A review on how Big Data can help to monitor the environment and to mitigate risks due to climate change

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***Abstract*—Climate change triggers a wide range of hydrometeorological, glaciological and geophysical processes that span across vast spatiotemporal scales. With the advances in technology and analytics, a multitude of remote sensing, geodetic and *in situ* instruments have been developed to effectively monitor and help comprehend the Earth's system including its climate variability and the recent anomalies associated with global warming. A huge volume of data is generated by recording these observations, resulting in the need for novel methods to handle and interpret such Big Datasets. Managing this enormous amount of data extends beyond current computer storage considerations; it also encompasses the complexities of processing, modeling, and analysing. Big Datasets present unique characteristics that set them apart from smaller datasets, thereby posing challenges to traditional approaches. Moreover, computational time plays a crucial role, especially in the context of geohazard warning and response systems which necessitate low latency requirements. In this review, we delve into the monitoring and analysis of various climate change-related phenomena, including, but not limited to, droughts, floods, cyclones-induced storm surges, urban heat islands, ice mass balance, sea-level rise, and the modelling of the influence of solar variability on the Earth's climate. By examining these phenomena, we explore some of the current and future trends in Big Data, aiming to encourage and speed-up the development of such techniques and promoting their benefits to timely monitor and towards achieving climate sustainability, thereby addressing its threat to humanity.**

I. Introduction

The Earth is changing at an unprecedented rate. More than half of the Earth's ice-free land surface has been modified by human activities, and almost all land surfaces have been influenced by climate change and various kinds of land disturbances. Through the integration of multiple satellite missions and extensive ground-based networks, which consistently observe both the Earth and the Sun, we possess the capability to systematically monitor a wide array of environmental changes related to climate variability, as well as natural and anthropogenic phenomena [1].

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Temporal changes have been happening to the Earth's climate and on the geomorphology of the crust for (hundreds of) millions of years. However, the recent anthropogenic climate perturbations are a game changer, altering the climate together with the Earth's system (i.e. biosphere, hydrosphere, atmosphere) at a fast pace [2]. Scientists measure these changes based on different "temporal scales". At small scale (i.e., days, months, a few years), they monitor more recurring and rapid events related to severe land disturbances (e.g., land subsidance, geohazards, seasonal droughts) or weather phenomena (e.g., anomalies in precipitation, temperature, cyclones and storm surges). With a duration from several years to decades, they observe large-scale changes in the environment such as land and coastal subsidence (e.g., rapid relative sea-level rise abbreviated as SLR, implicating that both the vertical land motion and the geocentric sea-level change signals have to be separated, that the signals may include transient, periodic and accelerated variability, and that they are distinct for the land and the ocean in terms spatiotemporal scales), repetitive climate anomalies and extreme events (e.g., frequency of droughts) [3]. At much larger scales (i.e. several decades or longer), phenomena like the influence of solar variability on the Earth's climate require knowledge of solar-terrestrial interactions, and the underlying mechanisms determining the response of the Earth's climate systems [4].

The frequent monitoring and modeling of all, but not limited to, these phenomena produce vast quantities of data, commonly referred to as "Big Data." It is not only "big" in terms of volume (i.e., a few terabytes (TB) to the order of a petabyte (PB)), but also in terms of complexity (e.g., various resolutions), heterogeneity, and the posing of numerous challenges related with their processing and interpretation. Heterogeneous Big Data refers to the inclusion of diverse and varied types of information from multiple sources or formats within a large-scale dataset (or a data product). For example, the data inflow is amplified by connected sensors from the Internet of Things (IoT), seamlessly integrated into our environments. These IoT sensors continuously gather data from various sources, capturing real-time information about the physical world [5]. Figure 1 illustrates the whole chain (from top to bottom) on how observations recorded from various remote sensing (RS), geodetic and in situ instruments are processed and correlated together to inform quickly various entities (e.g., governmental agencies, environmental services, water resources and disaster management entities), which can then activate their emergency or resilience plans in order to prevail environmental and human catastrophes. Thus, Big Data fosters the need for processing and connecting large amounts of data, particularly in complex climate-related systems. It is essential to formulate algorithms that can effectively tackle these challenges.

Amid these techniques, Machine Learning (ML) and Deep Learning (DL) stand out and have been already employed for pattern recognition, anomaly detection, and predictive modeling. ML, a versatile field of artificial intelligence, involves the development of algorithms and statistical models that enable computer systems to improve their performance on a specific task through learning from data. DL, a subset of machine learning, focuses on neural networks with multiple layers, enabling them to automatically learn patterns and representations from complex data. These algorithms can uncover intricate relationships within the data and enhance our ability to make timely and accurate assessments and potentially save lives in the decision-making of emergencies. They have already found many applications across diverse domains, from healthcare and finance to image and speech recognition [6], [7], [8], [9], [10], [11].

With the fast development of these algorithms in the framework of Big Data, a review of the state-of-the-art of Big Data for Earth and Space observations related to climate variability is needed to clarify existing challenges and future developments. This review specifically addresses the following questions:

i) What is the current status of the processing and integration of this vast amount of information within the framework of monitoring climate variability and extremes events?

ii) At short-time scale, how are we able to extract useful (potentially life-threatening) information, that must trigger the required action? At long-time scale, how well can we forecast repetitive extremes events with the increase of the direct effects related to the anthropogenic climate change?

These questions are addressed through the investigations of three specific areas "the use of Big Data in geodynamics", "integrating Big Data and satellite gravimetry for enhanced hydrological extremes" and "climate variability". Thus, readers become aware of the importance of connecting multiple datasets to improve processes aimed at transforming information into knowledge.

II. The Use of Remote Sensing Big Data in Geodynamics at Regional and Large-Scales

This section treats two fields in geodynamics, namely environmental changes (geohazards) and SLR, with an emphasis on the spatiotemporal (regional and global) scale when processing Big Datasets.

1) Environmental changes at regional scale - looking for signals in large datasets: A specific application of Big Data in geosciences is related to the monitoring and prediction of environmental modifications. A combination of satellite geodetic techniques like the Global Navigation Satellite System (GNSS) and the Interferometric Synthetic Aperture Radar

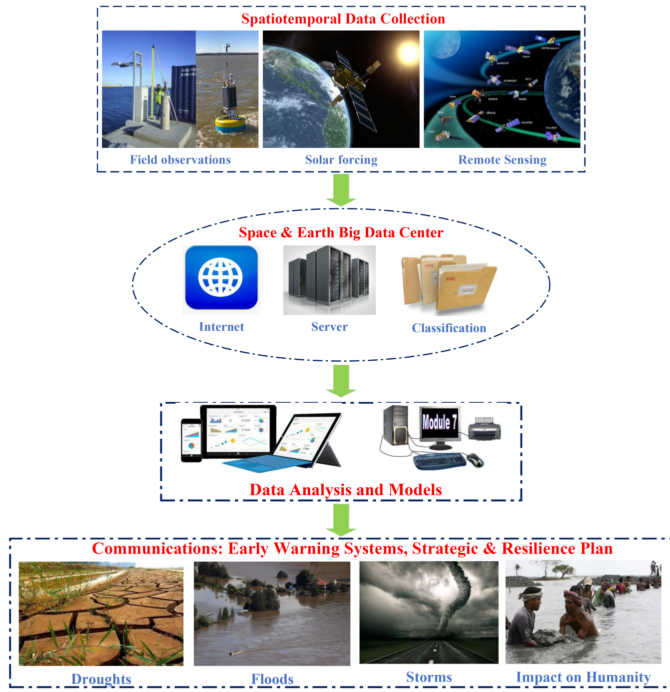


Fig. 1. Overview of the framework from recording data, to data storage, analysis and modelling, and finally communication of the results to relevant authorities.

(InSAR) help to gain knowledge about the geodynamics of the Earth's surface [12], environmental changes, and detection of anomalous deformations (i.e., geohazards) for the betterment of public safety (e.g., early-warning systems).

More than 15,000 GNSS stations are installed permanently around the world, recording data up to 10-50 Hz, providing valuable data on the position changes at the mm-level over time through time series of coordinates, and giving insights into various geophysical processes. All these stations generate TB of data every year. Analysis centers process all these datasets to provide the position time series to the public for various geodetic applications (e.g., surveying, hydrogeological studies, space-weather, estimation of the movement of tectonic plates, monitoring inflation and deflation events in volcanoes [13], [14]). Furthermore, dedicated investigations are conducted to estimate specific transient signals, such as slow slip events and co-/post-/inter-seismic transients [15], which can serve as precursors to natural hazards like landslides [16]. Traditionally, geotechnical surveys and GNSS permanent stations have been utilized to detect specific small amplitude short-time signals, aiding the activation of early-warning systems. Yet, the application of this method is frequently hindered

Fig. 2. Rockfall event image recorded by the integrated camera of the rockfall radar system at the town of Brienz/Binzauls in the canton of Graubünden captured on September 18, 2018. Courtesy of GEOPREVENT - part of Hexagon

by logistical and economic constraints [17], especially in expansive, isolated, and difficult terrains.

For example, monitoring high-mountain areas is mandatory within the context of climate change and the expansion of areas of urban settlement. In addition to the crucial role played by landslide identification in risk assessment, the ability to predict and provide early warnings is of utmost significance. An interesting example of such phenomenon is the Brienz/Binzauls landslide (see Figure 2), an event that unfolded in June 2023. Situated in the Swiss Alps, the village experienced an evacuation process commencing between May 9 and May 12, 2023. This evacuation garnered global attention and sparking widespread interest in the underlying causes of the landslide. The active segments of this complex landslide, moving at rates exceeding 0.1 m per year, collectively encompass a large volume of approximately 170 million cubic meters. A meticulous mapping effort including Doppler radars, Robotic Total Stations, Time-Lapse Cameras with automated Digital Image Correlation processing, Webcams, Seismic Stations, Climate Stations, permanent GNSS stations, periodic LiDAR scans (taken from drone/helicopter flights) coupled with the analysis of morpho-tectonic surface features and in situ data (e.g., samples from boreholes), reveals a convoluted structure and a multi-phased history of landslides dating back at least $13,000$ years. This large volume of data was processed daily to feed the predictive models of the landslide and to update quickly the risk assessment which finally ended up in the evacuation of the entire village [18]. Achieving this level of preparedness relies on the availability of high-quality datasets that offer both spatial and temporal granularity. GNSS and permanent terrestrial laser scanners (TLS), have emerged as economically viable and non-contact monitoring systems that find widespread utility in this context [19], together with Ground-Based Synthetic Aperture Radar Interferometry (GBInSAR) [20]. Permanent laser scanning, or long-term laser scanning, has emerged as a powerful technology for capturing detailed and precise 3D data of objects, structures, and environments (e.g., deformation monitoring [21], [22], civil engineering [23], rockfalls [24]). It also offers continuous and comprehensive monitoring capabilities unlike traditional surveying methods, which are often periodic and point-based. Permanent laser scanning stations allow studying geomorphological changes of, e.g., dunes or glaciers [25] or [26] for a correlation analysis with InSAR (and GBInSAR). A significant hurdle associated with these Big Data lies in effectively handling multi-temporal point clouds to extract information and identify patterns of change. The initial step frequently involves the classification of point clouds, a prerequisite for deformation analysis, as explored in [27] for rock slope monitoring. In [28], three clustering algorithms (k-means clustering, agglomerative clustering, and density-based spatial clustering of applications with noise) were evaluated for identifying regions exhibiting similar evolution patterns. A time series-based strategy, as described by [29], utilized a Kalman filter approach. In a related context, [30] applied a change point detection method to identify seeds for point cloud segmentation. Besides the conventional point cloud filtering techniques, [31] and [32] explored various ML classification algorithms, such as the deep learning approach incorporating automatic feature extraction (PointNet++). In [33], the advantages of an unsupervised ML approach called Gaussian Mixture Modeling, were demonstrated. The study introduced a feature extraction method from 2D depth images combined with an extended clustering technique which was successfully employed in landslide monitoring in the Alpine region (Valsertal in Tyrol, Austria) after a rockslide occurred on December 24th, 2017 (refer to Fig. 3). There were no fatalities or significant damage to buildings, but a total of 116,000 cubic meters of rock was removed from the mountain. In the ongoing permanent monitoring phase, the local authorities established a geodetic monitoring system, and the data became accessible through an innovative web-based Internet of Things (IoT) platform designed for risk management. All the datasets were collected in a database, displayed online, analyzed, and archived in near-real time to enable fast decisions. In the near future, automatic deformation analysis and timely, near-real-time risk assessments will be conducted using the dedicated ML and enhanced segmentation approaches mentioned earlier, which are currently under development. Further, new methods based on volume approximation for data reduction and visualization open new possibilities, facilitating the implementation of ML techniques and the transformation of the Big Data to information [31]. Similarly, recent studies have developed innovative approaches to monitor and forecast geohazards combining ML algorithms and various datasets. [35] presented an innovative approach integrating wireless sensors, such as a reservoir water level gauge, rainfall gauge, and GNSS. Their methodology, employing double exponential smoothing and the particle swarm optimization–extreme learning machine, introduces a unique architecture of artificial neural networks (ANN) tailored for forecasting landslide displacement. This approach yielded successful results, particularly in the context of the Baijiabao landslide in China. In a comparable fashion, [36] adopted a salp-swarm-algorithm-optimized temporal convolutional network to predict the periodic displacement of the Muyubao landslide. This result was achieved by considering the dynamic relationship between periodic displacements, as recorded by a GNSS monitoring system, and additional features such as rainfall and reservoir water levels. Moreover,

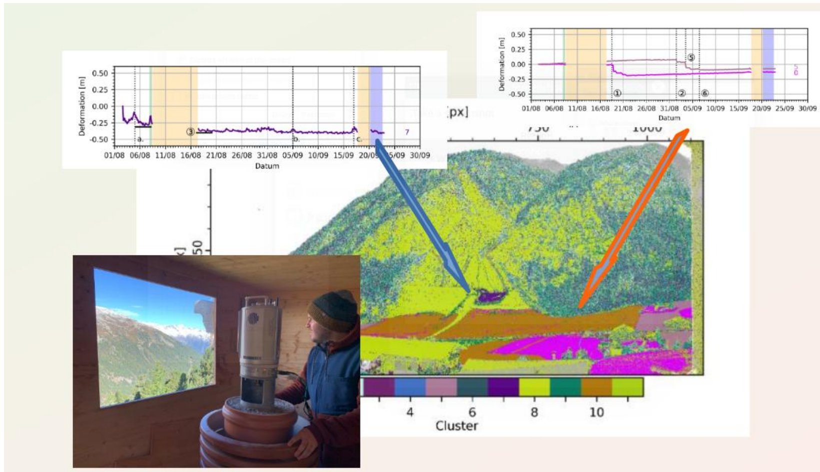


Fig. 3. On December 24th, 2017, in the Valsertal / Tyrol in Austria, a rockfall occurred consisting of 117,000 m³ rock volume. The Valser Landstrasse directly below the rockslide was buried with 8 m of rubble and rubble [34]. A geodetic monitoring consisting of a total station (model: LEICA TM30) and 21 prisms (model: LEICA GPR1), was launched on January 28, 2018 by the Tyrolean Land in Austria (Vals). The Big Data from the permanent TLS station was used to develop new algorithms based on clustering and ML techniques (time series) to classify domains with high risk of slides.

forecasting earthquakes presents a formidable challenge within seismology using ML/DL algorithms, crucial for safeguarding lives and minimizing devastating impacts [37]. For example, the authors in [38] have devised a real-time earthquake forecasting framework tailored for seismogenic regions in southwestern China. The framework harnesses data from the multicomponent seismic monitoring system known as Acoustic Electromagnetic to Artificial Intelligence (AETA). This system records data via two sensor types per station: electromagnetic (EM) and geo-acoustic (GA). The objective is to predict the location and magnitude of earthquakes anticipated in the forthcoming week, utilizing data from the current week. The proposed method is based on dimension reduction from EM and GA big dataset (i.e. EM and GA) using a specific type of ML algorithm, the random-forest-based classification.

Finally, new advances in remote sensing, geodetic and computer techniques result in a rapid growth of data [39]. For decades, the modelling and analysis of geodetic time series generally required knowing the underlying geophysical models (e.g., slopes, offsets, tectonic rate) together with the stochastic noise properties of the data [40] to perform statistical testing and avoid triggering unnecessary chain of actions (e.g., triggering emergency responses). The above landslide examples highlight the ongoing efforts in the domain of deformation prediction and, more broadly, geohazard monitoring. ML and DL techniques are positioned to play an increasingly pivotal role in classifying and analyzing extensive datasets, frequently sourced from multiple sensors. This is crucial for detecting the necessary signals while ensuring computational efficiency, as emphasized by [41].

2) Environmental changes on a large spatiotemporal scale - the case study of relative sea-level rise: One of the main natural phenomena associated with climate change is the significant rise in sea-levels due to the melting glaciers and land-based ice caps imbalance of water cycle, as well as ocean water expansion from rising temperatures. The scientific community estimates that SLR has increased by almost 0.08 m globally since 1992 and could reach between 0.3 and 0.9 m by the end of the century [42]. Coastal cities and low-lying regions (e.g., islands) face significant risks from tidal flooding, non-tropical-storm flooding, tropical cyclone storm surge, and other geohazards, which can have devastating impacts on both human populations and ecosystems [43]. From a coastal engineering point of view, sea-level change causes erosion and flooding problems. Therefore, analyzing and predicting the changes in sea-level are essential for the sustainable design and operation of coastal structures.

To estimate accurately SLR, scientists use and correlate various datasets such as tide gauges (TGs) data, and sea surface height (SSH) recorded from satellite altimetry. Thousands of TGs are located around the world and record data at a daily rate with some series dating back from the early 19th century. TG observations must be corrected for vertical land motion derived from GNSS data, to obtain an accurate estimate of absolute (geocentric) SLR without the bias of the local and/or regional geodynamical processes. However, the GNSS measured vertical land motions are likely not the same as the motion of the TG sensors which are usually attached to piers typically located on sediments. Various models have been developed to accurately estimate the rate and forecast it up to the next century, by correlating various observations and proxy data [44].

For example at the regional level, TG serve to estimate sea-level and record height with high-frequency (hourly) or low-frequency (semidiurnal and diurnal) measurements. These gauges can also record meteorological information with additional sensors such as air temperature, humidity, and air pressure on an hourly or daily basis. The scientific community

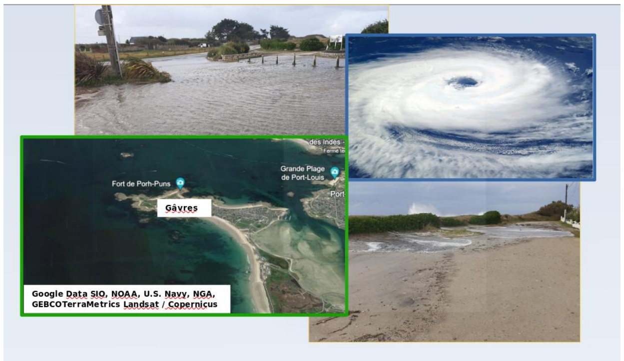


Fig. 4. Storm Ciarán whips western Europe, blowing record winds in France in November 2023, leaving millions without power. Local authorities closed forests, parks, beachfronts in some regions, and local trains were canceled. In this context, SLR is made a reality and the consequence on coastal areas is clearly visible as shown for the Gâvres peninsula in Brittany (France): Concrete dunes give way, flooding streets and houses by the sea. Mitigating strategies based on remote sensing Big Data using, e.g., ML techniques for the prediction of floods are to be developed urgently.

uses the harmonic analysis method to forecast changes in sea-level. This way, all tidal constituents are separated, which necessitates a time span of 18.6 years or longer of sea-level data. In addition, much longer periodicities up to six decades or longer exist in the ocean and elsewhere on Earth, as well as in other climatic variables including temperature and CO2. More accurate estimates of rapid sea-level rise (trend and acceleration) globally and at regional scale potentially remain illusive. An inadequate time span for sea-level measurements can lead to substantial errors and undermine the reliability of sea-level predictions. Thus, long-term sea-level data is mandatory for predictive research. Nevertheless, obtaining such data can be challenging due to the high cost of monitoring [45]. When extended sea-level measurements are unavailable, ML methods present a feasible alternative, as they necessitate shorter time periods. In recent years, numerous ML applications have emerged for predicting both short- and long-term sea-level changes using TG data. Researchers have explored the use of lagged sea-level measurements and meteorological factors for this purpose. Various studies have focused on sea-level prediction using lagged sea-level values: Makarynskyy et al. [46] devised an ANN model to forecast sea-level based on data from Hilary Harbor in Australia spanning from 1992 to 2002. Makarnynska and Makarynskyy [45] also utilized an ANN model with sea-level data collected from a tide gauge on the Australian Island of Cocos (Keeling) between 1992 and 1999. They developed historical sea-level values using a genetic programming (GP)-based model and the ANN model [46] as inputs.

Large-scale phenomena (e.g., SLR) can be continuously monitored and forecasted by combining Big Data. Current developments focus on algorithms to classify, analyze, model, and forecast the impact of these phenomena at specific locations which should speed up and help in the development of climate resilience strategies for adaptation and mitigation [47].

Note that tsunami warning systems (indirectly related to SLR at a much shorter time-scale) are another example of the importance of the computational time in correlating and analyzing various heterogeneous datasets, e.g., GNSS receiver installed on buoys together with pressure sensors and seismographs, to inform countries (or regions) and trigger a fast response when this geohazard is detected [48], [49]. Recent work uses the dense network of tsunami observing systems worldwide to provide a real-time tsunami inundation prediction based on ML algorithm [50].

III. Integrating Big Data and Satellite Gravimetry for Enhanced Hydrological Extremes Monitoring

In this section, we delve into the innovative fusion and processing of two distinct yet potent sources of information: Big Data analytics and satellite gravimetry. This allows us to discuss the current and emerging applications linked with hydrological extremes such as droughts and floods.

The techniques for monitoring soil moisture are undergoing rapid growth with the advent of new in situ and proximal sensors, new satellites (e.g., Soil Moisture Active Passive - SMAP- mission and the Soil Moisture and Ocean Salinity - SMOS) and other remote sensing technologies (e.g., Sentinel and LandSat), and enhanced modeling capabilities. This is leading to an increasing number of soil moisture data products in development, where these large datasets are being used for various applications including agricultural drought monitoring. Surface Soil Moisture (SSM) represents less than 0.001 % of the global freshwater budget by volume but plays an important role in the water, carbon, and energy cycles [51]. It is also essential for growing plants and agriculture, and can be used as indicator of diseases such as malaria [52]. SSM is also important for understanding the coupling of the continental surface and the atmosphere to improve rainfall estimations. Within the European Flood Awareness System (EFAS) framework, it is demonstrated that SSM can significantly enhance flood forecast accuracy by 5% to 10%, supplementing the utilization of discharge data [53].

To measure SSM globally, remote sensing instruments typically measure electromagnetic radiance emitted by the Earth surface or collect waveforms returned from radar pulses. However, the relationship between these measurements and the quantities of interest, such as SSM, can be complex. Therefore, various retrieval techniques have been developed, which work based on signal processing algorithms, statistical inversion, land surface modelling, and artificial neural networks [54], [55], [56], [57], [58]. The European Space Agency (ESA) Climate Change Initiative (CCI), supports SSM monitoring, by providing a climate data record of daily SSM estimates at a 0.25° resolution, which relies on: 1) a physical-based inversion scheme to retrieve SSM from passive MicroWave (MW), 2) a statistical retrieval for active MW, and 3) an *a posteriori* merging of these two products [59]. Ensemble learning and multiple input data are used, within a machine learning procedure, to produce global 1 km resolution daily SSM estimates [60].

Furthermore, since the launch of the Gravity Recovery And Climate Experiment (GRACE) satellite gravity mission in 2002, and its successor mission (GRACE-Followon, or -FO) in 2018, monitoring studies have been using its estimates of changes of Terrestrial Water Storage (TWS, a vertical integration of surface water, soil moisture, groundwater, water vapor and biomass water content) changes to understand global and regional hydrological processes [61]. GRACE/GRACE-FO products are provided after various processing algorithms, for example, the level 2 (L2) products are available in terms of the spherical harmonics potential coefficients. These time-variable fields, after a proper filtering (e.g., [62], [63]) and , destripping, geophysical corrections via forward modeling (glacial isostatic adjustment, geocenter, ellipsoidal corrections) (e.g., [64]) can be used to estimate level 3 (L3) TWS. Alternatively, mascon solutions are also available that provide GRACE data as regularized gridded TWS estimates [65], [66], [67].

Various studies have demonstrated the connection between the long-term trends or changes in the amplitude of seasonal (net) precipitation and TWS. Since GRACE TWS reflects both climate change and anthropogenic modifications impacts, it has an invaluable contribution in monitoring the water storage decline (mainly in groundwater) in transboundary river basins [68]. GRACE/GRACE-FO data are being used to study hydrological droughts. For example, [69] developed monthly global Drought Severity Index (DSI), Standardized Storage Index (SSI) and Multivariate Standardized Drought Index (MSDI) based on space-based TWS estimates and they showed their importance for identifying drought events globally, see also [70]. Today, the USA's drought monitoring system incorporated both GRACE and GRACE-FO TWS measurements for producing its continental SSI. Applications of GRACE and GRACE-FO for monitoring flood events are mostly restricted to mapping the flood potential areas. The limitation is mainly due to the coarse spatial resolution of TWS products and the latency in producing these fields. The relatively low spatial resolution of satellite data (e.g., few 100 km for GRACE/GRACE-FO, see Figure 5 (A), and few tens of km for SSM remote sensing) and inadequate representation of physical processes, related to e.g., evapo-transpiration (ET) or groundwater flows, in the Earth System models are among challenges that limit the accuracy of hydro-meteorological predictions.

To mitigate these issues, studies have incorporated in-situ observations and GRACE data in their hydrological models. For example, various works, e.g., [71], [72] used GNSS data to constrain and enhance the resolution of GRACE/GRACE-FO data resolution for specific areas or large aquifers. Some others developed a hydrological model specific to the area of investigation and correlated the data with the GRACE/GRACE-FO observations [73], [74]. The model-based Data Assimilation (DA, [75], [76], [77]), as well as simultaneous Calibration and Data Assimilation (C/DA, [78]) frameworks are developed to take advantage of model equations to downscale GRACE/GRACE-FO datasets, see Figure 5 (B). This is also beneficial for models because the TWS estimates of these missions reflect the water storage variability caused by the anthropogenic climate change [79], [80], thus, they can be used to constrain the water balance equation as new information [81]. Furthermore, data-driven approaches such as ML and more advanced DL techniques are being developed to (i) replace some model elements by satellite data [82], e.g. ET, SSM, and groundwater [83]; (ii) to downscale satellite data to be used for extracting information or constraining available models through, e.g., DA frameworks [84], [85], [86]; (iii) and a pure data-driven DL approach using satellite gravimetry, satellite laser ranging, hydrometeorological model outputs as learning datasets iteratively downscale TWS and groundwater storage (GWS) globally for water resources and climate-induced floods/droughts and cyclone-induced storm surges. The DL techniques for downscaling, e.g., [87], [88], [89], [90], [91] try to relate the smoothed GRACE/GRACE-FO signals to desired high-resolution fields, using training data, which can be those of available hydrological model outputs, forcing fields such as satellite-derived or reanalysis precipitation, evapotranspiration, and river discharge fields, along with auxiliary information such as high-resolution digital elevation fields to present the physical constraints. Figure 5 (C) provides a visual representation of this process. For example, [92] integrates GNSS coordinates and GRACE/GRACE-FO satellite gravimetry estimated TWS, demonstrating the generation of optimizes hydrological drought index with refined spatial scale which can better characterizes decadal drought episodes over Southwest China (2011-2020).

Tracking and monitoring water storage accurately by processing and correlating an enormous volume of satellite observation, along with in situ hydrological data (e.g. precipitation) is highly complex. Through the fusion of various dataset, and their processing with innovative approaches such as ML and DL algorithms, it is now possible to generate new set of data products that allow meteorological organizations and government authorities to detect and forecast floods and droughts worldwide. Similar benefits emerge when employing Big Data for monitoring climate variability, either at a local (cities) or global (solar system) level.

IV. Monitoring Climate Variability

This section first discusses the current and future applications of Big Data analysis within weather forecasting. We will focus on Urban Heat Islands (UHI), an extremely sensible topic regarding the rapid evolution of global temperature worldwide, particularly in big cities [93]. The second part is dedicated to Earth's climate simulations and the solar forcing.

1) Urban Heat Island: forecasting extreme weather events: The worldwide rise in temperatures is a matter of public concern, impacting not only human health but also our environment. The increase of geohazards such as hurricanes, twisters, heat waves, or sudden extreme precipitations (rain, snow...) will have a major impact on populations, local or regional economies [94]. A prominent example is the worldwide phenomenon of UHI. UHI refers to localized areas within cities and metropolitan regions where the temperature is consistently higher than the surrounding rural areas. In the late 60's, Tim Oke contributed toward a definition and an understanding of the processes responsible for the urban effect [95]. It was shown that various factors contribute to UHIs, e.g., (i) the

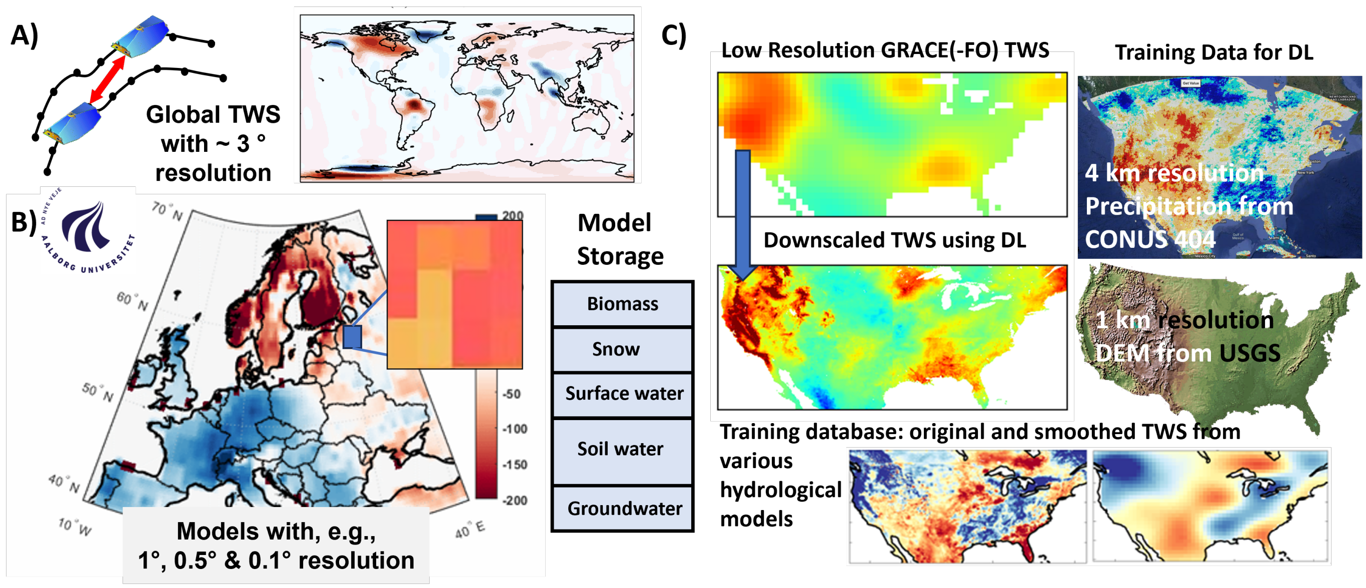


Fig. 5. An overview of the GRACE and GRACE-FO processing to enhance the spatial and vertical resolution. A) indicates a sample global TWS field of GRACE(-FO), where the spatial resolution is few 100 km. B) represents the DA and CDA methodology, where GRACE(-FO) data is integrated into models to vertically separate TWS and disaggregate them into finer grids. C) provides an overview of the data-driven techniques, where training data are used to downscale TWS observations.

replacement of natural vegetation with impervious surfaces such as asphalt and concrete which reduces the land's ability to absorb and dissipate heat. This phenomenon increases urban temperatures as a snowball effect [96], [97], (ii) anthropogenic heat coming from the concentration of human activities and infrastructure in urban areas (vehicles, industrial processes, and building energy consumption) [98], [99], [100] or (iii) dark-colored roofs and walls absorbing and re-radiating heat, which contributes to elevated temperatures [101], [102]. UHI not only affects human health [103], [104] but also the migratory patterns of birds and the growth of vegetation, leading to potential ecological imbalances [105]. Mitigation strategies need to be developed, as sustainable urban planning will decrease the energy consumption linked to UHIs [106], [107]. Effective approaches include the implementation of green roofs and cool roofing materials [108], [109]. Furthermore, integrating passive cooling systems and renewable energy systems into buildings has also been identified as a valuable strategy for reducing UHI intensity [110], [111], [112].

The majority of the aforementioned studies propose solutions to tackle the challenge of UHI by utilizing remote sensing, which includes the deployment of satellite, aerial, and ground-based sensors as valuable methods for quantifying UHIs, monitoring their spatiotemporal dynamics, and implementing targeted mitigation strategies. This includes: Satellite-based thermal infrared imaging, such as data from MODIS (Moderate Resolution Imaging Spectroradiometer) [105], [113], or Landsat [114], [115], [116] for monitoring over large urban areas. The various scales allow the global reach of the UHI phenomenon and also enable the identification of hotspots [117], [118]. Further sensors are, e.g., hyperspectral imaging from aerial and unmanned aerial vehicles which provide high-resolution spatial data revealing the influence of land cover patterns on UHI formation [119], [120]. Urban weather stations and sensor networks, can provide localized UHI monitoring and enable real-time insights into microclimates within cities [121], [122]. Such investigations necessitate critical spatial and temporal resolutions for predicting UHI in urban areas as shown for the city of Berlin in Germany in [123]. All these studies generate and utilize Big Data by integrating data from various sensors, as exemplified by [124], which employed multitemporal satellite data (Landsat thermal datasets, field data, and meteorological observations) to analyze UHI in Noida city, India.

Big Data can support data-driven urban planning by identifying areas with the most significant UHI intensity. However, the forecasting of local phenomena at small scales necessitates the processing, every day, of TB of information about the condition of the atmosphere and the oceans from all kinds of sources to provide accurate and reliable analysis. These raise two major questions (i) how to handle and store such an amount of data, and (ii) how to use modern techniques for processing them.

- How to handle data: Urban sensors collect massive dynamic, high-frequency, and multi-dimensional data. One of the main challenges is the management of data acquisition and storage as well as the processing of complex files saved with various formats. This includes database administration, allocation and management of machines, jobs, and job queues, and utilization of CPU, GPU. [122] addressed these challenges by utilizing cyberGIS-Jupyter for the city of Chicago, Illinois, enabling a seamless integration of advanced cyberinfrastructure, Geospatial Information Systems, and spatial analysis. [125] employed geospatial data analytics to assess UHI variations in New York City, aiding the city's "cool neighborhoods" program to target areas most in need of cooling interventions. [126] combined with short turnaround times satellite imagery, Earth observation data, and ML algorithms based on the Google Cloud computing platform.

- ML techniques: While traditional statistical methods, such as those based on the Pearson coefficient to identify relationships, are still employed for UHI analysis, an increasing number of scientists are turning to ML methods for processing and forecasting UHI, as noted in [124]. Fueled by Big Data, ML techniques can contribute to predicting UHI patterns with high accuracy. [127] used a feed-forward deep neural network architecture to predict UHI in Seoul (South Korea). [122] developed ML algorithms for UHI prediction with random forest regression to predict UHI in Chicago. [128] used ML models and meteorological data to forecast UHI intensity in Singapore, enabling timely interventions and resource allocation. Correlation and regression methods utilized in [129] facilitated an understanding of the relationship between biophysical composition and the UHI effect in Jeddah, Saudi Arabia. Additionally, in [130], air temperature was downscaled from 1 km to 250 m for high-resolution atmospheric UHI analysis. This was achieved by establishing a regression model between urban structure and temperature with the aim of predicting high-resolution temperature data.
- Simulations: Apart from data-driven methods, computer simulation programs such as UMEP-SOLWEIGH10, ENVI-MET11 or PALM can be used to model UHI behavior based on concepts from the turbulence theory. Many works have been done to democratize such techniques and decrease the necessity to have expert knowledge. They are crucial to understanding the underlying physical processes and improving weather forecast model parametrization but also for sensitivity analysis to identify several competing physical processes from the UHI effect. [131] investigate the interaction between the UHI circulation and the sea breeze circulation in an idealized city using simulation. [132] combined observational and modeling analyzes with Large Eddy Simulation (LES) to identify synergies between UHIs and heat waves, a still unanswered question. [133] used the mesoscale weather research and forecasting model to identify the UHI effect induced by the urbanization of the megacity Beijing.
  Simulations can come into support of data-driven models that necessitate sensors deployed and continuously displaying UHI levels at a given time based on prevailing environmental conditions and without human intervention. The obtained refinement using simulations such as LES can illustrate how mitigation strategies would impact urban comfort, as discussed in [134]. The combinations will further allow predicting local extreme meteorological events more accurately [135].

Note on forecasting and nowcasting in weather research:

in [138], the discussion centers on how Big Data analytics can enhance the accuracy of weather forecasts through the analysis of substantial volumes of weather data. Addressing UHI nowcasting specifically, [139] put forth a promising online system for nowcasting satellite-derived temperatures in major cities. This system aims to facilitate real-time forecasting of UHI as well as timely predictions of energy demand and the potential impact on human health.

Fig. 6. The development of turbulence structures induced by a densely built-up artificial island off the coast of Macau affects the urban climate in the city itself. The intensity of turbulence is visualized by the rotation of the velocity vector (absolute values), with the highest values in red and the lowest values in white. Buildings are displayed in blue. Especially in Macau's humid subtropical climate natural ventilation should be used to decrease thermal stress [136]. Such simulations with LES using PALM [137] can help city planners mitigate the impact of new buildings. The simulation required 1 hour of CPU time using 128 cores on the Cray-XC30 of the North-German Supercomputing Alliance.

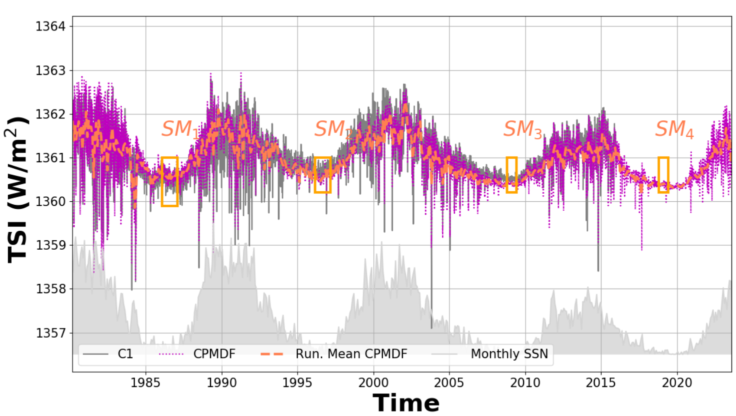
Collaborative efforts among researchers, urban planners, and data scientists are essential for the successful implementation of data-driven UHI mitigation strategies [140]. Big Data presents a transformative opportunity in the mitigation of UHI and enables more comprehensive monitoring as well as informed decision-making [141], contributing to more sustainable and resilient urban environments.

2) Earth's climate simulations and solar forcing models: The Earth climate is determined by the energy that enters and leaves the Earth's system at the top of the atmosphere (ToA). Natural and anthropogenic forcing mechanisms influence this ToA radiative balance. While e.g., solar variability and volcanic eruptions are natural drivers, the emission of greenhouse gases from fossil fuel burning and change of land use, amongst others, are man-made [142]. Compared to recent anthropogenic influences, the effect of solar variation is small [143], [142].

However, modelling studies suggest that variations on timescales, such as the 90-year Gleissberg cycle [144], and up to millennial timescales [145] influence the climate through modification of the hydrological cycle [146], [147], [148], ocean circulation [149], and radiative forcing [150], [151]. Moreover, there is evidence for a surface response on regional scales to solar cycle variability [152], though the magnitude, spatial extent, and robustness of the signal are still under consideration.

Global temperature and total solar irradiance (TSI) are linked by the energy equilibrium equation (i.e., Earth energy budget) for the Earth system, see e.g., [153]. Therefore, both the spectrally-integrated irradiance, TSI, as well as the spectrally resolved solar irradiance, SSI, arriving at the top of the atmosphere need to be observed with high precision and accuracy to understand both the energy balance of the Earth's climate system and the impact of these irradiance variations on decadal and centennial timescales. These timescales are essential to understand the relative contribution of solar variability (i.e., the solar forcing mechanisms, e.g., [154]) to global climate change, including recent estimates of anthropogenic, and future, climate change. TSI observations have been recorded by various satellite missions since 1978. As all space instruments have finite lifetimes and space observations therefore cover limited time intervals, constructing composites is a key aspect of the investigation of TSI over several decades. Merging all available observations is a difficult exercise encompassing both scientific and statistical hurdles [155]. Several authors [156], [157], [158] produced TSI composite time series by daisy chaining all the available TSI observations, but without including any models of the stochastic noise properties. The first methodology which relied on some knowledge of the underlining noise characteristics was developed by [159] and [155] including a data-driven noise model and a multiscale decomposition, and later also applied to spectral irradiance by [160]. Recently, [161] developed a methodology to further advance the data-driven approach first adopted by [155] based on data fusion, including a stochastic noise model to take into account short and long-term correlations in the observations. Figure 7) displays two composite time series: the PMOD/WRC composite (CPMDF [161]) and the so-called "community consensus" time series [155]. These composite time series are

Fig. 7. PMOD/WRC composite (*CPMDF*, purple) based on merging 41 years of TSI measurements. For comparison, we display another composite the *C1* [155] (grey line). A 30-day running mean of *CPMDF* is shown as a orange dashed line. The orange boxes are associated with the solar minima (SM) for each solar cycle described in [161]. For context, the monthly sunspot number is also displayed.



crucial for constraining the solar forcing datasets used in the Earth's climate simulations [162]. Furthermore, various TSI reconstructions to the past, e.g., [163], [164], [165], [166], which are all based on different assumptions are available for the climate modelling community to study the influence of different scenarios of solar variability on the Earth's climate. For comprehensive studies, such as the 6th Climate Model Intercomparison project (CMIP6), a recommended solar forcing dataset [167] was made available to the climate modelling community. For the upcoming CMIP7 an updated solar forcing dataset is currently in preparation [168]. For future climate projections, it is essential to have a robust future scenario of solar irradiance available. Forecasting solar variability is challenging due to the complex nature of the Sun. Traditional methods, such as empirical models [169], have been employed to predict solar forcing. Nevertheless, these approaches often have limitations in accurately capturing the intricate dynamics of the Sun. In recent years, new algorithms based on ML have been developed that combine computational models and algorithms to automatically learn patterns and make predictions from data. These new approaches have shown promise in capturing the complex relationships between solar parameters and predicting solar activity [170]. Various scenarios of the past [171] and future solar forcing [167] are based on different assumptions as to how (proxy) data from various observations could be used to model solar variability and ultimately study the influence of solar activity on climate. These scenarios take into account (i) the forecast of solar activity (up to 2100 and beyond) and (ii) the reconstruction of past solar activity up to several centuries or beyond (depending on the type of proxy data used). There is now a large amount of climate simulation data available using different scenarios of solar forcing as part of specific intercomparison campaigns (see e.g., CMIP6). All these simulations and datasets offer new opportunities for expanding our knowledge of the Earth system. By training ML models on historical solar data and corresponding climate records, these algorithms have the potential to improve our understanding of solar forcing and its relationship with Earth's climate, contributing to more accurate climate predictions and extracting new non-linear relations and patterns [172].

V. Discussion on Climate Change Research Through Big Data Insights

This section highlights the timeliness and significance of the proposed theme through an analysis of editorial statistics, such as the number of recently published publications and interconnections with various sub-themes. The second part engages in a discussion on the ongoing trends and challenges linked to Big Data and climate change.

A. Analysing Editorial Themes and Contributions: A Statistical Overview of Climate Change Studies

To conduct an editorial analysis emphasizing the significance of Big Data analysis in geosciences and space sciences, we examined the literature, comprising 76,646 papers published in the last 20 years. The analysis was based on 8 selected keywords relevant to this review (i.e., Climate change, Big Data, Machine learning, Deep learning, Environmental monitoring, Earth system, natural phenomena, sea-level change), utilizing the Web of Science core library.

Figure 8 shows the statistics based on the literature published the past two decades. Figure 8a and Figure 8b display the distribution of the top 15 most cited authors together with the geolocation of their affiliation and the 15 most cited scientific journals with the number of published articles and the associated citations respectively. Figure 8c is a visualization of the co-occurrence keywords retrieved from the selected references analyzed by the VOSviewer software [173]. Co-occurrence analysis is a commonly used method in text mining and topic modeling. The principle of this analysis is to extract keywords and analyze the connections between them based on their co-occurrence frequency. One can then identify various clusters and their interconnection. In Figure 8c, we observe two main ones ”climate change” and ”machine-learning”. Various interconnections emerge across different sub-themes (e.g., artificial intelligence, SLR). By conducting this literature analysis, we integrate a quantitative assessment of both the research theme and study area. This dual verification method traces the evolution of the field in terms of published topics. This vast literature and the interconnection between the sub-themes underline the research activity over the past two decades. Note that using too many keywords degrades the clarity of the co-occurrence figures. Our interest lies in visualizing the graphical interconnections between Big Data, algorithms (ML, DL), natural phenomena (geohazards, landslides), and climate change. This led us to narrow our search to these specific keywords, allowing us to scrutinize and analyze the intricate relationships within this focused domain.

B. Chasing Climate Clues through Big Data: Current & Emerging Trends and Ongoing Challenges

The recent advances in Big Data include the integration of multiple sensors into unified platforms, enabling the simultaneous collection of diverse datasets. A significant number of specific scientific programs have been launched the past decade in order to implement such unified platforms. For example, the Global Earth Observation System of Systems (GEOSS) is a global network of content providers allowing decision-makers to access a wide range of data and information [174].

The NASA's Earth Science Data Systems program oversees the life cycle of NASA's Earth science data—from acquisition through processing and distribution of the observations (see URL). Within this framework and through the ACCESS programs, technologies are developed and implemented to efficiently manage, discover, and leverage NASA's repository of Earth observations for scientific research and practical applications. In particular, the project Radiant Earth which has created an open-access repository for Earth observation training data and machine learning models as part of the ACCESS-19 project, or the Cloud-based Data Match-Up Service (CDMS) project, which offers users a platform to input geospatial and temporal references for satellite observations, enabling them to receive matched in situ or satellite observations within customizable temporal and spatial search parameters. In China, the Big Earth Data Science Engineering Program (CASEarth) was officially launched in 2018 by the Chinese academy of sciences with the goal to construct an advanced Big Earth Data infrastructure to address issues concerning data access, sharing, and the seamless integration of dispersed data, models, and services. This infrastructure was targeted to create a cutting-edge Big Earth Data platform to stimulate research and innovation, facilitating the exploration of novel paradigms in big data-driven, multidisciplinary, collaborative scientific discovery (see URL). The German Aerospace Center DLR created the “terrabyte” platform (see URL), an innovative High Performance Data Analytics platform operated by the DLR and the Leibniz Supercomputing Center to provide scientists with efficient access to Earth Observation (EO) data, a high-performance processing environment, and practical tools for data analysis. The Centre National d'Etudes Spatiales (CNES), the government agency responsible for shaping and implementing France's space policy in Europe, is partner of Data Terra and relies on the infrastructure's data and services centres to process, archive and disseminate science products derived from its Earth-observing missions. More specifically, Data Terra facilitates the collection of data from the European Copernicus program, including its basic services and Data and information access services promoting solutions with Copernicus data. Additionally, Data Terra hosts the DINAMIS portal, providing convenient access to satellite data from private entities, primarily Airbus, for scientists and institutions (see URL).

ESA has created several flagships programs (managed by the phi-lab) that are expected to deliver huge changes in the way Earth observations will impact our society and technology. In particular, the AI for EO (AI4EO) focuses on harnessing the power of Artificial Intelligence (i.e. promoting the implementation of ML and DL algorithms) with the vast amount of EO data now available. Similarly, Destination Earth, an initiative by the European Commission, aims to create a sophisticated AI-driven decision support system which will rely on a highly precise digital model of the Earth (i.e. digital twin Earth) to monitor and simulate both natural phenomena and human activity. The goal is to develop and evaluate scenarios that promote sustainable development and provide support for European environmental policies. Past and actual projects of the ESA on Earth observation can be found on URL.

It is also worth noting the number of large grants funded the past 5 years by the European union under the European Council scheme (ERC). More than 262 proposals were founded in the ‘Earth System Science’ panel for a total of nearly 550 millions of euros within the period 2014-2020. We cite exemplary the BigEarth project which aims to develop highly innovative feature extraction and content based retrieval methods and tools for remote sensing images or So2Sat which targeted the use of Big Data for 4D Global Urban Mapping combining social media information and EO. Within the framework of this project a contribution of the DL algorithms in remote sensing applications was published in [175] to promote remote-sensing scientists and to leverage their expertise in deep learning, harnessing it as a powerful general model to address unprecedented, large-scale challenges like climate change and urbanization.

The integration of multi-satellite datasets not only provides a comprehensive view of environmental changes over time but also contributes to improved accuracy and reliability in forecasting and predictive modeling. The advent of the IoT has

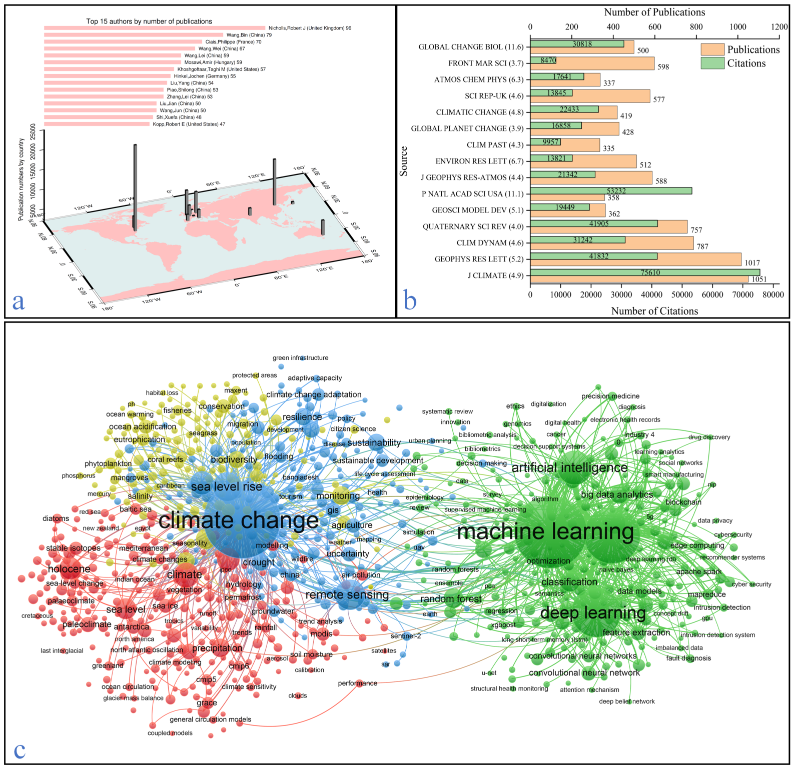


Fig. 8. Analysis of the literature published between 2003 and 2023 using 76,646 papers (journal articles and review studies). A) statistical results of the top 15 authors with the number of published papers and their country distribution. B) The number of published papers ranked $TOP15$ journals and the related number of citations. C) Keyword clustering network. The network only shows keywords that have co-occurred more than 120 times.

opened up new possibilities for real-time data collection and analysis through sensor networks. Within the geosciences, researchers are deploying IoT-based systems comprising weather stations, seismic sensors, groundwater monitors, and an assortment of other sensors [176], [177]. By interconnecting these devices, scientists can seamlessly gather and analyze data from multiple sources, enabling them to observe trends and patterns that were previously elusive. This interconnectedness further facilitates a deeper understanding of the interdependencies among various environmental factors and their implications for Earth's systems.

Moreover, forecasting research has revolved around the use of stochastic models, such as the autoregressive integrated moving average model, which can understand seasonality and lags in time series [178]. Dealing with nonlinear phenomena, recent studies have shown that data-driven models (e.g., ANNs) are more effective tools for making predictions in the short and long term. However, the next step is to process and correlate large amounts of data. ML (and DL) has the characteristics of non-linearity, high estimation accuracy, and high generalization ability, which can effectively handle this processing [179]. It is noteworthy that certain areas, like geophysics, have not experienced significant benefits from expansive datasets until now.

As highlighted through the various examples, addressing complex phenomena like global warming presents numerous challenges across different spatial and temporal scales. Coping with the substantial influx of data generated by instruments designed to observe, model, and comprehend these phenomena necessitates placing ML and DL algorithms at the forefront. This strategic integration can significantly accelerate the development of both present and forthcoming solutions in today's climate crisis [180]. Managing the Earth's natural resources and systems together with mitigating the impact of the (global) population growth will require the efficient use in near real-time of all these large datasets to create a harmonious system that works consistently for the betterment of the entire ecosystem and detect (adjust) to the current and future changes in the Earth System.

VI. Conclusions

This review highlights the pivotal role of Big Data and advanced analytics in addressing the multifaceted challenges of climate change. Our examples span from SLR investigations to solar forcing analysis and UHI mitigation. Our work focuses on two main axis: the current status of Big Data integration within the context of climate change and how the different scales can improve our understanding to enhance our forecast ability for critical decisions. We emphasize that the integration of remote sensing and in situ instruments has led to an unprecedented production of Big Datasets, demanding innovative methods for processing and analysis. Efficient computational processes, particularly in geohazard warning systems, are essential for promptly initiating emergency responses, as exemplified by various instances of landslides. As an example, the utilization of permanent laser scanning goes beyond offering insights into landslides and rockfalls. Through the development of ML-based algorithms and specific classification tasks for recognizing change patterns, it facilitates timely assessments of mine sites. This capability remains effective even in challenging operational environments.

Examining the current trends and challenges, we observe the integration of multiple sensors through platforms and programs like the GEOSS and the NASA's Earth Science Data Systems, enhancing data collection and forecasting accuracy. In addition, the IoT's role in real-time data collection, coupled with the integration of multi-satellite datasets, contributes to a comprehensive understanding of environmental changes. Shifting from stochastic models to data-driven models, such as ML and DL, is essential in tackling non-linear phenomena like global warming. These approaches showcase high accuracy in processing and correlating large datasets, offering potential benefits to fields like geophysics, which have traditionally not benefited significantly from expansive datasets.

This review further underscores the urgency of leveraging Big data, ML, and DL in climate change research. This can be expressed via the large number of substantial grants funded the past 5 years by the European union under the ERC in the past decade to address this urgency. The strategic integration of these technologies can accelerate the development of effective solutions to the current climate crisis and its impact on humanity. For instance, ML is anticipated to revolutionize our approach to mitigating the UHI effect, which poses a growing threat to human health. Big Data, whether derived from diverse measurements or extensive simulations, will facilitate the development of novel strategies for optimizing real-time extreme event prediction (nowcasting). While the incorporation of DL into environmental remote sensing holds promise, it is not without its hurdles. Data scarcity, particularly in certain regions or environmental scenarios, has the potential to impede the performance of models. Labeling extensive remote sensing datasets can be a time-intensive process susceptible to errors. The interpretability should be ensured through a robust uncertainty analysis for better acceptance.

In conclusion, the interconnectedness of environmental factors, coupled with the efficiency of ML or DL algorithms, offers a pathway to effectively manage Earth's resources and mitigate the impact of climate change, fostering a harmonious system for the betterment of humanity and the entire planet.

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