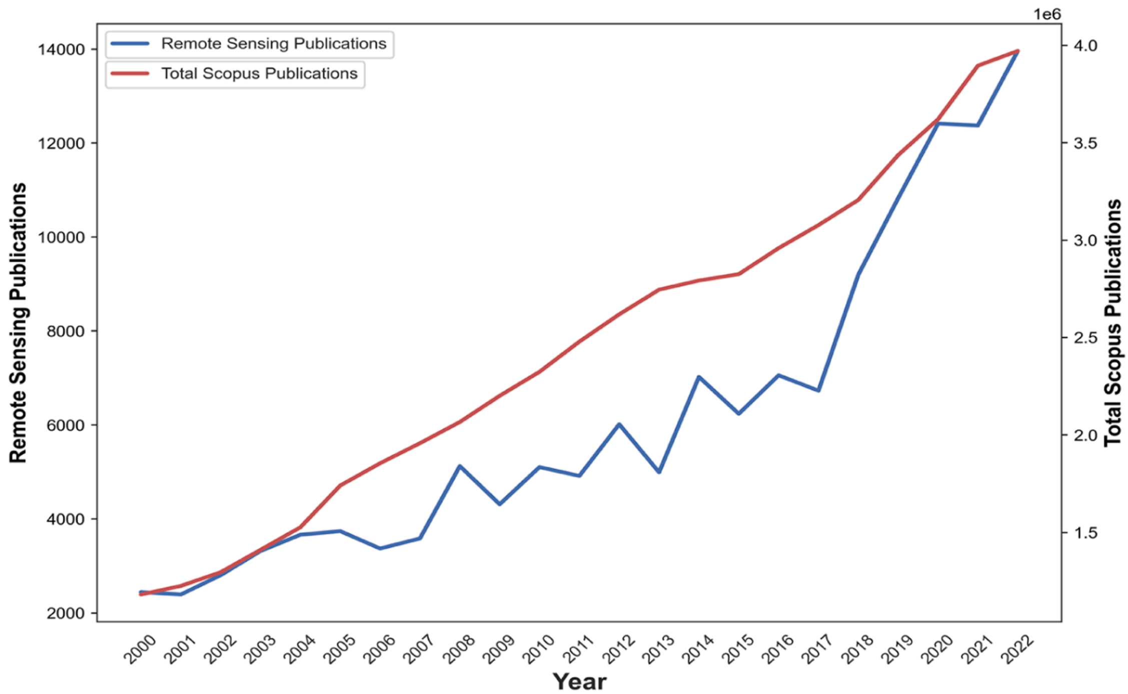

Fig. 2. The evolution of total publications in Scopus (red line) and publications related to remote sensing in Earth and planetary and agricultural sciences (blue line) during 2000–2022.

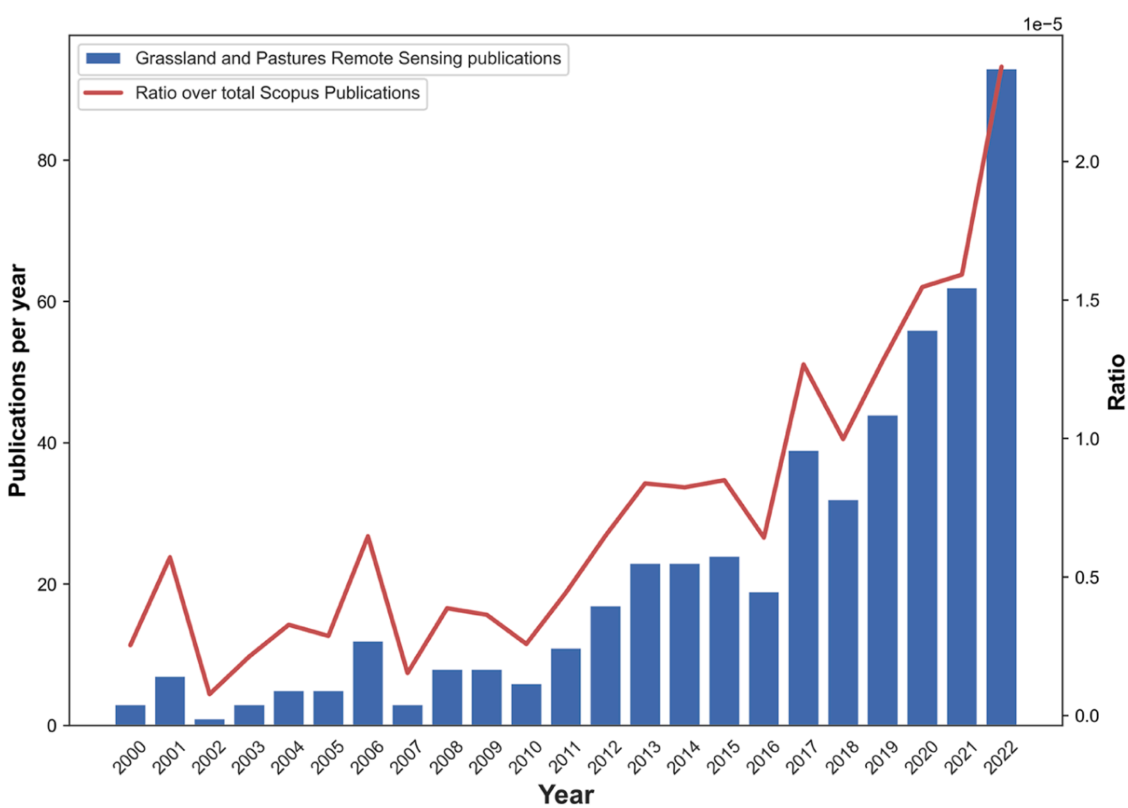

Fig. 3. The evolution of publications related to remote sensing applied to grassland and pasture studies in the Earth and planetary and agricultural sciences topics (blue column) and their ratio by the number of total publications in Scopus during 2000–2022.

including the words “UAV”, “drone” or “unmanned aerial vehicle” in their abstracts was 55, 11 % of the total, while the number of articles considering at least one of the considered satellite platforms was 445, 88 % of the total.

Fig. 5 shows the results of the quantitative analysis of the number of studies in which each satellite platform was considered. The 10 most recurring platforms are plotted. MODIS is the most utilised, appearing in 160 papers, followed by Sentinel-2 with 99 appearances and Landsat (all

Table 4
Lists of the top 10 contributing countries, their number of publications, percentage of the total and evolution in the considered period (2000–2022).

Country	Total number of publications	Percentage
China	142	28.2 %
United States of America	77	15.3 %
Germany	51	10.1 %
Canada	31	6.2 %
Australia	24	4.8 %
Italy	24	4.8 %
France	19	3.7 %
Brazil	17	3.4 %
South Africa	11	2.1 %
New Zealand	10	2 %
Others (38 countries)	98	19.4 %

the Landsat satellites were analysed together), with 81. Among the other platforms not specifically cited in the plot, it is important to highlight the presence of Quickbird, which has been working since 2001, and the Gaofen constellation, a Chinese-based program first launched in 2013 that includes multispectral, radar and electro–optical sensors, which will become popular in the coming years.

Considering the evolution of the employment of different satellites in the characterisation and monitoring of grasslands and pastures over time, as shown in Fig. 6, MODIS had led for many years, from 2008 to 2019, but since its launch on the 23rd of June 2015, Sentinel-2 has rapidly gained popularity among scientists and researchers, and since 2020, it has been the most utilised satellite platform in this field. In 2022, Sentinel-2 was the most considered satellite, utilised in 32 studies, almost double that of Modis, which stopped at 17.

Using satellite platforms by researchers in grassland and pasture studies reveals notable differences based on the authors' geographical origins. Fig. 7 illustrates the proportional usage of various satellite platforms by different countries. Each pie chart on the map represents the distribution of satellite platform usage for a particular country, with the chart size corresponding to the total number of publications involving these platforms. Countries such as China, the USA, Canada, and Brazil predominantly rely on NASA's Modis and Landsat platforms. Modis is the most utilised platform in these countries, appearing in 59 %, 48 %, 59 %, and 36 % of the studies, respectively. Landsat also plays a significant role, being used in 18 %, 29 %, 20 %, and 28 % of the studies in these countries.

Conversely, Australia, South Africa, and European countries such as Germany, Italy, and France display a more balanced distribution across several platforms, with a relevant presence of Sentinel-2 and Spot. This distribution highlights the diverse approaches and capabilities of each country in utilising satellite technology for their respective needs.

The use of advanced statistical modelling techniques as machine learning algorithms has gained much importance throughout the scientific world in recent years [66,67]. The application of remote sensing technologies to the monitoring and characterisation of pastures and grasslands often requires the manipulation of large amounts of data, and machine learning algorithms are increasingly the most utilised tools by scientists and professionals in the sector [28,68].

Fig. 8 shows the results of the quantitative analysis of the number of studies in which each machine learning algorithm was utilised, and the 10 most recurring algorithms are plotted. Random Forest was the most common, with 66 papers, followed by linear regression and support vector machine, with 28 papers each.

Considering the evolution of machine learning algorithm utilisation over the past 20 years, it is important to note that, aside from linear regression, the first studies applying these techniques to monitor and characterise grasslands and pastures emerged only from 2012 onwards. Random Forest has gained significant popularity in the scientific community, with its usage increasing rapidly in recent years. Notably, these studies, excluding those involving linear regression, reached their peak in 2022, with 22 publications focusing on grassland and pasture monitoring and characterisation.

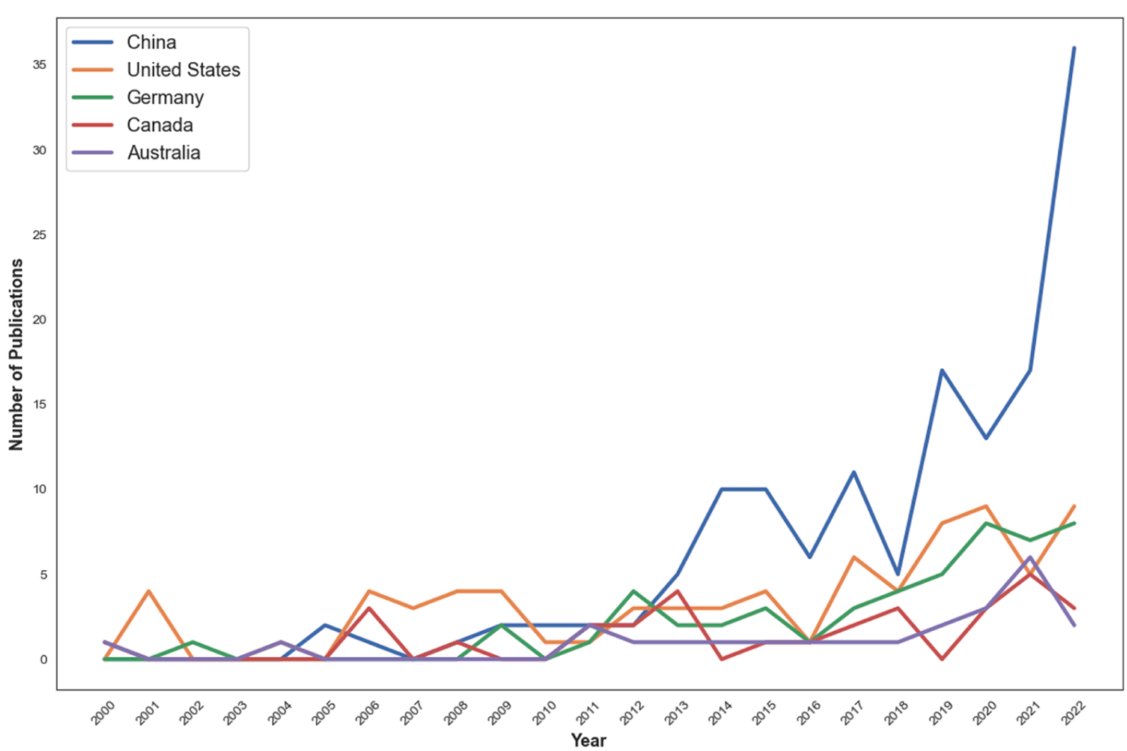

Fig. 4. The evolution in terms of the number of publications during 2000–2022 of the top 5 contributing countries in regard to the research topic.

Table 5
Lists of the top 10 publishing journals on the topic of remote sensing applied to grassland and pasture studies, their number of publications, percentage of total publications, impact factor, SJR and Cite Score (all metrics are available for 2022).

Journal	Total number of publications	Percentage	Impact Factor (2022)	SJR (2022)	Cite Score (2022)
Remote Sensing	103	20.4 %	5.0	1.136	6.6
International Journal of Remote Sensing	37	7.3 %	3.4	0.732	7.0
Remote Sensing of Environment	32	6.3 %	13.5	4.057	24.8
Ecological Indicators	17	3.4 %	6.9	1.396	10.3
International Journal of Applied Earth Observation and Geoinformation	17	3.4 %	7.5	1.628	10.2
Canadian Journal of Remote Sensing	9	1.8 %	2.6	0.619	3.9
GIScience and Remote Sensing	8	1.6 %	6.7	1.340	9.4
ISPRS Journal of Photogrammetry and Remote Sensing	8	1.6 %	12.7	3.308	19.2
Journal of Applied Remote Sensing	8	1.6 %	1.7	0.388	3.4
Rangeland Ecology and Management	8	1.6 %	2.3	0.776	4.6
Others (149 journals)	257	51 %	–	–	–

3.3. Cluster analysis

The last part of the review focused on analysing the most recurring words in titles, abstracts and keywords of the published journal articles concerning the applications of remote sensing to characterise and monitor grasslands and pastures.

The titles, abstracts and keywords were processed using natural language processing techniques, and a list of words and their number of occurrences was extracted. As some bigrams, made of two words, can have great relevance considered together (for example, “Remote Sensing” or “Climate Change”), our research considered bigrams occurring >30 times as single words.

The first 70 terms and bigrams among the pre-processed terms were grouped into five conceptual clusters. The weight of a cluster was determined by the sum of the weights of the terms that belong to it over the total number of term occurrences.

The cluster with the highest weight was that with the theme “Instruments”, at 25.83 %, which included all words and concepts regarding all the tools involved in the applications of remote sensing technologies to the monitoring and characterisation of grasslands and pastures, including both data collection tools (e.g., ‘Remote Sensing’, ‘Satellite’, and ‘UAV’) and statistical data processing and modelling instruments (i.e., ‘Model’, ‘Regression’, and ‘Algorithm’). The most common terms in the cluster were, in descending order, model (20 %), remote sensing (13.8 %), image (11.3 %), satellite (7.9 %), MODIS (7.7 %), Sentinel (7.4 %), R (5.2 %), map (4.8 %) and Landsat (3.5 %). Even the “Parameters” cluster had a similar weight, 24.96 %, as shown in Table 6.

The cluster “Parameters” included the terms and concepts linked to the applications of remote sensing for grasslands and pastures that can calibrate and evaluate the quality of the technological applications, such as the vegetation index (11.9 %), accuracy (9.9 %), index (9.9 %), NDVI (8.2 %), AGB (7 %), productivity (6.2 %) and time series (4.6 %).

As reported in Table 6, the “Vegetation” cluster was only slightly less important, with a weight of 24.15 %. We collected words and bigrams concerning grassland and pasture vegetation and habitats and their components, such as grassland (51.9 %), pasture (13.5 %), biomass (8.4 %), species (5.6 %), plant (3.9 %), grass (3.9 %) and phenology (5 %). The “Environment” (13.11 %) and “Management” (11.94 %) clusters had lower but still significant weights. The “Environment” cluster contains those terms and concepts related to the environmental elements and processes that characterise and affect grasslands and pastures; the most important terms in the cluster are soil (11.4 %), ecosystem (11.3 %), degradation (8.8 %), water (8.7 %), carbon (7.2 %), ground (6.6 %), drought (5.9 %), land (5.9 %), climate (5.7 %) and ecological (5.6 %). In the “Management” cluster, the terms that represent the most important actions involved in the applications of remote sensing to grassland and pasture monitoring and characterisation are estimation (34.9 %), monitoring (17 %), classification (13.9 %), grazing (10.3 %), mapping (8.5 %) and conservation (5.5 %). terms. Thus, for each of the 70 most commonly used words in the title, keywords, and abstract sections, pairings were made with the other 69 words, resulting in 1447 potential pairings. These pairings were analysed based on their frequency in the literature over 20 years and depicted visually, creating a complex network of relationships (Fig. 8). Additionally, the occurrences of these combinations grouped by cluster are also presented in tabular form (Table 7).

Given the centrality of the term “grassland” in the research topic, the “Vegetation” cluster was expected to have the highest number of co-occurrences. In contrast to expectations, the “Parameters” cluster showed the greatest number of co-occurrences, both between terms inside the cluster and those belonging to different clusters. The “Environment” and “Vegetation” clusters were second and third, respectively, in terms of co-occurrences both within and between the clusters. However, the reasons for their similar weights were different: while the environment cluster contained a large number of terms with very balanced weights, the vegetation cluster was characterised by the presence of the term “grassland”, which was the most important and common term in the whole research topic, as clearly visible in Fig. 9.

Interestingly, although the ’Instruments’ cluster had the highest total occurrences as shown in Table 5, it ranked fourth in terms of co-occurrences, both within the cluster and with other clusters. Finally, the "Management" cluster was identified as having the least interactions with other terms, also showing the lowest number of connections among words within the same cluster.

As shown in Fig. 9, the term showing the strongest connections was grassland. The connection between ‘grassland’ and ‘spatial’ was the strongest, but ‘model’, ‘satellite’, ‘monitoring’, ‘index’, ‘accuracy’ and ‘biomass’ also showed strong relationships with the central term of the topic. It is not surprising to see how these terms and their combinations are central to the research topic, as they represent some of the main instruments, parameters and management operations that are central in characterising and monitoring grasslands and pasture environments. Overall, despite the ’Instruments’ cluster having more occurrences in the initial analysis, the ’Parameters’ cluster showed greater centrality in terms of word relationships and bigrams.

The analysis of single pairs of terms, without considering the cluster to which they belong, allowed us to show which topics were the most related.

Table 8 was constructed by taking the first 30 pairs of terms by relationships. The term “grassland” and its relationships were excluded because they would hegemonise the table, making the analysis less interesting and significant. Some of the most recurring terms were “spatial”, “Model”, “index”, “accuracy” and “resolution”, suggesting that the focus of studies related to the characterisation and monitoring of grasslands and pastures using remote sensing is the development of tools and the evaluation and tuning of their technical parameters.

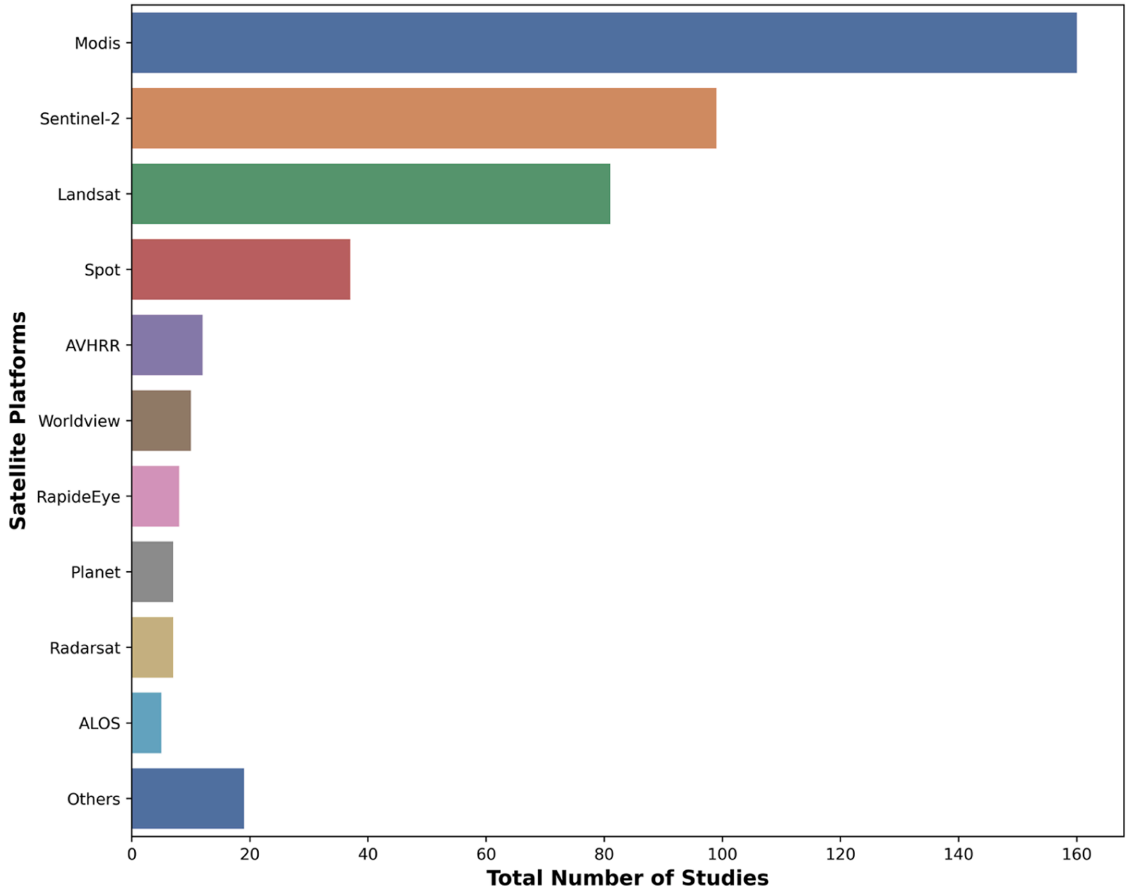

Fig. 5. The top 10 utilised satellite platforms according to the number of studies in the field of remote sensing applied to grassland and pasture studies in 2000–2022.

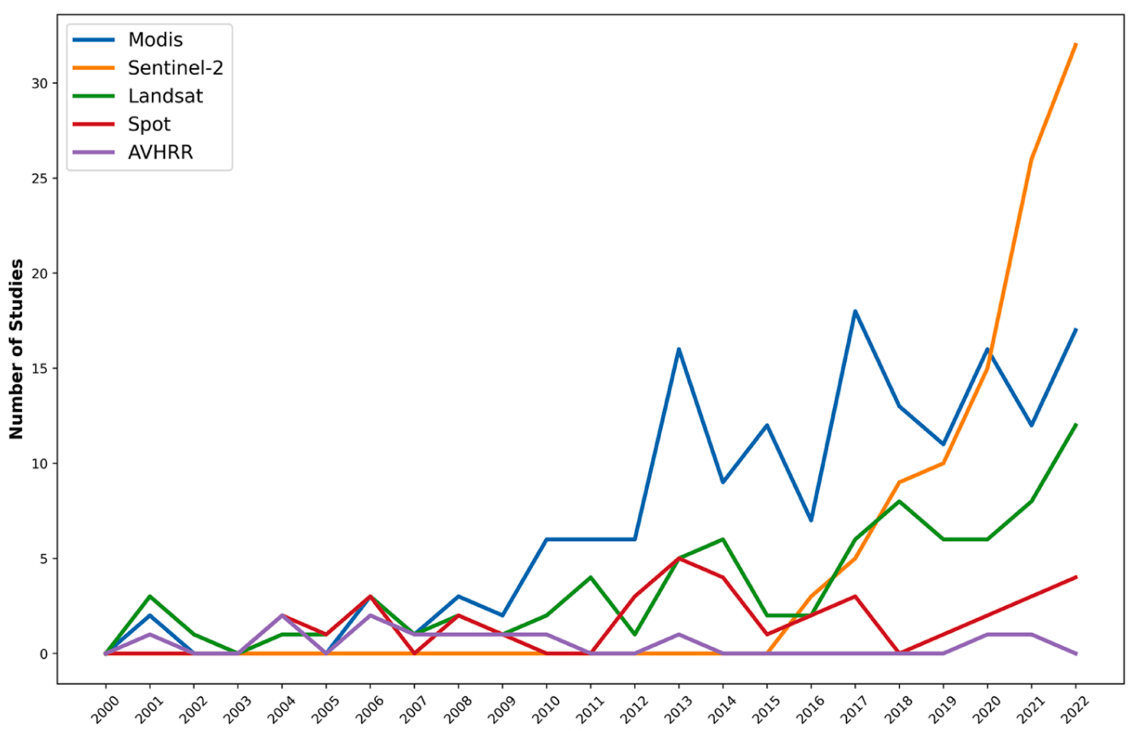

Fig. 6. The evolution in terms of the number of studies during 2000–2022 of the top 5 satellite platforms in the research area.

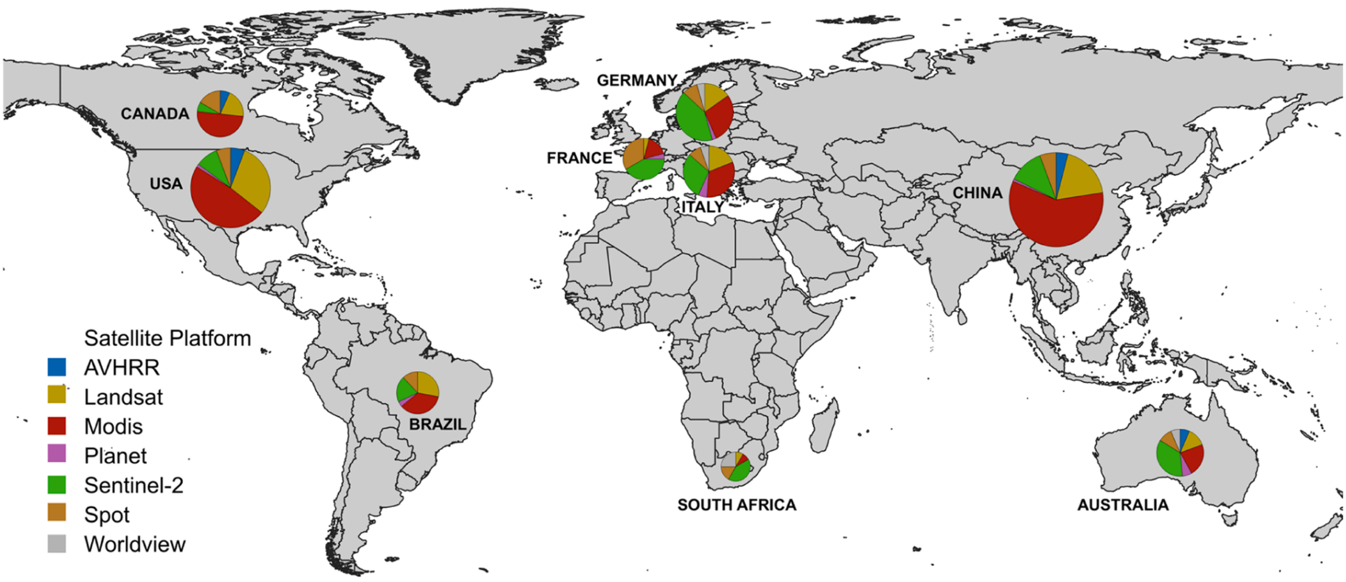

Fig. 7. The proportion of the utilisation in grassland and pasture studies of satellite platforms in the most important contributing countries, the size of the pie chart is proportional to the total number of publications involving satellites platforms.

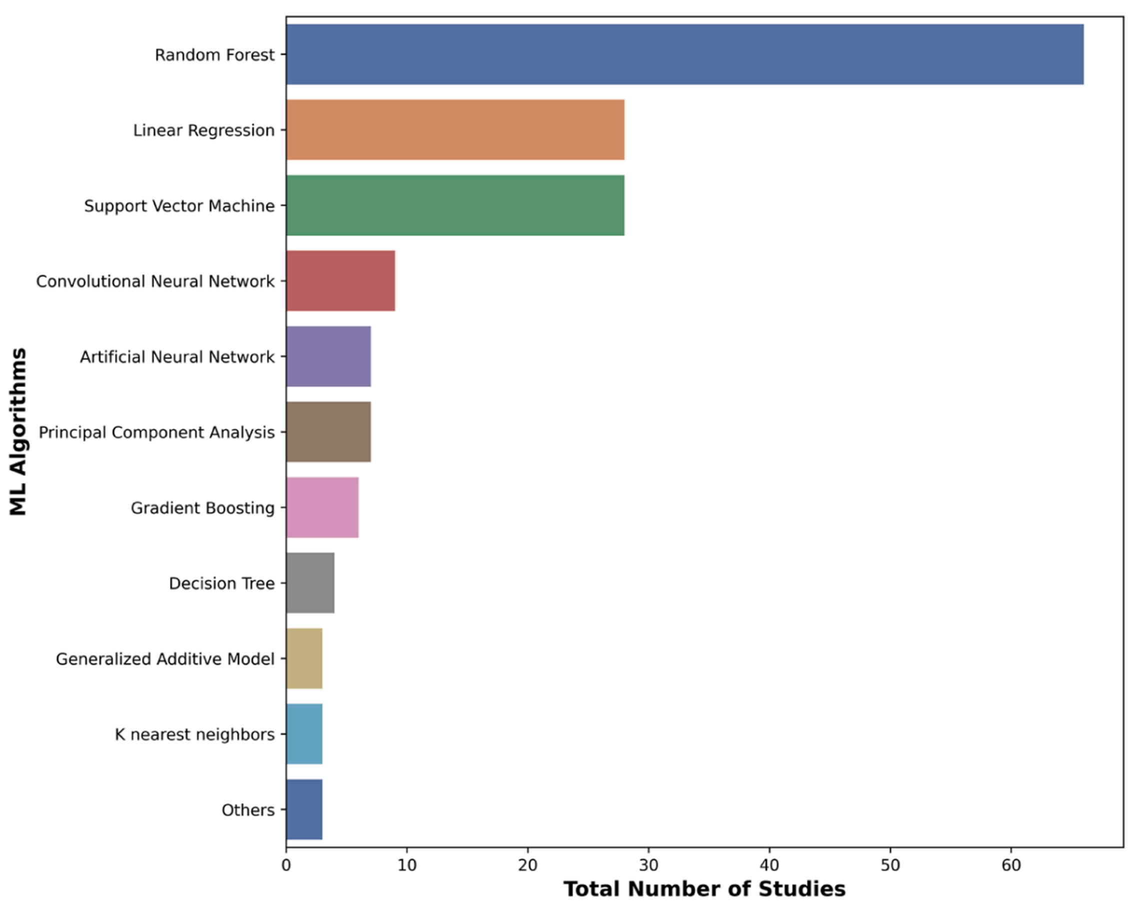

Fig. 8. The top 10 utilised machine learning algorithms according to the number of studies in the field of remote sensing applied to grassland and pasture studies in 2000–2022.

4. Discussion

The research utilised text-mining techniques to analyse the titles, abstracts, and keywords of each article. Key terms that were both critical and frequent were pinpointed and examined. Noteworthy connections were identified among specific terms as well as between aggregated clusters. Through a temporal analysis, the evolution of publications was tracked, highlighting topics that have become significant over time and

Table 6
Clusters and their composing terms reported by highest occurrence frequency.

Cluster	Terms and Bigrams
Instruments (25.8 %)	Model (20 %), Remote Sensing (13.8 %), Image (11.3 %), Satellite (7.9 %), Modis (7.7 %), Sentinel (7.4 %), R (5.2 %), Map (4.8 %), Landsat (3.5 %), Regression (3.3 %), Algorithm (2.9 %), Random Forest (2.7 %), UAV (2.6 %), Correlation (2.3 %), Hyperspectral (2.1 %), Multispectral (2 %)
Parameters (24.9 %)	Vegetation Index (11.9 %), Accuracy (9.9 %), Index (8.6 %), NDVI (8.2 %), AGB (7 %), Productivity (6.2 %), Spatial (6 %), Spectral (4.8 %), Time Series (4.6 %), Normalized Difference (3.7 %), LAI (3.4 %), GPP (3.1 %), Resolution (3 %), Temporal (3 %), Variability (2.8 %), Reflectance (2.5 %), Optical (2.3 %), Bands (2.3 %), Seasonal (2.2 %), EVI (2.2 %), RMSE (2.1 %)
Vegetation (24.1 %)	Grassland (51.9 %), Pasture (13.5 %), Biomass (8.4 %), Species (5.6 %), Plant (3.9 %), Grass (3.9 %), Phenology (5 %), Agricultural (2.8 %), Canopy (2.4 %), Forage (2.3 %)
Environment (13.1 %)	Soil (11.4 %), Ecosystem (11.3 %), Degradation (8.8 %), Water (8.7 %), Carbon (7.2 %), Ground (6.6 %), Drought (5.9 %), Land (5.9 %), Climate (5.7 %), Ecological (5.6 %), Precipitation (5.2 %), Fire (4.8 %), Steppe (4.42 %), Temperature (4.4 %), Alpine (4.1 %)
Management (11.9 %)	Estimation (34.9 %), Monitoring (17 %), Classification (13.9 %), Grazing (10.3 %), Mapping (8.5 %), Conservation (5.5 %), Livestock (4.9 %), N (4.8 %)

relationships that have grown stronger.

4.1. Analysis of publication trends

Themes related to the application of remote sensing to Earth and agricultural sciences and, more specifically, to the characterisation and monitoring of grasslands and pastures, are relatively recent topics. During the last 22 years (2000–2022), interest in this topic has risen sharply, and the number of publications on remote sensing in the Earth and agricultural sciences grew slightly <11 times and >3 times the weight of total articles published in Scopus during the same period, respectively.

Analysing the publications concerning the applications of remote sensing to the characterisation and monitoring of grasslands and pastures, the growth was even sharper, with the number of publications growing by 31 times and the ratio of total Scopus publications growing by >9 times. Studies within this field have explored all facets related to the topic from various perspectives, as illustrated by the cluster analysis, with a focus on instruments and parameters.

The analysis of the geographic distribution of the literature carried out through the examination of the authors' affiliations (Table 3) revealed that the most active nations were China (28.3 %), the USA

Table 8
Couples of terms with the highest co-occurrences (excluding 'grassland').

Source	Target	Weight	Source	Target	Weight
Spatial	Resolution	86	Monitoring	Index	54
Satellite	Spatial	82	Monitoring	Accuracy	54
Model	Spatial	81	Spatial	Estimation	53
Spatial	Index	80	Satellite	Resolution	53
Accuracy	Spatial	78	Satellite	Land	52
Spatial	Temporal	78	Biomass	Estimation	50
Monitoring	Spatial	72	Index	Resolution	49
Model	Accuracy	71	Pasture	Satellite	49
Model	Biomass	67	Model	Monitoring	48
Model	Index	65	Accuracy	Index	48
Accuracy	Satellite	65	Spatial	Soil	47
Biomass	Spatial	63	Index	Temporal	47
Monitoring	Satellite	63	Spatial	Land	47
Accuracy	Classification	61	Biomass	Index	47
Model	Estimation	54	Monitoring	Resolution	46

Table 7
Co-occurrences of terms within and between clusters.

	Environment	Instruments	Management	Parameters	Vegetation
Environment	1986	1382	1003	2146	1669
Instruments	–	1186	1020	2031	1530
Management	–	–	664	1530	1208
Parameters	–	–	–	3932	2312
Vegetation	–	–	–	–	1412

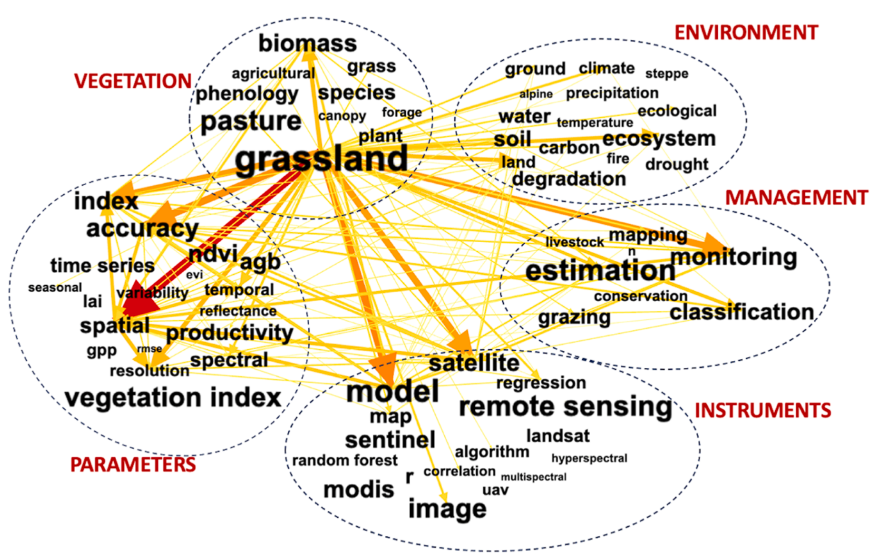

Fig. 9. Graphical representation of the 70 most recurring words in the research topic. The font size is adjusted to be proportional to the number of occurrences, and the thickness and darkness of the connecting arrows represent the number of co-occurrences between linked terms.

(15.3 %) and Germany (10.1 %). China is unquestionably the largest contributor, with Fig. 4 indicating a rapidly increasing number of publications. The analysis of the editorial distribution of publications highlighted that the selected topic has a precise editorial definition and allocation, as 44 % of published articles are in three journals, with "Remote Sensing" collecting 20.4 % of the considered articles on its pages.

4.2. Quantitative analysis of satellite platforms and machine learning algorithms

Satellite platforms are the most utilised source of remote sensing data [69–71], especially when related to the characterisation and monitoring of grasslands and pastures. Of the 503 papers collected for our analysis, 88 % contained the word "satellite" in their title, abstract or keywords.

The quantitative analyses of the utilisation of the individual satellite platforms allowed us to identify some important facts, as shown in Fig. 5. Due to the high versatility, daily revisit time and availability of multiple pre-processed products, the Moderate Resolution Imaging Spectroradiometer (MODIS), which is mounted on the Terra (launched in 1999) and Aqua (launched in 2002) satellites from NASA, is the most utilised tool in grassland and pasture studies.

However, when analysing the temporal trend in the use of satellite platforms, it is worth noting that Sentinel-2, which was launched in 2015 by the ESA, has gained massive popularity in the scientific community and has become the most utilised platform in recent years.

The availability of 13 spectral bands ranging from 443 to 2190 nm at high spatial resolution, ranging from 10 to 60 m, with a revisit time of 5 days, makes it a versatile and very suitable tool for Earth observation and monitoring studies [34,47,72,73]. Despite the high spatial resolution, the data from these satellites suffer from long time intervals and cloud cover interference [74]. Several studies have fused data from different satellite sources to enhance temporal continuity and fill in data gaps [75]. In smaller grassland fields, the need for high-resolution images is critical, and commercially available platforms such as Planet Scope and Worldview have gained significant importance in biomass estimation studies [71,76]. They offer daily revisit times with great spatial resolution (1.8 m for Worldview and 3 m for Planet Scope), even though the number of multispectral bands is still limited compared to that of Landsat and Sentinel platforms. While all satellite platforms provide valuable data for grassland and pasture monitoring, it is crucial to recognise the limitations and trade-offs associated with varying resolution levels. Mid- to low-resolution products, such as those from MODIS, are well-suited for large-scale applications due to their extensive coverage and frequent revisit times, which are particularly useful in global and regional monitoring efforts [77–79]. However, these products may need more detailed precision for more localised studies, where fine-scale vegetation characteristics and management practices must be accurately assessed [80,81]. Conversely, high-resolution data from platforms like Sentinel-2, PlanetScope, and Worldview are essential for small-scale, detailed analyses, such as distinguishing pasture species or monitoring phenological changes at the paddock level [82–84]. Nonetheless, these high-resolution datasets come with increased resource demands, including higher data acquisition costs and processing time, which can limit their feasibility for widespread use [85]. Therefore, selecting the appropriate resolution depends on the specific scale and objectives of the study, balancing the need for detailed information against the practical considerations of resource availability and processing capabilities.

With the rise in the availability of large volumes of raw and processed data, there is a growing need for statistical methods capable of handling this data and extracting significant and useful information. Machine learning algorithms have been increasingly utilised in studies related to the application of remote sensing technologies to the characterisation and monitoring of grasslands and pastures [86–88], as shown in Fig. 8. The choice of data analysis methods is influenced by several factors, such as the size and heterogeneity of the study area, the number of predictor variables, and the study's objectives. Interestingly, random forest [89] and linear regression, the most utilised methods, have very different characteristics. Linear regression has a better capacity for generalising the relationships among variables, thus producing robust models that can perform well on different datasets. On the other hand, the random forest algorithm is known to adapt more to the training dataset; it can detect and model complex relationships among multiple variables. These features make it very suitable for modelling biological variables such as biomass production, but at the same time, it has an intrinsic tendency to overfit the data [90], producing models that do not generalise well and thus are not useful for practical purposes [91]. Although some authors, such as Smith et al. [68], have recently attempted to assess the performance and transferability of several machine learning algorithms (particularly PCR, PLSR, LASSO, RF, SVM and GBM), the variability and complexity of grassland and pasture environments and features need further investigation and research.

4.3. Cluster and network analysis

The described cluster analysis shows that, during the last 20 years, the focus has been on the instruments and the evaluation and tuning of the parameters that are involved in the development of tools able to estimate, evaluate and monitor environmental variables, mainly vegetation characteristics such as biomass content and quality. The high importance of the "Instruments" and "Parameters" clusters, visible in Table 5, perfectly highlights the abovementioned concepts, and the focus of scientists involved in the applications of remote sensing to grassland and pasture studies has been on the technologies and their development. The analysis of the most significant relationships, apart from the centrality of "grassland", confirmed the centrality and importance of the "Parameters" cluster, but the increasing importance of the "Environment" cluster, characterised by the presence of a high quantity of words, was quite balanced in terms of occurrences.

5. Conclusions

Over the past two decades, there has been an increasing focus on utilising remote sensing technologies to map and monitor grasslands and pastures. This surge in interest has led to a deeper exploration of various and distinct topics within the broad domain of remote sensing applications in Earth and agricultural sciences. This research seeks to map these evolving trends by identifying and emphasizing the most significant terms or relationships based on their frequency in scientific publications.

The most important contributions are in three macroareas—China, North America, and China—while developing countries are less represented. Although the publications are spread across 159 different journals, the top five journals contribute to >44 % of the publications. This indicates that the topic is well defined and possesses a clear editorial niche.

The quantitative analysis of satellite platforms showed that Moderate Resolution Imaging Spectroradiometer (MODIS) data are the most widespread among grassland and pasture studies, mainly because of its availability and daily revisit time, even though Sentinel-2, characterised by a higher spatial resolution and relatively low revisit time (5 days), has become the most common choice in recent years.

Additionally, the results of the review suggest that future efforts might focus on the implementation, testing, and tuning of instruments and parameters related to mapping and monitoring tasks, especially with a focus on biomass estimation and land degradation monitoring. The major concern that researchers are facing regards the development of models and tools that reach a high level of accuracy. The increasing availability of large amounts of data from satellite sources will demand tools that can analyse and extract valuable information. Thus, machine learning algorithms will be increasingly involved. The quantitative analysis of machine learning algorithms highlighted that the most commonly used algorithm for grassland and pasture studies is random forest, followed by linear regression and support vector machine methods.

Developing accurate and precise tools will aid farmers and policymakers in better managing grassland and pasture environments [92]. This improvement will enhance these areas' agricultural and environmental roles. It is particularly crucial in regions where grasslands are a fundamental resource [24]. Despite the growing availability of free or cost-effective satellite data from both public entities (e.g. NASA, ESA, CNMS, etc.) and private companies (e.g. AgroInsider, SPACETM, DataFarming, GeoGraze, pasture.io, etc.), leveraging this data for effective grassland monitoring involves significant associated costs. These costs include data preprocessing, which requires computing infrastructure for downloading, storing, and processing raw satellite data into analysis-ready formats. The entry of high-tech corporations with services and platforms such as Microsoft Planetary Computer, Google Earth Engine, Amazon Web Services, and Oracle Cloud Infrastructure, which offer cloud computing solutions to support digital agriculture and earth monitoring platforms, may facilitate the development of user-friendly tools and services as GeoServer platforms, but involving direct costs for users and developers [85]. For example, while Microsoft Planetary Computer offers a free platform, users might still face costs depending on the amount of data processed and stored. Processing large datasets can necessitate an Azure Cloud Services subscription, with storage fees ranging from $0.003 to $0.15 per GB per month and data processing costs between $0.35 and $1.40 per GB per hour, depending on the service tier. Similarly, Google Earth Engine provides a free tier for researchers, but commercial users may encounter significant expenses. For instance, Google Cloud Platform charges between $0.006 and $0.023 per GB per month for data storage, while virtual machine costs start at $0.038 per vCPU per hour, offering scalable processing capacity. Amazon Web Services (AWS) also presents a flexible pricing structure, with storage costs ranging from $0.005 to $0.024 per GB per month. AWS provides a variety of virtual machine options, including free-tier services like AWS Lambda, but more robust solutions may come with additional costs. In comparison, Oracle Cloud Infrastructure offers competitive rates, with storage fees as low as $0.002 per GB per month, scaling up to $0.30 per GB for premium options. Their virtual machines are priced at $0.032 per vCPU per hour, making them a cost-effective choice for intensive data processing tasks.

Additionally, collecting ground data to calibrate and validate satellite models involves fieldwork expenses and laboratory analysis costs. Moreover, developing and refining machine learning algorithms demands computational resources and expert personnel, while operational monitoring necessitates ongoing staff support and robust data management systems.

Finally, the implemented semiautomatic methodology integrates natural language processing techniques to quantify the occurrence of concepts and their relationships within a specific research topic, allowing the identification and quantitative analysis of the main trends within a specific research topic and laying the path for similar work in the future.

Future efforts might focus on implementing, testing, and tuning instruments and parameters related to mapping and monitoring tasks, especially with a focus on biomass estimation and land degradation monitoring. The major concern that researchers are facing concerns the development of models and tools that reach a high level of accuracy. The increasing availability of large amounts of data from satellite sources will demand tools that can analyze and extract valuable information. Thus, machine learning algorithms will be increasingly involved.

Integrating data from various sources, advancing machine learning algorithms, assessing climate change impacts, conducting region-specific studies, developing user-friendly tools for stakeholders, and examining economic and environmental trade-offs are crucial areas for future research. These efforts will help improve the management of grassland and pasture environments, enhancing their agricultural and environmental roles.

CRediT authorship contribution statement

Daniele Pinna: Writing – original draft, Software, Investigation, Formal analysis, Data curation, Conceptualization. **Andrea Pezzuolo:** Writing – review & editing, Visualization, Validation, Resources, Methodology, Funding acquisition, Conceptualization. **Alessia Cogato:** Writing – review & editing, Visualization. **Cristina Pornaro:** Writing – review & editing. **Stefano Macolino:** Writing – review & editing, Visualization. **Francesco Marinello:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Methodology, Conceptualization.

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.

Data availability

Data will be made available on request.

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