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OVERVIEW

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A review of freely accessible global datasets for the study of floods, droughts and their interactions with human societies

Sara Lindersson[1] | **Luigia Brandimarte**[2] | **Johanna Mård**[1] | **Giuliano Di Baldassarre**[1]

[1]Department of Earth Sciences, Uppsala University, Uppsala, Sweden

[2]School of Architecture and the Built Environment, KTH Royal Institute of Technology, Stockholm, Sweden

Correspondence
Sara Lindersson, Department of Earth Sciences, Uppsala University, Uppsala, Sweden.
Email: sara.lindersson@geo.uu.se

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Abstract

The availability of planetary-scale geospatial datasets that can support the study of water-related disasters in the Anthropocene is rapidly growing. We review 124 global and free datasets allowing spatial (and temporal) analyses of floods, droughts and their interactions with human societies. Our collection of datasets is available in a descriptive list for download at https://zenodo.org/record/3368882. The purpose of providing an overview of datasets across a wide range of hydrological and socioeconomic variables is to highlight research opportunities across scientific disciplines for the study of the water-society interplay. Our collection of datasets confirms that the availability of geospatial data capturing hydrological hazards and exposure is far more mature than those capturing vulnerability aspects. We do not only highlight the unprecedented opportunities associated with these global datasets for the study of water-related disasters in the Anthropocene, but also discuss the challenges associated with their exploitation. These challenges include: (a) time varying datasets advised not to be used in time series analyses; (b) fine spatial resolution datasets advised not to be used in local scale studies; (c), datasets built by a wide variety of data sources prohibiting systematic uncertainty assessments; and (d) datasets built by covariate variables preventing interaction studies.

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Engineering Water > Planning Water
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KEYWORDS

disaster risk, droughts, Earth observation, floods, open geodata

1 | INTRODUCTION

Why does water-related disaster risk remain high in many parts of the world? A short answer is that human exposure is increasing at a faster rate than the decrease of vulnerability (United Nations Office for Disaster Risk Reduction [UNISDR], 2015). But behind this statement lie deep and complex dynamics, connecting natural and societal factors in a tight web. The need to disentangle these explanatory interconnections is as nontrivial as it is important: floods and droughts are the environmental hazards that have affected the largest number of people during the last two decades, over 2 and 1.5 billion people respectively (Centre for Research on the Epidemiology of Disasters [CRED] & UNISDR, 2018). The United Nations (UN) highlights the urgency of reducing the humanitarian and economic losses from water disasters within the sustainable development goals, with an emphasis on protecting the poor and most vulnerable groups of humanity (UN, 2015).

Even though regularly described as "natural" hazards, floods and droughts are fundamentally anthropogenic disasters with strong societal interconnections in form of drivers, impacts and feedback mechanisms (Best, 2019; Van Loon et al., 2016; Wens, Johnson, Zagaria, & Veldkamp, 2019). The main driver of past decades' flood damages, for instance, is population growth and socioeconomic development in flood-prone areas (Di Baldassarre et al., 2010; UNISDR, 2015). Human water consumption has been the primary cause of droughts in rivers, lakes and groundwater (Wada, van Beek, Wanders, & Bierkens, 2013). Projections show further transformation and intensification of both flood and drought risk from socioeconomic development, amplified by the impending climate crisis (UNISDR, 2015). By mid-century, we expect over 230 million people to be living in cities where water demand exceeds water availability (Florke, Schneider, & McDonald, 2018). By the end of the century, global flood losses are expected to increase by a factor of 20 (Winsemius et al., 2015), although such an estimation neglects the benefits of adaption measures that are being implemented in most regions around the world (Di Baldassarre et al., 2015; Jongman et al., 2015; Kreibich et al., 2017).

Knowing these drivers, should it not be straightforward to mitigate the disaster risk? Not necessarily. One problem is that many contemporary water management strategies, aiming to reduce water disaster risk, can eventually increase risk in the long term or contribute to inequality (Di Baldassarre, Kemerink, Kooy, & Brandimarte, 2014; Di Baldassarre, Wanders, et al. (2018); Pande & Sivapalan, 2017; Zwarteveen et al., 2017). Large-scale scientific inquiries, studying one phenomenon across many locations through time, have the benefits of detecting patterns beyond anecdotal observations, reaching generalizable results, and building hypotheses about water risk propagation (Falkenmark & Chapman, 1989; Kovács, 1984; Pande & Sivapalan, 2017). This type of large-scale studies also raises data needs that are completely different from those of a single case study. Coincidentally, the pressing global water challenges and the corresponding need for large-scale datasets are accompanied by an ongoing big data revolution (Vogel et al., 2015).

Our capability to monitor and access large amounts of data poses unprecedented opportunities to reveal spatiotemporal patterns of human interaction with hydrological processes (Mård, Di Baldassarre, & Mazzoleni, 2018; UNDRR, 2019; Vogel et al., 2015). These available large-scale datasets span from being remotely sensed and gridded to being measured on the ground and given in point format. In between, a wide number of datasets are being released, building on and combining with other datasets. Progress within planetary-scale datasets related to hydrology and societal development is well covered within the literature, including reviews of: precipitation datasets (Kidd & Huffman, 2011; Sun et al., 2018), soil moisture datasets (W. Dorigo et al., 2017; Ford & Quiring, 2019), surface water datasets (Huang, Chen, Zhang, & Wu, 2018), flood risk models (Ward et al., 2015), land cover datasets (Pérez-Hoyos, Rembold, Kerdiles, & Gallego, 2017), population datasets (Leyk et al., 2019; Palacios-Lopez et al., 2019; Smith et al., 2019), nighttime light datasets (Bennett & Smith, 2017), large-sample hydrological datasets (Gupta et al., 2014), and global hydrological models taking human activities into account (Wada et al., 2017). All these reviews, however, focus on single topics. In-depth reviews are unarguably both valuable and needed, but we also think that widening the scope across variables and disciplines can benefit the research community—not least due to the multidimensional and interdisciplinary nature of disaster risk (UNDRR, 2019).

Here we review the current availability of free and planetary-scale geospatial datasets to facilitate further research of floods, droughts and their interactions with human societies. We present a collection of 124 freely available geospatial datasets, with the aim to illustrate research data opportunities and current data gaps. We expect that this compiled list, entailing a wide range of variables, can facilitate interdisciplinary work and thus reveal dynamics between societies and water disasters. We also discuss challenges of the data usability for conducting comparative studies. Specific discussion points include data resolution challenges, inequalities of geographic representation, data consistency and accessibility, and dependencies between the datasets prohibiting interaction studies.

2 | THE ROLE OF EARTH OBSERVATION DATA WITHIN WATER DISASTER RESEARCH

The use of data from space is not new to the community of hydrology, which has been using remotely sensed data for decades (McCabe et al., 2017). At least three factors make remotely sensed data particularly valuable for hydrological applications. First, remote sensing enables monitoring across a wide range of spatiotemporal scales (Huang et al., 2018). Second, in situ measurement stations, providing data on essential variables like precipitation and discharge, are declining and are unevenly distributed worldwide (Kidd et al., 2017; Musa, Popescu, & Mynett, 2015). Third, a growing number of remotely sensed datasets are free and widely accessible, valuable for not only global analysis but also for data poor countries (Ehrlich et al., 2018; Famiglietti et al., 2015; Schumann, Bates, Horritt, Matgen, & Pappenberger, 2009).

Recent development in global Earth observation (EO) data relatable to disaster risk poses opportunities to reveal interactions of natural systems and human activity (UNDRR, 2019). EO gathers information on the physical, chemical or biological environments of the planet, through data monitoring, analysis and presentation (European Union, 2016). This rapid development has been triggered by new monitoring technologies, new processing capabilities, and a growing willingness to share data (UNDRR, 2019). In particular, open-access satellite data have increased the number of scientific data applications (UNDRR, 2019; Zhu et al., 2019), mirrored in the increasing number of scientific publications on hydrological extremes from a global point of view (Figure 1). The finest spatial resolutions among the open-access satellite programs are currently offered by the Sentinels of ESA (down to 10 m offered by Sentinel-2) (UNDRR, 2019). Its first satellite mission, Sentinel-1, was launched in 2014, the temporal depth is thus still limited. The moderate spatial resolution imagery of Landsat offers the longest temporal records from remote sensing (1970s and onward), made open-access by United States Geological Survey (USGS) in 2008 (Zhu et al., 2019).

The EO world outside of the large-scale space agency satellite systems is also rapidly progressing (Palmer & Ruhi, 2018). New and alternative remote sensing methods to conventional satellites include: ultra-high-resolution compact satellites (e.g., CubeSats), drones, high-resolution videos from aircrafts, and "citizen science" including environmental monitoring through smartphone applications (McCabe et al., 2017) and volunteered geographic information (Waldner et al., 2019). Water disaster researchers, for instance, have integrated social media data in flood inundation models (Le Coz et al., 2016; Rosser, Leibovici, & Jackson, 2017). So far, these alternative remote sensing methods typically give products for local applications with limited spatial extent. The products from privately funded satellites are most often not open-access but the technologic developments spread and affect other parts of the EO domain (McCabe et al., 2017). "Citizen science" data are usually open-access but have limitations typical for nontraditional data sources: calibration issues, quality control issues, and population centric data distributions (Kidd et al., 2017).

Long and stable space agency satellite programs are currently gaining new momentum from being reanalyzed to new products, made possible by advancements in computational processing power and analytical techniques such as machine learning. One example is the Global Surface Water Explorer using Landsat data and cloud computation to map spatiotemporal surface water changes over the past three decades (Pekel, Cottam, Gorelick, & Belward, 2016). Cloud computation platforms are virtual servers that provide access to data, processing power and analytical scripts,

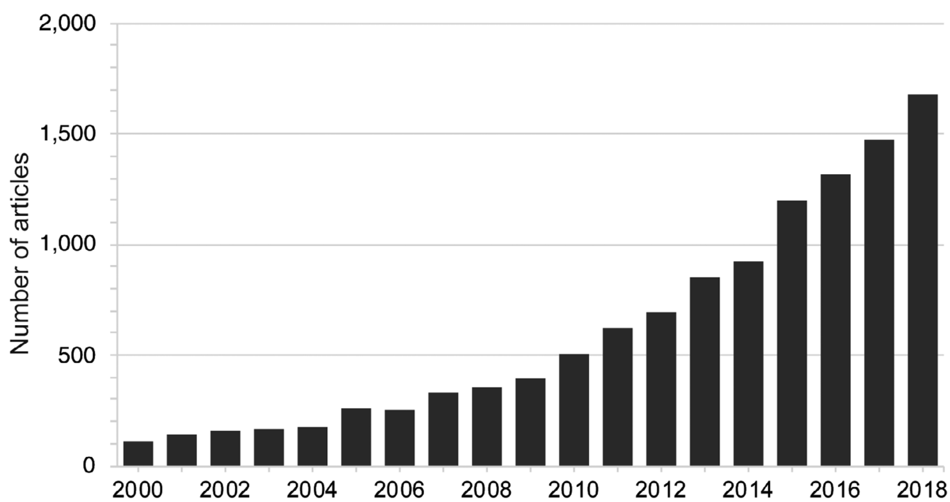

FIGURE 1 Number of articles (2000–2018) in Web of Science Core Collection database (Clarivate Analytics, 2019) containing the terms "flood" or "drought" or "hydrological extreme" when refined by "global." The five most common article categories are Environmental sciences, Meteorology atmospheric sciences, Geosciences multidisciplinary, Water resources, and Ecology

including Google Earth Engine (Gorelick et al., 2017), NASA Earth Exchange (Nemani, Votava, Michaelis, Melton, & Milesi, 2011), and Open Data Cube (Killough, 2018).

This rapid EO progress consequently poses data opportunities for water disaster research. A wide range of geospatial datasets are continuously being released, capturing both natural and anthropogenic environments. The fast exchange of data also boosts interdisciplinary cooperation and has made it more common for researchers to search for data within other scientific disciplines (UNDRR, 2019). Planetary-scale datasets are today particularly skilled at mapping disaster exposure and disaster hazards (Ehrlich et al., 2018). Large-scale geospatial representations of vulnerability aspects are, however, generally still immature and need further systematic data collection efforts (UNDRR, 2019).

3 | REVIEW METHODOLOGY

Here we review the availability of planetary-scale geospatial datasets that have the potential of supporting the study of floods, droughts and their interactions with human societies. This review primarily targets readers from the research domain of water-related disasters, yet we also expect that a wider group might find this review useful. We present a descriptive table of freely accessible planetary-scale geospatial datasets related to floods, droughts and societies. The purpose of presenting one list of datasets across a wide range of variables is to highlight research opportunities across scientific disciplines.

3.1 | Choosing data categories

We compiled a list of relevant variables based on published conceptualizations of human–water disaster systems (Di Baldassarre, Nohrstedt, et al., 2018; Di Baldassarre, Martinez, Kalantari, & Viglione, 2017; Van Loon et al., 2016). Variables from every part of the human–water disaster system have been included: environmental change, socioeconomic trends, frequency, magnitude and extent of natural hazards, vulnerabilities, disaster impacts, and human water alterations.

We structured the variables into categories and sub-categories for clarity. The sub-category *Flood and drought events*, for instance, includes the two variables flood inundation maps and drought events. Our review primarily focuses on inland floods; consequently, we do not include datasets covering oceanographic conditions such as sea levels, tsunamis or storm surge disasters. We do not include datasets explicitly covering variables from the cryosphere either.

3.2 | Searching for and selecting datasets

Publications from both data providers and data users have supported the search of data. We have used a wide range of data sources, including peer reviewed literature, large geodata providers (e.g., NASA and ESA), institute reports, official webpages, and other websites such as geodata blogs. For each variable, we searched for the variable name (e.g., flood inundation map) refined with the words "global" and "data" in the Web of Science Core Collection (Clarivate Analytics, 2019). The Global Climate Observing System program lists Essential Climate Variables (World Meteorological Organization, 2016), for which we have included a majority of the variables within the Land category, including variables from the hydrosphere, biosphere, and anthroposphere.

We have only included datasets with license policies allowing free scientific use. The license agreements, however, vary among the individual datasets. For example, some datasets are available free of charge to the research community only, while other datasets are classified as open data or even public domain. Required or recommended attribution also varies among the individual datasets. We therefore strongly recommend data users to carefully consult the usage licenses as given by the data providers, to assure that the exact permissions and restrictions are followed.

The data principles of FAIR have guided our selection of datasets, encouraging findability, accessibility, interoperability and reusability (Wilkinson et al., 2016). More specifically, we have only included datasets accessible online and have given priority to datasets accessible all at once (through download or cloud infrastructure). We have given priority to datasets with unique identifiers and clear documentations that will remain available even when the dataset itself is no longer available. Datasets in geographical data formats have been prioritized over tabular data formats. We have given priority to datasets meeting community standards in data formats and only included ready-to-use datasets, excluding data from publications shared through source codes only.

We have also considered spatiotemporal characteristics when selecting the datasets (Table 1). Only datasets with global or near-global spatial extents have been included. We have given priority to dynamic datasets, capturing temporal change, over static datasets. We have primarily chosen to include historic datasets, not focusing on future projections. The prioritized resolution intervals vary among the broad range of variables, depending on data availability and variable characteristics (Table 1). Gridded datasets with coarser spatial resolutions than 50 km have not been included. We have chosen to include both alternatives when two competing datasets show a trade-off between spatiotemporal coverage and resolution. We have chosen to include datasets that increase accuracy and coverage through building on multiple parent datasets, rather than to include each individual parent dataset.

4 | DATASET COLLECTION

Our review results in a data collection of 124 global and freely accessible geospatial datasets, all related to hydrological extremes and societies (Figure 2). We provide an overview of these 124 datasets in a descriptive data table, available at https://zenodo.org/record/3368882. This data table contains, for each dataset, information on: dataset title, related product(s) offered by the dataset, brief description, spatiotemporal coverage and resolution, recommended map scale, data type, and available file format(s). We also report whether the dataset primarily builds upon data from ground measurements, remote sensing, or a mix. Reference is also given to creating institute(s), documentation and web address for data access.

4.1 | Data categories

We have structured the dataset collection into 7 main categories and 36 subcategories (Figure 2). The category *Hydrographic baseline* includes static datasets that outline the shape of surface waters, including: rivers, lakes, wetlands, basins, and floodplains. Static hydrogeological baseline data such as soil properties and groundwater characteristics are also included in the *Hydrographic baseline* category. The category *Hydrological dynamics* includes datasets on hydrologic variables showing temporal variability, including surface water extents, river discharge, water levels, and water quality. Water level measurements include both surface and groundwater measurements, with data sources from satellites, ground measurements, and modeling. Datasets of hydrometeorological parameters such as precipitation, temperature, soil moisture and drought indices are also included in this category. The category *Hydrological extremes* holds datasets that map past disaster extents, provide statistics on disaster losses, map modeled hazards, and collect flood-related tweets. This review only includes ready-to-use datasets and hence does not list general satellite imagery programs, even though these are important data sources for flood inundation maps. Data from the category *Hydrological dynamics* can also be useful for capturing past natural conditions of extreme hydrological events.

The category *Land cover and agriculture* holds datasets with information on land cover, land use, vegetation, irrigation, livestock, and crops. Datasets mapping wildfires are also included in this category, since the focus is land surface

TABLE 1 Criteria of inclusion and priority, guiding the selection of datasets to be included in the review

Strict inclusion criteria	
Accessibility	Online
License policy	Free research usage
Spatial extent	Global or near-global
Spatial resolution	Finer resolution than 50 km for gridded datasets
Prioritized resolution intervals	
Spatial resolution	30 m to 10 km
Temporal resolution	Days to months

Note: Strict inclusion criteria indicate minimum requirements for datasets being included. Prioritized resolution intervals indicate how we have selected between competing datasets. Prioritized resolution intervals vary with variable, due to differences in data availability or variable characteristics.

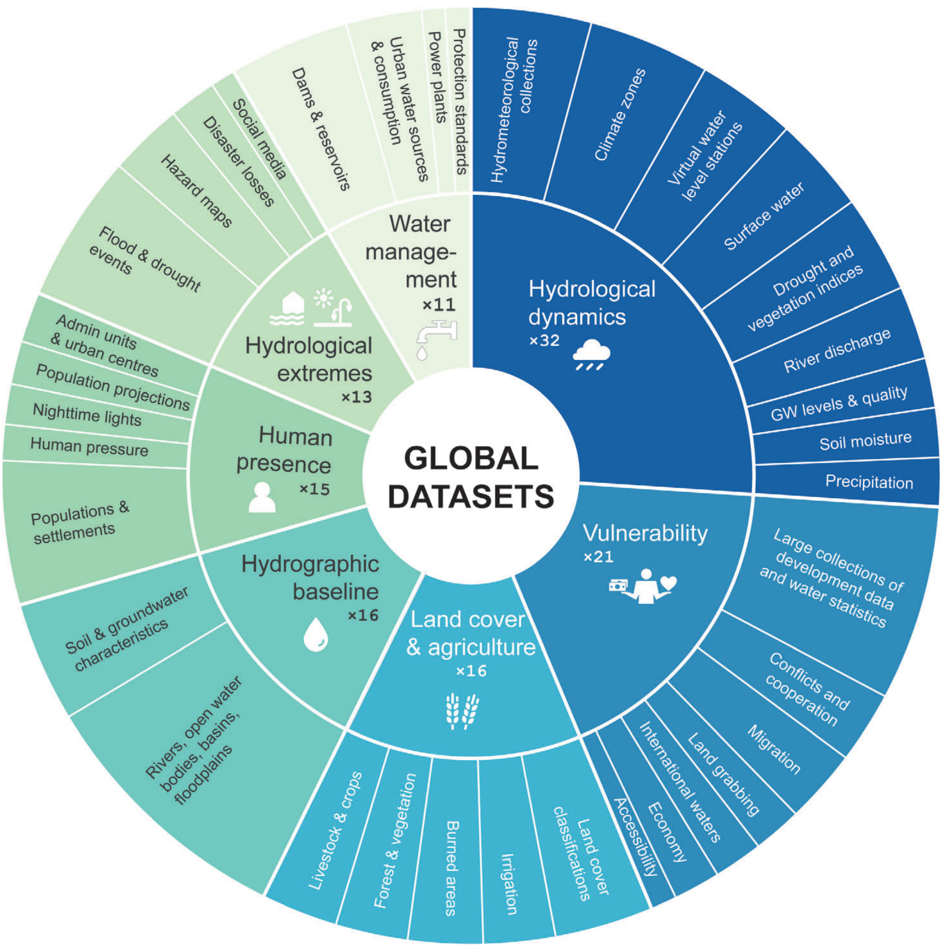

FIGURE 2 Categories and subcategories of the 124 freely accessible global datasets included in this review. Included variables all relate to hydrological extremes and societies, based on published conceptualizations of human–water disaster systems. Number of datasets in each category is given underneath the title. The width of the categories and sub-categories indicate the number of datasets. All datasets are described in the data table available at https://zenodo.org/record/3368882

change. The *Vulnerability* category captures variables that might influence the human vulnerability to water disasters, including: economic measures, accessibility, transboundary inland-waters, land grabbing, migration, conflicts, and cooperation. Here we have also included large collections of human development data and water statistics, even though these data collections generally offer poor geographic representation. The category *Human presence* holds datasets that capture the distribution of populations, settlements, urban centers, anthropogenic biomes, and administrative units. Finally, the category *Water management* includes data on flood protection standards, dams and reservoirs, power plants, urban water sources and water consumption.

5 | DATASET APPLICATIONS

To illustrate opportunities and challenges of our collection, we describe a selection of recent studies exploiting one or more of the collected datasets. This selection is unavoidably unexhaustive, but we expect that it can, along with our collection, inspire and spur new research ideas for unraveling different facets of the complex interplay between droughts, floods and human societies.

5.1 | Human influence on hydrology

Many of the datasets in our collection are vital for setup, calibration and validation of large-scale hydrological models considering human activities. Sutanudjaja et al. (2018), for instance, used global datasets of both environmental and human variables to setup a global hydrological-water resources model. Mao et al. (2019) utilized datasets of observed streamflow and satellite-derived inundation extents to simulate 50 years of flood extents in major river basins across the globe. de Graaf, Gleeson, van Beek, Sutanudjaja, and Bierkens (2019) used data on climate and human water demand to setup and run a global surface water-groundwater model, exploring the influence of groundwater pumping on environmental water flows. Lack of data on human behavior has been compensated in model parametrization by employing environmental data. Reservoir operational behavior, for instance, can be mimicked using reservoir volume data derived from satellite altimetry (Busker et al., 2019). Combining a range of variables is also useful for building indices related to sustainability and human development, such as the human pressure on rivers index (Ceola, Laio, & Montanari, 2019).

A great amount of research investigates changing hydrological processes in a warming world. Cuthbert et al. (2019), for instance, analyzed groundwater system response to climate change. Lehmann, Coumou, and Frieler (2015) identified a global increase of record-breaking rainfall events. Ficklin, Abatzoglou, Robeson, Null, and Knouft (2018) found streamflow signals of climate change at both natural and human-modified sites and Sharma et al. (2019) quantified trends of lake ice loss. Climate change attribution is also central for drought evolution (Wang, Liu, & Guo, 2019) and drought risk changes (Gudmundsson & Seneviratne, 2016). E. Vogel et al. (2019) analyzed the effects of climate extremes on global crop yield, using subnational yield data and machine learning.

5.2 | Droughts and floods

Large-scale datasets have been utilized to construct catalogs or maps of past disaster events on a global scale (Spinoni et al., 2019; Spinoni, Naumann, Carrao, Barbosa, & Vogt, 2014), continental scale (Barredo, 2007; Masih, Maskey, Mussá, & Trambauer, 2014), and local scale (Gründemann, Werner, & Veldkamp, 2018). Masih et al. (2014) incorporated a disaster loss database, literature review and a gridded drought indicator dataset to compile a descriptive and geospatial catalog of past drought events in Africa. Climate zones have been related to precipitation and temperature trends (Mohammad & Goswami, 2019), drought indices sensitivity (Vicente-Serrano, Van der Schrier, Beguería, Azorin-Molina, & Lopez-Moreno, 2015), and river topography (S.-A. Chen, Michaelides, Grieve, & Singer, 2019).

Large-sample observational datasets are vital for validating new datasets from models or remote sensing. Frasson, Schumann, Kettner, Brakenridge, and Krajewski (2019), for example, used a global flood observatory dataset to evaluate the capability of a new satellite mission to detect floods. Observational datasets are also valuable in combination with model and remote sensing data to generate new knowledge. Döll, Müller Schmied, Schuh, Portmann, and Eicker (2014) combined hydrological modeling with well observations and satellite measured gravity anomalies to quantify groundwater depletion on a global scale. Wu et al. (2019) used a number of global datasets to identify factors that influence the consistency between satellite observations and a global flood model, including climate zones and land cover categories.

5.3 | Data-poor areas

Research on local scale may also benefit from global geospatial datasets, especially when located in data-poor regions. For instance, planetary-scale datasets have been used to analyze long-term meteorological changes in Pakistan (Ahmed, Shahid, Wang, Nawaz, & Khan, 2019), India (Mohammad & Goswami, 2019), Inner Mongolia (Wang et al., 2019), and Nigeria (Shiru, Shahid, Chung, & Alias, 2019). Similarly, global and long-term precipitation datasets have been utilized to derive time series of drought indices for locations such as Arkansas (Craig, Feng, & Gilbertz, 2019), Sweden (Campana et al., 2018), and Central Asia (Guo et al., 2018). Anh and Aires (2019) derived river discharge data in the Amazon using planetary-scale datasets. Global datasets have also been used for drought prediction in East Africa (AghaKouchak, 2015) and operational drought monitoring in Kenya (Klisch & Atzberger, 2016).

5.4 | Water management and agriculture

Many large-scale studies about water management focus on agriculture or reservoir storage. Brocca et al. (2018) used satellite soil moisture data to estimate irrigation water use. Thebo, Drechsel, Lambin, and Nelson (2017) mapped irrigated croplands also influenced by urban wastewater. Jägermeyr et al. (2016) analyzed the potential of integrated crop management to close the global food gap. Gao, Liang, and He (2019) quantified past agricultural greening trends using satellite data. Di Baldassarre, Wanders, et al. (2018) related the global development of reservoir storage to water demand and Zarfl, Lumsdon, Berlekamp, Tydecks, and Tockner (2015) identified a global increasing trend in hydropower dam constructions.

5.5 | Human–water interactions

Large-scale datasets on population, land-use and disaster hazards have enabled global maps of human flood exposure, either focusing on long-term trends (Ehrlich et al., 2018; B. Jongman, Ward, & Aerts, 2012) or fine resolution snapshots (Smith et al., 2019). Some global exposure studies focus on specific objects, such as road and railway infrastructure (Koks et al., 2019). Human behavior in proximity to rivers has also been widely covered within the literature, for instance exploring global settlement patterns in river networks (Fang et al., 2018) and global trends of human pressure imprints on river systems (Ceola et al., 2019). Mård et al. (2018) used nighttime lights and a global dataset on flood protection standards to analyze how flood protection shapes human resettlement after major flood events. Some research utilizing large-scale datasets also focus on social aspects of hydrological disasters. Carrão, Naumann, and Barbosa (2016) mapped global patterns of drought risk, revealing low spatial correlation between hazard occurrence and drought risk. Sutanto, van der Weert, Wanders, Blauhut, and Van Lanen (2019) analyzed gridded drought indices and drought impact reports with machine learning to forecast drought impacts on a European level. Albrecht (2018) combined a global disaster loss database with European survey data to analyze how natural hazard-related disasters affect social capital.

6 | DATASET USABILITY CHALLENGES FOR COMPARATIVE STUDIES

Here we underline some challenges for using these EO datasets in comparative studies. Specific discussion points include spatiotemporal resolution and coverage, inequalities of geographic representation, omission of detailed information at large scales, data consistency and accessibility, and dependencies between the datasets prohibiting interaction studies.

6.1 | Spatiotemporal depth and coverage

Temporal depth is crucial for capturing dynamical phenomena like disaster risk. Almost 40% of the included datasets are, however, static: offering snapshots rather than changes over time (Figure 3). Static datasets particularly dominate the categories *Hydrographic baseline*, *Water management*, and the sub-categories within *Land cover and agriculture* and *Human presence* that primarily rely on reported data sources rather than automatic monitoring (e.g., statistics on irrigation, crops, livestock, and administrative units). The lack of temporal depth can be more or less problematic for the representation of geographic reality, depending on the real variability of the represented elements. Remotely sensed hydrographic datasets like HydroSHEDS (Lehner, Verdin, & Jarvis, 2008), for instance, are unarguably important data resources despite the lack of temporal depth. Nonetheless, static datasets are restricted to offer snapshots of elements that in reality are evolving over time. The majority of the datasets within *Hydrographic baseline* relies upon elevation models from around the year 2000 (e.g., NASA's SRTM and USGS' HYDRO1K).

The static limitations of the baseline datasets can also propagate to dynamic datasets. The near real-time flood maps from MODIS, for instance, use a static water mask to distinguish permanent water from flood water (Policelli et al., 2017). This weakens the representation of seasonal water body behavior and might result in some mapped areas being outdated (Policelli et al., 2017). Some static datasets do, however, give information on the underlying variability of the element. One example is the dataset G3WBM (Yamazaki, Trigg, & Ikeshima, 2015), which maps water cover frequency from multi-temporal satellite imagery. This static map thus discriminates permanently water-covered areas from the periodic ones.

The planetary-scale datasets of this review rely on relatively young technologies (Figure 4); there is generally a temporal representation bias towards the year 2000 and onward. A few datasets reach all the way back to the early 1900s, such as CRU-TS (Harris, Jones, Osborn, & Lister, 2014) and the Historical Irrigation Dataset (Siebert et al., 2015), but they typically report larger uncertainties for the first part of the 21st century due to data limitations. Virtual water station measurements and remotely sensed maps of burned areas do not reach further back in time than the 1990s and the

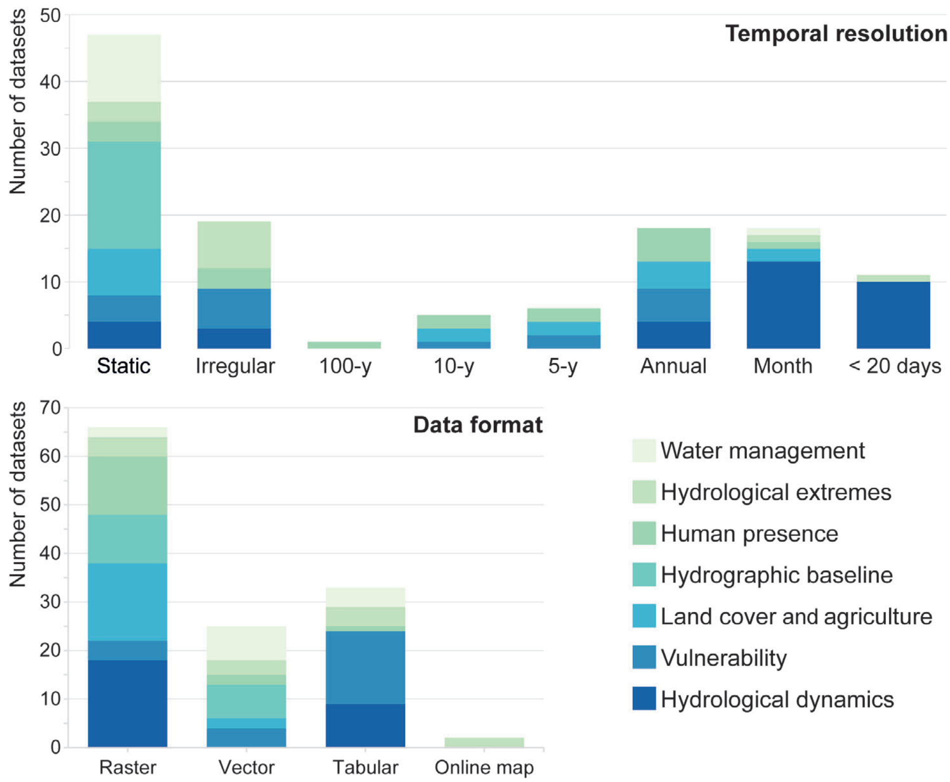

FIGURE 3 Temporal resolution and data format of datasets by category. Static datasets are snapshots and do not capture change over time. Irregular datasets include datasets with irregular recurrence time and event-based datasets. Tabular data format includes both tables with and without geographic representation, such as coordinates. Datasets lacking specification of temporal resolution or data format, for example due to variations between measuring stations, are not included in this figure. Some datasets offer multiple temporal resolutions and data formats, for which all alternatives are included in this figure

year 2000. In some cases, however, combining datasets can be a means of compensating for short time series. For instance, Busker et al. (2019) analyzed volumes for 137 reservoirs and lakes by combining a long-term surface water dataset (32 years) with a young satellite altimetry dataset (<10 years), whereby the volume time series could be estimated for the full 32 years through derived hypsometry relationships.

The datasets within the category *Human presence* show how there is typically a trade-off between long temporal coverage and fine temporal resolution (Figure 4); the datasets with the longest temporal records (1970s) also exhibit coarse temporal resolutions (10 or 15 years). We have also noted that the population datasets with finest temporal resolutions, for example, LandScan (Dobson, Bright, Coleman, Durfee, & Worley, 2000) and GPW (Center for International Earth Science Information Network [CIESIN] & Columbia University, 2017b), advise against time series applications due to changes in methods and data sources between the records. The finest temporal resolutions of datasets applicable to time series analysis can generally be found among the variables detectable from space. This entails many of the datasets within the category *Hydrological dynamics*, and datasets such as the nighttime lights used as proxies for socioeconomic development (Bennett & Smith, 2017).

We cannot see any evident trade-offs between spatial and temporal resolution among the raster datasets also having fixed revisit times (Figure 5). We do observe typical resolution intervals for some of the categories: Land cover and population datasets tend to combine high spatial with low temporal resolutions, whereas the opposite applies for meteorological datasets.

6.2 | Aspects of geographic representation

The spread of data formats across the data categories confirms that EO technology is currently more skilled at capturing disaster hazards and exposure, compared to vulnerability aspects. Datasets populating vulnerability aspects are mostly tabular (Figure 3), supporting the statement that further systematic EO work is needed for improving the geographic representation. This applies for datasets within the category *Vulnerability*, but also other datasets such as disaster loss data within the category *Hydrological extremes*.

The category *Hydrological dynamics* holds raster and tabular datasets (Figure 3), generally the raster datasets are detected from satellites and the tabular datasets are measurements from the ground (soil moisture, discharge, water

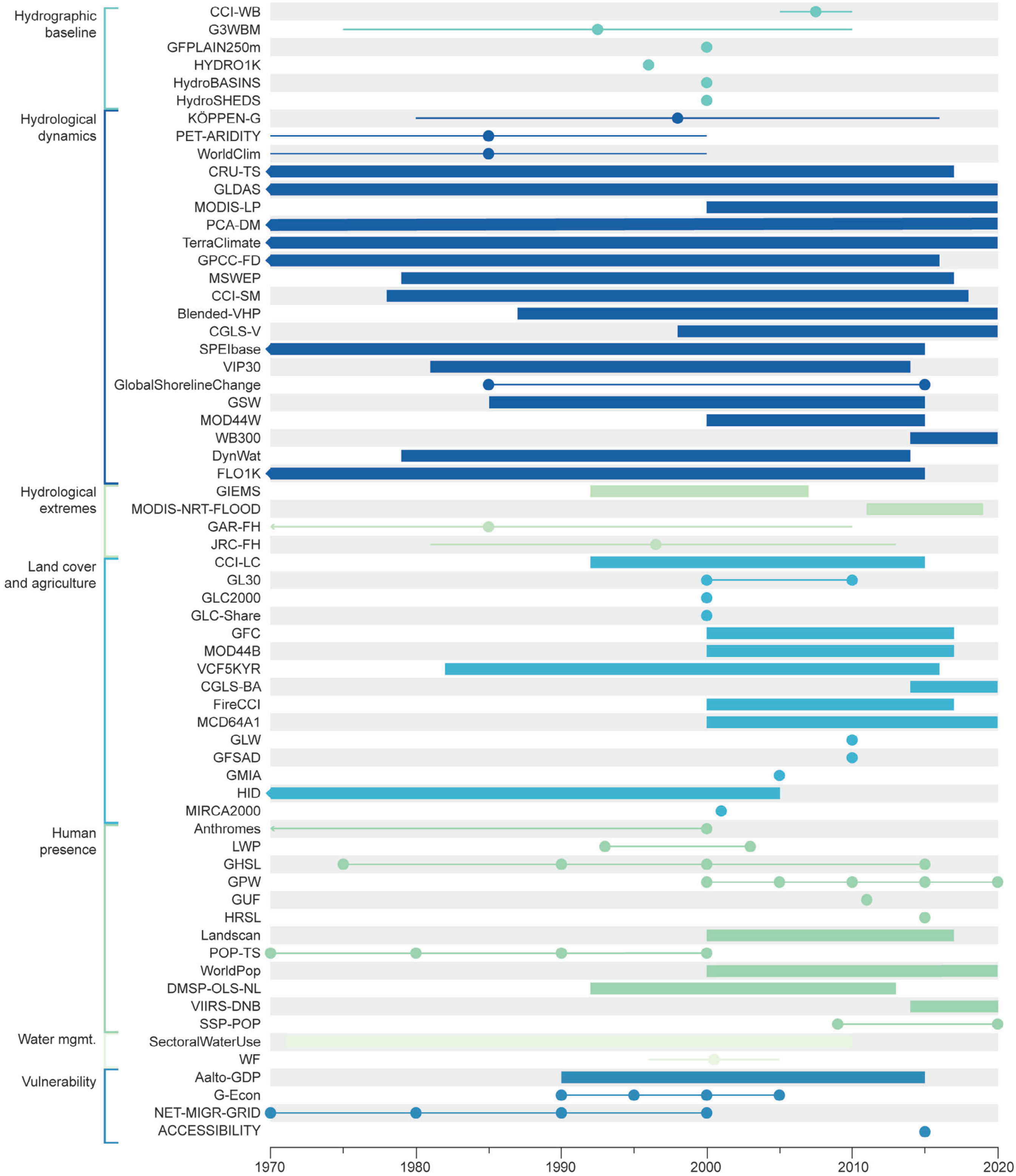

FIGURE 4 Time period and resolution of datasets grouped by categories. Thick bars indicate datasets with annual temporal resolutions or finer. Dots with thin lines indicate datasets representing individual year(s). Arrowheads indicate that temporal coverage extends further back in time than displayed in this chart. Datasets without specified temporal representations, for instance static datasets based on a variety of data sources, are not included in this figure. Full descriptions of all datasets, with respective references, are available at https://zenodo.org/record/3368882

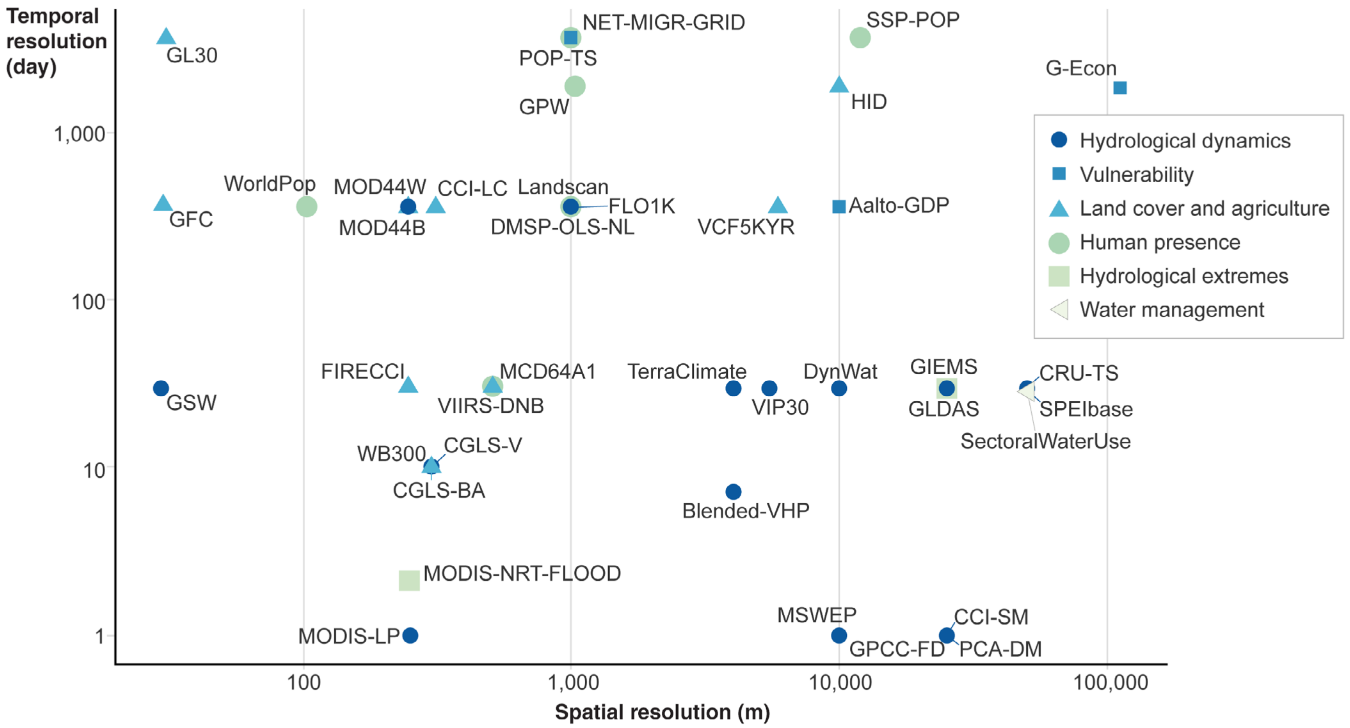

FIGURE 5 Temporal and spatial resolutions of raster datasets by category. Only raster datasets with specified spatial resolutions are included in this figure. Datasets with static or irregular temporal resolutions are not included in this figure. Full descriptions of all datasets, with respective references, are available at https://zenodo.org/record/3368882

levels and water quality). Some datasets, for example, CRU-TS (Harris et al., 2014) and GPCC (Schneider, Becker, Finger, Meyer-Christoffer, & Ziese, 2018), offer gridded products based on station data. CRU-TS offers both the grids and underlying station data, while only the gridded GPCC data are available due to policy restrictions (Schneider et al., 2018).

Many of these planetary-scale datasets do exhibit geographical representation biases, generally favoring central latitudes and socioeconomically developed countries. Remotely sensed datasets tend to exhibit nonuniform coverages across the globe, offering nonglobal coverage (Carroll et al., 2017; Lehner & Grill, 2013; Yamazaki et al., 2015) and/or coarser resolutions toward the poles (Esch et al., 2017; Lehner, 2014). Near-polar areas are also periodically missing in datasets from optical satellite imagery, due to low solar zenith angles (Pekel et al., 2016).

Climatology, topography and vegetation also influence the geographic representation in these remotely sensed datasets. Hydrologically complex systems like braided rivers, deltas, and narrow gorges are typically prone to show error in radar satellite products (Lehner, 2013). Heterogeneous terrains, such as coastlines and mountainous areas, typically exhibit errors in climate datasets (Abatzoglou, Dobrowski, Parks, & Hegewisch, 2018; Barbarossa et al., 2018). Mountainous regions tend to result in precipitation being underestimated (Beck et al., 2019). These limitations carried by hydrographic and climatic datasets also affect global flood hazard maps (Dottori, Salamon, et al., 2016; Trigg et al., 2016). Heavy vegetation tends to interfere with soil moisture retrievals and surface water detection (W. Dorigo et al., 2017; Pekel et al., 2016). Tropical regions periodically exhibit cloud obscuration, affecting datasets like nighttime light imagery (National Oceanic and Atmospheric Administration [NOAA], 2017). Fusing data from microwave, optical and radar datasets is one example of an approach to overcome the challenges posed by the individual technologies, for instance when mapping inland water in tropical areas under dense vegetation (Parrens et al., 2019).

Socioeconomic factors also play a role in geographic representation among the datasets building on reports or station measurements. The decline of river discharge measurement stations has particularly affected Africa, Eastern Europe, and the Arctic (Hannah, Demuth, van Lanen, & Looser, 2011). Precipitation measurements are particularly scarce in inland South America, Africa, Australia, Antarctica, and the poleward regions of the Northern Hemisphere (Kidd et al., 2017). We underline that this bias also propagates to remotely sensed or modeled datasets, since in situ monitoring is critical for validation and improvement (Abatzoglou et al., 2018; Kidd et al., 2017; United Nations Environment Programme, 2016). Datasets built on media reports, like databases on conflicts and cooperation (Bernauer et al., 2012) and land grabbing (Anseeuw, Lay, Messerli, Giger, & Taylor, 2013), exhibit biases from media interest and differences in openness among countries. Databases on disaster losses (CRED & UNISDR, 2018) exhibit systematic underreporting from lower income countries.

6.3 | Omission of detailed information at large scales

The large spatial scales of the datasets in this review also mean that they tend to only capture large elements. This includes being restricted to only capturing wide rivers (Lehner, 2013; Yamazaki et al., 2014), flood hazard from large river basins (Dottori, Alfieri, et al., 2016), large land cover changes (Defourny et al., 2017), large burned areas (Chuvieco et al., 2018; Giglio, Boschetti, Roy, Humber, & Justice, 2018), large settlement areas (Dobson et al., 2000; Doxsey-Whitfield et al., 2015), severe disasters (CRED, 2019), large land deals (Anseeuw et al., 2013; GRAIN, 2016), and big dams (Lehner et al., 2011). The remotely sensed datasets are logically constrained to only capture changes larger than the pixel size.

This tendency towards large spatial elements can easily generate a mismatch in scales, for example if attempting to use a global flood hazard map in an urban-scale study where the river flowing through the city is not even included in the global map. This also means that the true intrinsic resolution can be lower than the stated spatial resolution (Smith et al., 2019). Studies on past flood events are also affected, since smaller flood events are missed by both the remotely sensed flood maps and the disaster loss reports. This data gap especially affects the study of extensive disaster risk (defined as the risk of low-severity but high-frequency hazardous events), typically hitting low-income households and communities (UNISDR, 2015). However, the disaster loss database DesInventar particularly targets small and medium disaster events (UNISDR, 2015).

Many recent datasets offer fine spatial resolutions from being downscaled or modeled. We notice, however, that many of these maps are recommended to be used in continental or global applications only—due to individual pixel uncertainties. This applies for datasets such as the Global Estimated Net Migration Grids By Decade (Socioeconomic Data and Applications Center [SEDAC] & CIESIN, 2015), Gridded Livestock of the World (Gilbert et al., 2018), Historical Irrigation Dataset (Siebert et al., 2015), Global Population Grid Time Series (CIESIN & Columbia University, 2017a), and SoilGrids250m (Hengl et al., 2017).

6.4 | Data consistency, accessibility, and dependency

Comparative research needs datasets that are consistent across space and time. Many of the dynamic datasets bring inconsistencies, hindering the ability to compare cases across space and time. Many remotely sensed datasets are burdened by data gaps and inhomogeneities (Carroll et al., 2017; W. Dorigo et al., 2017; NOAA, 2017; Pekel et al., 2016; Sheffield et al., 2014), due to technical variability along the temporal records and/or natural conditions such as cloud obscuration. Examples on approaches to compensate for temporal data gaps due to cloud contamination include: data fusion with spatially coarser but temporally finer data (Li, Skidmore, Vrieling, & Wang, 2019), machine learning in combination with topographic, hydrological and climatic variables (Shaeri Karimi, Saintilan, Wen, & Valavi, 2019), recovering cloud cover contaminated images with isobaths derived from cloud-free images (Yao, Wang, Wang, & Crétaux, 2019), and automatic correction of cloud contamination images through an algorithm based on a long-term water occurrence dataset (Zhao & Gao, 2018). Ground measurement datasets are laden by inconsistencies between measuring stations, for instance offering different time periods, measuring frequencies, and technical qualities (W. A. Dorigo et al., 2013; Hannah et al., 2011; Harris et al., 2014; United Nations Environment Programme, 2019). Crochemore et al. (2019) provides a methodological framework for quality checking large-sample river flow datasets.

These inconsistencies between measuring stations also bring data availability biases, access to long-term data records being more common for socioeconomically developed countries (Hannah et al., 2011; United Nations Environment Programme, 2019). Also virtual water level station datasets exhibit inconsistencies between stations (Schwatke, Dettmering, Bosch, & Seitz, 2015; United States Department of Agriculture, 2019). Data accessibility can also be a challenge for event-based and station measurement datasets, as the users are often not given access to the entire dataset all at once.

Many of the datasets build upon a large number of input sources, resulting in many datasets being unable to specify the data accuracy. Other challenges come from some datasets using all available data for creating the dataset hindering the opportunity to validate the dataset, for instance the Historical Irrigation Dataset (Siebert et al., 2015). Instead, it is commonly stated how the dataset performs in comparison to other datasets, for example, HydroSHEDS (Lehner & Grill, 2013), Copernicus CCI-WB (Lamarche et al., 2017), Köppen-Geiger climate classifications (Beck et al., 2018), CRU-TS (Harris et al., 2014), precipitation dataset of MSWEP (Beck et al., 2019), virtual water station measurements of DAHITI (Schwatke et al., 2015), land cover classification of GlobeLand30 (Chen, Cao, Peng, & Ren, 2017), CCI-LC (Defourny et al., 2017), wildfires mapped by FireCCI (Chuvieco et al., 2018), and SoilGrids250m (Hengl et al., 2017). This can of course help data users to choose among alternative datasets, but the general challenge to obtain absolute accuracy information still remains.

Finally, many of the datasets build upon other datasets, causing dependency issues that can hinder interaction studies, as visualized in Figure 6. HydroSHEDS (Lehner & Grill, 2013), land products from MODIS sensors, CRU-TS (Harris et al., 2014), and the global lakes and wetlands database GLWD (Lehner & Döll, 2004) are some of the most frequently used datasets by the others within this data collection. Many downscaled or modeled datasets exhibit data dependency issues preventing interaction studies. Economic gridded datasets, for instance, use population data for gridding regional data to cell level, which prohibits using the data in interaction studies with population data (Kummu, Taka, &

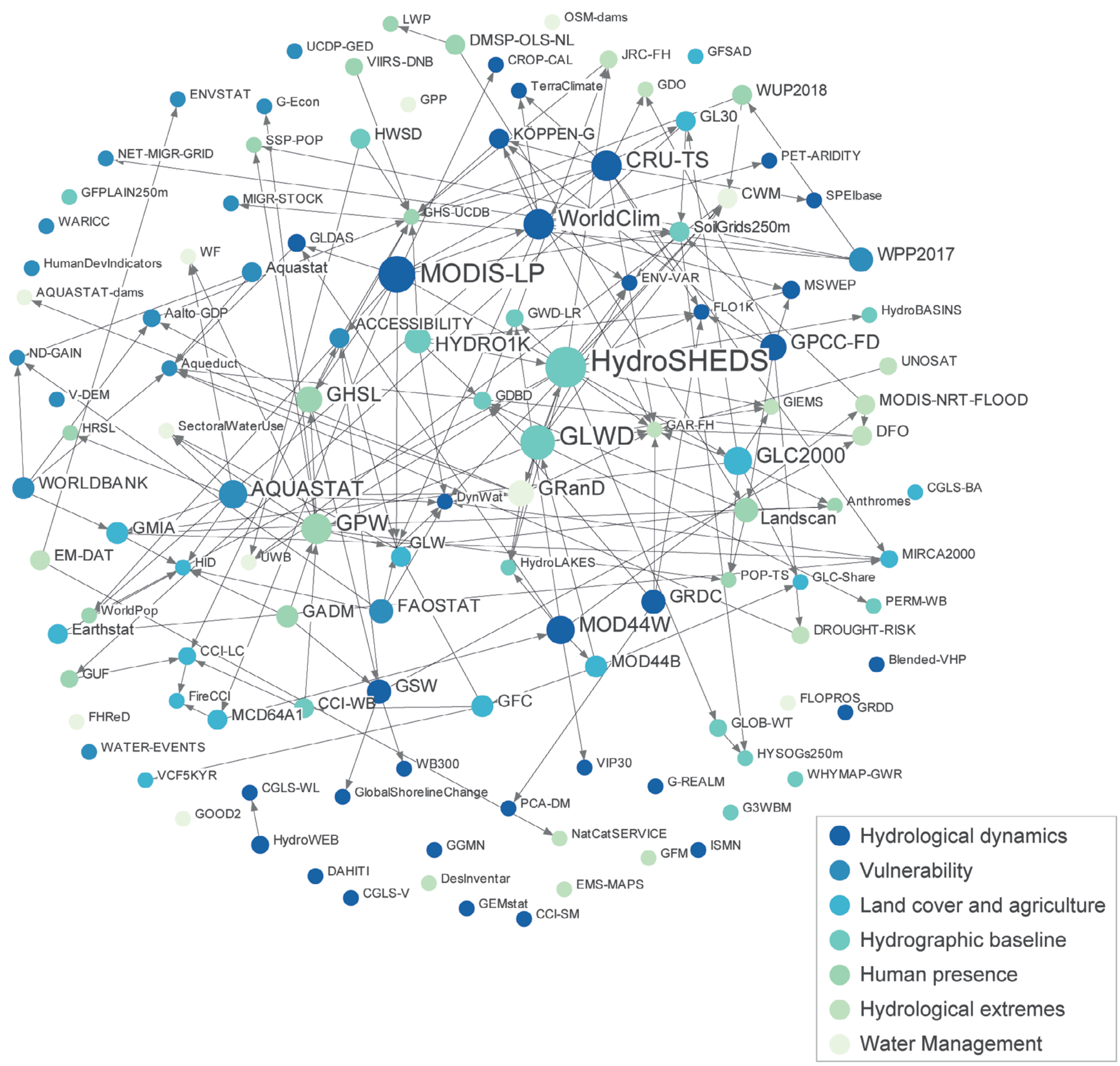

FIGURE 6 Data dependencies among datasets of different categories. Arrow direction shows which dataset is using the other as data source. Symbol size indicates how frequently it is used by other datasets in this data collection. Only direct relationships among the datasets are included in this figure. Indirect dependency relationships, for instance if two datasets are based on the same satellite imagery, are therefore not shown here. Layout of network chart follows ordination, produced in software NetDraw (Borgatti, 2002). Full descriptions of all datasets, with respective references, are available at https://zenodo.org/record/3368882

Guillaume, 2018). This is not true for all modeled datasets, for example, the Historical Irrigation Dataset is independent from economy and population but has some dependency towards environmental properties (Siebert et al., 2015).

7 | CONCLUSION

To support the spatial (and temporal) analyses of floods, droughts and their interactions with human societies, we created and structured an extensive collection of freely accessible global scale geospatial datasets. Taken together, this collection illustrates the versatility of research opportunities given by the current growth of free and openly accessible datasets. The spatiotemporal characteristics do, however, vary among the wide range of variables. First of all, the underlying processes behind the individual variables occur at a variety of spatiotemporal scales. Floods, for instance, are typically rapid disasters, spatially bounded to flood-prone areas. Droughts, on the other hand, have a creeping way of arriving and cover larger spatiotemporal extents (Wens et al., 2019). This difference consequently results in distinct spatiotemporal data requirements and opportunities. Secondly, some variables simply lack data availability within the desired spatiotemporal characteristics. This can in some cases be explained by the nature of the underlying processes as well. Comparing floods and droughts, our data collection holds several global flood hazard datasets while the data availability of drought hazards and events is limited. This is also expected, knowing that the transition from hazard to disaster is generally more complex for droughts compared to floods (Wens et al., 2019). The large spatiotemporal scale of drought events, however, is an advantage since it enables using meteorological datasets for detecting past events. The rapid and smaller events of floods, on the other hand, can more easily be missed by the global datasets.

EO is today a highly vibrant field, as new geospatial datasets are continuously being released and developed. Our collection of datasets is a snapshot of the current availability at the time of writing. As such, we could not capture the full availability of datasets, but rather present current data opportunities that can facilitate further water disaster research at large scales. We have used this review as a benchmark to further discuss the usability of planetary-scale datasets and to identify areas where improvements of geographical representations are needed.

In ending this paper, we want to underline our findings that many of the new technologies contributing to unprecedented opportunities also generate limitations on usability. Challenges for downscaled datasets, for instance, involve: time varying datasets advised not to be used in time series analyses, fine spatial resolution datasets advised not to be used in local studies, datasets built on a wide variety of data sources prohibiting systematic uncertainty assessments, and data dependency issues preventing interaction studies. The review also confirms that the geographic representation of disaster hazards and exposure is far more mature than the geographic representation of vulnerability aspects. To completely grasp the social side of water disaster research, we need further EO efforts working to capture spatiotemporal dynamics of vulnerability aspects. We are nonetheless optimistic that the following years will see further progress in capturing the vulnerabilities of humanity as well, not least due to current progress in very high-resolution satellite imagery in combination with machine learning techniques.

CONFLICT OF INTEREST

The authors have declared no conflicts of interest for this article.

AUTHOR CONTRIBUTIONS

Sara Lindersson: Conceptualization; data curation; formal analysis; investigation; methodology; visualization; writing-original draft. **Luigia Brandimarte:** Conceptualization; methodology; supervision; writing-review and editing. **Johanna Mård:** Conceptualization; methodology; supervision; writing-review and editing. **Giuliano Di Baldassarre:** Conceptualization; funding acquisition; methodology; supervision; writing-review and editing.

ORCID

Sara Lindersson https://orcid.org/0000-0001-9359-6218

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FURTHER READING

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