remote sensing

MDPI

Review

Scientific Evidence from Space—A Review of Spaceborne Remote Sensing Applications at the Science–Policy Interface

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Abstract: On a daily basis, political decisions are made, often with their full extent of impact being unclear. Not seldom, the decisions and policy measures implemented result in direct or indirect unintended negative impacts, such as on the natural environment, which can vary in time, space, nature, and severity. To achieve a more sustainable world with equitable societies requires fundamental rethinking of our policymaking. It calls for informed decision making and a monitoring of political impact for which evidence-based knowledge is necessary. The most powerful tool to derive objective and systematic spatial information and, thus, add to transparent decisions is remote sensing (RS). This review analyses how spaceborne RS is used by the scientific community to provide evidence for the policymaking process. We reviewed 194 scientific publications from 2015 to 2020 and analysed them based on general insights (e.g., study area) and RS application-related information (e.g., RS data and products). Further, we classified the studies according to their degree of science–policy integration by determining their engagement with the political field and their potential contribution towards four stages of the policy cycle: problem identification/knowledge building, policy formulation, policy implementation, and policy monitoring and evaluation. Except for four studies, we found that studies had not directly involved or informed the policy field or policymaking process. Most studies contributed to the stage problem identification/knowledge building, followed by ex post policy impact assessment. To strengthen the use of RS for policy-relevant studies, the concept of the policy cycle is used to showcase opportunities of RS application for the policymaking process. Topics gaining importance and future requirements of RS at the science–policy interface are identified. If tackled, RS can be a powerful complement to provide policy-relevant evidence to shed light on the impact of political decisions and thus help promote sustainable development from the core.

Keywords: earth observation; evidence-based policy; policy cycle; decision-making; sustainable development; science–policy interface

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1. Introduction

Since roughly the 190s, governments worldwide have increasingly been following an evidence-based policy (EBP) approach to take action on policy coherence, shed light onto policy impact and enhance the effectiveness and efficiency of policies [1–4]. The prevailing COVID-19 pandemic and humanitarian crises along with the natural disasters over the last decade, in light of climate change, are however powerfully displaying a continuing pattern of unsustainable natural resource depletion and policymaking (https://press.un.org/en/2022/envdev2046.doc.htm) [5]. With the 2030 Agenda for Sustainable Development and the Paris Agreement, recent efforts have been made at the international level to discuss shared values and goals for sustainable development and strategies to achieve these at both national and global levels [6,7]. Both agreements demand an EBP approach to evaluate whether the set policy goals and measures are leading to the required progress towards meeting the agreements [8]. Yet, considering the rather limited success, with few exceptions such as the Montreal Protocol, in achieving global sustainable development and enforcing sustainable development into all national policies, strengthening old and developing entirely new pathways within the EBP approach will be pivotal to successfully translate evidence-based findings into sustainable, effective decisions and make leadership sustainable beyond the legislature [9,10].

EBP assures along the so-called policy cycle that governments and their programmes, laws and regulations can achieve their defined goals [11]. The policy cycle can be seen as an analytical tool that divides the policymaking process into several simplified stages, thereby allowing one to closely monitor the process. Different definitions of the policy cycle exist; however, the most common stages are: agenda setting (i.e., identification of emerging issues), formulation of policy objectives and policy adoption, implementation, and monitoring and evaluation [12,13]. Lessons learnt should then be fed back into the cycle, thereby helping to make policies more efficient and effective. Further, this approach can assist in ensuring that policy decisions and their trade-offs are made transparent, minimizing institutional bias und overcoming the tendency to hold on to traditional, conservative structures. Additionally, EBP can lessen the power of fake news by making governmental decisions more credible and assessable through facts—both the coronavirus pandemic as well as the Russia–Ukraine war underline how important credible policymaking can be, particularly in times of crisis (https://www.theguardian.com/world/2020/may/05/trust-in-scientists-grows-as-fake-coronavirus-news-rises-uk-poll-finds, https://www.theguardian.com/world/2020/apr/24/coronavirus-sparks-perfect-storm-of-state-led-disinformation) [14].

Certain key conditions must be met in order to apply an EBP approach, which—if not met—can hinder the successful application of this approach [3,15]. EBP requires clearly defined policy objectives and measurable indicators. Furthermore, to monitor and feedback on both, relevant data must be available. This is a factor predominantly affecting the quality and feasibility of EBP assessments. Additionally, methods for data collection vary within as well as among countries, leading to problems in harmonising data for global progress reporting. In addition, public officials should be able to analyse and evaluate the data, and there must be a close understanding regarding the various roles among the different parties (e.g., policymakers, scientists) involved in the assessment [11]. Finally, a key consideration is also the assessment of policy interactions (e.g., existing and potential future policies) while addressing the policy along the policy cycle [13].

Spaceborne remote sensing (RS) can provide sound, independent and area-wide information on the physical appearance of the world. Especially where data gaps exist, RS can help to detect as well as understand environmental dynamics (e.g., climatic and atmospheric dynamics, urban structures, extreme events) and deliver unique insights into life on Earth, such as for ecology, agricultural systems and conservation, at different spatiotemporal scales [16]. Governments and private companies have long recognized the potential of RS. Especially for meteorological application, such as weather forecasts, the assimilation of RS data has been a standard procedure for decades [17,18]. More recently, the potential of applications in the agricultural and forestry sector, disaster monitoring, infrastructure management, defence and security, and for sustainable development has been recognised. For instance, the Global Earth Observation System of Systems (GEOSS), a joint international venture, was founded with the ulterior motivation of contributing to the development of efficient technologies for sustainable development. It contributes to this goal by harnessing and integrating existing infrastructures and Earth observation data, thereby fostering a globally networked Earth observation system to underpin sound decision making for diverse users. This growing appreciation of RS has increased investments into this technology, which have resulted in worldwide RS data coverage encompassing coarse to very high spatial, temporal, and spectral resolutions over the past decades [19,20]. Particularly, the availability of long-term continuous free and open satellite data together with new space developments create the basis for operational applications [21]. Further, high-resolution RS is creating new possibilities for EBP, such as in the fields of agricultural (e.g., crop detection) and forest (e.g., plant traits, forest structure assessment) monitoring [22]. Through these developments, RS can help to overcome the problem of data availability for EBP by delivering evidence for different stages of the policy cycle and at different scales.

One of the first and most prominent examples of using RS successfully in policy is the Montreal Protocol. It is one of the most successful global environmental treaties to date and regulates as well as guides the phase-out of ozone-depleting substances (ODS), with impacts on both the environment and economy. RS has been pivotal in monitoring the development of the stratospheric ozone layer and in providing sound evidence for decision making under the protocol's umbrella. Moreso, the measures taken under the Montreal Protocol have led to a steady recovery of the stratospheric ozone layer, as a recent study from the World Meteorological Organization (WMO) shows [23].

Today, several governmental bodies, institutions, and organisations exist, which use RS to deliver knowledge for the policymaking process and to investigate the efficiency and effectiveness of policy measures within an EBP approach to some extent. As one of the first, the United States Geological Survey (USGS), which is devoted to monitoring and analysing Earth–system interactions to provide timely relevant information for decision makers, holds with the Earth Resources Observation and Science (EROS) Center a prominent RS imagery archive [24]. A prominent example within the European Union includes work by the Joint Research Center of the European Commission focusing on the Common Agricultural Policy while Geoscience Australia is the nation's public sector geoscience organisation that supports EBP through information gathered through Earth observation in Australia [25,26].

However, a sufficient overview is missing regarding new scientific work using RS for studies at the science–policy interface. A review paper from 2010 found that researchers use RS unevenly along the entire policy cycle and that "there is apparently little academic interest in the societal contribution of environmental remote sensing" [27]. Wellmann et al. (2020) recently reinforced this picture for urban planning, showing that few studies are directly relevant for policy and that most studies focus on delivering knowledge or monitoring policy impact [28]. How far the situation has changed for the whole RS-related science–policy picture over the last years and how the scientific field is now contributing evidence for the different stages of the policy cycle for EBP remain largely unclear.

Objective of the Review

The objective of this paper is to provide an overview of current scientific applications of spaceborne RS for EBP by investigating peer-reviewed literature. We explore to which degree scientists work at the science–policy interface by categorising them regarding their degree of engagement with the political field and in targeting policies throughout their studies. Further, we investigate the potential contribution they could make towards the policy cycle against the background of policy sectors and processes they address. By doing so, we aim at drawing a picture of the state of using RS at the science–policy interface and to derive insights into existing gaps of the application of RS for EBP as well as potential future directions of development and application.

The review is structured in the following way: In the results section, general insights (e.g., on the study area and the sector of focus) and RS application-related information (e.g., used RS data and existing products) of the studies are presented, followed by insights into the science–policy integration (e.g., contribution of studies to the policy cycle). The discussion aims at embedding in particular the results of the section on science–policy integration into the larger context and provides an overview of how the application of RS for policy can be promoted by drawing on the concept of the policy cycle, discussing topics gaining importance at the science–policy interface, and, finally, by presenting necessary improvements from the RS side to make better use of the capacity of applying RS at the science–policy interface.

2. Materials and Methods

The literature search (Figure 1) was conducted using Web of Science (WoS) Core Collection from January 2010 to December 2020 (N = 416). This literature search showed an increase in the number of published papers per year within the time range, with two distinct leaps in the increase in publications in 2015 and 2019 (Figure 2) Therefore, and to narrow down the number of relevant articles, we focused the review paper on publications of the years 2015 to 2020. We restricted the literature to articles written in English. All other types of literature (e.g., grey literature) are excluded from this review. Further, articles had to meet certain criteria to be considered for the review, namely that they must (i) use data from spaceborne RS for their analysis, meaning that articles solely using airborne RS were not considered, and (ii) mention at least a policy relevance of their results or methodological approach. With this defined selection process, we aimed at applications of RS for policy that are feasible from a methodological perspective, i.e., with a reviewed methodical approach and published in peer-reviewed literature, even though we are aware that applications of RS regarding the science–policy interface which have been published outside of peer-reviewed literature, in languages other than English, or use RS other than spaceborne RS may have been missed. In the end, the literature list encompassed 194 articles Figure 1 provides an overview of the search string, eligibility criteria, and screening process applied.

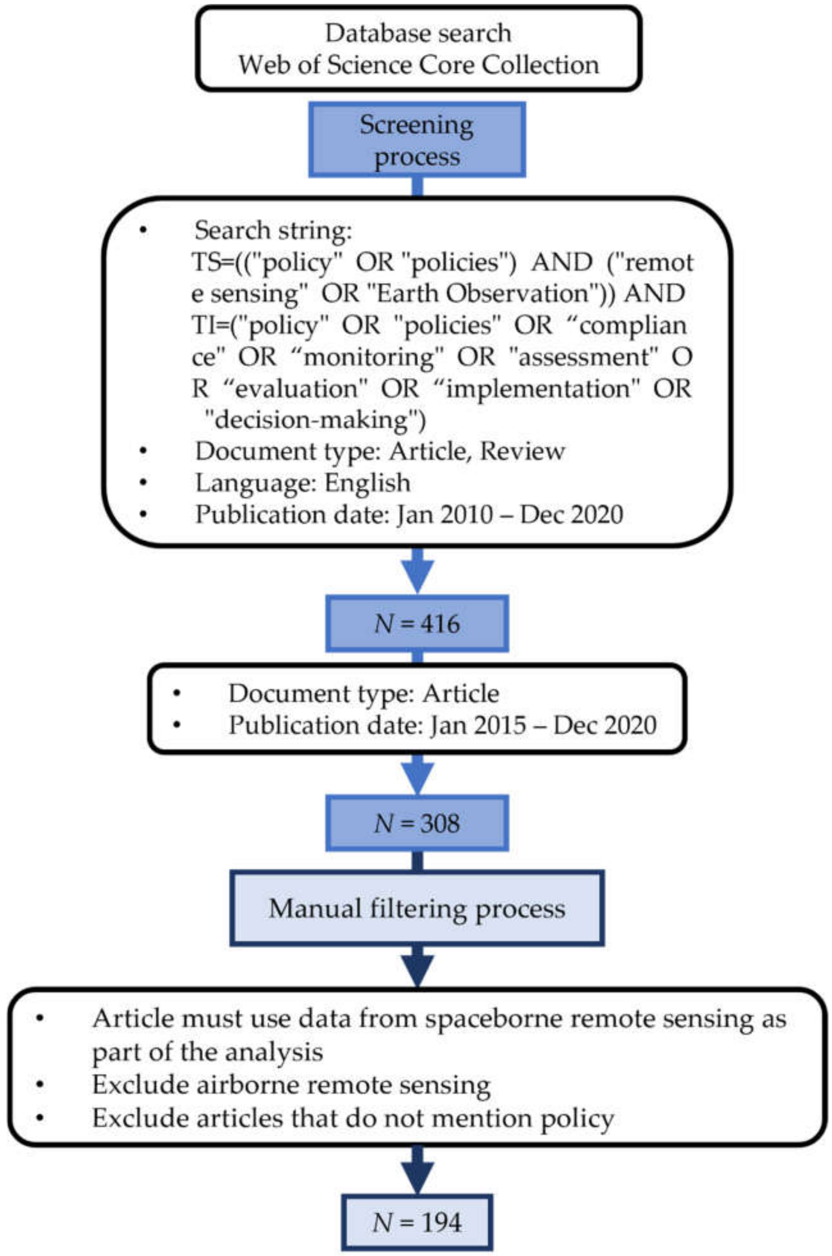

Figure 1. Overview of literature retrieval. Shown is the full electronic and manual search strategy with keyword string, eligibility criteria indication, and screening process.

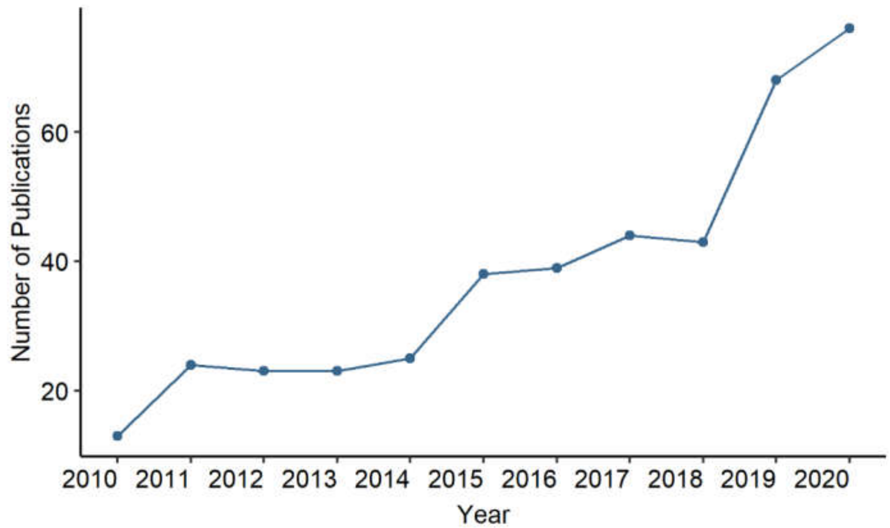

Figure 2. Number of articles published from 2010 to 2020.

All papers were analysed with respect to aspects relevant to the topic of the review. Accordingly, information on general insights, such as study area, RS-related applications, and to investigate the degree of science–policy integration was extracted. The data were extracted manually and organised in a table (Microsoft Excel).

2.1. General Insights

Data were obtained on the study area and its geographic extent. Further, the main sector of focus as well as processes considered (e.g., land use/land cover (LULC) change; lakes and eutrophication; cities and urbanisation) were identified.

Sectors of focus were defined according to typical policy sectors encountered in the political arena [29–31]. These were agriculture, forest, water resources, health, coastal zone, settlement, energy, disaster and risk management, and biodiversity and conservation. Further, we included a sector named "cross-sectoral" to describe those studies that cover several sectors in their study. Sectors were classified based on information contained in the article.

We defined the geographic extent of a study also from a policy perspective. Local studies include, for example, city-wide studies in the sector settlement. An important consideration is that cities can range in their size from, e.g., 219 km^2 in the case of Amsterdam to 16.411 km^2 regarding Beijing. However, common topics in the studies of cities included, e.g., the assessment of urbanisation or environmental and ecological assets, and the potential past and future impact of urban policies—all of which can be described from a local perspective at the city level.

2.2. Spaceborne Remote Sensing Application

The use of RS was analysed according to the input data and products, the temporal resolution of the study, and to which extent non-RS data were integrated.

2.3. Science–Policy Integration

To evaluate the science–policy integration, the degree of engagement with the political field, here termed as "policy focus", was determined, and the potential contribution of the study to the policy cycle was evaluated. In addition, the integration of RS data, products and ancillary data along the policy cycle was analysed. To gain an overview of the policy sectors and related policy measures covered by the studies of this review, we analysed those studies with a focus on investigating policies (i.e., studies with a concrete ex ante and post ante policy assessment or contributing to policy implementation). We categorised these policies according to policy areas and their context of application, i.e., the process involved. Policy areas were defined either through information provided by the article or by classifying the policy field to the best of our knowledge (including consultation through the internet).

2.3.1. Policy Focus

Based on their degree of engagement with the political field, studies were classified according to three categories:

- "Policy-applied": Studies that clearly made a link with policy, i.e., studies which developed methodological approaches or provided research results that are evidently used in policy, such as for the policymaking process, or who worked with policymakers or representatives to develop and provide research and methods.
- "Pre-policy": Studies that developed an approach or method to look at, e.g., LULC trajectories to investigate and define drivers, including those from policy, in an analytical or descriptive manner.
- "Scientific": Studies that solely stated the relevance of the methodology or the information or evidence provided by the analysis for policy.

Some few articles were difficult to classify regarding the policy focus, as the information provided manoeuvred the study between two categories. Yurui et al. (2019), for example, includes interviews with government representatives and mentions in their article a future close collaboration with different actors, including governments, to further explore the impacts of gully land consolidation projects and implications at various levels [32]. As we are not provided with more details regarding the governmental collaboration and implications for policymaking, the article is classified as "pre-policy".

2.3.2. Policy Cycle

The policy cycle is an analytical tool often used in EBP to divide the policymaking process into several stages. This allows one to closely monitor and consider evidence along the policymaking process. To determine the potential contribution of each study towards the policy cycle, the cycle was divided into the following stages: problem definition and knowledge building, policy formulation, policy implementation, and policy monitoring and evaluation [12,13]. The decision of classifying a study's potential contribution to the policy cycle was based on relevant information contained in the results and discussion section of the articles. For instance, a study was classified as contributing to the cycle "policy monitoring and evaluation" if it either conducted an impact analysis of a specific policy or policies or discussed the impact of a specific policy or policies as a driver of change.

3. Results

3.1. General Insights

3.1.1. Overview of the Countries in Focus

The research areas of the studies are distributed world-wide in 83 countries, thereby covering different continents, climatic zones, and nations with various development statuses (Figure 3). Most studies concentrate on China as the study country (n = 66; [32–97]), followed by India (n = 16; [98–113]), the USA (n = 12; [95,114–124]), Brazil, Italy, Pakistan, and Spain (each occurring in seven studies) [125–151] and Australia (n = 5; [95,124,152–154]). The other countries are represented by less than five studies, with one case study being the most frequent count (n = 42; [66,95,96,118,155–187,187–198,198–222]). Some regions are underrepresented, including Europe, Central and South America, and regions of the African continent (West, Central and Southern Africa). In addition, Antarctica is not represented. A reason for the underrepresentation or non-occurrence of countries in this review may be due to our restriction such as to English language papers and peer-reviewed literature (see screening process of literature, Section 2. Materials and Methods).

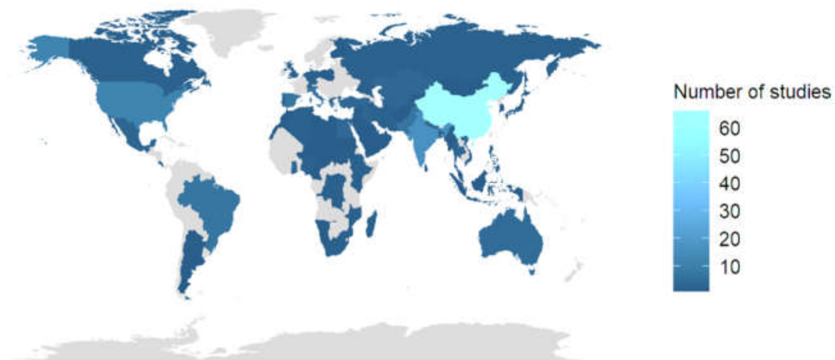

Figure 3. Focus countries: number of case studies per country. Grey indicates no occurrence.

3.1.2. Geographic Extent of the Studies

Most articles focus on either local (i.e., city level; small-scale analysis or multiple small-scale analyses within a country or several countries; 45%; e.g., [34,115,152]) or regional studies (focus on a larger, heterogenous area (e.g., rural–urban gradient)) within one country or several countries (38%; e.g., [33,42,60]). Articles conducting nation-wide studies account for 12% of all articles (e.g., [59,79,185]), whereas interregional and global studies are represented by 6% and 1%, respectively (e.g., [96,170,202]) (Figure 4A)

3.1.3. Sectors of Focus

The most common sector is settlement (23%), followed closely by agriculture (22%). Other important sectors are water resources (16%) and forest (14%) (Figure 4B). All four sectors depict policy sectors of essential human needs. Remaining studies address the sectors biodiversity and conservation (6%), health, (3%) disaster and risk management (3%), coastal zones (2%), energy (1%) or have a cross-sectoral focus (11%).

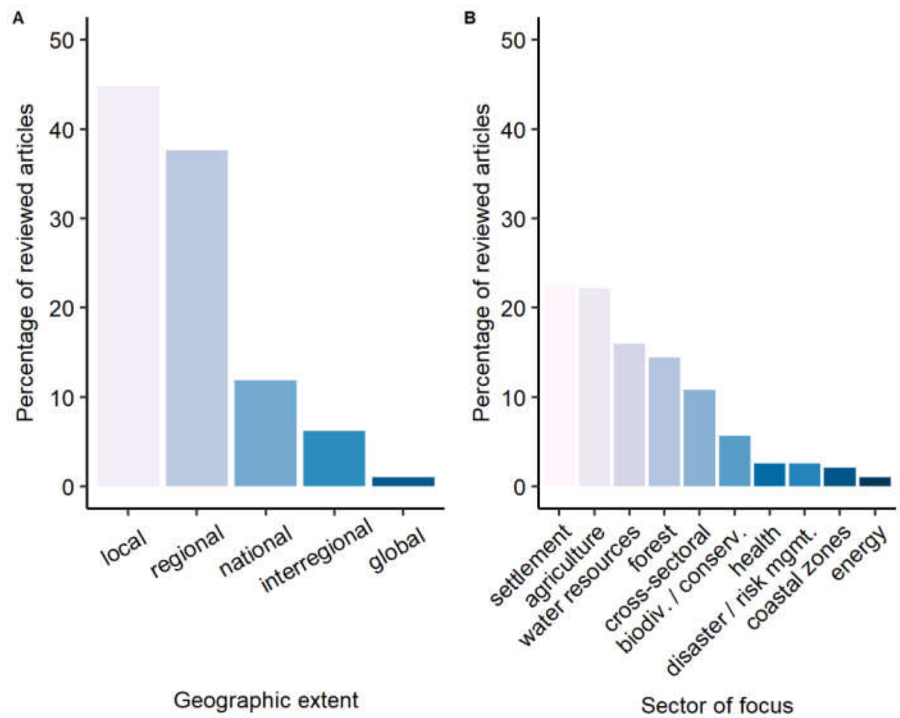

Figure 4. (**A**) Occurrence (i.e., percentage of all articles, n = 194, used in this review) of geographical extents within the review. Local = city level and small, local studies; regional = studies covering a wider, heterogenous area (subnational); national = studies covering an entire country; interregional = studies covering regions, which cross nations; global = studies covering the entire globe. Articles covering multiple local or regional studies within one or several countries are included in "local" or "regional", respectively. Similarly, articles covering multiple nations, which are geographically not connected, are termed as "national". (**B**) Sectors of focus and the percentage of studies concentrating on the specific sector in this review. Cross-sectoral focus = studies investigating changes or drivers of change across different sectors (e.g., general LULC change assessment).

3.1.4. Applications and Processes

Across these sectors, various processes are analysed (Figure 5). The most frequently investigated processes are LULC change (44%), degradation (14%), changes in emissions, pollution, and impairment (9%), and hazards, disasters, and risks (5%).

Within LULC change, processes related to the settlement sector were investigated most frequently (35%). Here, urban development (i.e., urban expansion, growth, and sprawl, e.g., [44,87,99]), the assessment and/or change in urban green infrastructure (e.g., [93,212]), and general change in LULC and urbanisation (e.g., [184,201]) were the most frequently addressed processes. Other articles concentrating on LULC change investigated processes related to the sectors forest (21%), such as forest cover change or fragmentation (e.g., [200,208]), agriculture (14%; such as agricultural expansion, land use change, and crop detection; e.g., [67,137]), cross-sectoral (13%; e.g., general LULC change [194]), and water resource (9%; e.g., change in wetland area [121] or LULC change in river basins and watersheds [179,217]).

Important processes of degradation include erosion (30%; e.g., [124,129]), drought and desertification (19%; e.g., [81,108]), and grassland degradation and grazing (15%; e.g., [45]). They were predominantly discussed in the agriculture (59%) and cross-sectoral sector (19%). Processes related to emissions/pollution/impairments were investigated primarily in the water resources sector (47%) and include algae bloom and water quality assessments [139,165]. In addition, change in atmospheric pollution in the sectors settlement (29%) and health (18%) were investigated. Examples include the analysis of the impact of COVID-19 regulations on aerosols or the impact of air pollution control policies on PM2.5 emissions [37,59]. Processes related to hazards, disasters, and risks include flooding, fires, ground deformation or landslides [122,195,196]. However, most of these processes were covered solely by one study in this review.

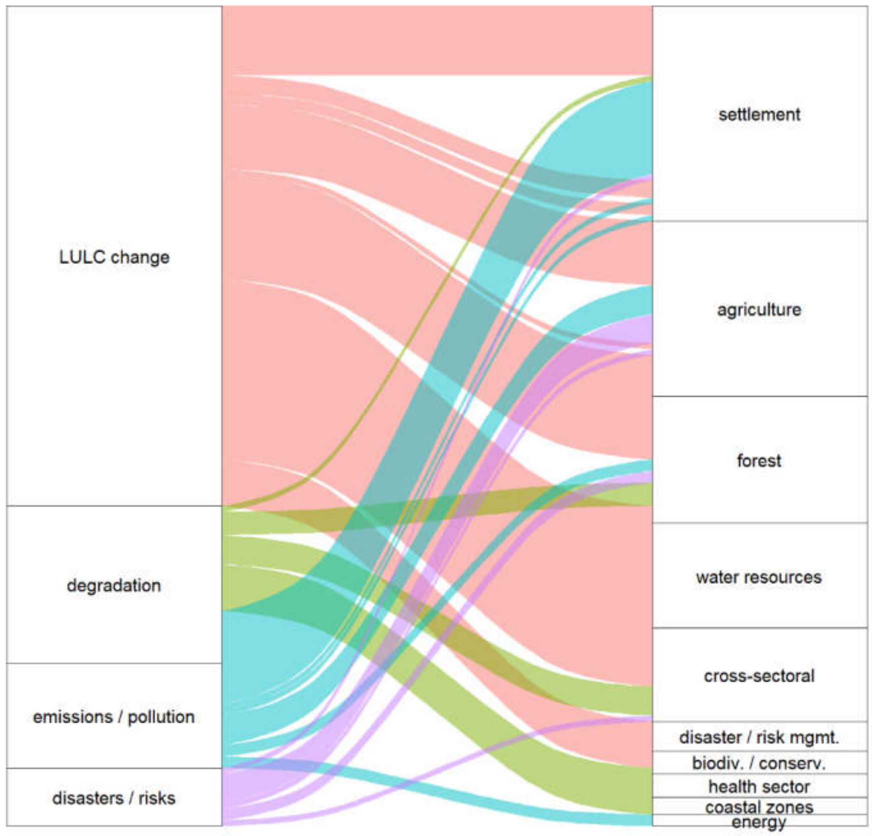

Figure 5. Overview of processes investigated in at least 5% of all reviewed articles and the sectors in which they are studied**.**

3.2. Spaceborne RS Application

3.2.1. Temporal Resolution of the RS Analysis

Most of the reviewed studies focused on time series (e.g., [122,123,158,165]) and multitemporal analysis over several years (e.g., [33,46,223]; Figure 6A). Bitemporal analyses (i.e., comparison of two timesteps) were the third most performed analyses (e.g., [32,130,156,172]), followed by research focusing on unitemporal analyses (e.g., [137,185,212,220]). Only 5% of all studies conducted forecasts (e.g., [76,94,164,174]). This result corresponds with the nature of the most common processes investigated, which often call for an analysis over several years (e.g., LULC change, such as urban or forest cover development). Studies with an unitemporal analysis involved methodological developments, such as for forest map comparison [171] or agricultural field detection [149], as well as for assessing natural capital and ecosystem services [188]. Processes investigated in forecasts included the impact of urban development policies on past and future urban development [91] or the impact of forest policy scenarios on habitat suitability of the flying squirrel [174].

Regarding the different temporal resolutions over time (Figure 6B), we can see a general increase in the application of multiple timestep analyses. Multitemporal RS analyses show a distinct increase in applications in 2020 in comparison to the previous years. However, comparing the increase in each temporal resolution in relation to the number of published articles per year, none of the temporal resolutions show a significant and thus unexpected high increase over the five years (a chi-squared test was applied).

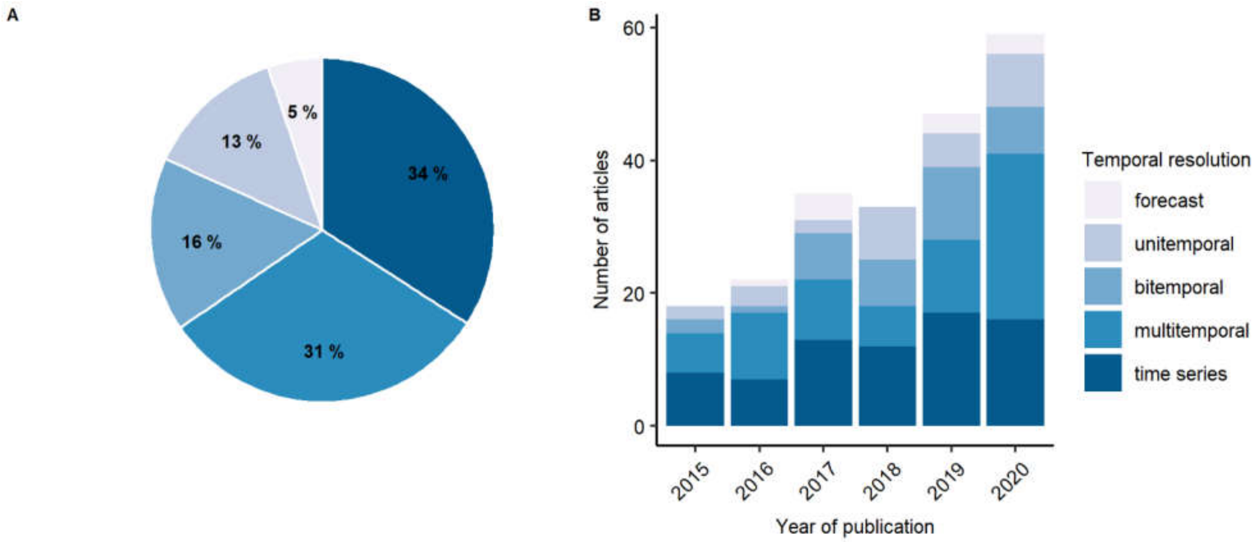

Figure 6. (**A**) Displayed are the percentages of different temporal resolutions applied in the reviewed studies. (**B**) Displayed is the frequency of temporal resolutions (here as the number of articles) used by the studies in this review according to their year of publication. Unitemporal: one time step is applied; bitemporal: comparison of two timesteps; multitemporal: time series analysis applying up to 9 timesteps; time series: time series analysis using >9 timesteps; forecast: prediction into the future.

3.2.2. Spaceborne Remote Sensing Platforms and Products

Most studies utilised free available higher resolution data from optical sensors, particularly Landsat (51%; e.g., [164,220]), followed by Sentinel-2 (7%; e.g., [130,150]). This is a stable trend over the years (Figure 7) and is expected since Landsat provides the longest time series with a higher resolution and is now complemented by Sentinel-2 since 2015. MODIS data, with a medium resolution, but also available for more than 20 years, was used by 6% (e.g., [122,123]). Sentinel-1 is the most frequently utilised SAR sensor (2%; e.g., [167,222]). A notable role was additionally played by national optical higher resolution satellite data such as the Indian IRS, the French SPOT, and Chinese GaoFen data (e.g., [53,64,103]; see Supplementary data, Figure S1, for an overview of all sensors used in this review).

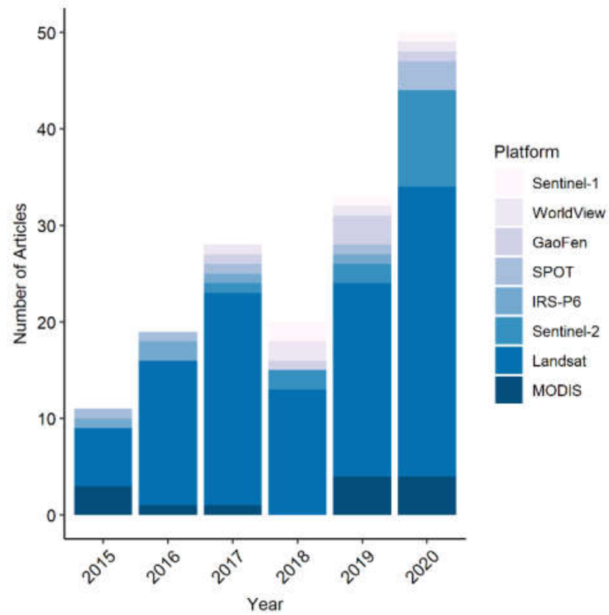

Figure 7. Frequency (number of articles) of the application of the most commonly used sensor data over time.

Studies used RS data either solely (43%) or combined RS data with existing RS products (35%). A smaller proportion of the studies exclusively made use of RS products (23%) for their analysis.

The most frequently used RS products included DEMs (29%) and LULC products (25%), followed by Vegetation Index (VI) (11%) and meteorological products (8%) (see Supplementary data, Figure S2, for an overview). DEMs are used for various reasons, often to derive topographic information, such as elevation and slope, as drivers of change. In a few cases, DEMs are used to investigate compliance with policies restricted to regions with particular slopes, for instance [64,91]. LULC products included standard LULC products, such as MODIS, CORINE, or national land cover maps, as well as sector specific products, for instance for forests, settlements, or general vegetation cover. These products were used for different purposes, such as for LULC change assessment [114] or metrics (e.g., proximity and accessibility variables [194]) and environmental indices calculations (e.g., to investigate processes related to land productivity and degradation [219]). VI products (e.g., MODIS VI, MODIS NDVI) were frequently used for VI change analysis to provide information such as for crop identification or ecosystem degradation [54,125,173]

3.2.3. Non-Remote Sensing Data for Analysis at the Science–policy Interface

Policymaking is a highly complex process that involves accounting for different factors, such as social as well as economic dimensions [3,224]. Thus, we were interested in investigating which additional, non-RS data are used to facilitate studies at the science–policy interface (see Supplementary data, Figure S3, for an overview of ancillary data used across all reviewed articles). Meteorological (22%), socioeconomic (19%; e.g., [41,74,163]), demographic (16%), administrative/cadastral data (16%), and agricultural land use data (15%) were the most frequently applied data. Socioeconomic data included, for example, information on GDP and economic information related to agriculture (e.g., livestock price and production [54]). Cao et al. (2017), for instance, investigated the impact of different socioeconomic data, such as GDP, on patterns and variations of ecology–production–living land, derived using a LULC product provided by the Chinese Resources and Environmental Science Data Center (RESDC) [33]. Other studies combine data sets for interdisciplinary studies. Nagabhatla and Brahmbhatt (2020), for example, used Landsat sensor data with meteorological and demographic data to investigate water-migration interlinkages in three case study regions [186]. Wenhui Kuang (2020) investigated socioeconomic and macropolitical drivers of regional urban land use/cover change by combining Landsat, population demographic and socioeconomic data with policy-relevant documents to provide insights into policy implications [44]. Ground truthing data were also frequently used (22%). As these data are a pivotal component of RS analyses and can impact the success of a study, independent of the application and processes investigated, this data category is not necessarily unique for studies at the science–policy interface and was therefore seen as an essential part of the RS data.

3.3. Science–Policy Integration

3.3.1. Policy Focus

We found that most studies (64%; [32–34,37,39–44,46,49,50,52–54,56–65,67,68,70,71,73–84,86,87,89,91–94,96,97,99,100,109,114,117–119,121,125,126,129,130,132–142,144,147,149,150,152,154,156,161,163–168,170,172,174,177,178,181,183–188,191,193,194,197–202,205–208,211–214,217,220–223,225,226]) could be classified into pre-policy and 34% as scientific studies [35,36,38,45,47,48,51,55,66,69,72,85,88,90,95,98,101–108,110–113,116,120,124,127,128,131,143,145,146,148,151,153,155,157,159,160,162,169,171,173,175,176,179,180,182,189,190,192,195,196,203,204,209,210,215,216,218,219], meaning that studies either went into a deeper level of policy analysis or merely mentioned the relevance of their results, approach or methodology for policymaking. Solely 4 of the 194 articles [115,122,123,158] reviewed had developed approaches that contributed or provided evidence to policy ("policy-applied"). Thus, only a small number of studies was conducted at the science–policy interface and contributed directly to EBP.

3.3.2. Policy Cycle

In accordance with the degree of policy focus of the studies, we found that most of the studies (83%) could potentially contribute to the "knowledge building/problem identification" stage of the policy cycle (Figure 8, here described as "problem identification"). The second most important potential contribution towards the policy cycle was the stage "monitoring and evaluation" (36%), while 13% and 4% of the studies could provide information to the stages "policy formulation" and "policy implementation", respectively.

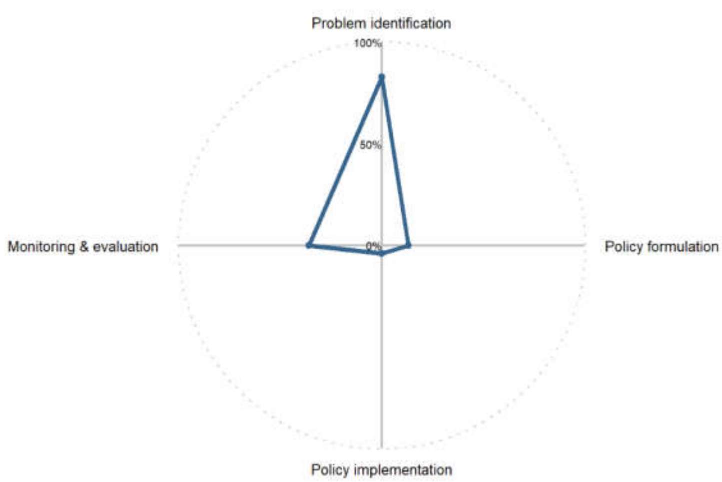

Figure 8. Distribution of all articles of this review according to the contribution of their study along the policy cycle as classified in this review.

We observed a distinct difference regarding the degree of method development and potential application of the studies approach to provide evidence for the policy cycle. For instance, studies contributing to the stage knowledge building/problem identification could be grouped into three classes. Most studies assessed historical changes to identify problems or to generate knowledge about processes, such as the impact of urban growth on green space [101]. Other studies developed and implemented specific indicators or indicator frameworks to assess drivers of change [165]. The third class focused on methodological issues related to RS application, e.g., important aspects such as accuracies and errors associated with the RS data input [178]. Such differences in the proximity of studies to the policy cycle were observed at all stages of the policy cycle.

In a next step, we analysed how far the three categories of policy focus (scientific, pre-policy and policy-applied articles) differed regarding their potential contribution towards the policy cycle. As expected, all scientific articles, which are most far from engaging at the science–policy interface or from contributing evidence for policy, potentially contributed exclusively towards knowledge building/problem identification (34%). Pre-policy studies also contributed to the stage of knowledge building/problem identification (47%) as well as to the stages monitoring and evaluation, policy formulation, and policy implementation (35%, 13% and 4%, respectively). We found that policy-applied studies contributed either to one or both stages of knowledge building/problem identification and monitoring and evaluation.

3.3.3. Integration of RS Data, Products, and Non-RS Data along the Policy Cycle

Studies at the science–policy interface often require input data from different fields and disciplines. We were therefore interested in investigating the integration of different RS data, RS products, and ancillary data along the policy cycle, as we assumed that this may provide insights into the complexity of analyses depending on the level of contribution. We found that for some specific applications, even one single RS data set was useful for investigating policy impact, such as using openly available LULC products to investigate policy impact on forest conservation or grassland degradation, respectively [42,187]. However, most studies combined one or more RS data and/or existing products with ancillary data to conduct their analysis (85%; N = 165). When looking at the policy cycle, we found that science-related studies most often used meteorological data. In the pre-policy studies, the main application included socioeconomic and administrative/boundary/cadastral, and population demographic data. Owing to the small number of policy-studies (N = 4), it is not possible to derive a general picture of data applied for such studies. However, the studies included administrative/boundary/cadastral, collateral, land use (agriculture), meteorological, population demographic and socioeconomic data, each included once in a study. A distinct difference in the inclusion of non-RS data based on the stages of the policy cycle was not detected.

3.3.4. Potential Policy Areas and Processes of Application

RS was used as the main tool or jointly with other methodological approaches to investigate concrete policies in 56 articles (i.e., either by monitoring and evaluating the impact of the policy or policies prior to or after policy implementation or to provide recommendations for policy implementation), thereby covering a wide range of policies from diverse policy fields and applying them in different sectors (Figure 9). Mainly, national policies were investigated at the local or regional scale [44,54,114,133]. Exceptions include the EU Common Agricultural Policy, which was the focus in several studies [149,167,183].

The distribution of investigated policies among sectors correlates with the general frequency of the sectors of focus in the review (e.g., main application of policies in the sectors settlement, agriculture, and forest). However, within the sectors, policies from diverse policy fields were investigated. For example, within the sector settlement climate, eco-environmental, economic, infrastructure, regional development, and urban planning policies were analysed [44,56,114,118,172,206].

Taking the policy perspective, eco-environmental policies are the main policies investigated (*n* = 13; e.g., [34,41,54,83]), followed by agricultural (*n* = 8; e.g., [183,207]) and conservation policies (*n* = 7; e.g., [134,205,211]). Eco-environmental policies cover the largest number of sectors (i.e., biodiversity and conservation, agriculture, settlement, water resources, and cross-sectoral). In contrast, agricultural policies are solely investigated within the agricultural sector (e.g., [32,53,122,149,167,191].

Most studies which incorporated a policy analysis investigated the impact or effectiveness of the policy on a particular aspect of the sector in focus, e.g., Soulis et al. (2020) investigated the impact of the EU Rural Development Program on irrigation water savings, and Xu et al. (2017) investigated the effect of desertification policies in agricultural areas, thereby both targeting the agricultural sector from a different application perspective [78,207]. Few articles predicted the future impact of policies in the sector of interest or assessed a specific condition within, e.g., areas of policy implementation (e.g., [136,174]). For example, two studies concentrating on conservation policies predicted the effect of protected areas on land use decisions and deforestation [134,211].

These results give insights into the status quo of using RS as a tool to provide evidence on the impact of policies from diverse policy fields and within various sectors from a scientific perspective and offer a first indication of the wide applicability of RS for EBP. However, complementary input data, such as socioeconomic or interview data, may be required for ex and post ante policy impact assessments [78].

Figure 9. Investigated policies according to their affiliated policy field (left column) and their application in the different sectors (right column). The thickness of the connecting lines correlates to the number of different policies investigated.

4. Discussion

In 2010, the application of RS at the science–policy interface had not arrived yet to its full potential in the scientific discourse [27]. Although more than 10 years have passed since then, we must conclude that no significant changes have occurred to date. Rather, exceptions confirm the rule. The number of studies mentioning the potential relevance of their results or method for policy without providing any further recommendation for policy is numerous. If at all a main goal of the study, a considerable gap exists between the outlined options of RS applications at the science–policy interface and the actual discussion of their implementation. Furthermore, studies, which are classified as "pre-policy", vary in their quality and level of depth regarding the information they provide for the policymaking process. Although a fair number of studies aim to evaluate the impact of policies using RS, only a small number of articles go the next step to provide concrete recommendations for future policy development, policy (re)formulation, or improved policy implementation [39,94,109,193]. This is also reflected in the low number of conducted predictions. To this end, there is a clear preferred contribution towards knowledge building/problem identification and the analysis of policy impact in peer-reviewed literature, the latter often in a descriptive manner and from a land use perspective (e.g., [42]).

Correspondingly, a small number of studies in our review set their analysis against the background of the topic of evidence-based policy (EBP), e.g., by directly contributing concrete evidence or information to a stage of the policy cycle in the realm of EBP. To give one example of a study that touches on EBP, Imran et al. (2019) investigated social inequalities based on access to public service facilities [144]. They specifically mention the usefulness of spatial aspects of policies for EBP and highlight the value of using RS in this context. Other articles focus on developing and showing the advantage of using satellite RS-based indicators for policy monitoring and evaluation and for larger data-scarce regions, but without specifically addressing EBP or its relevance [223,226]. Hence, the final step of making evidence relevant for policy, providing future advice regarding the use of RS for policy or to collaborate with policymakers to inform on the results is still widely missing.

The main policy focus of those studies assessing policies in this review lay on national and on eco-environmental, agricultural, forest, water, and conversation policies. Few exemptions concentrated on or mentioned the relevance of their work for larger regions such as the EU's CAP or international agreements (e.g., the Paris Agreement or Sustainable Development Goals). This said, the impacts of national policies were investigated within the borders of the country in which the policy was implemented, often focusing on a local to regional impact assessment. An important topic of today's policymaking that seeks to achieve sustainable development in a globally interconnected world, but one that is missing in the reviewed papers, is the assessment of the (potentially negative) impacts of political decisions and actions outside of our national borders [227].

Although only a low number of policy-applied studies (N = 4) has been published over the last years, one indication for a successful implementation of RS for policy seems to be the demand from the user. For instance, two of the policy-applied studies were initiated or conducted at the government level. The European Union Satellite Center (SatCen), for example, investigated the application of satellite imagery to explore and report on cultural heritage damage in areas occupied by the Islamic State of Iraq and the Levant (ISIL) [158], meaning that there seems to have been a direct demand from the political side for policy-specific research. Such a political demand may be pivotal to promote research contributions towards using RS at the science–policy interface and to foster RS application directly for EBP.

Congruently, a close, continued, and agile collaboration of the science and policy side to identify user needs and, in some cases, the involvement of other relevant stakeholders seems key for such endeavours. Di et al. (2017), for example, developed a prototype of a decision support tool for flood crop insurance compliance assessment in close collaboration with the relevant governmental agencies [122]. In Davis et al. (2019), a framework [228] to determine waterbody-specific criteria for impairment designation was developed in a joint effort of different stakeholders, including academia, a private non-profit company, academic research centre as well as governmental administration (The Ohio Environmental Protection Agency) [123]. A further investigation of the collaboration and the underlying processes of using or institutionalising RS applications in the political field would therefore be of interest.

Moving beyond peer-reviewed literature, we will see that applications of RS in the political field and for EBP exist and cover a variety of policy sectors [19,20]. The aforementioned Montreal Protocol belongs to one of the early success stories. Other examples include the EU's Common Agricultural Policy (CAP), which holds an operational use of RS for the implementation of EU subsidy policies, and the development of RS-based tools to assist national and local authorities in crisis situations and with hazard management [228,229]. This points towards the hypothesis that RS applications contributing directly to the policymaking field manifest rather outside of the scientific literature and field, such as in companies, intermediary and political organisations, whereas the early RS-based methodological phase of the work is visible in the peer-reviewed scientific literature.

4.1. Narrowing the Science–Policy Gap: The Policy Cycle from a RS Perspective

Our review shows that researchers attempt to carve out the contribution of their work for policy, but these attempts are distant from the political application. This does not mean that their results do not find their way into the political field [230]. Nevertheless, narrowing the gap between the early phase of RS application development or knowledge provisioning and the policymaking process may help to move faster towards implementing RS applications in policy and to accelerate successful EBP.

Although the policy cycle is a simplification of the policy process, and the policy process may not always be circular and straightforward, it provides a basis for understanding how policymaking is organised and at which stage scientific evidence can be integrated into the policymaking process [231]. By actively considering the policy cycle during the research process, such as in the phase of research question determination, developing research methods, and identifying outcomes and goals, it may help to make research more applicable for the political field. In the following, we briefly outline the possible contributions of RS along the policy cycle as drawn from the reviewed articles.

4.1.1. Stage Problem Definition/Knowledge Building

The first step in the policy cycle is the identification of a problem and agenda setting. This stage can be shaped by diverse factors, including the representative institutions themselves (e.g., political parties), media, civil-society actors, and through data and evidence on an issue [232]. RS can provide objective insights into sector-specific and cross-sectoral trends and processes. Further, it can deliver knowledge on the scale of change and relevant spatiotemporal relationships of ecosystems and the environment and help to identify existing or arising problems. Entire monitoring frameworks and tools can be implemented based on this powerful feature, such as by developing indicators that can measure and evaluate the process in question (e.g., urban sprawl) [169].

4.1.2. Stage Policy Formulation

During the second stage of the policy cycle, policy options are formulated, and their potential success in achieving the policy objectives is discussed [233]. Policy models are often used for policy design, to identify where a policy can best be implemented, to compare the outcome of alternative policies, or to assess synergies or conflicts between different policies [233]. The spatiotemporal insights from RS can be a powerful compliment to such modelling approaches for (e.g., scenario-based) predictions of future policy impact responses and trajectories. Studies in this review have demonstrated this for different sectoral policies, including conservation, eco-environmental, urban planning and development, water, and climate policies [134,164,168,174,198]. Further, sound modelling approaches may be particularly interesting to save costs associated with in situ policy pilots, which may be otherwise necessary. Finally, they can help to better communicate underlying mechanisms and outcomes of policy options [234].

4.1.3. Stage Policy Implementation

This stage can be observed from different perspectives, as certain policies can also lead to an indirect demand to use RS for policy implementation. Environmental legislation and the requirement for liability by affected companies can create a demand for RS application during this phase. Examples include the necessity of compliance with certain standards, spatial planning (regulations), and environmental impact assessments (see Leeuw et al. (2010) for further details). Further, similarly to stage two of the policy cycle, evidence from RS can be valuable input to formulate advice for policy implementation, such as by investigating spatiotemporal aspects of policy implementation. This is demonstrated by a few studies, which used RS for policy monitoring and evaluation and which provided recommendations for policy implementation based on the result. Recommendations include, for instance, implementation procedures for land use policies in identified regions of concern or priority sites for the establishment of conservation areas [52,166].

4.1.4. Stage Monitoring and Evaluation

Important aspects of this stage of the cycle are policy control and evaluation, such as through monitoring. RS can be useful in providing spatiotemporal patterns and trends of ecosystems and the environment owing to implemented policy measures and can be a powerful tool for policy control and compliance [59,122,123]. It can be used to evaluate policy implementation by investigating environmental impacts, whether the policy measure has been effective, and the policy goal reached. RS can also contribute to monitoring compliance with governmental legislation and measures, such as demonstrated in the context of the EU CAP or the US Federal Water Pollution Control Act of 1972 [115,123,167]. Further, RS data and products can be used for the development of policy-relevant indicators and indicator frameworks that can help evaluate policy implementation and compliance more effectively/directly, such as through monitoring green infrastructure for policy-relevant frameworks [115,123,126,167].

4.2. Topics Gaining Importance for RS at the Science–Policy Interface

The following core areas of focus and improvement are discussed regarding the application of RS for studies at the science–policy interface.

4.2.1. Ex Post and Ex Ante Policy Assessment

An important player and challenge in promoting sustainable development is the forecasting, modelling, and scenario-building analysis of policies prior to their implementation [235,236]. RS can help develop policies that allow for managing our resources at different spatiotemporal scales. Congruently, predicting policy impact to contribute towards quantitative measurements of policy effectiveness is a pivotal topic mentioned in some studies [40,42,164], but which showed to be largely missing in the reviewed studies.

Further, articles state the growing necessity for governmental monitoring tools for ex post policy evaluation and compliance monitoring and demonstrate the application of RS in this field [167]. For instance, in the agricultural sector, high-resolution data, such as 1-m Terra Bella or RapidEye imagery, are suggested as inexpensive tools to monitor crop cultivation for agricultural or environmental policies [137,162]. There is also the call for increased governmental involvement to support the implementation of monitoring instruments to observe and protect land and valuable areas [137], which could be used for ex post policy assessment as well.

4.2.2. Interdisciplinary Approaches

Studies at the science–policy interface must consider the complexity of sustainable policies by making use of interdisciplinary assessments [237]. Creating a shared lens across sectors requires the application of different input layers and methodological approaches. Although a relatively high number of studies classified as pre-policy discussed their findings, drawing upon answers from different disciplines, analyses often concentrated on investigating one specific process within a sector, thereby providing concrete evidence in a unidimensional perspective. Most articles included ancillary data in their studies, but only a small number developed an interdisciplinary approach by encompassing ancillary data outside of the purely natural science disciplines, such as by including socioeconomic data (19%; e.g., [41,163]). A similar picture was found in a recent review paper concentrating on RS and urban planning by Wellmann et al. (2020) [28]. It is not surprising that there remains the call for future research to promote interdisciplinary approaches that take into account the complexity of sustainable development, such as through data (e.g., multi-source data approaches) and method integration [34,111,151,156].

4.2.3. Methodological Development and Integration

Today, technological advances, such as machine learning and statistical approaches, as well as on-demand analysis and data storage platforms, provide research with powerful, diverse prediction and assessment methods [138,182,238,239]. Some studies demonstrate and state the value of these technological developments, such as the efficiency of cloud computing platforms for analysis with big data or using high-resolution RS data with deep learning methods for land use and ecosystem dynamics monitoring [43,169]. However, only very little studies utilise these approaches for concrete policy assessment [168].

Studies and approaches from scientific fields and policy which already make good use of these technological advances could serve as an example for scientists aiming to contribute knowledge towards the policymaking process and evidence about specific policies [233,238]. RS is already used as input for modelling and forecasting analyses in several research fields, such as in climate, habitat, or crop prediction models, however, often not from a political perspective [238,240–242]. Similarly, policy impact assessment is by now an integral part of national and international politics [233,243,244]. Thus, a stronger convergence of methods and approaches for specific purposes is crucial, in our case to promote RS-integrated analyses at the science–policy interface, such as for ex ante policy impact assessment.

4.2.4. RS Indicators and Proxies for EBP Studies

The development and implementation of RS indicators and proxies to assess environmental conditions and provide corresponding evidence for policy development is still at the forefront of research. Indicators or proxies for policy analysis are successfully developed, such as to measure water quality and monitor and evaluate water policies, investigate the impact of land consolidation projects on the ecological environmental quality or to measure urban liveability [38,39,165,226]. However, often their final applicability for policy remains a discussion. Finally, the necessity for indicator frameworks is discussed as a means of a common language among stakeholders from different fields and to promote interdisciplinary processes [212].

4.2.5. Emerging Sectoral Topics

Our results show that studies tended to focus on the "traditional" topics of RS analysis, above all on LULC processes in the settlement, forest, agriculture, and water sectors. In the future, we can expect a shift or expansion to new, more complex, interdisciplinary topics, especially to social matters, disaster and risk management, and biodiversity in a wider context, enabled by the emerging methodological possibilities due to growing RS capacity and technological advances, as described in the previous section (Sec. 4.2.3). For instance, Imran et al. (2019) mentioned the use of RS for research targeting public health, in particular in relation to future climate change impacts and health equality [144]. Further, the possibility to use RS to develop policy frameworks with integrated location-based vulnerability approaches in disaster and risk management is mentioned [142]. Christensen and Arsanjani (2020) suggest taking advantage of LULC model simulations to evaluate the effectiveness of protected areas and to identify challenges and conflicts for the sector biodiversity and conservation [164].

Nevertheless, studies which investigated LULC processes often discussed important sectoral topics that have been extensively addressed by the science community, but for which the need to improve and implement interdisciplinary approaches is mentioned. To provide one example, several studies focusing on the sector forest, highlight RS for REDD+ implementation and call for more accurate methods for REDD+ compensation, carbon storage evaluation, and an analysis of drivers, such as from policy and socioeconomics, to better understand deforestation trends [136,136,141].

4.3. RS Requirements at the Science–Policy Interface

Several requirements mentioned in the reviewed studies will need further consideration to make use of the full capacity of applying RS at the science–policy interface.

4.3.1. Data Availability and Quality

Long term continuous data sets form the basis for the analysis of change trajectories. These are especially useful when impacts of policies need to be monitored or when knowledge about change trajectories is required. Yet, despite the availability of open access data, the problem of good quality data and data coverage remains an important discussion regarding different regions and topics [151,169]. In several policy sectors, there exists a call for spatially high-resolution data as input for, e.g., modelling approaches for environmental assessment [99,177]. This requirement is mentioned for instance for crop identification in the realm of agricultural policies, for modelling past and future forest dynamics to evaluate policy measures, to provide fine-scale spatial maps of water quality for policy-related water management questions, and to assess different urban sprawl indicators to investigate urban agglomerations and their urban sprawl typologies in relation to different driving factors, including economic policies [99,138,151]. Higher temporal resolutions are mentioned to assess and monitor sectoral processes, such as to investigate total suspended solids (TSS) from dredging activities in coastal regions to inform on water quality for environmental policies [151]. The requirement for high-resolution data is also indicated by the frequency of RS platforms used in the review, with a high number of studies using national optical higher resolution satellite data for their approaches. Higher spatiotemporal resolution data will become increasingly available as existing platforms such as Sentinel cover required periods and the capacity of new sensors and geostationary sensors/satellites grows [151]. Nevertheless, RS application and monitoring length depend on the type of policy measure, meaning on the dynamics of policy implementation and impacts [138], all of which must be taken into account for effective policymaking [245]. Finally, in certain instances, the RS data may exist, but the according ancillary data may not be available. This issue is mentioned, for example, for forest inventory data to quantify carbon stocks and emissions, and for local demographic data needed to implement the two SDG indicators 11.1.1 and 11.3.1 [130].

4.3.2. Product Requirements and Consensus on Definitions

For certain policy goals and measures, data may require new classifications. For instance, LULC maps may require refinement to "better" represent specific topics and sectors and to improve the analysis of certain processes. Cao et al. (2017), for example, reclassified LULC maps to better represent the ecology–productive–living land in Chinese urban agglomerations and to investigate driving factors of trajectories [33]. *S*uch information and reclassification, however, may be best implemented by consulting policymakers to match their requirements, thereby making evidence and information provided by such new classifications valuable for policy and the decision-making process [246].

Further, consensus on definitions is mentioned as an issue related to some topics and processes. For instance, the varying definitions of the term "forest" in different countries is still not entirely tackled and the necessity to solve this issue remains highlighted by Estoque et al. (2018) [171]. They further mention that, particularly, policymakers should be aware of the different definitions and their limitations. Researchers should provide according references, such as by including accuracies (classification errors), when providing information on forest cover change [171]. In addition, the definition of thresholds used for indices, such as NDVI, is dependent on the process investigated, the locality, and in situ validation. Therefore, predictions based on these indices and specific threshold should be evaluated before using them for policy [169].

4.3.3. Ground Truth and Field Data

Ground truth data are important components of RS approaches owing to their relevance for RS data calibration and interpretation, and they remain a pivotal gap for diverse applications [162,167]. Good ground truth and field data can help reduce current known sources of error in predictions and provide more reliable and better means of evaluation of policy programs [162]. Therefore, there is a call for long-term in situ programs and validation data [123]. However, today, alternative modes of accessing ground truth data are also available and increasing, including the potential of using crowdsourcing applications (e.g., Google Street View) to gain access to necessary information for evaluation [167].

4.3.4. Accounting for Scale

Related to the problem of data quality and availability is the challenge to account for spatiotemporal patterns while implementing interdisciplinary approaches [246]. The necessity to account for scale touches upon several topics, such as the spatial scale of analysis while using RS data, indices, and products at global, national, or regional levels, and depending on the processes and disciplines observed. The question of the appropriate scale is discussed frequently for forest policies. For example, Allen and Vásquez (2017) argue that using forest cover as a proxy for investigating conservation efficiency may be insufficient when investigating drivers at the parcel level [156]. Brovelli et al. (2020), however, highlight the necessity to adapt the monitoring period to the policy in question, thereby stating that shorter monitoring periods may be more useful for forest preservation policies that rely on short-term results, whereas longer periods benefit policies that are slow in implementation [138].

5. Conclusions

RS is one of the most powerful tools to provide objective and robust evidence for various processes. It delivers valuable insights into spatiotemporal dynamics of ecosystems and our environment at various scales, some of which are partially impossible to track from the ground, and it can help us to understand relationships. Most importantly for EBP, RS can support policymaking throughout all stages of the policy cycle and in diverse policy sectors as found in this review. To this end, RS provides a comprehensive source for multidisciplinary and diverse research fields and policy applications [247].

However, we found that there remains a gap between science-driven evidence, which is (either mainly or partially) based on RS, and the political field. RS is particularly useful (and mostly used) for stage one of the policy cycle—problem identification/knowledge building—and only rudimentary for the other stages policy formulation and policy implementation, while some more examples exist for monitoring and evaluation. Congruently, evidence or recommendations targeted for policy and joint ventures with the political field are still widely missing. Indicators or proxies for policy analysis are successfully developed, but often, their final applicability for policy remains a discussion. In addition, few studies developed an interdisciplinary approach, such as to include a multidimensional perspective. Concerning investigated policies, studies focused mainly on national policies within a nation's border, whereas assessments of transnational policies and treaties as well as the (potentially negative) impacts of political decisions and actions outside of national borders are scarce. Accordingly, studies should be promoted that aim at implementing forecasting, modelling, and scenario-building analysis of policies prior to their implementation as well as ex post policy assessments [164]. Here, policy could play a driving role to support and implement monitoring tools [137]. Further, future research that considers the complexity of sustainable development by means of interdisciplinary approaches is needed. To promote the latter, indicator frameworks could serve as a common language among stakeholders from different fields [212].

Our review also underlines the assumption that RS applications already contributing directly to the policymaking field manifest rather outside of the peer-reviewed literature, such as in intermediary and government-close organisations. Past scientific contributions are the heritage of today's more operationally geared satellite missions, and we can expect to see some of the applications or explorative studies found in this review or peer-reviewed literature, which we may not have captured, to become at least part of the applications of tomorrow. In the future, we may see an accelerated integration of RS in policy owing to the increasing recognition of the economic viability and contribution of RS to national and global challenges [19,20]. In addition, efforts of intermediary organisation, such as ESA, and relevant programmes, such as the European Union's Earth Observation Programme Copernicus in Europe, are increasingly driving applications at the science–policy interface and are promoting downstream uptake of RS in diverse sectors and markets. Current developments, such as the EU's Destination Earth (DestinE) System with the Digital Twins, which will leverage RS data and the potentials of AI, are promising new tools to unlock the potentials of EBP, particularly for the stages policy formulation, implementation, and monitoring of the policy cycle in the near future [247]. Together with the growing RS capacity, e.g., an increasing availability of a variety of RS data and time series, and political demand for robust and objective management tools, we can expect an expansion in the use of RS to new, more interdisciplinary topics at both national and international levels, such as in the health sector (e.g., epidemiology, air-quality), disaster and risk management, to support new energy solutions, and for biodiversity monitoring in a wider context [248]. These developments will also strengthen the application of RS for global treaties, such as the Paris Agreement and the Agenda 2030. The use of RS for meteorological services is well established. However, considering the disputed political impact of global endeavours concerning climate change and sustainable development, such as the Paris Agreement and the UN SDGs, new pathways and tools are required to allow for their success. With the technological advances and methodological integrations, RS can play a pivotal role in boosting the success of these treaties, such as by supporting the implementation of climate mitigation and adaptation policies at the national level and monitoring the overall success at the international level.

Similarly, studies have already highlighted the substantial and potential contribution that RS could have to monitor a wide range of SDG indicators [249]. Today, initiatives, such as the Earth Observations for the Sustainable Development Goals (EO4SDG) initiative from the Group on Earth Observations (GEO), aim to present and realise the benefits of RS for the SDGs, such as by presenting national experiences and good practices, including case studies, which will help to foster the integration of RS for the SDG process.

Nevertheless, pivotal for the success of these endeavours and to integrate RS in policy is the active support by the Earth observation and statistical community. Particularly, the science field can be a motor of new developments, such as regarding new methodological approaches, and to showcase applications. We would thus like to conclude with a few suggestions on how to close the gap between scientific RS research and the use of its results for policy, which may help to accelerate the use of RS at the science–policy interface. To start with, more targeted evidence for the political field is needed by acknowledging the complexity of political decision making and policy measures. More vigorously making use of today's technological advances and interdisciplinary approaches will be required. Developing nexus approaches at the science–policy interface could be a way to foster the use of RS for policy and assist in elevating policy coherence and sustainable development across sectors [250]. At the same time, communicating and promoting the limitations and strengths of using RS in policy-related analysis is desirable. For evidence to find its way into the political field, researchers must invest time in understanding the needs of the users of their work. This includes developing their research goal and methodological approaches through user-specific consultation, and understanding at which stage of the policy process their evidence could be most valuable (as well as accepted) [10,237]. Accordingly, investigating existing collaborations and the underlying processes of using or institutionalising RS applications in the political field would be of interest.

On the other hand, the political field should also take a more active role in either providing themselves or pushing towards an effective monitoring and evaluation of policy interventions to overcome the policy-driven focus on monitoring and evaluation of states and trends [251]. Likewise, it is important that the policy field understands the usability and limitations of the RS-based evidence provided, for instance, that the spatiotemporal availability of the RS data, products and model output must match with the scale of the policy goal, measures, and resulting process in question [246]. Such knowledge development on both sides of the science–policy interface would help both the science and policy field to better identify criteria and necessary formats for evidence. Together, with better communication and co-production along the science–policy interface, this could help foster the integration of RS applications in the policy field.

These are some insights from the scientific perspective to pave the way for better collaboration between science and policy and more targeted research questions to improve the uptake of evidence at the science–policy interface.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs15040940/s1, Figure S1: Remote sensing platforms utilised across all reviewed articles; Figure S2: Existing remote sensing products used in all reviewed articles. Products occurring below 2% were removed; Figure S3: Additional data utilised across all reviewed articles. Occurrences below 5% were removed.

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Data Availability Statement: All data can be accessed via the articles of this review. Articles can be downloaded as described in our Materials and Methods section (literature search using Web of Science (WoS) Core Collection).

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