International Journal of
Geo-Information

MDPI

Article

An Earth Observation Framework in Service of the Sendai Framework for Disaster Risk Reduction 2015–2030

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Citation: Li, B.; Gong, A.; Liu, L.; Li, J.; Li, J.; Li, L.; Pan, X.; Chen, Z. An Earth Observation Framework in Service of the Sendai Framework for Disaster Risk Reduction 2015–2030. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 232. https://doi.org/10.3390/ijgi12060232

Academic Editors: Diego González-Aguilera, Pablo Rodríguez-Gonzálvez and Wolfgang Kainz

Received: 3 April 2023
Revised: 28 May 2023
Accepted: 1 June 2023
Published: 6 June 2023

Abstract: The Sendai Framework for Disaster Risk Reduction 2015–2030 (SFDRR) proposed seven targets comprising 38 quantified indicators and various sub-indicators to monitor the progress of disaster risk and loss reduction efforts. However, challenges persist regarding the availability of disaster-related data and the required resources to address data gaps. A promising way to address this issue is the utilization of Earth observation (EO). In this study, we proposed an EO-based disaster evaluation framework in service of the SFDRR and applied it to the context of tropical cyclones (TCs). We first investigated the potential of EO in supporting the SFDRR indicators, and we then decoupled those EO-supported indicators into essential variables (EVs) based on regional disaster system theory (RDST) and the TC disaster chain. We established a mapping relationship between the measurement requirements of EVs and the capabilities of EO on Google Earth Engine (GEE). An end-to-end framework that utilizes EO to evaluate the SFDRR indicators was finally established. The results showed that the SFDRR contains 75 indicators, among which 18.7% and 20.0% of those indicators can be directly and indirectly supported by EO, respectively, indicating the significant role of EO for the SFDRR. We provided four EV classes with nine EVs derived from the EO-supported indicators in the proposed framework, along with available EO data and methods. Our proposed framework demonstrates that EO has an important contribution to supporting the implementation of the SFDRR, and that it provides effective evaluation solutions.

Keywords: Sendai Framework for Disaster Risk Reduction (SFDRR); Sustainable Development Goals (SDGs); disaster; earth observation (EO); essential variable (EV); tropical cyclone (TC); Google Earth Engine (GEE)

1. Introduction

The Sendai Framework for Disaster Risk Reduction 2015–2030 (SFDRR) is a 15-year agreement adopted by the United Nations (UN) Member States in 2015 at the Third UN World Conference on Disaster Risk Reduction (DRR) in Sendai City, Japan. The SFDRR aims to reduce the existing disaster risk, level of exposure, and vulnerability to disasters, and to enhance international cooperation in disaster risk reduction and the availability and access to pre-disaster warnings and post-disaster assessments [1]. The SFDRR has seven targets and four action priorities to achieve a substantial reduction of disaster risk and losses in the global population, gross domestic product (GDP), and infrastructure. Since the SFDRR is a product of interconnected natural, social, and economic processes, it is also closely associated with the Sustainable Development Goals (SDGs) (Figure 1). Three goals of SDGs involving 11 indicators are monitored and measured by the SFDRR, facilitating considerable synergy between the two policy instruments [2]. Therefore, the SDGs and the SFDRR constitute an overarching global milestone for creating a better and more sustainable future worldwide [3–5].

Figure 1. The synergistic relationship between the SFDRR and SDGs. Data source: https://www.undrr.org/implementing-sendai-framework/sf-and-sdgs, accessed on 26 March 2023.

To monitor the progress of the seven SFDRR targets, the open-ended intergovernmental expert working group (OIEWG) on indicators and terminology relating to disaster risk reduction has recommended a set of 38 indicators and relevant sub-indicators to track the progress made in implementing the seven targets of the SFDRR [6]. These indicators play a key role in demonstrating global progress in achieving the goals of the SFDRR. Member states are required to report on these indicators over two ten-year periods to assist in assessing the global trends in disaster risk reduction and supporting informed decision-making and policy-making at the national/global level. In 2018, the United Nations for Disaster Risk Reduction (UNDRR) launched the Sendai Framework Monitor (SFM) as an online database platform to help countries report on the indicators and progress of the SFDRR targets and make risk-informed policy decisions. The UNDRR also produced *Technical Guidance for Monitoring and Reporting on Progress in Achieving the Global Targets of the Sendai Framework for Disaster Risk Reduction* (henceforth referred to as the *Technical Guidance*), which outlined the computation methodologies as well as the minimum and desirable data requirements for each indicator [7].

The introduction of measurable and monitorable indicators for the SFDRR has spurred a global initiative to develop more accurate and comprehensive assessment approaches for disaster impact [8]. However, the effectiveness and long-term utility of the proposed indicators for meeting the aims of the SFDRR remains uncertain. The seven targets with their 38 indicators as well as various sub-indicators pose challenges for countries to collect disaster-relevant data to measure and monitor all these indicators [9]. In 2017, the UN produced a summary report in which 87 countries assessed their levels of availability of national disaster-related data, their disaster-related data gaps, and the type of resources needed to fill these data gaps. The report showed that not all countries had the capacity to report on each of the SFDRR indicators. For example, in terms of Target B, only 66% of the countries could report on the number of people directly affected by disasters; in terms of Target C, less than 50% of countries were able to report on the indicators regarding productive assets, critical infrastructure, and cultural heritage [10]. Following the adage that "you cannot manage what you cannot measure", the lack of data availability presents challenges for monitoring the progress made towards achieving all the SFDRR targets and hinders countries from developing disaster risk reduction strategies and allocating resources for preventing new disaster risks.

Earth observation (EO) has become a widely-used solution for obtaining Earth surface information. EO data, including satellite, airborne, land, and marine-based data, can track changes in ground features before and after a disaster with proper spatial and temporal resolution. Compared with traditional data collection approaches in disaster situation assessment, such as field surveys, census datasets, and statistical reports, EO provides spatial, spectral, and temporal information that can be extracted and associated with relevant indicators. With advantages including rapid imaging capability, large scanning ranges, and free from ground limitation, EO data, especially satellite remote sensing images, have been widely applied in assessing natural disasters, such as fires [11], floods [12,13], earthquakes [14], and tsunamis [15,16]. Providing a historical record of Earth changes, EO can be combined with demographic, statistical, and other data to measure the SFDRR indicators and to support indicator monitoring data-driven decision-making and action across government institutions and programs [10].

To fill the gap between accurately measuring the progress of the SFDRR or SDGs and the availability of disaster-relevant data and solutions, scholars and relevant organizations are sparing no efforts to apply EO data, methods, and frameworks in measuring and monitoring related indicators [8,17–19]. Some studies focused on constructing comprehensive frameworks or technique guidelines for indicator measurement. The Group on Earth Observations (GEO) proposed an EO4SendaiMonitoring Initiative to promote the use of earth observation data and the collaborative development of EO datasets, analytical tools, and quality standards to support the implementation and the monitoring of indicators of the SFDRR [20]. Considering that free satellite data is increasingly becoming available and accessible, the United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP) aimed to strengthen regional mechanisms for implementing the SFDRR and proposed a procedural guideline for sharing space-based information during emergency response to embrace the use of EO data in disaster risk management [21]. The Asian and Pacific Centre for the Development of Disaster Information Management (APDIM) released a step-by-step guide to monitoring the impact of sand and dust storms using the SFDRR indicators, where satellite data provide an opportunity to fill in data gaps for monitoring losses in population, GDP, and infrastructure resulting from sand and dust storms [22]. Masó et al. [23] proposed EO networks that produced essential variables to link with the SDGs and improved the SDG indicators framework by suggesting new EO-based indicators.

Other studies focused on specific targets or indicators of the SFDRR and provided effective measuring approaches. To report on the progress of SFDRR Indicator B-5a, i.e., the number of workers in agriculture with crops damaged or destroyed, Urrutia II et al. [24] used Sentinel-1 synthetic aperture radar (SAR) data and relevant spatial data to quantify indicator B-5a for Ecuador and developed a geospatial modelling approach for this indicator in the context of flooding. Ghaffarian et al. [25] developed an approach combining high-resolution satellite images and machine learning methods to monitor the urban deprived areas in Tacloban city in the Philippines over a four-year period after super Typhoon Haiyan, which focused on the resilience of the human community and addressed one of the action priorities of the SFDRR.

Although the gap between the measurement of indicators and the availability of disaster-relevant data and solutions is narrowing, there is still a lack of a complete EO-based framework to support the global progress towards fulfilling the SFDRR. First, a systematical identification of which SFDRR indicators can be measured and monitored by EO is needed. With the integration of some key SFDRR indicators into the global indicator framework of the SDGs, the potential of EO-derived monitoring and methodologies for the SFDRR indicators should be explored. Second, few studies have focused on matching EO data and methods to specific SFDRR indicators. Satellite-derived and geospatial information is increasingly used for SFDRR implementation, while there are no comprehensive methodologies for making the best use of these resources or listing the options that are suitable and applicable in different disaster scenarios. Therefore, an integrated framework that links the EO database, EO-based evaluation methods, and SFDRR indicators is needed.

In terms of the construction principle, both the SFDRR and the SDGs constitute a "network of targets" that links goals into a system, requiring trade-offs and interdependencies, and facilitating policy integration across sectors [26]. In some cases of the SDGs, different indicators converge in a minimum set of essential variables (EVs) to match with EO data in terms of spectral, spatial, and temporal dimensions. This methodology has been applied in various fields such as climate [27], biodiversity [28], and social economy [29]. A similar situation can also be found for the SFDRR while relevant studies are still lacking. In terms of decoupling indicators, regional disaster system theory (RDST) is a systematic theory concerning the formation mechanism and development process of natural disasters. Since the SFDRR interlinks indicators within and across seven targets using a synergistic approach, it accounts for the existing targets' trade-offs and reinforcements and avoids the unintended consequences that focusing on a single target or indicator can often have on the other indicators [26]. Aiming to solve the problems that exist in previous studies, the specific objectives of this study are: (1) to review the scope for using EO, especially for the full breadth of the SFDRR indicators, and to assess its potential for providing data, and select indicators that can be supported by EO; (2) to decouple and recouple the initial SFDRR indicators as EVs based on the RDST; and (3) to match EO data and methods to the proposed EVs and to construct the mapping relationship between the measurement requirements of EVs and the capabilities of EO. We finally proposed an EO-based framework in the scenario of tropical cyclones (TCs) that defines a minimum set of EVs to guide the application of EO data and methods.

2. Methods

We proposed an EO-based framework to support the measurement and monitoring of the SFDRR, which consists of three layers: indicator layer, EV layer, and EO layer (Figure 2). The indicator layer identifies which SFDRR indicators can be supported by EO. We used quantitative and qualitative methods to analyse the potential of EO for each indicator and select those that can be supported by EO. The EV layer defines the set of EVs to be measured by EO. We decoupled the SFDRR indicators that were directly supported by EO into EVs based on the RDST. The EO layer represents the mapping relationship between the monitoring requirements of EVs and the capabilities of EO. We analysed the monitoring capabilities of existing satellite remote sensing data products and provided available EO data and methods for each EV on Google Earth Engine (GEE), a remote sensing big data platform. Finally, based on the established principles of comprehensiveness, systematicity, independence, and operability, we constructed an EO-based framework to support the SFDRR.

2.1. Indicator Layer: SFDRR Indicators Supported by EO

The SFDRR is articulated by 7 targets, 38 main indicators, and many sub-indicators under each main indicator [27]. However, not all indicators and sub-indicators can be supported by EO data and methods, or the results, especially those related to socioeconomic indicators of sustainable development, are not exclusively based on EO data due to the important role of non-EO data. Therefore, it is a challenging task to evaluate the potential of EO for measuring and monitoring the SFDRR indicators, and to select those indicators that can be directly or indirectly supported by EO. Based on current indicator evaluation methods and the requirements for basic data, we classified the SFDRR indicators into four categories, as shown in Table 1.

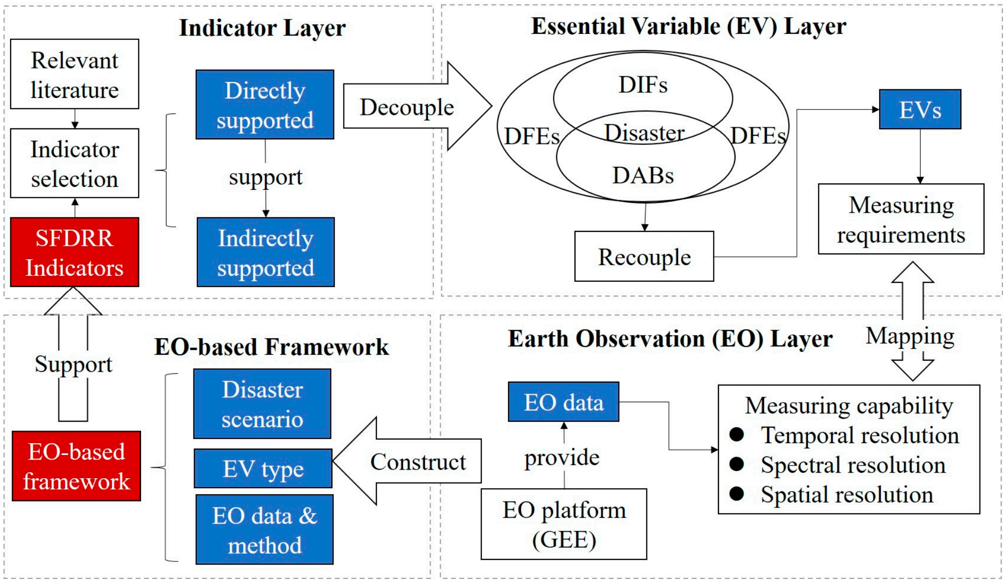

Figure 2. Flowchart for constructing the EO-based framework in service of the SFDRR (DIFs: disaster-inducing factors; DABs: disaster-affected bodies; DFEs: Disaster-formative environments).

Table 1. SFDRR indicator tier definitions.

Tier	Definition	Example
Tier I	Independent indicator directly supported by EO, that is, by inputting EO data as well as other sources of basic data into the evaluation method, the value of the indicator can be obtained.	Indicator B-3a: Number of dwellings/houses damaged attributed to disasters
Tier II	Compound indicator that are indirectly supported by EO, that is, it needs to be calculated through the use of independent indicators, basic data, and specific algorithms provided by the UNDRR [22].	Indicator D-1: Damage to critical infrastructure attributed to disasters
Tier III	Indicator cannot be supported by EO, that is, post-disaster data and information need to be collected by such means as filed surveys rather than by EO.	Indicator B-2: Number of injured or ill people attributed to disasters
Tier IV	Indicator that does not need to be supported by EO, that is, data and information acquirement and indicator evaluation can be completed before the disaster, and no post-disaster evaluation work is needed.	Indicator G-1: Number of countries that have multi-hazard early warning systems

To ensure the objectivity of indicator selection and spontaneously consider the practical significance of indicators, we adopted a combination of quantitative and qualitative methods for classifying indicators into their corresponding tiers [30,31]. We systematically reviewed relevant literature that mainly included papers, reports, and standards with the following content: (1) data sources for the SFDRR indicators or similar indicator systems such as the SDGs; (2) methods that use EO data to extract ground objects and retrieve earth parameters; and (3) disaster situation assessment methods based on EO. We synthesized the opinions in the acquired literature and reasonably determined the possibility and degree of SFDRR indicators being supported by EO, which was implemented based on a hierarchical selection structure, as shown in Figure 3.

We classified the SFDRR indicators into corresponding categories according to the following steps: (1) determining the level of dependence of each indicator on other indicators; (2) determining the demand for post-disaster data and information relating to each indicator; and (3) analyzing the potential of EO data and methods for measuring and monitoring each indicator, including the common technical issues faced in basic data acquisition and processing, such as statistical data decomposition, international data applicability, and crowdsourcing data applicability. Through the progressive selection structure design, we selected the SFDRR indicators and determined their characteristics based on two premises and the answers to previous questions. Question 1 determines which types of indicators (independent/compound) are sought. Considering that some composite indicators need to be calculated with the involvement of other indicators, the different response options for this question are used to provide two different premise conditions for subsequent questions. Question 2 determines whether the indicator can be evaluated by relevant statistical data before the disaster, with the goal of eliminating indicators that do not need EO support. Question 3 determines whether these indicators are directly or indirectly supported by EO. Among these EO-supported indicators, independent indicators can be directly supported by EO data and methods, while compound indicators can only be indirectly supported because they have been derived from other indicators and calculation methods. Except for Question 1, the subsequent questions are based on two premise conditions revealed by the answers to previous questions. While summarising the opinions from different literature, we gave preference to higher EO-relevant potential for the indicator categories. When the questionnaire was finally completed, we obtained detailed opinions from the respondents regarding the characteristics of the indicators that were relevant to EO.

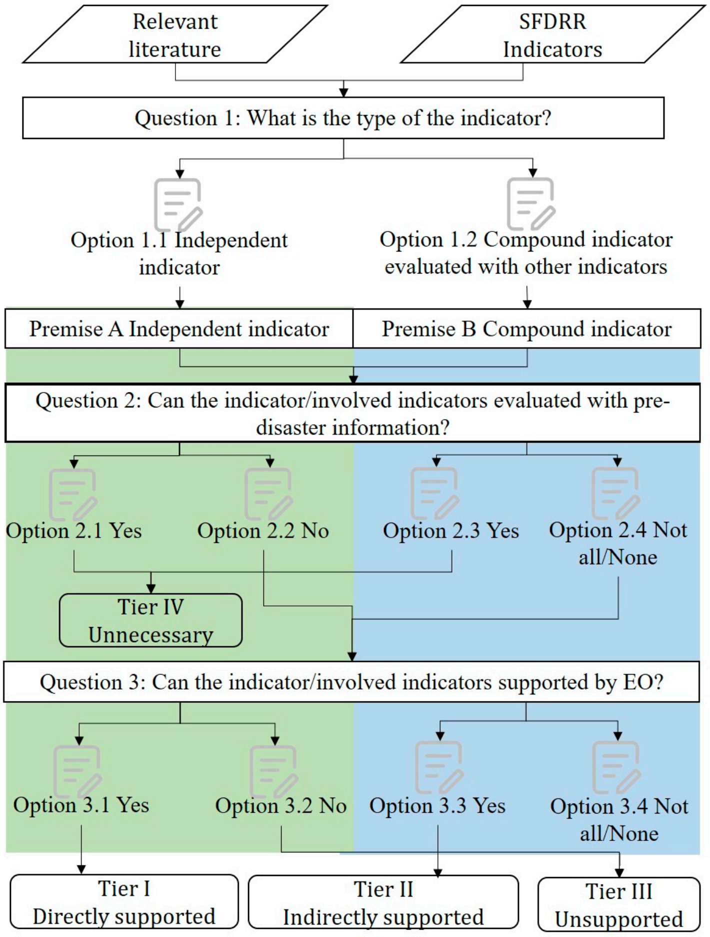

Figure 3. Workflow of the SFDRR indicators classification.

2.2. EV Layer: Decoupling and Recouping SFDRR Indicators

In Section 2.1, we selected those SFDRR indicators that can be supported by EO (Tier I and Tier II). However, these indicators are organized according to the seven targets of the SFDRR, which involve multiple aspects, such as human casualties, economic losses, and infrastructure damage. These indicators involve measuring variables involving multiple types, wide ranges, scattered distributions, and large data volumes and pose challenges for constructing a systematic measuring and monitoring framework. Decoupling and recoupling the SFDRR indicators as EVs that can be evaluated using EO provides an opportunity to monitor and report on regional goals and indicators, to monitor the progress made in reducing and enhancing disaster risk reduction efforts, and to better capture and understand the cross-border impacts and effects involved in disaster and risk reduction. We decoupled the SFDRR indicators as EVs based on the RDST under the scenario of TCs, where cascading disasters were also considered; then we recoupled those EVs based on their physical characteristics as well as their affected mechanism by disasters. Figure 4 shows the decoupling and recoupling process under the scenario of TCs.

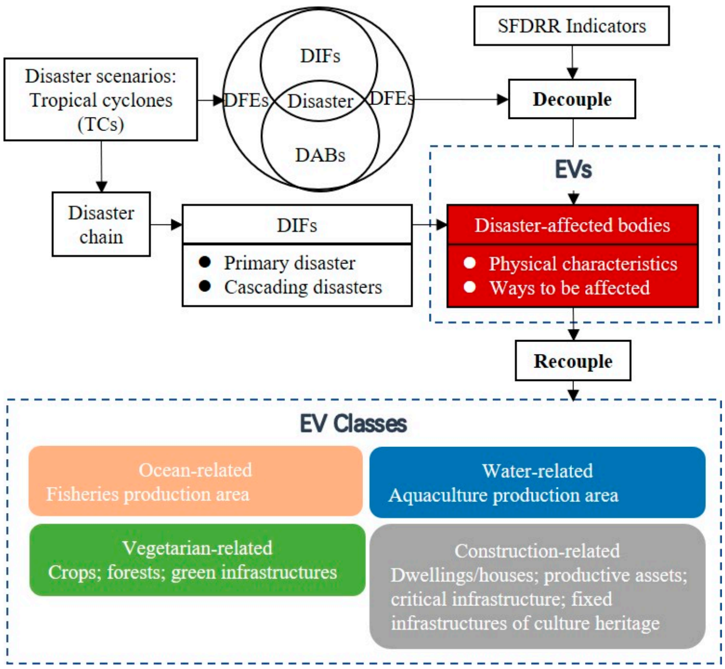

Figure 4. Workflow of decoupling the SFDRR indicators followed by recoupling as EVs under the TC scenario.

According to the RDST, a disaster is considered to be a comprehensive outcome resulting from the interactions among disaster-inducing factors (DIFs), disaster-affected bodies (DABs), and disaster-formative environments (DFEs) [32–34]. DFEs play a crucial role as the settings where DIFs originate and where DABs suffer damage (Figure 4). The complex relationship between DIFs and DABs often forms disaster chains and causes a series of disaster events. Since compound disaster chains commonly refer to the interaction of multiple hazards or events that combine to produce extreme disasters capable of generating widespread losses, it is advisable to consider primary disasters as well as cascading disasters in a specific disaster scenario in order to decouple SFDRR indicators into measuring variables. In the scenario of TC, this kind of low-pressure system often results in strong winds, heavy rainfalls, and cascading disasters such as storm surges and floods. Table 2 shows the disaster chain of TCs.

Table 2. Disaster chains of TCs.

DEFs	DIFs [1]	Influences on DABs
Ocean	T-W-S	Disruption of productive activities
Coast	T-W	Hit by strong winds
	T-W-S	Hit by water flows
	T-W-S-F	Flooded by seawater
	T-R-F	Flooded
Plain	T-W	Hit by strong winds
	T-R-F	Flooded
Mountain land	T-R-F	Flooded
	T-R-F-L	Hit by debris flow

[1] T: TC; W: Strong wind; S: Storm surge; F: Flood; R: Heavy rainfall; L: landslide.

On the indicator layer, the EO-supported SFDRR indicators were classified as either directly (Tier I) or indirectly supported (Tier II). Directly supported indicators can be measured through EO data and methods, while indirectly supported indicators need to be calculated with the help of directly supported indicators and in conjunction with other pre-disaster information. Therefore, we reviewed all directly supported indicators, detailed their characteristics, and decoupled them into EVs to be measured by EO. Different communities have used various criteria to choose their EVs [27–29]. We selected and defined EVs according to the following justifications: (1) describing the disaster system with a minimum set of variables; (2) using variables that can be measured by EO; and (3) defining them to respond to specific reporting needs of SFDRR and useful to EO-supported indicators.

Based on the RDST, we chose the elements of DABs as EVs because they are the core components of disaster loss evaluation and determine which variables need to be monitored. In the SFDRR, DABs are mainly presented in terms of fatalities, missing persons, affected populations, direct economic losses, and infrastructure damage, including damage to measuring objects such as crops, forests, and aquaculture areas. Those DABs are affected by TCs as well as cascading disasters while considering the disaster chain of TCs. Therefore, we explored the DIFs that impact DABs and analyzed what kind of damage would occur to the DABs in specific disaster scenarios. Since each EV is identified as particularly relevant to one EO-supported SFDRR indicator and can be observed by EO data such as satellite images, it provides the opportunity to monitor and report the progress of the SFDRR and increase mitigation efforts to better capture the transboundary effects and impact of the SFDRR. However, the extraction of EVs from remote sensing data may be a challenge for the limited capacity of the ground segment, which may have difficulty supporting the timely creation of a large number of variables. Fortunately, different sets of variables are not completely isolated from one another but are rather interlinked across SFDRR indicators and targets, and some common EO data and methods can be used to identify those variables, acquire their disaster-related attributes, and further evaluate the corresponding SFDRR indicators. We classified our EVs according to their physical characteristics, which are key characteristics that determine the selection of EO data and methods for identification. Finally, we decomposed those directly supported indicators into EVs and reorganized them as 4 classes (Figure 4).

2.3. EO Layer: Mapping the Links between the Requirements of EVs and the Capabilities of EO

The process of determining the set of EVs helped to harmonize and simplify the usage of EO data and methods. However, the EO data requirements for measuring those EVs were still ambiguous. Indeed, a solid framework of indicators needs multiple types of good and reliable data and clear methodological guidelines for their metadata. The global policy landscape relevant to disaster reduction is vast, while the synergies across reporting requirements and relevant actors have not yet been optimized. The progress of disaster reduction and emergency management is hindered by the application of EO data with inappropriate spectral bands and spatiotemporal resolutions to understand the changes in EVs. The question of how to quickly obtain available EO data and apply proper methods to measure different EVs during huge and complex disasters affects the effectiveness of disaster reduction and relief. Previous disaster services mainly evaluated the physical amount of disaster damage and underestimated the dynamic monitoring and analysis of disaster situations. It is crucial to improve the timeliness of disaster emergency monitoring through the collaborative observation and application of various EO data.

In the era of big data, Earth's big data real-time monitoring platforms represented by GEE have emerged. They provide cloud-based geospatial processing computing platforms that enable geospatial data retrieval, processing, and analysis from the local to planetary scales [35]. Compared with traditional disaster loss evaluation workflow, a framework built on GEE has certain advantages: (1) GEE provides petabytes of EO big data that can be available in near-real time, and those data produced by different organizations have been gathered by GEE and can be made freely available, catching up to the deluge of open data; (2) GEE provides open application programming interface (API), which can be embedded in the user's custom framework, and the GEE API allows an end-to-end disaster loss evaluation workflow, where one can acquire EO data, implement measuring methods, and obtain evaluation results based on an integrated platform. Therefore, we analysed commonly used EO data products and their monitoring capabilities from the perspective of data acquisition capability (temporal resolution) and data representation capability (spatial resolution and spectrum) by GEE, as shown in Figure 5.

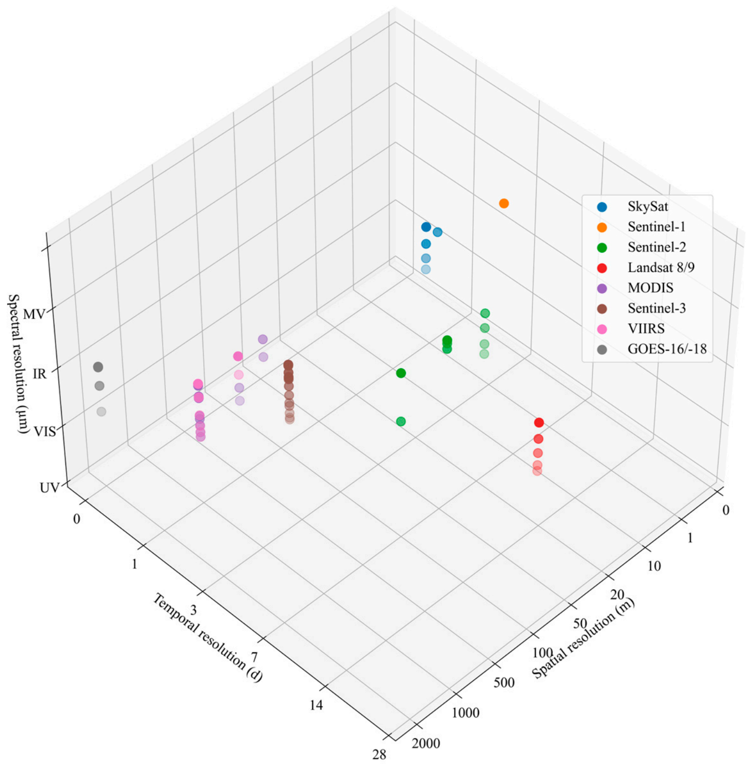

Figure 5. Three-dimensional visualization (elevation = 45°; azimuth = 45°) of EO capabilities in terms of their temporal, spatial, and spectral factors (MODIS: Moderate Resolution Imaging Spectroradiometer; VIIRS: Visible Infrared Imaging Radiometer Suite; GOES: Geostationary Operational Environmental Satellites).

We analysed the capabilities of commonly used EO data on GEE and surveyed the data requirements for measuring and monitoring EVs according to the relevant literature acquired in Section 2.1. This process varied by disaster contexts, because different disaster events and progress and also types of EVs require different quantities of EO data. From the perspective of observation spectrum, visible and microwave data have certain application abilities and the potential for measuring various EVs, among which microwave data with different bands and polarization modes can achieve all-weather disaster monitoring. From the perspective of spatial resolution, TCs with large impact areas require large, wide, medium, and low-resolution EO capabilities, while constructions and other DABs need spatial identification capabilities of meters or even submeters for refined evaluation. From the perspective of observation frequency, the requirements for disaster revisiting observation time vary by disaster context. For example, TCs develop and change quickly, and the observation interval needs to reach hours or even minutes, requiring geostationary weather satellites such as the Geostationary Operational Environmental Satellites (GOES). In contrast, the ground change in delayed disasters such as floods is relatively slow, so the observation can be conducted in units such as days and ten day spans.

3. Results

3.1. SFDRR Indicators Supported by EO

We reviewed the scope for using EO for the full breadth of 75 SFDRR indicators and sub-indicators by combining quantitative and qualitative methods. More than 80 papers and reports that explore the use of EO data and methods were systematically reviewed to deliver results that support the monitoring of SFDRR indicators. We found that the literature directly targeting the design of evaluation methods for specific SFDRR indicators was lacking. However, many strands of the literature have provided EO-based methods for the measurement of EVs involved in the SFDRR indicators. Figure 6a,b show the quantitative distribution of indicators supported by EO across Targets A–G. 38 indicators and 37 sub-indicators were recommended by the SFDRR, among which 14 indicators and 15 indicators could be directly and indirectly supported by EO, respectively, accounting for 38.7% of all SFDRR indicators. A total of 27 indicators cannot be supported by EO, because the variables (such as injured people) involved in those indicators cannot be observed from remote sensing images. Tier IV had 19 indicators that could be measured before the disaster. Therefore, except for those indicators free from the requirements of post-disaster information, 51.8% of the SFDRR indicators could be supported by EO, which demonstrated the huge potential of EO in service of the SFDRR.

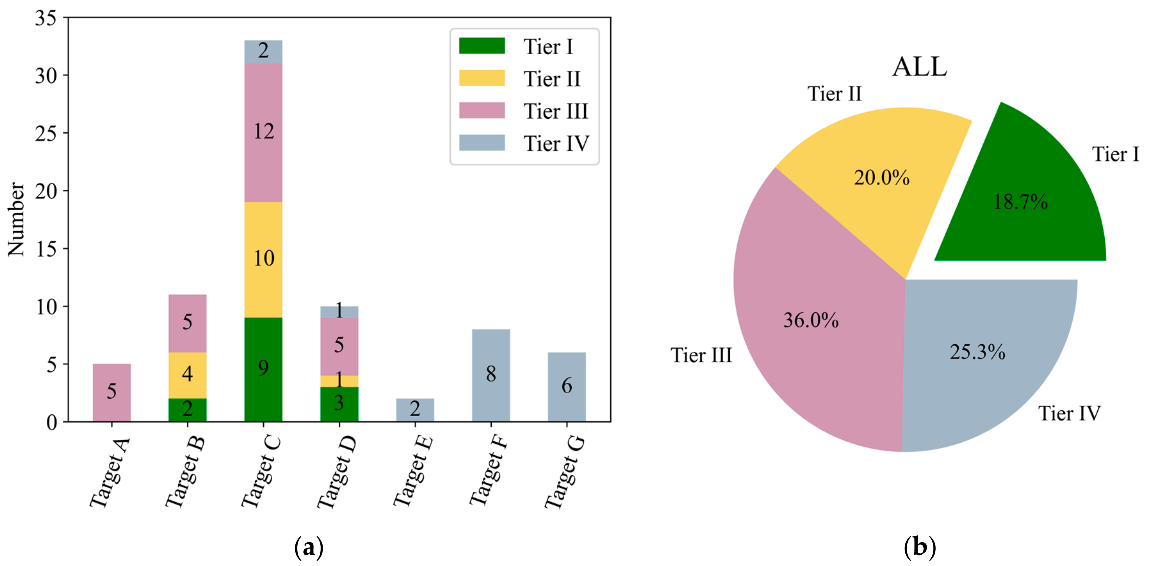

Figure 6. Quantitative distribution of all SFDRR indicators within Tier I-IV across Targets A-G: (**a**) for numbers and (**b**) for proportions (Tier I: Indicators directly supported; Tier II: Indicators indirectly supported; Tier III: Indicators that cannot be supported; Tier IV: Indicators that do not need to be supported).

Figure 7 shows the proportions of SFDRR indicators from Tier I to Tier IV for each target. All indicators supported by EO were gathered in Target B–D. Target B concerns the number of people affected by disasters; 61.6% of the indicators within this target could be directly/indirectly supported by EO, which is able to measure the relevant losses of dwellings, productive assets, and crops. Target C focuses on direct economic loss; 58.8% of indicators within this target could be supported by EO, among which those indicators directly supported by EO are used to measure the physical influences of disasters on productive assets. The indicators of Target D depict the influences caused by disasters on infrastructures, 12.5% of those indicators could be directly/indirectly supported by EO; another 12.5% of those indicators were of Tier IV and can be measured based on pre-disaster data. No EO-supported indicators exist in Targets A, E, F, and G. Target A aims to measure disaster mortality, which requires field surveys to obtain usable results and cannot be estimated merely by EO data and methods. Targets E–G focus on disaster risk reduction strategies, international cooperation, and disaster early warning; the indicators of these targets are administrative and political and are free from evaluation with post-disaster information, which explains why the EO-based indicators disappeared in these targets.

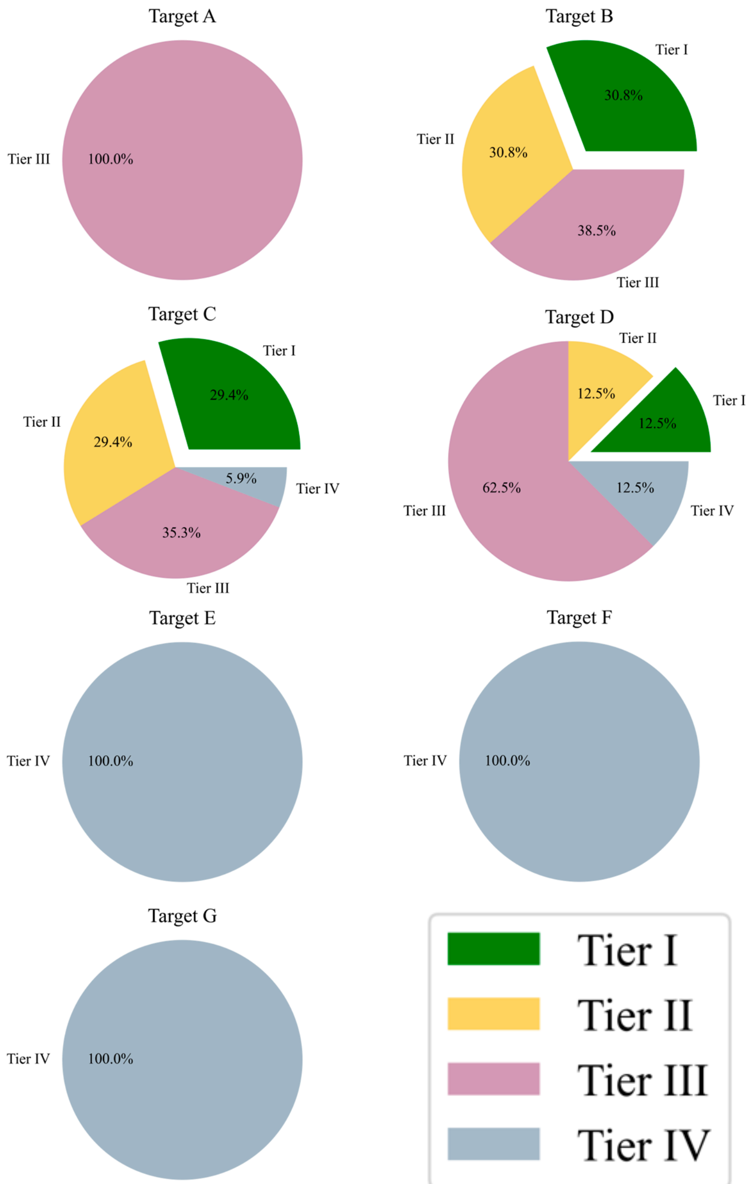

Figure 7. Proportions of SFDRR indicators from Tier I to Tier IV for each SFDRR Target.

3.2. Links between EVs and SFDRR Indicators

Based on the RDST and disaster chains of TCs, we decoupled the SFDRR indicators as EVs in Section 2.2. Figure 8 shows the linkage between EVs and SFDRR indicators, where the user can navigate from SFDRR indicators to networks for EVs to further get the EO data and methods. Those indicators of Tiers II–IV were removed (as there were not relevant here) and only Tier I indicators, i.e., those directly supported by EO were shown. We selected DABs from those 14 Tier I indicators and chose 9 EVs, which were recoupled as 4 classes: ocean-related, vegetation-related, water-related, and construction-related classes. Those DABs in each EV class were impacted by 5 DIFs according to the disaster chains of TCs. All Tier I indicators of Target B were matched with EVs of the construction-related class because they measured the damage situation of dwellings/houses, which can be reduced to construction-related losses. Indicators of Target C measured direct economic losses of multi-types of DABs including crops, houses, and so on. From the physical characteristics of DABs, EVs matching indicators of Target C were divided into all four classes. Most indicators of Target D were construction-related, except green infrastructures. According to *Technical Guidance*, green infrastructures are one of the infrastructure sectors according to the proposed UNDRR classification; this sector includes green areas and rain gardens, which are vegetarian-related.

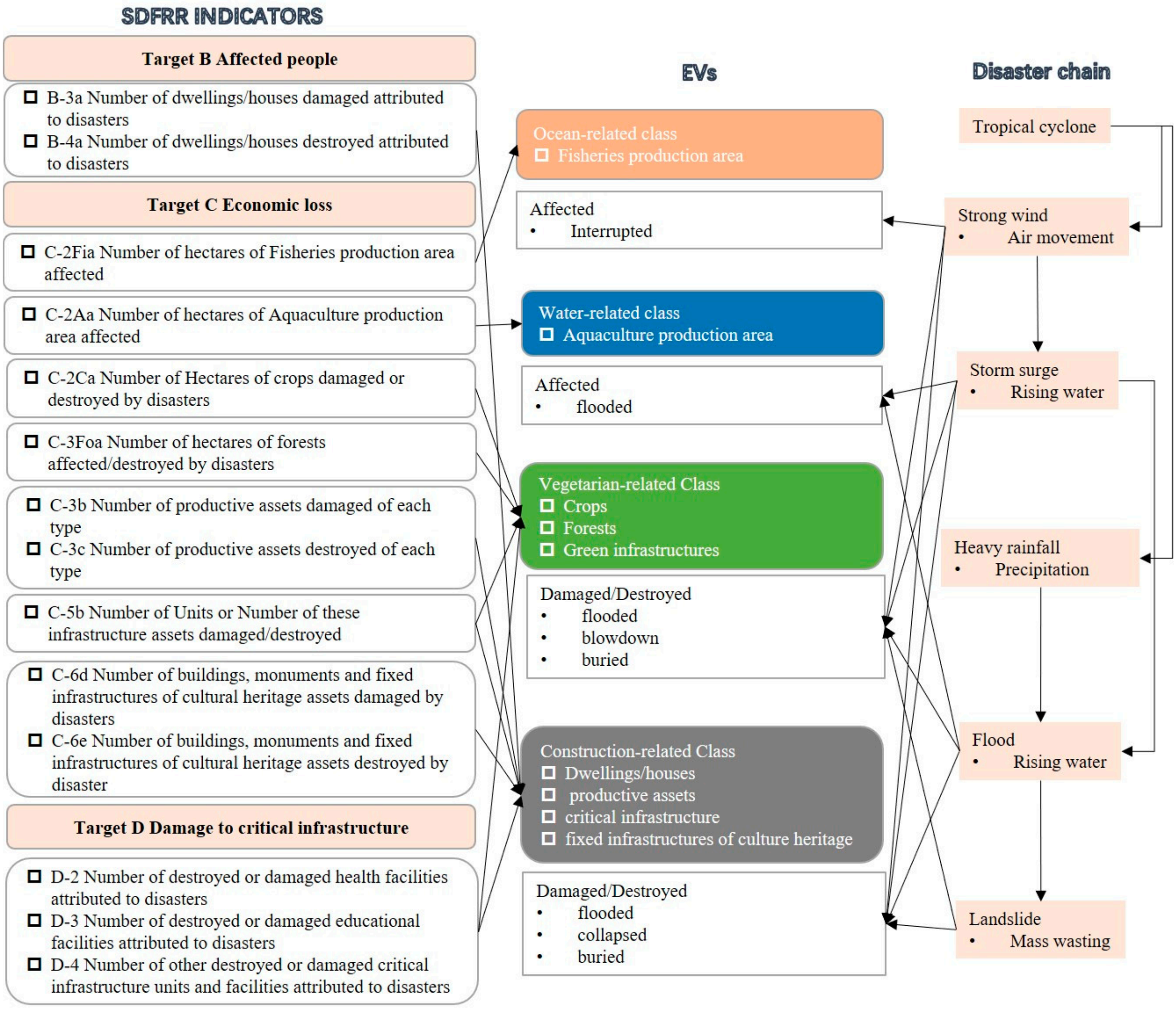

Figure 8. Linkage between EVs and SFDRR indicators directly supported by EO.

3.3. Mapping Relationship between EVs and EO

The EO-based framework aimed to provide a simple yet robust approach to address all targets and indicators outlined in the SFDRR. In order to achieve this, we constructed the EO layer in our proposed framework and mapped the relationship between the measurement requirements of EVs and the capabilities of EO. Figure 9 illustrates the EO data available for different disaster elements, considering the time scale of observation frequency and the spatial scale of spatial resolution. Given the diverse monitoring requirements of EVs, it is essential to leverage multi-source data to enhance the capability of comprehensive disaster observation through the networking of high-low-orbit and medium-high resolution satellites. There are now freely and openly available images visible through shortwave infrared that are available every 2–4 days at a spatial resolution of less than 30 m (combining Landsat 8–9 and Sentinel-2), as well as 10 m dual-polarization C-band SAR every 1–6 days (Sentinel-1) [36]. Geostationary weather satellites such as the GOES can even provide observations with intervals shorter than 15 min. As a constellation of 21 high-resolution Earth imaging satellites, Skysat can acquire sub-meter resolution satellite images with sub-daily revisit time. However, stable and real-time data delivery of high-resolution images from Skysat on GEE has not yet been achieved. Nevertheless, due to worldwide collaborations such as the International Charter Space and Major Disasters, EO data, especially those high-resolution images, can be combined from different space agencies and be acquired in time when a disaster event occurs, which allows for the coordination of resources and expertise to facilitate rapid response to major disaster situations [37].

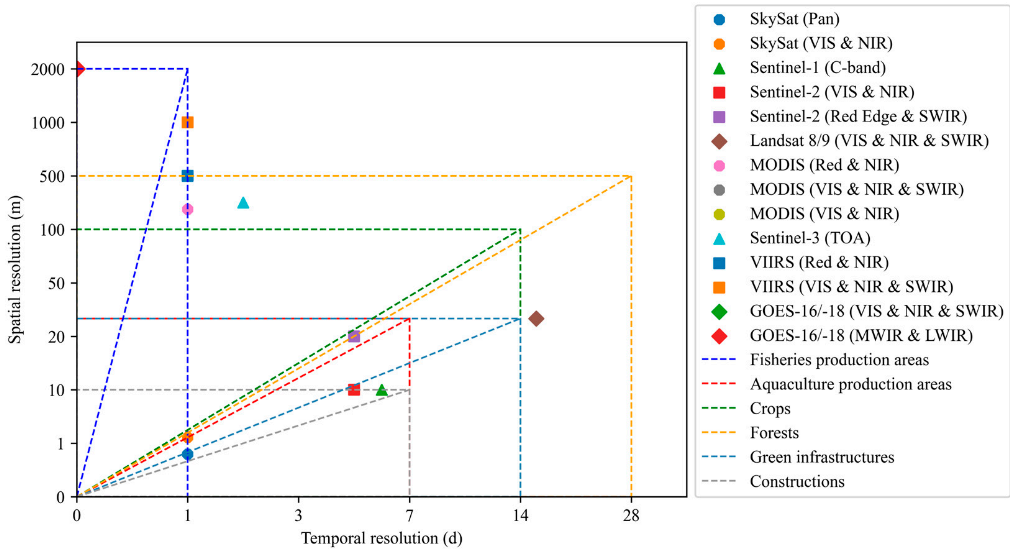

Figure 9. Mapping relation between the requirements of EVs and the capabilities of EO in the scenario of TCs (Pan indicates panchromatic band, VIS indicates spectral coverage in the visible range, NIR is "near infrared", SWIR is "shortwave infrared", MWIR is "mid-wave infrared", LWIR is "long wave infrared", and TOA indicates the top of atmosphere radiances).

3.4. Matching EO to SFDRR

We built an EO-based framework for monitoring and measuring the SFDRR progress in the context of TCs with the combination of the indicator layer, EV layer, and EO layer. The new framework gives full play to the advantages of EO data and methods and provides a comprehensive system that matches EO data and methods to the SFDRR indicators. Figure 10 shows the workflow of our framework. The end-to-end framework took EO data as input, measured EVs using suggested methods, and output the assessment results of the SFDRR indicators. In the scenario of TCs, we suggested EO data and method references for measuring and monitoring all EVs in the proposed framework.

3.4.1. Ocean-Related Class

The monitoring of EVs in the ocean-related class requires EO data with frequent revisits. According to the mapping relationship between the measurement requirements of EVs and capabilities of EO (Figure 9), images from geosynchronous earth orbit satellites such as GOES can provide continuous monitoring of the Earth's surface and get useful information about the storms' location, strength, and movement. This can be helpful in forecasting and disaster management. As shown in Figure 11, we suggested cloud and moisture imagery from GOES to measure the EVs of the ocean-related class. These data can be obtained from GEE and have been widely used to measure the movement and strength of TCs [38]. It is viable to extract fishery production areas based on the daily fishing and vessel hours from Global Fishing Watch (GFW) data, and then identify affected areas by assessing the extent of the storm's impact on fishing production areas [39].

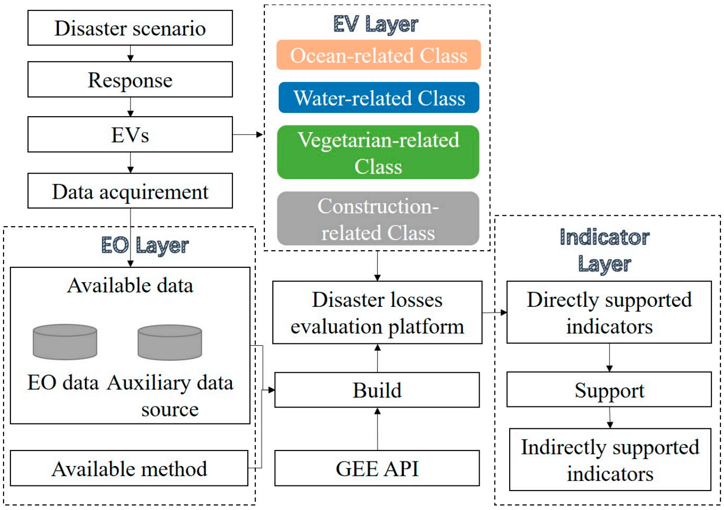

Figure 10. Workflow of the EO-based framework for the SFDRR.

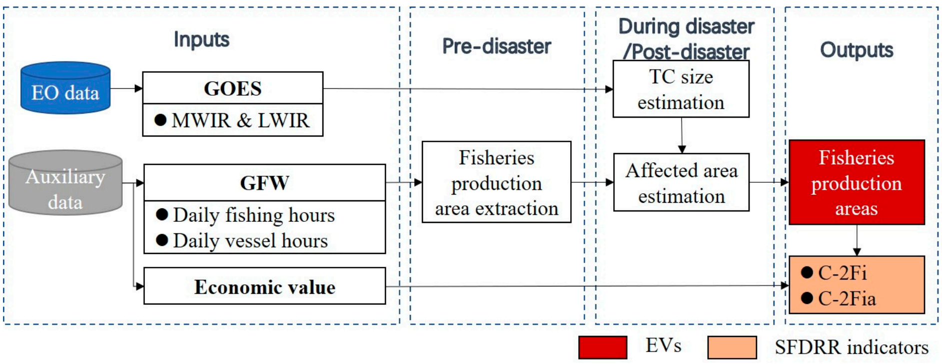

Figure 11. Procedure for measuring EVs of the ocean-related class.

3.4.2. Water-Related Class

As shown in Figure 12, the measurement of EVs in the water-related class involves a two-step process. First, the extraction of pre-disaster spatial information of aquaculture production areas from EO data is required. We recommended utilizing medium-resolution optical images with time series obtained from GEE for pre-disaster information extraction [40]. Second, the identification and measurement of post-disaster information pertaining to water bodies, specifically floods, is necessary [12]. In the case of extreme weather events, such as TCs, it is often challenging to access cloud-free images both before and after the main impact for several days. In this situation, SAR data serve as a unique and reliable source of information, as they work irrespective of weather and sunlight conditions.

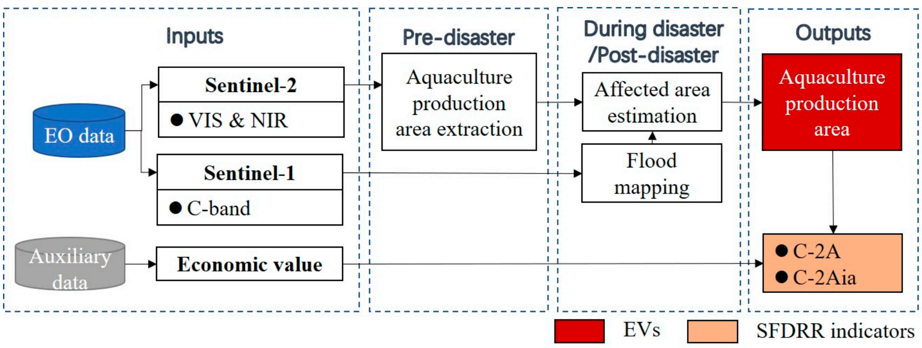

Figure 12. Procedure for measuring EVs of the water-related class.

3.4.3. Vegetarian-Related Class

The procedure for measuring Evs of the vegetarian-related class using EO data and methods is illustrated in Figure 13. The pre-disaster spatial information of Evs in the vegetarian-related class was easy to acquire because several studies have produced land-use land cover (LULC) products and made them available on open-access platforms. The spatial information of crops and forests can be obtained from the European Space Agency (ESA) WorldCover 10 m products on GEE. Additionally, the information regarding green infrastructures such as parks and green areas can be acquired and selected from the area of interest (AOI) and area of point (POI) data provided by OpenStreetMap (https://wiki.osmfoundation.org/wiki/How_To_Get_OpenStreetMap_Data, accessed on 18 March 2023). To assess the damage or destruction to those vegetarian-related Evs, changes in the normalized difference vegetation index (NDVI) can be used. Therefore, we recommended utilizing optical data such as Landsat and Sentinel-2 to measure those Evs, and we provided EO methods from the relevant literature that used NDVI to evaluate disaster losses for further guidance [41,42].

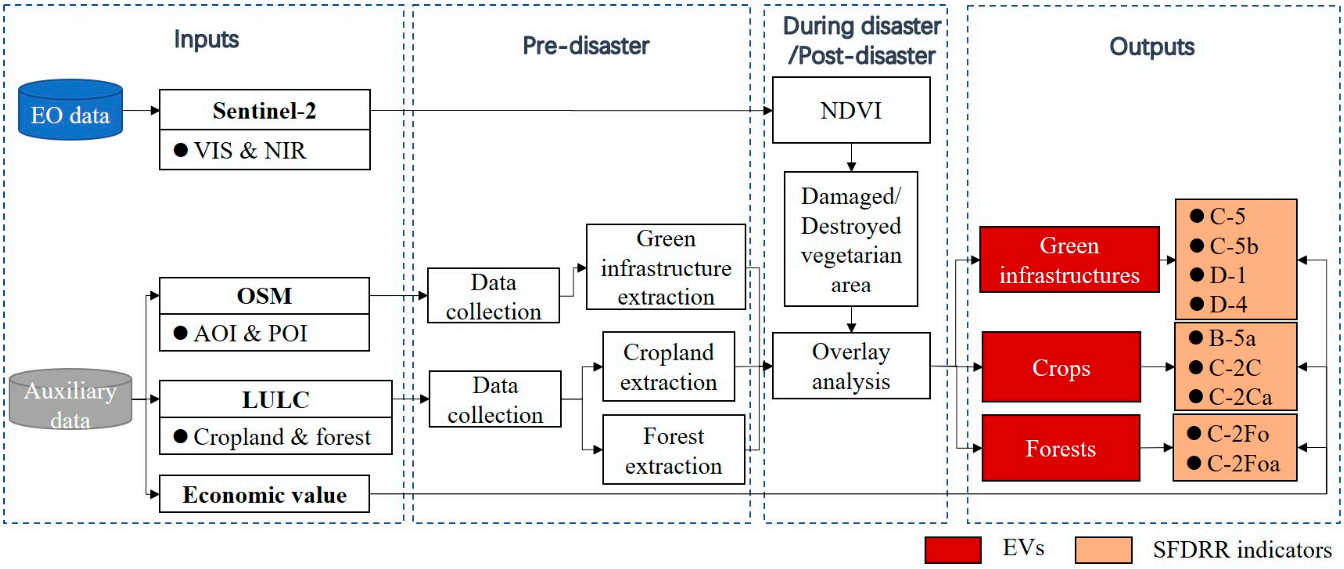

Figure 13. Procedure for measuring EVs of the vegetarian-related class.

3.4.4. Construction-Related Class

Similar to the EVs in the vegetarian-related class, pre-disaster spatial information of those in the construction-related class is also easy to acquire. OpenStreetMap (OSM) provides global construction data, including building classifications. GEE also provides large-scale open datasets consisting of the outlines of buildings derived from high-resolution satellite imagery (https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_Research_open-buildings_v2_polygons, accessed on 18 March 2023). For measuring construction-related EVs, the main tasks involve construction classification and change detection. The type of acquired constructions can be identified according to spatial-related AOI or the point of interest (POI) data, and then can be classified as four kinds of EVs according to the *Technical Guidance*. In SAR imagery, changes in amplitude and coherence occur when there are changes in ground surface properties (e.g., reflectance, roughness, and dielectric properties) before and after disaster events [43]. Therefore, we recommended utilizing 10m Sentinel-1 imagery to measure construction changes and provided corresponding evaluation methods [44,45]. The procedure for measuring EVs of the vegetarian-related class using EO data and methods is shown in Figure 14.

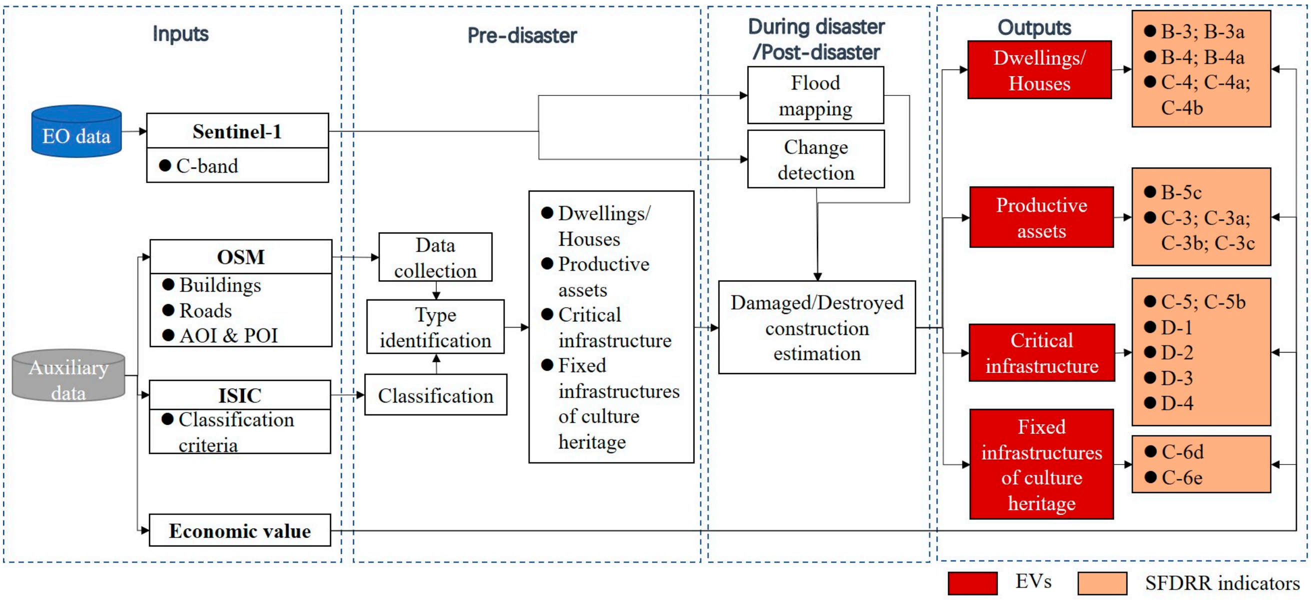

Figure 14. Procedure for measuring EVs of the construction-related class.

4. Discussion

In the proposed EO-based framework, we provided EO data and methods that directly supported the SFDRR indicators. EO data was recommended based on the mapping relationship between the measurement requirements of EVs and capabilities of EO; corresponding EO methods were also recommended on the basis of relevant literature acquired in Section 2.1. Though our framework gave full play to the advantages of EO data and methods and provided a comprehensive system that matched EO data and methods to the SFDRR indicators, it could go further with the improvement of EO data and methods.

4.1. EO Data: Space-Air Platform Collaboration

To effectively address the needs of major disasters, disaster chain monitoring, early warning, dynamic assessment, emergency response, rescue, and relief efforts, it is crucial to implement task-driven joint scheduling of space-air data resources and utilize multi-platform collaborative planning methods. EO data from spaceborne platforms can be used to measure those EVs in a wide range and monitor their changes during the whole evolution stage of the disaster. While our framework primarily relies on satellite remote sensing data provided by GEE, there are limitations in terms of weather conditions and spatial resolution, which can result in unavailable observation and incomplete coverage in disaster areas. To overcome these limitations, it is significant to incomplete spatial sampling acquisition technology methods for both spaceborne and airborne platforms. For example, unmanned aerial vehicle (UAV) platforms equipped with visible-light cameras or light detection and ranging (LiDAR) can provide precise assessment during the post-disaster stage, particularly in heavy disaster areas, thereby ensuring timely information support for emergency command [46], search operations [47], and rescue efforts [48]. However, it should be noted that implementing the flight, processing the aerial images, and obtaining disaster information take time and resources. Pre-disaster information also cannot be obtained from airborne platforms due to the lack of historical data. To meet the decision-making needs associating with emergency response, rescue and relief, and search and rescue efforts for major disasters and disaster chains, we should build a collaborative monitoring planning system of EO resources with high-low orbit multi-satellite collaboration, space-air collaboration, remote sensing-station collaboration, multi-temporal-spatial resolution combination, and multi-sensor complementary advantages. Therefore, it is encouraged to: (1) establish a disaster emergency collaborative observation technology and application system driven by the disaster event process; (2) study the integration techniques for the collaborative monitoring resources that combine EO data from GEE and airborne platforms; and (3) ensure that the disaster collaborative monitoring scheme can be completed in the shortest time following the launch of disaster responses.

4.2. EO Methods: Available for Various Disaster Contexts

EO methods have been widely used in land cover information extraction, disaster situation monitoring, and assessment. Through EO methods, on the one hand, we can identify the distribution of monitoring elements before disasters and obtain pre-disaster baseline data; on the other hand, we can compare pre-disaster and post-disaster ground conditions through change detection or classification comparison of multi-temporal EO data. We have proposed an EO-based framework for the SFDRR, which provided a set of methodologies with recognized or mature calculation approaches to support SFDRR indicators. However, the methods provided by this framework are specifically available for the scenario of TCs. Since it is required to report on SFDRR indicators over two ten-year periods at the national/global level, a comprehensive framework that applies EO data and methods to a broader range of disaster contexts needs to be further developed. For this purpose, universal methods for measuring the SFDRR indicators as well as considering their applicability in different disaster scenarios should be developed. For example, the affected areas of TCs change over time as the storms move, necessitating methods applied at a large scale. In contrast, the impact of earthquakes tends to focus on epicenters, requiring more precise evaluation methods. To enhance the role of EO methods in serving the SFDRR, improvements can be made in the following areas. First, EO methods could be improved with the combination of artificial intelligence and spatiotemporal big data. In the era of big data, data science and artificial intelligence have played crucial roles in knowledge discovery, as the volume of data continues to explode in practically every research domain. By leveraging artificial intelligence models to learn from disaster big data and embedding these models into our framework, we can improve the time efficiency of handling the disaster situation and enhance the evaluation accuracies of SFDRR indicators. Secondly, we could also consider developing multi-scenario simulation methods oriented to the SFDRR. By considering various development modes that may emerge in the future, we can lay the foundation for conducting a comprehensive multi-scenario simulation analysis. These simulations can provide valuable insights to propose optimized regulation countermeasures. To accomplish this, synergistic integration of EO data and Geographic Information Systems (GIS) is essential. By leveraging the combined power of EO data and GIS technology, we can establish a comprehensive disaster loss and risk assessment model. This model would simulate typical disaster risk scenarios that may occur in future disaster-prone areas. Furthermore, it would establish the corresponding relationship between the intensity of typical hazards and the resulting disaster risk scenarios.

5. Conclusions

This study proposed an EO-based framework to support the measurement and monitoring of the SFDRR. The framework consists of indicator layer, EV layer, and EO layer. We systematically reviewed the relevant literature and assessed the potential of EO data to directly or indirectly support each SFDRR indicator. We decoupled the indicators directly supported by EO and recoupled them as EVs based on the RDST and disaster chains. The mapping relation between the measurement requirements of EVs and the capabilities of EO was proposed. The proposed EO-based framework can be used for further development and provide opportunities to enhance the role of EO in offering rich support for the SFDRR via robust, timely, readily updated, independent, transparent, and relevant data at disaster losses. The following conclusions can be drawn from this research:

- Except for the indicators free from the requirements of post-disaster information, 51.8% of the SFDRR indicators could be supported by EO, which demonstrated the huge potential of EO in service to the SFDRR.

- In the TC scenarios, we proposed 11 EVs within four classes. This provided a clear system by which variables could be measured by EO for the SFDRR indicators, which demonstrated the potential to develop EVs outside the established set of SFDRR indicators that may be more amenable to the use of EO-derived data.
- An EO-based framework for the SFDRR was proposed, with an end-to-end workflow where one can acquire EO data, implement measuring methods, and obtain evaluation results based on an integrated platform on GEE.
- Future work with space-air collaborative EO data and universal EO methods oriented to the EO-based framework and the SFDRR is expected. For example, more EO data from airborne platforms would be available for the framework, and artificial intelligence models with disaster big data and knowledge would be integrated into the framework.

Author Contributions: Conceptualization, Jing Li and Adu Gong; methodology, Boyi Li; software, Boyi Li and Xiang Pan; validation, Longfei Liu, Adu Gong and Jing Li; formal analysis, Boyi Li and Jinglin Li; investigation, Boyi Li and Zikun Chen; resources, Longfei Liu; data curation, Boyi Li and Zikun Chen; writing—original draft preparation, Boyi Li; writing—review and editing, Boyi Li and Adu Gong; visualization, Boyi Li and Lingling Li; supervision, Jing Li and Adu Gong; project administration, Jing Li, Adu Gong and Longfei Liu; funding acquisition, Jing Li. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Key Research and Development Program of China (Grant No. 2019YFE01277002), the Open Fund of State Key Laboratory of Remote Sensing Science and Beijing Engineering Research Center for Global Land Remote Sensing Products (Grant No. OF202216), and the National Natural Science Foundation of China (Grant No. 41671412).

Data Availability Statement: Our research data are from relevant open data websites, which can be obtained according to the links listed in our references.

Acknowledgments: The authors would like to thank the high-performance computing support from the Center for Geodata and Analysis, Faculty of Geographical Science, Beijing Normal University. We would like to express deep gratitude to Zhiqing Huang and Wenxuan Bao from Beijing Normal University for their help in manuscript editing. We are also very grateful to the anonymous reviewers for their valuable comments and suggestions for the improvement of this paper.

Conflicts of Interest: The authors declare no conflict of interest.

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