

Review

# Text Mining in Remotely Sensed Phenology Studies: A Review on Research Development, Main Topics, and Emerging Issues

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Abstract: As an interdisciplinary field of research, phenology is developing rapidly, and the contents of phenological research have become increasingly abundant. In addition, the potentiality of remote sensing technologies has largely contributed to the growth and complexity of this discipline, in terms of the scale of analysis, techniques of data processing, and a variety of topics. As a consequence, it is increasingly difficult for scientists to get a clear picture of remotely sensed phenology (rs+pheno) research. Bibliometric analysis is increasingly used for the study of a discipline and its conceptual dynamics. This review analyzed the last 40 years (1979-2018) of publications in the rs+pheno field retrieved from the Scopus database; such publications were investigated by means of a text mining approach, both in terms of bibliographic and text data. Results demonstrated that rs+pheno research is exponentially growing through time; however, it is primarily considered a subset of remote sensing science rather than a branch of phenology. In this framework, in the last decade, agriculture is becoming more and more a standalone science in rs+pheno research, independently from other related topics, e.g., classification. On the contrary, forestry struggles to gain its thematic role in rs+pheno studies and remains strictly connected with climate change issues. Classification and mapping represent the major rs+pheno topic, together with the extraction and the analysis of phenological metrics, like the start of the growing season. To the contrary, forest ecophysiology, in terms of ecosystem respiration and net ecosystem exchange, results as the most relevant new topic, together with the use of the red edge band and SAR (Synthetic Aperture Radar) data in rs+pheno agricultural studies. Some niche emerging rs+pheno topics may be recognized in the ocean and arctic investigations linked to phytoplankton blooming and ice cover dynamics. The findings of this study might be applicable for planning and managing remotely sensed phenology research; scientists involved in such discipline might use this study as a reference to consider their research domain in a broader dynamical network.

**Keywords:** bibliometric analysis; land surface phenology; network analysis; research topic; scientific mapping



#### 1. Introduction

Phenology is an integrative environmental science embracing biometeorology, ecology, and evolutionary biology [1]; it has become a major concern in current global change research due to its ability to monitor, understand, and predict the periodicity of biological events related to climate [2], from intra- to inter-specific level to global scale.

As discussed by Forrest and Miller-Rushing [3], historically, because of its concrete application in agricultural cultivations, much phenological research has focused on issues, such as pest management, agro-meteorology, and horticulture, overlooking purely phenological topics. Even ecology-based studies with a marked phenological focus did not refer to phenology as a science per se [3].

In the last two decades, the growing attention on the impacts of climate change has exponentially enhanced the interest towards phenology. The recent launch of the USA National Phenology Network (USA-NPN; https://www.usanpn.org/), the Pan European Phenology Project (PEP725; http://www.pep725.eu/), the Phenological Eyes Network in Japan (PEN; http://www.pheno-eye.org), the GLOBE phenology project (https://www.globe.gov/web/phenology-and-climate) confirm the current necessity of understanding phenological dynamics under a changing environment and at multiple geographical scales [4,5].

Plant phenology has been studied at a range of spatial and temporal scales and by employing a variety of tools [6]. Phenological studies can be led through small scale, ground-based studies [7], and large-scale investigations using proxy approaches through remote sensing (the so-called land surface phenology, LSP) [8,9]. Significant limitations exist in monitoring phenology at the ground level, mainly due to the difficulty of (i) harmonizing data records over plant species and phenological events; (ii) using such data at global or regional scales due to the time and efforts consuming nature of field observations; (iii) integrating field data with observations of climatic variables, which have a very coarse spatial resolution; and (iv) extending the phenological events identified from individual species to communities [10].

Remotely sensed phenology (rs+pheno), or LSP, has the potentiality to overcome some of the field observation limits, filling the gap between traditional phenological (field) observations and the large-scale view of global models [11], enabling the mapping and monitoring of phenology at the ecosystem level, and providing an integrative framework at the landscape scale [12]. Satellite observations constitute a spatially aggregated signal from heterogeneous surface conditions that may not be representative of any single plant species response (pixel size from meters—e.g., Sentinel-2, to km—e.g., SPOT (Satellite Probatoire d'Observation de la Terre) Vegetation) [9]. Rs+pheno is defined as the seasonal pattern of variation of vegetation indices (i.e., greening, senescence, dormancy, etc.) in vegetated land surfaces observed from satellite remote sensing [13]. Accordingly, the length of the time series (from 5 years of Sentinel-2 to 30 years of Landsat), the high temporal frequency (from twice daily of MODIS (Moderate Resolution Imaging Spectroradiometer) to 5 days of Sentinel-2), internal consistency, and continuous availability of the satellite measurements are fundamental requirements when dealing with ecosystem responses to climate change dynamics [14].

Large to small scale remote sensing techniques are based on deriving vegetation indices (VIs), leaf area index (LAI), a fraction of absorbed photosynthetically active radiation (fAPAR) from satellite-based sensors [15]. Most studies on vegetation phenology are based on the normalized difference vegetation index (NDVI, [16]) or the enhanced vegetation index (EVI, [15]), measures of 'greenness' [17] that can be related to plant canopy absorption of photosynthetically active radiation [18] and Gross Primary Productivity (GPP) [19]. The evolution of remotely sensed VIs through time exhibits a strong correlation with the typical vegetation growth stages. The VIs temporal curves allow to quantify intra-annual changes in the timing and intensity of vegetation activity and to extract useful metrics about the vegetation growing season, such as the timing of the start, the end, and the length of the growing season, at various scales [20].

In the past few decades, within the framework of increasing interest in phenology, rs+pheno studies showed a marked intensification that could be explained by the nonstop development of

satellite remote sensing technology and its ability to provide temporally continuous information about the ecosystem responses to climate change at different spatio-temporal scales. The length of the time series (from 10 to 30 years), the high temporal frequency (from twice daily to 5 days), internal consistency, and continuous availability of the satellite measurements are highly desirable qualities when dealing with ecosystem phenological responses to climate change dynamics [14]. Satellite observations are hence becoming increasingly important for phenological investigations, and given the growing interest towards rs+pheno, an overall vision of what has been explored up to now, together with the identification of research trends, key topics, gaps, and new questions may represent an important knowledge tool when framing a research and exploring the state-of-the-art of a scientific issue.

In recent years, bibliometric analysis has played an increasingly important role in the framework of understanding science and technology tendencies [21], thanks to its potentiality to document the development of a wide range of research fields [22–25]. Some studies started to explore topic frequencies and concept trends in phenological studies, but only for a specific country or a specific subject area. For instance, Adole et al. [26] examined all peer-reviewed literature on Africa's vegetation phenology to provide a synthesis of such studies and classified them based on the methods and techniques used in order to identify major research gaps; Nagai et al. [27] reviewed remote sensing phenological studies in Japan and discussed current knowledge, problems, and future developments based on these studies; Uribe-Toril et al. [28] in the bibliometric overview of the Forests journal aimed at highlighting the state of the art of forestry, cited as a major research cluster the integration of MODIS and Landsat imagery for mapping forest biomass and phenology. Other bibliometric studies analyzed major topics and concepts in remote sensing research fields either in general [29,30] or based on specific issues, like crop growth monitoring [31], water research [32], archaeology [33], etc.

To the best of our knowledge, this is the first attempt to carry out a broad literature analysis to explore and summarize the remotely sensed phenology (rs+pheno) studies through time at a global level. We performed such analysis through a text mining approach. Text mining is the use of automated methods for exploiting the huge amount of knowledge available in the scientific literature [34]; it consists of deriving high-quality information (in terms of relevance, novelty, and interest) from text through the recognitions of patterns and trends by means of statistical pattern learning [35]. In this review, we performed a bibliometric text mining analysis of rs+pheno research over the last 40 years (1979–2018) aimed at (1) quantifying the distribution of publications and journals for articles covering rs+pheno research, (2) examining the rs+pheno keywords frequency and tendencies, and (3) exploring the rs+pheno research development to identify key topics, new research niches, and emerging issues.

#### 2. Materials and Methods

## 2.1. Data Retrieving

The rs+pheno literature search was performed using Elsevier Scopus electronic scientific databases. The search terms were 'phenolog\*' and 'remote\* PRE/0 sens\*' in the title, abstract, and keywords; only peer-reviewed documents published in English between 1979 and 2018 were considered. The subject areas covering 'medical', 'economical', 'artistic', 'chemical', 'veterinary' issues were excluded. This search yielded documents composed of articles, conference papers, reviews, books chapter, conference reviews, notes, articles in press, books, editorials, and letters.

After recovering the data, a first analysis was performed according to the Scopus statistics on the publications retrieved. We analyzed the temporal trend of the number of rs+pheno papers from 1979 to 2018 with respect to the number of all the scientific papers published in the same time interval.

#### 2.2. Text Mining Analysis

A text mining analysis was performed on the rs+pheno literature data of the last 20-year period to analyze the rs+pheno research evolution through term network extraction and scientific mapping.

We focused only on the periods 1999–2008 and 2009–2018 because the number of rs+pheno publications in the periods 1979–1988 and 1989–1998 was too small to allow a comparison among the four decades. To this aim, the VOSviewer software (www.vosviewer.com) was used: first, a network is constructed on the basis of the data made available to VOSviewer; then, accordingly, clustering is performed, and groups of related terms are mapped [36]. The data provided to VOSviewer might be bibliographic data or text data. Bibliographic data are all the information easily retrievable from a publication like Authors, Organizations, Countries, Year of publication, Author keywords, Index keywords, Citations; on the contrary, text data are terms that can be extracted from Abstract and/or Title by means of an ad hoc algorithm. When dealing with bibliographic data, a co-occurrence analysis can be directly performed based on both authors' and indexed keywords, and a network is constructed accordingly. On the contrary, when analyzing text data, firstly terms need to be identified in the text (i.e., title and abstract). VOSviewer defines a term as a noun phrase, i.e., a sequence of one or more consecutive words within a sentence. For selecting the most relevant terms, the distribution of co-occurrences across all noun phrases is computed. While occurrence expresses the number of times a term occurs in a set of papers (i.e., how many papers cite that term), relevance depends on the co-occurrence of a given term with others: low relevant terms tend to co-occur with several different terms; on the contrary, high relevant terms tend to co-occur always with a specific set of terms. Terms with a low relevance (or with a general meaning) have a more or less equal distribution of their co-occurrences, while terms with a high relevance (or with a specific meaning) have a distribution of their co-occurrences that is significantly biased towards certain noun phrases. In a co-occurrence network, terms with a specific high relevance are clustered together; each cluster may be seen as a scientific domain or topic [37]. Finally, both for bibliographic and text data, a bi-dimensional map is created based on the constructed network of the selected terms, where the smaller the distance between two terms, the larger the number of their co-occurrences and hence their relatedness [38].

Based on bibliographic data, in order to study the evolution of keywords in the last two decades, we analyzed the most used keywords separately for 1999–2008 and 2009–2018. We kept only keywords with a minimum number of occurrence threshold equal to 20, i.e., the number of times a keyword must be present in the dataset to be used in the analysis. The term 'remote sensing', 'phenology', and 'vegetation' were excluded from the mapping in order to avoid overcited keywords. Then, we analyzed the text data for 1999–2008 and 2009–2018 separately. A term minimum number of occurrence threshold equal to 10 was used. For each of the retrieved terms, a relevance score (rel. score) was calculated. Based on this score, among all the terms identified, only the most relevant terms were selected (60% as default choice). The occurrence threshold was chosen based on a subjective criterion in order to have a manageable and, at the same time, a representative number of keywords and terms.

Finally, we analyzed the temporal trend over the last 40 years (1979–2018) of the ten most relevant terms identified in the 2009–2018 decade. To this aim, we trained a topic (i.e., term) model over the entire dataset and extracted for each article the related topics. The topic model was developed according to Lau and Baldwin [39] by jointly training the word2vec (an algorithm able to learn the similarity among words; [40]) and paragraph vectors (an algorithm able to learn the similarity among documents; [41]) models: in the embedding distribution space, a certain document will be placed close to terms describing its related topics. The frequency of each selected term (i.e., the number of publications where it occurred) in a certain year was normalized with respect to the amount of all the rs+pheno articles published in that year. A 5-years moving average over the 40 years trend was used to smooth out short-term fluctuations in time series data and highlight long-term trends. For this analysis, only the most relevant terms identified in 2009–2018 were selected among all the terms.

In order to avoid term repetition and to assure VOSviewer consistency, a thesaurus file was drafted. This file linked synonyms, different terms that express a unique concept, different spellings of the same word or the same abbreviation, plural/singular terms, common/Latin names of plants, etc. with one unique, unambiguous term.

# 3. Results

In the period analyzed (1979–2018), the Scopus archive search identified 2315 scientific publications (see Supplementary Materials). According to Figure 1, the rs+pheno research field has been significantly increasing ( $r^2 = 0.75$ ) independently from the general tendency of producing more and more publications.



**Figure 1.** Temporal trend of rs+pheno (remotely sensed phenology) papers over the period 1979–2018. In blue, the total number of rs+pheno papers; in orange, the ratio between the total number of rs+pheno papers and the total number of all the scientific papers multiplied by 1,000,000.

Comprehensively, 117 journals have been used to publish researches about remotely-sensed phenology. Table 1 shows the journals that published more than 20 papers from 1979 to 2018. Among these, the most prestigious journals (impact factor, IF > 5) used in rs+pheno studies were: Global Change Biology (GCB, IF = 8.88), Remote Sensing of Environment (RSE, IF = 8.218), ISPRS-Journal of Photogrammetry and Remote Sensing (ISPRS, IF = 6.942), and IEEE-Transactions on Geoscience and Remote Sensing (IEEE, IF = 5.63); on the contrary, the most cited (H index > 200) were: RSE (H index = 238), GCB (H index = 217), and IEEE-Transactions on Geoscience and Remote Sensing (H index = 216). The most active journals (>100 publications) were: RSE, International Geoscience and Remote Sensing Symposium-IGARSS, Remote Sensing (RS), International Journal of Remote Sensing (IJRS), and Proceedings of SPIE-The International Society for Optical Engineering (SPIE) with, respectively, 232, 166, 150, 148, and 117 papers. It is to be noticed that, among the most publishing, the only journals without remote sensing-like terms in their title were Agricultural and Forest Meteorology (AFM, 57), Global Change Biology (GCB, 30), and Ecological Indicators (EI, 23). According to Figure 2, the journals with the longest history in rs+pheno studies were RSE and IJRS (since 1980), while the most recent was RS (since 2009). However, the latter showed a marked increase in the last three years, twice the other journals. As for the purely ecology-based journals, the first one publishing a paper

in rs+pheno was AFM in 1996, followed by GCB in 2003 and EI in 2009; AFM still represents the most active.

**Table 1.** List of the most used scientific journals in rs+pheno (remotely sensed phenology) studies (>20 documents in 1979–2018), with corresponding impact factor (source: Thomson Reuters) and H index (source: SCImago Journal Rank - SJR).

Journal	Rs+Pheno Docs	Impact Factor	H Index
Remote Sensing of Environment	232	8.218	238
International Geoscience and Remote Sensing Symposium–IGARSS	166	na	58
Remote Sensing	150	4.118	81
International Journal of Remote Sensing	148	2.493	151
Proceedings of SPIE - The International Society for Optical Engineering	117	na	151
Agricultural and Forest Meteorology	57	4.189	144
ISPRS - Journal of Photogrammetry and Remote Sensing	52	6.942	110
IEEE - Journal of Selected Topics in Applied Earth Observations and Remote Sensing	35	3.392	64
IEEE - Transactions on Geoscience and Remote Sensing	32	5.63	216
International Journal of Applied Earth Observation and Geoinformation	32	4.846	86
Global Change Biology	30	8.88	217
Ecological Indicators	23	4.490	97
Photogrammetric Engineering and Remote Sensing	21	3.15	114
Journal of Applied Remote Sensing	20	1.344	39



**Figure 2.** Temporal trend of publications in rs+pheno studies over the period 1979–2018 for the five most publishing remote sensing-based journals (upper panel) and the three most publishing ecology-based journals (lower panel).

From the bibliographic data network analysis, two maps were derived (Figures 3 and 4) with 47 keywords for 1999–2008 and 214 keywords for 2009–2018: the closer the keywords, the higher their relatedness. The comparison between the two keyword maps underlined, on one hand, the growing role of MODIS and time-series data in rs+pheno studies, and, on the other hand, the larger dispersion of terms in the first decade with respect to the higher concentration in the second decade, which was also characterized by a massive enrichment of new research arguments. In particular, in 2009–2018, 'forestry', 'crops', 'biology', 'ecosystem', 'climate change', and 'time-series' represented the main issues around which the other keywords were distributed. Some examples of new major keywords appeared

in 2009–2018 were: 'primary productivity', 'growing season', 'spatial variability', 'biodiversity', 'image reconstruction', 'harmonic analysis', 'trend analysis', 'accuracy', 'machine learning', 'uav', 'radar', etc. According to Figure 3, one of the newest keywords in 1999–2008 was 'spatial resolution'; while in 2009–2018 (Figure 4), the keywords most used in the recent years were 'cost efficiency' and 'random forest', while those mainly used at the beginning of the decade were 'geology', 'water supply', 'irrigation', and 'carbon flux'.

The text data analysis produced the term network maps of Figures 5 and 6, respectively, for the period 1999–2008 (99 terms) and 2009–2018 (383 terms). In the first decade (Figure 5), two groups could be identified, even if quite interspersed. The red cluster was mainly characterized by terms strictly associated to phenology metrics (e.g., greenness, start, end, and length of season), vegetation and canopy indices and their annual profiles (e.g., NDVI time-series, EVI, LAI, fAPAR, amplitude, peak), climate change-related issues (e.g., temperature, trend, interannual variability, drought, fire), and forestry (e.g., canopy, leaf, forest type, tropical forest, boreal forest). The blue cluster was mainly composed of terms related to the classification (i.e., accuracy, mapping, change detection, discrimination, land cover, unsupervised classification), crop modeling (e.g., crops, growth, yield, prediction, cost efficiency, management), and the crop growing season (i.e., months from March to November). It is to be noticed that the only highly cited sensor was Landsat that belongs to the blue cluster.

In the second decade (Figure 6), three groups could be clearly distinguished. The red cluster was mainly characterized by terms associated to phenology climate-based drivers (e.g., precipitation, temperature, LUE (light use efficiency), latitude, altitude, solar radiation), phenology metrics and their trend (e.g., start, end, and length of season, response, increase, delay, MODIS time-series), climate change-related effects (e.g., disturbance, dry season, moisture, fire, resilience, species composition), forest ecophysiology (e.g., carbon, carbon cycle, carbon flux, ecosystem respiration, fAPAR, GPP, net ecosystem exchange (NEE), exchange), ocean and arctic dynamics (e.g., phytoplankton, phytoplankton bloom, ice, ice cover, GIMMS (Global Inventory Modeling and Mapping Studies), and regions like Cerrado, Tropic, Savanna, North America, and Tibetan Plateau. The blue cluster was mainly composed of terms related to phenology applications in agriculture (e.g., yield, food, crop classification, growth stage, sowing date, crop management, low cost), crop types (e.g., crops, wheat, maize, vineyard, soy, barley), water resource (e.g., irrigation, water use, water stress, soil moisture), crop modeling (e.g., assimilation, model result, evapotranspiration, ancillary data, sensitivity analysis), sensor and bands used (e.g., SAR - Synthetic Aperture Radar image, Rapideye, SPOT, Sentinel, MODIS products, backscattering, SWIR - Short Wave Infrared, NIR - Near Infrared, red edge), and regions like Thailandia, Northern China, and Germany. The orange cluster was mainly composed of terms related to classification methods and validation (i.e., endmember, object-oriented, support vector machine (SVM), spectral angle mapper (SAM), random forest, kappa coefficient, accuracy, field survey), spectral data characteristics (e.g., Worldview, Landsat, high spatial resolution, hyperspectral data, coarse spatial resolution, shadow, spectral response, cost efficiency), environmental resources (e.g., conservation, biodiversity, long term change, human activity, urbanization, deforestation, invasion, habitat, land cover, species distribution), and regions like Greece and Japan.





**Figure 3.** Network mapping of the keywords most used (occurrence threshold = 20) in the rs+pheno research in 1999–2008. Color bar indicates the year in which each keyword was mainly used. Lines represent the link strength between two terms (minimum link strength = 10).



2014 2016 2018



**Figure 4.** Network mapping of the keywords most used (occurrence threshold = 20) in the rs+pheno research in 2009–2018. Color bar indicates the year in which each keyword was mainly used. Lines represent the link strength between two terms (minimum link strength = 10).

vield

vheat

crop type

cost efficienc

chlorophyll

spectral analysis



tropical fores

E

nsa

class

satellite imagery

liscrim

change detection

**Figure 5.** Network mapping and clustering of terms in 1999–2008. Since it is a 3-d map, not all the terms are represented. Lines represent the link strength between two terms (minimum link strength = 10). Red cluster = phenology/climate topic; Blue cluster = classification/agriculture topic.

mappi

phenology metrics

phenological variabili

manageme

regetation cover

rees

phenology stage

唐

bare soil

0

unsupervised classification

land cover land use

andscape

landsat

landsat tm

phenological change

prediction

carbon flux

march

august

dry season

forest type

8



**Figure 6.** Network mapping and clustering of terms in 2009–2018. Since it is a 3-d map, not all the terms are represented. Lines represent the link strength between two terms (minimum link strength = 10). Red cluster = phenology/climate topic; Blue cluster = agriculture topic; Orange cluster = classification topic.

The comparison of the ten most occurrent terms for 1999–2008 and 2009–2018 (Table 2) highlighted that terms like 'classification', 'accuracy', 'mapping', and 'temperature' were the most used one, with similar relevance and similar (relative) occurrence, in both decades. On the contrary, 'SOS', although present in both decades, in 1999–2008 was characterized by a higher relevance with respect to 2009–2018. 'LAI' was the main term in 1999–2008, but it disappeared in 2009–2018; while, 'response', 'trend', and 'climate change' appeared in the last decade. It is to be noticed that the term 'NDVI' was not present in the list of ten most occurrent terms. This could probably be explained by the fact that, as largely adopted, NDVI could appear not only as a single term but also as a composed term, like 'NDVI time-series', 'NDVI data', 'MODIS NDVI data', 'NDVI value', 'NDVI image', etc. As a consequence, the NDVI term occurrence is diluted into the different forms of use.

The comparison of the ten most relevant terms for 1999–2008 and 2009–2018 (Table 3) showed that, apart from terms like crop type that can be recovered as crop classification and carbon flux as carbon uptake, almost all of the terms and related concepts of the first decade tended to lose their relevance in the following decade. In the first decade, the majority of the relevant terms belonged to the agriculture/classification (blue) cluster and were mainly related to crop type (rel. score = 2.14), yield (rel. score = 1.83), and growing season (e.g., July, rel. score = 2.60; May, rel. score = 2.30), and secondarily to image classification (unsupervised classification, rel. score = 2.09); for the phenology/climate (red) cluster, the only most relevant term was related to the geographical area of the analysis, i.e., North America (rel. score = 2.32). On the contrary, the most relevant terms in 2009–2018 were related to the phenology/climate cluster (red), e.g., ecosystem respiration (rel. score = 4.24), NEE – Net Ecosystem Exchange (rel. score = 3.20), and carbon uptake (rel. score = 2.85), and the use of red edge band (rel. score = 2.53) and SAR images (rel. score = 2.47). The most relevant terms belonging to the classification (orange) cluster was SVM–Support Vector Machine (rel. score = 2.34). Finally, it is to be noticed the presence in 2009–2018 of the term yield prediction (rel. score = 2.28).

	Term	Rel. Score	Occurrence	Cluster Color
	Classification	0.56	93	blue
	Accuracy	0.44	81	blue
	Mapping	0.51	77	blue
	Temperature	0.80	68	red
1999_2008	Day	0.68	67	red
1999-2008	Reflectance	0.62	60	blue
	Start of season	1.16	55	red
	Crops	0.64	53	blue
	Phenology stage	0.41	53	red
	LAI	0.71	50	blue
	Image	0.53	422	blue
	Accuracy	0.68	403	blue
	Classification	0.57	264	blue
	Mapping	0.57	261	red
2009-2018	Temperature	0.89	253	red
2009-2018	Start of season	0.77	242	blue
	Response	0.67	229	red
	Trend	0.59	221	blue
	Climate change	0.86	217	red
	Climate	0.75	211	blue

Table 2. List of the ten most occurrent terms in 1999–2008 and in 2009–2018.

Finally, Figure 7 shows the temporal trend of the frequency of the ten most relevant terms identified in 2009–2018 (see Table 3) over the whole study period. The papers, dealing with the selected terms, passed from being 2% to 15% with respect to the total rs+pheno papers. In the early 1980s, only some of the most relevant terms were found, i.e., red edge, major crops, yield prediction. Overall, the majority of the terms were characterized by a gradually growing trend; on the contrary, yield prediction showed

a fast increase in the last decade (2009–2018). The terms with the highest frequency were red edge and SAR. The red edge term showed a quite constant trend until the beginning of the last decade when it showed a slight increase. Particularly interesting were the trends of SAR and SVM terms. The former presented a fast growth until its peak around 1995, and then a fast decreasing trend, with a moderate recovery in the last decade. The latter was characterized by an initial interest that ended completely at the end of the 1980s and arose again after the year 2000. It is to be noticed that some terms, like eddy covariance, carbon uptake, and ecosystem respiration, were not taken into consideration until the beginning of the 1990s.

	Term	Rel. Score	Occurrence	Cluster Color
	July	2.60	21	blue
	North America	2.32	11	red
	May	2.30	14	blue
1000 0000	Crop type	2.14	10	blue
1999–2008	August	2.11	18	blue
	Chlorophyll	2.10	12	blue
	Unsupervised classification	2.09	13	blue
	June	1.96	25	blue
	November	1.87	12	blue
	Yield	1.83	27	blue
2009–2018	Ecosystem respiration	4.24	12	red
	NEE	3.20	17	red
	Carbon uptake	2.91	19	red
	Crop classification	2.85	22	blue
	Red edge	2.53	11	blue
	SAR image	2.47	11	blue
	Major crops	2.43	14	blue
	Eddy covariance	2.38	33	red
	SVM	2.34	36	orange
	Yield prediction	2.28	18	blue

Table 3. List of the ten most relevant terms in 1999–2008 and in 2009–2018.



**Figure 7.** Temporal trend and proportion of the rs+pheno papers dealing with the ten most relevant terms identified in 2009–2018 (see Table 3) to the total rs+pheno papers over the period 1979–2018. A 5-year moving average was applied.

### 4. Discussion

## 4.1. Publication Trends

Rs+pheno studies have significantly increased in number over the last decade and, as also for other disciplines (e.g., [42,43]), the USA and China are the leading countries in terms of the number of papers. The main peaks may be recognized in correspondence with some critical dates: around 1980 (one year after the publication of the seminal work of [44] about the use of red and NIR for monitoring vegetation), 1985–86 (after Landsat-5 launch in 1984 and the year of the publications of [45] about LAI, and [46] about NDVI for remotely sensed phenology), 1995 (one year after the pivotal work of [20] about the extraction of phenological metrics from NDVI annual profile), 1999 (in 1997, the Kyoto

protocol about global warming was signed), 2002–05 (Landsat-7 was launched in 1999, MODIS in 2000, and the EVI was proposed for the first time by [15]), 2008–09 (after the publication of [6] about plant phenology, shifting in response to global change using NDVI data), and 2015 (in 2011, 30 years of Landsat archive became freely available [47]; in 2013, Landsat-8 was launched, and, in 2015, Sentinel-2 was launched).

In this framework, MODIS can be considered the most common satellite used in rs+pheno studies, covering almost all the topics identified, thanks to its very high temporal resolution (twice a day, with a 8- to 16-day and 1-month composite), moderate spatial resolution (250 m), large availability of ready-to-use products, and consistent coverage all over the world. On the contrary, Landsat represents the series of satellites that allows the larger temporal archive since the early 1980s and hence the larger time span for rs+pheno studies; while Sentinel-2 (launched in 2015) is the emerging technology in rs+pheno research, thanks to its high spatial resolution (10 m) and high temporal resolution (every 5 days). Based on such satellites, several ways of integrating the proposed remote sensing VIs into phenological modeling analysis have been suggested through time, e.g., for studying anomalies in spring and autumn phenology [48,49], analyzing the effects of warmer temperatures on the incidence and severity of frost damage [50,51], exploring the role of phenology in fire dynamics [52,53], combining multi-resolution products [54,55], smoothing satellite time-series data [56,57], integrating remotely sensed phenology data and climate [58,59]. While NDVI and EVI represent the most agreed VIs in rs+pheno studies, LAI and FAPAR, although largely used as inputs in crop modeling studies [60–62], remain only partially adopted.

The majority of the journals used in rs+pheno studies are characterized by high impact factor (>4) and high H-index (>100), and, apart from RS, by a 30-years long history of rs+pheno publications. Yet, the journals mostly involved are largely biased towards remote sensing applications in ecology and/or biology rather than towards pure ecology and/or biology. This evidence demonstrates how rs+pheno is foremost considered as a subset of remote sensing science rather than a branch of phenology. As an example, the RSE journal also covers ecology and biology but not without remote sensing techniques. Purely ecological/biological journals are only partially used to publish rs+pheno studies. This may be interpreted as that, unlike traditional phenology, rs+pheno is not considered yet as a well-established branch of ecology. Finally, it is to be noticed that the first most-publishing purely ecological journals in rs+pheno were AFM and GCB (or International Journal of Biometeorology—data not shown here), both with a clear climate-based target. However, in the last decade, journals like EI (or Ecological Modeling and Science of the Total Environment—data not shown here), with a wider ecological perspective, have increasingly been used, suggesting a progressive tendency towards a less technical approach, and a new clearance for remotely sensed phenology.

### 4.2. Major Research Topics

The term network maps for the period 1999–2008 and 2009–2018 allowed to identify the main clusters, i.e., the main scientific domains, or macro-topics, in the rs+pheno field. In the first decade, according to the terms distribution, two groups can be distinguished: one cluster (red) is an expression of a pheno-climatic macro-topic and its application in forestry, the other (blue) represents the research

studies related to classification and its application in agriculture. In the second decade, three groups can be distinguished: one cluster (red), like in the previous decade, is expression of a pheno-climatic macro-topic and its implications in forest dynamics, the second cluster (blue) is expression of the agriculture-related domain, and the third cluster (orange) represents the research studies related to the classification field. Such results highlighted that, while in the first decade, agriculture was included in the classification cluster and did not represent an independent macro-topic, in 2009–2018, it arose as a single, standalone research theme, with specific targets and objectives; on the contrary, both in the first and in the second decade, forestry remained linked with the pheno-climatic macro-topic. This suggests that while rs+pheno is a key tool for agricultural studies, forest studies represent a key tool to investigate rs+pheno and climate change impacts.

The term occurrence analysis proved that mapping and its accuracy were the most common topics for both 1999–2008 and 2009–2018. Also, thanks to the increasing availability of new high-resolution satellites and cloud computing platforms, a growing number of papers have been published on thematic mapping, as well as on classification/validation methods. In the framework of both forestry and agriculture rs+pheno studies, classification methods like spectral angle mapper (SAM), object-oriented techniques, random forest, and support vector machine (SVM), among others, have been to be used since 2000. However, the high relevance gained in the last decade by such techniques highlights the recent use of specific classification methods for addressing specific rs+pheno targets, like land cover mapping [63–65], phenological characterization [66,67], and anomalies detection [68,69]. The use of *ad hoc* methodological approaches according to different objectives, scales, sensors, temporal, and spatial resolutions represents an important achievement. The continuous exploitation of new technological resources is one of the main characteristics of rs+pheno science, which guarantees this discipline to be up-to-date and always evolving, according to the availability of innovative instruments, the development of novel methodologies, and the emergence of new questions [70].

The attention towards the phenology metrics detection and extraction also represented the main topic for both 1999–2008 and 2009–2018, with the majority of the studies focusing on harmonic analysis [52,57,63]. The start of the season (SOS) represents the metric most investigated; its study has increased through time to such an extent that it became a major, common topic and, hence, lost its relevance. In the last decade, a large number of papers were published about spring phenology and its response to climate change [51,71–73]; on the contrary, end of season (EOS) and length of season (LOS) received far less consideration. As clearly stated by [50], autumn remains a relatively disregarded season in climate change research both in temperate and arctic ecosystems, notwithstanding the role of autumn in determining the length of the growing season [74,75] and in controlling influence on the carbon-uptake period [76]. However, EOS is generally considered to be more variable than SOS phenology and less often observed, making its detection and analysis challenging [75,77].

#### 4.3. Emerging Research Topics

The term relevance analysis highlighted how some topics emerged as new research areas in rs+pheno studies, as well as how some relevant issues of the 1999–2008 decade lost their significance. In particular, the attention towards the vegetation growing season that characterized the first decade has increased through time to such an extent that it became a major, common topic and, hence, lost its relevance. On the contrary, some issues related to the climate change/carbon cycle linkage emerged in the 2009–2018 decade, for example, ecosystem respiration, net ecosystem exchange (NEE), and carbon uptake. These represent new research issues that scientists started to face at the beginning of the 1990s, and that in the last decade became the most relevant topic in rs+pheno studies, i.e., the most significant, with specific objectives and questions, mainly dealing with issues like forest ecophysiology [78,79] and biomass estimation and anomalies [73,80]. In this global energy balance context, special attention should be given to themes like ice cover dynamics and phytoplankton blooming. They gained a moderate relevance in the last decade, yet they are becoming increasingly significant, as demonstrated by several recent studies [32,81–83]. In particular, as stated by [32], phytoplankton is an essential

element of the ocean, influencing global biological, chemical, and physical environments in terms of water heat [81], net primary production, carbon cycling, and climate [81]. As a consequence, rs+pheno research focused on phytoplankton represents an emerging niche research area recognized as a key concern in the framework of the global climate observing system [32].

Some new topics came to light in the last decade, also, within the agricultural main domain. Actually, crop modeling and the use of SAR and red edge represent research issues that have gained some attention since the early 1980s and kept being studied throughout the 40 years. However, the initial interest was likely targeted towards several different research objectives, without a specific rs+pheno focus, to such an extent that these terms gained a high relevance only in the last decade. The use of new sensors and specific optical and radar bands [84–87], their data fusion [55,88], as well as the application of yield prediction and crop simulation models [89–91] may be, hence, considered as a new challenge for the next decade of rs+pheno studies.

Finally, in the last decade, a new front appeared in rs+pheno research, linked with habitat and biodiversity conservation. According to our results, this front was connected with terms associated with anthropogenic activities and human presence. For example, the impacts of urbanization processes on vegetation health status and its seasonal variations have been mostly analyzed in terms of the phenology of urban environments [92,93], effects of urban heat island [94,95], and different phenological responses of rural vs. urban areas [96,97]. At the same time, human management interventions, like deforestation, represent another issue faced in rs+pheno studies, mainly dealing with recolonization [98], mapping [99], and environmental damage estimation [100].

Biodiversity and related ecosystem services issues resulted as connected, also, to studies about environmental disturbance phenomena, like fire. Many papers in rs+pheno studies analyzed the role of wildfires' behavior both as a driver of vegetation recovery patterns [101–103] and as influenced by fuel phenology and flammability [104,105]. In this latter case, a high potential exists for characterizing, classifying, and mapping fuel based on rs+pheno dynamics. Several studies have used variations in remotely sensed VIs profiles, such as the NDVI, as indicative of variations in moisture content and nutrient availability, which in turn are indicators of a marked susceptibility of vegetation to fire [106,107]. In this framework, future research should go beyond the traditional use of NDVI (or similar VIs) as simple biomass proxy and identify fire-prone regions according to their phenological patterns [108].

## 4.4. Regions of Study

The geographic region of study started to assume an important role in rs+pheno research, mainly during the last ten years. In 1999–2008, boreal and tropical forests were the main ecoregions analyzed; the only countries largely considered were North America (in particular, USA) and Asia, with the former associated with the phenology/climate topic and the latter with the agriculture/classification one. On the contrary, in 2009–2018, the different topics identified involved different study regions, according to their specific characteristics and requirements. For instance, the pheno-climatic cluster included regions like Cerrado, Tropic, Savanna, North America, and Tibetan Plateau, which are broad, highly natural, and homogeneous areas where climate change effects can be clearly identified and monitored [80,109–113]. In the agricultural cluster, Thailandia, Northern China, and Germany were the most occurrent study regions, maybe due to the high food demand/production, water management, and the farming practices typical of these regions [114–116]. Finally, the classification cluster included regions like Greece and Japan, where issues related to crop mapping and anthropogenic impacts (e.g., fire, urbanization, invasive species, etc.), also characterizing the cluster, represents a major concern [103,117,118].

Such pieces of evidence highlight the general tendency that rs+pheno studies are moving from global to regional/local scales. The main research questions are not only dealing with large scale dynamics but also with small scale observations, being driven by site-specific characteristics and requirements. While the former seemed to be mainly linked to forestry and climate-based studies

(by using platforms like MODIS and GIMMS), the latter was mostly regarding agriculture and classification topics (by using satellites like Rapideye, SPOT, Sentinel, Worldview, and Landsat). In this perspective, the recent advent of very high spatial resolution satellites (like S2) and new missions (like PRISMA—Hyperspectral Precursor and Application Mission, VIIRS—Visible Infrared Imaging Radiometer Suite, and ECOSTRESS onboard the International Space Station) represents a major support tool, able to guarantee, and, at the same time, to boost multi-scale rs+pheno studies.

# 5. Conclusions

Relations between phenological responses and global change have become a major concern, and several disciplines, like remote sensing science, are contributing to find answers and meet such challenges, with new theories, methods, and technologies. As the number of studies integrating remote sensing and phenology is growing faster in recent years, it is becoming more complex to get a clear picture of knowledge structure, research hotspots, and development in this study area. Analyzing the research development dynamics of rs+pheno studies allowed to disentangle the complexity of this discipline, by identifying key well-established (e.g., climate change impacts), emerging (e.g., ecosystem energy balance, phytoplankton blooming), or underexplored (e.g., autumn and senescence processes) topics. However, the evidence obtained in this review highlighted that, even if rs+pheno research is gaining its position in ecological studies, it is still not considered as a self-explained science. In the framework of scaling from regional phenological patterns down to site-specific, species-level seasonal observations, the continuous availability of new technologies, as well as the growing interdisciplinary component of rs+pheno studies, represent a conditio sine qua non for new scientific questions and new answers, able to ennoble remotely sensed phenology as a purely ecological science. The findings of this study might be applicable for planning and managing remotely sensed phenology research; scientists involved in such discipline might use this study as a reference to consider their research domain in a broader dynamical network.

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