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Houston, we have a problem: Can satellite information bridge the climate-related data gap?

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Abstract

Central banks and international supervisors have identified the difficulty of obtaining climate information as one of the key obstacles impeding the development of green financial products and markets. To bridge this data gap, the utilization of satellite information from Earth Observation (EO) systems may be necessary. To better understand this process, we analyze the potential of applying satellite data to green finance. First, we summarize the policy debate from a central banking perspective. We then briefly describe the main challenges for economists in dealing with the EO data format and quantitative methodologies for measuring its economic materiality. Finally, using topic modeling, we perform a systematic literature review of recent academic studies to uncover in which research areas satellite data is currently being used in green finance. We find the following topics: physical risk materialization (including both acute and chronic risk), deforestation, energy and emissions, agricultural risk and land use and land cover. We conclude providing a comprehensive analysis on the financial materiality of this alternative source of data, mapping these application domains with new green financial instruments and markets under development, such as thematic bonds or carbon credits, as well as some key considerations for policy discussion.

Keywords: satellite data; sensors; green finance; central banking

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1 Introduction

Since the publication of the initial report from the Network for Greening the Financial System (NGFS, 2019), there is consensus among central banks and international supervisors that closing existing data gaps and obtaining reliable data is crucial to analyze climate-related risks and opportunities. Although much effort has been made in this direction, as evidenced by, for example, the improvement in climate-related corporate disclosures (Bommel, Rasche, and Spicer, 2023; Diwan and Amarayil Sreeraman, 2023; Singhania and Saini, 2023), the need for better climate-related data remains true today. This is illustrated, for instance, by the recent publication by the European Central Bank (ECB) of a new set of experimental climate-related statistical indicators to narrow the climate data gap (ECB, 2023), or the recent effort from the International Monetary Fund (IMF) to strengthen its climate information architecture (Ferreira, Rozumek, Singh, and Suntheim, 2021).

In the financial system, it is noteworthy that the challenge of collecting and maintaining high-quality, granular climate data involves not only financial institutions, but also central banks, which are consequently increasing efforts to integrate sustainability and climate-related considerations into their operations (Delgado, 2023; Dikau and Volz, 2021; Durrani, Rosmin, and Volz, 2020; Volz, 2017). This includes investment decisions (BdE, 2023; Bundesbank, 2023; ECB, 2021b; NGFS, 2019), monetary policy tools (ECB, 2021a), financial stability assessments through climate stress tests (Acharya et al., 2023; Alogoskoufis et al., 2021; Battiston, Mandel, Monasterolo, Schütze, and Visentin, 2017; European Central Bank, 2022), and the supervision of financial institutions (ECB, 2022; Heynen, 2022; Kedward, Ryan-Collins, and Chenet, 2023).

As pointed out by NGFS (2022), however, gaps in climate-related data encompass three dimensions: availability (e.g., coverage, granularity, and accessibility), reliability (e.g., quality, auditability, and transparency) and comparability (as there is not yet a unique official reporting standard).[1] In some instances, relevant ground-based datasets are not available.[2] In other cases, the data exists but lacks the appropriate granularity, cannot be verified, or is of poor quality. Finally, in some cases, the available data sources are incomparable or inconsistent. Beyond data needs and gaps, climate-related data sources that do exist are underexploited by finance professionals. This can occur for a number of reasons: The specific data formats might not be immediately tractable for economic modeling, as it might require expert domain of its parametrization, complex pre-processing pipelines to generate interpretable information, or it might simply not be widely known enough.

Satellite data is a potential candidate to help alleviate these challenges. Satellite data sources, also referred to as Earth Observation (EO) systems, could significantly narrow existing data gaps: This data source, collected by satellites orbiting Earth, is highly granular and has an important spatial component. As some satellites are able to capture high-resolution images with resolutions as little as 30 by 30 meters, they can provide consistent, objective, and close to real-time information – all while covering virtually the entire world. These unique characteristics of satellite data address common issues of using official (administrative) statistics for climate finance, such as publication time lags, data quality issues (especially in Global South economies), and the spatial heterogeneity

1 Though, notably international organizations like the International Financial Reporting Standards (IFRS) and the European Financial Reporting Advisory (EFRAG) are working on it thoroughly, e.g.: IFRS (2024) or EFRAG (2024).
2 Ground-based data refers to data not collected remotely, e.g., by sensors or satellites.

of the real effects of climate change.[3)]

The information contained in satellite data can be used to measure different features of the Earth's surface or atmosphere, such as temperature, terrain, or pollutants, which in turn could be helpful to build indicators for environmental health, land use, deforestation rates, and more. The recent and widespread availability of this (largely free) data source opens unique pathways for researchers and practitioners to track economically relevant activity.[4)]

In the context of economic modeling for developing economies, remotely sensed data has been used for quite some time.[5)] In the context green finance, however, its use began in the insurance market, where it has been suggested and, in some instances, successfully implemented as a productive tool for claims settlement or risk estimation (Nagendra, Narayanamurthy, and Moser, 2022; Nagendra, Narayanamurthy, Moser, Hartmann, and Sengupta, 2022; Stigler and Lobell, 2020).

In new domains of sustainability and green finance, the application of satellite data and remote sensing expands far beyond traditional use cases like catastrophes' insurance. Simultaneously, however, satellite data has its limitations, all of which pose significant barriers to entry for newcomers to the field. For instance, the databases with the highest-resolution images tend to be private, the matching to external data sources is complicated, it might be difficult to track long periods of time.

Blindly using more data – even if it has high quality and/or granularity – is not in itself sufficient to conduct robust climate risk analyses (WWF, 2023). Notably, this requires an investment with a considerable upfront cost, including the acquisition of new information technology resources and training employees with multidisciplinary skill sets, in order to be able to shift international capital flows towards more environmental friendly objectives (Elderson, 2023). All in all, a sound understanding of how to integrate climate-related information with financial asset-level data is imperative. This general notion is acknowledged by the principle of double materiality, which describes the two reciprocal facets of climate change (Gourdel, Monasterolo, Dunz, Mazzocchetti, and Parisi, 2022): the materiality, or impact, of economic activity on the environment on the one hand, and how the materialization of climate change affects businesses' financial well-being on the other hand.[6)]

The establishment of the Innovation Hub of the Bank of International Settlements in 2019 (BISIH)

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3 We will discuss spatial heterogeneity in more detail later on. At this point, we are referring to the fact that the effects of catastrophic climate events are not spatially or geographically homogeneous. The Global South suffers much stronger adverse effects than the North, and even within continents, countries, or counties, transition and physical risks as well as repercussions are different. Depending on the level of granularity of the official statistic in question, these heterogeneities cannot be captured by administrative datasets and the associated common modeling techniques, such as spatially invariant regressions.

4 See for instance private sector initiatives like Planet Labs (https://www.planet.com/), DrivenData Labs (https://drivendata.co/), or GMV (https://www.gmv.com/es-es/sectores/espacio).

5 See, e.g., Rangel-Gonzalez and Llamosas-Rosas (2019) or Beyer, Hu, and Yao (2022).

6 To comprehend the financial materiality of a climate event, it is crucial to convert an environmental measure (e.g., droughts, forest area coverage, greenhouse gas emissions) into an economic indicator (e.g., employment rates, inflation rates, industrial production growth, see Gratcheva et al., 2021), and consequently its impact on corporates and financial institutions performance. This requires appropriate data modeling techniques which are capable of illustrating complex environmental-financial relationships. Examples include causal machine learning techniques (Giannarakis, Sitokonstantinou, Lorilla, and Kontoes, 2022; Iglesias-Suarez et al., 2024), which enable the identification and analysis of cause-effect relationships between climate variables and economic outcomes, and other econometric approaches which facilitate understanding the immediate response of economic variables to climate shocks (such as the Local Projections Method, see Jordà, 2005).

showcases how important data quality and availability – as well as the technology required to analyze it – are for green finance in central banking. While not being the sole priority area, since the inception of this joint initiative led by the international community of central banks, green finance has been at its core. The goal of this collaborative platform is to exchange knowledge between its members and experiment using different technologies, such as Natural Language Processing (NLP) or blockchain, to help solve current issues in (sustainable) finance.[7)] In this respect, the BISIN working group on green finance identifies satellite data as one the main technologies which could assist both scaling up the availability of climate-related data and assessing its environmental materiality, which in turn could enable the creation of digital measurement, reporting and verification (MRV) systems, for instance (BISIN, 2023).[8)]

Therefore, we aim to investigate the potential of satellite data for green finance. To this end, Section 2 provides background information on financial innovation and bridging sustainability data gaps at the policy level. In Section 3, we introduce the main characteristics of satellite data formats and the limitations of satellite data, and we discuss the main econometric modeling challenges. We devote Section 4 to a survey of the academic literature on satellite data for different applications in economics and finance, such as development economics or quantitative trading strategoes. Herein, we identify a gap in the prior literature on green finance. Based on this finding, our main contribution will be presented in Section 5, where we use NLP techniques to uncover new domains of satellite data application for sustainable finance. We do so in collecting and sorting a large set of over 17,000 scientific sources in a semi-automated fashion. Based on a final sample of over 200 *relevant* sources, we use topic modeling analysis to uncover the specific domains of (sustainable) finance and economics where satellite data has been explored to date. Finally, we provide concluding remarks including our assessment of why this time (i.e., the case of green finance) might be different for the successful and productive use of the potential offered by satellite data in Section 6.

2 The role of technology to bridge climate data gaps

Central banks and international financial authorities are faced with the question of the role they can play in improving the availability, reliability and comparability of climate-related data. A survey conducted by the Irving Fisher Committee (IFC) on Central Bank Statistics found that central banks are increasingly focusing on climate-related data in particular, but also sustainable finance data issues as a whole, pointing to the following main recommendations for central banks (IFC, 2021):

1. One prerequisite for sustainable finance is to identify the data needed by central banks to support their policy objectives in order to fulfill their mandates at both the micro- and macroprudential levels.
2. Given the novelty of the subject, central banks should cooperate with traditional and new stakeholders to close data gaps, dealing with new environmental information providers; and

7 For instance, the Eurosystem Center of the BISIH is exploring the use of Large Language Models (LLMs) to automate the collection and management of climate-related information from corporates at scale with Project Gaia (https://www.bis.org/about/bisih/topics/suptech_regtech/gaia.htm), while the Hong Kong Center has finalized Project Genesis 1.0 (https://www.bis.org/about/bisih/topics/green_finance/green_bonds.htm) and 2.0 (https://www.bis.org/about/bisih/topics/green_finance/genesis_2.htm), which aim to help gauge how distributed ledger technologies (DLT) could aid the development of digital green bonds. Meanwhile, the Singapore Center has conducted Project Viridis, a digital dashboard which tracks the exposure of banks to extreme weather events (https://www.bis.org/about/bisih/topics/green_finance/viridis.htm).
8 The BIS created the Innovation Network in 2021 to track technological trends and developments with relevance to the thematic areas of the BISIH (for more information, visit https://www.bis.org/about/bisih/network.htm?m=273).

working on acquiring new skillsets at working staff level, either through dedicated training or inter-disciplinary hiring.
3. In addition, central banks should lead by example in that they improve the usage of the new data being collected.

As pointed out by the IFC Bulletin "*Post-pandemic landscape for central bank statistics*", the statistical sources and tools have to be continuously refined to match the landscape of ever-evolving challenges (IFC, 2023). Furthermore, the IFC stresses that the quantity and quality of sustainable finance data need to be increased to assess climate-related risks in the financial sector and monitor the green transition.

To narrow the existing climate data gap and fulfill the commitments of its climate action plan, the European Central Bank (ECB) has published a first set of climate-related statistical indicators (ECB, 2023).

However, these indicators are experimental. As such, they comply with many, but not all of the quality requirements of official ECB statistics. The three main areas covered are: an overview of green debt products, analytical indicators of carbon emissions financed by financial institutions, and indicators on the impact of physical risk events, such as the impact of natural hazards (e.g., floods, wildfires, or storms) on investment portfolios. Nevertheless, this factual information is not sufficient to enable forward-looking analysis of climate-related risks. Also, to ensure that these indicators are accessible and replicable, the authors use existing data from the European System of Central Banks (ESCB) or other publicly available data where possible. Another example in the field of natural capital and ecosystems is the work of Giglio, Kuchler, Stroebel, and Zeng (2023), who aim to measure biodiversity risk exposure using a novel set of information. However, all of the proposed metrics are collected from company disclosures or opinions elicited from professionals. Both of these examples demonstrate how the inherent challenges of using novel data sources can be exacerbated by regulatory requirements which impede the speedy adoption of new environmental data types and sources for the green transition.

More recent work postulates that the path towards more and better climate-related information underpins technological innovation (Ofodile et al., 2024). Going forward, it is likely that central bank statistics need to rely heavily on the use of data science techniques to perform their traditional tasks and adhere to their missions. Therein, they would have to acknowledge that – while largely unparalleled in terms of quality – ground-based (administrative) datasets might not be suitable, or enough, to gain scalability in many types of sustainable finance applications. Consider this example: One company may have hundreds of assets connected to tens of thousands of sites through global supply chain processes. Therefore, in the absence of prohibitively costly ground-based data collection methods, actors might decide to turn to geospatial or remotely sensed alternatives for insights at scale (WWF, 2023).

Among geospatial data sources, we particularly focus on the use of Earth Observation (EO) systems, leaving out of this study uses of satellite information for astronomical purposes, navigation or communications. Indeed, we define EO systems as data collected by satellites which orbit the Earth, including both land imagery and sensor data, such as greenhouse gas (GHG) emissions or heat loss. This type of data adds a new layer of valuable information for economists and financial analysts by including geolocated observations at a neutral stance. Therefore, the data is also reliable and objective. Importantly, the use of satellite data for official statistics is subject to some limitations which need to be considered. E.g.: we discuss the format of satellite data and its limitations in more detail in Section 3.

3 What is satellite data

The data collected by satellites from outer space varies depending on its orbital altitude, which influences both coverage area and travel speed. Typically, satellites are classified into four main types according to their function: Communication, Earth Observation, Navigation, and Astronomical. In this paper, our focus is primarily on Earth Observation satellites. These can be further divided into categories such as Weather satellites, which are crucial for monitoring and forecasting weather patterns, and providing up-to-date meteorological data. Another category, known as Remote Sensing satellites, is vital for environmental monitoring and geographic mapping. Notably, three outstanding primary sources for medium resolution imagery, which are available for public use, are Landsat data from the USGS Earth Explorer, Sentinel data from the Copernicus Open Access Hub, and MODIS data from the NASA Earth Data website.

Furthermore, a single satellite can have multiple instruments, and each instrument can have multiple sensors. Each sensor can detect light in one or more spectral bands, i.e., specific ranges of wavelengths of light, at one or more levels of spatial resolution. This means that one pixel corresponds to some geographic area at units such as "meters per pixel". Complete images have a total size which is often referred to as a frame.

Finally, satellite instruments can be passive, meaning that they simply collect the photons radiating from the Earth or bouncing off it from the Sun; or active, meaning that they send some form of signal down to the Earth's surface or atmosphere and measure how it is reflected back. Active sensors help overcome certain limitations of passive sensors because they can penetrate clouds and capture images at night.

The information thus captured by satellites can be used to measure different features of the Earth's surface or atmosphere, such as temperature, terrain, or pollutants. Signals from sensors can be combined to form a wide variety of images, from (i) "natural color" images, resembling what we humans might see if we were in orbit, to (ii) false-color images, which either show light we cannot perceive or enhance certain types of features, to (iii) videos, even. In Box 1, we explain how meaningful metrics can be obtained from this information. In the example cases shown in Box 1, the parameters can be used to measure the impact of economic activity on the ecosystem with the Normalized Difference Vegetation Index (NDVI), inspect wildfires using the Normalized Burn Ratio (NBR), or assess water scarcity with the Normalized Difference Water Index (NDWI).

The recent and widespread availability of this data source opens unique pathways for researchers and practitioners to track economically relevant activity. As seen in Box 1, metrics derived from satellite data allow us to estimate indicators on environmental health, land use, and deforestation rates in a consistent and objective fashion, in real-time, and with coverage of virtually the entire world. These unique traits hold enormous potential for economics and finance, as we show in the large-scale literature review (Sections 4 and 5).

Notably, these unique opportunities are mirrored by unique challenges not only in terms of data access, cleaning, and pre-processing, but also econometric modeling. When acquired by satellite sensors and downloaded to ground stations, data is in raw format. Most use cases will, however, require different treatments of this raw EO data to ensure its interpretability. To evaluate the potential of EO data for sustainable finance, we identify and discuss data formats and (econometric) modeling as the two major challenges to its economic materiality.

Understanding Satellite Color Bands and building metrics

Landsat collects 8 color bands:

- **B1 captures deep blue and violet light.**
  Useful for identifying aerosol particles which scatter short wavelengths like deep blue and violet.
- **B2 Captures blue light.**
  Helps differentiate between water bodies, as water reflects blue light more effectively.
- **B3 Captures green light.**
  Green light is strongly reflected by healthy vegetation, aiding in its assessment.
- **B4 Captures red light.**
  Essential for identifying plant types and assessing their health.
- **B5 Captures near-infrared light.**
  Biomass content: Indicates the health and density of plants.
- **B6 Captures shortwave infrared light (SWIR 1).**
  Useful for differentiating moisture levels in soil and vegetation.
- **B7 Captures shortwave infrared light (SWIR 2).**
  Maps geological features and vegetation through vapor penetration for clearer images.
- **B8 Captures panchromatic light.**
  Offers a broad wavelength range for detailed landscape imagery.

Each pixel of the image holds a value for each band. These values can be combined to create detailed layers depicting various features such as vegetated areas, burned areas, water extents, and urban zones. Some examples of metrics we can build are:

NDVI (Normalized Difference Vegetation Index) = $\frac{Band5-Band4}{Band5+Band4}$

Primarily measures vegetation health by contrasting near-infrared and red light. NDVI is useful for monitoring vegetation over time, including pre- and post-fire conditions to assess recovery. Healthy vegetation typically shows NDVI values from 0.3 to 0.8, with values greater than 0.3 indicating vegetated areas.

NBR (Normalized Burn Ratio) = $\frac{Band5-Band7}{Band5+Band7}$

Specially designed for identifying burned areas and estimating burn severity, utilizing near-infrared and shortwave infrared bands. Lower NBR values indicate higher burn severity, making it ideal for analyzing fire impacts and severity. Threshold adjustment should be based on specific burn severity levels and regional ecosystem characteristics.

NDWI (Normalized Difference Water Index) = $\frac{Band3-Band5}{Band3+Band5}$

Optimized for water body detection by highlighting liquid water absorption and reflectance. NDWI is used to monitor changes in water content of leaves and is also particularly effective in delineating open water features. This index helps differentiate between water bodies and other types of land cover.

Each pixel will have a value for these metrics. Using these indices, we can create detailed maps and areas from satellite images, enabling the assessment of vegetation health, water body extents, or burned area extents, among others.

3.1 Data format and parametrization

EO systems have a set of technical parameters that can be tuned to extract relevant information, and defines the quality of the data obtained. In general, some key parameters of EO data are resolution, size, and frequency (or refresh time, ESA, 2020).

The spatial resolution of an image relates to the level of detail that can be retrieved from a scene. Image resolution can be measured in several ways; one of the most common, the Ground Sample Distance (GSD), is the distance between adjacent pixel centers measured on the ground. The lower this number is, the finer the detail that can be interpreted from the image. High resolution images will be required, for instance, to collect data for high precision agriculture, while lower resolutions are enough for applications such as weather forecasting.

The size of the scene to be observed is another important parameter. EO sensors on board satellites are characterized by their swath. The swath of an instrument is the width of the path or the strip on the ground it can image when the satellite orbits around the Earth. The swath depends on the features of the instrument and on the orbit of the satellite. Generally, the higher the spatial resolution, the lower the swath of the instrument.

Finally, the revisit time of a satellite system is a decisive factor of choice. It is defined as the length of time to wait for the satellite system to be able to observe the same point on Earth. This parameter is closely linked to the type of orbit of the satellites.

There is an inherent trade-off between spatial resolution and refresh rate. To have a high refresh rate, the satellite needs to orbit the Earth quickly. But to capture a high-spatial-resolution photo, the satellite needs to collect data from each tiny area which takes longer. Though, it shall be noted that more technical parameters might further govern the usefulness and quality of an EO image, such as bit depth, off-nadir angle, and cloud cover. This required parametrization of the data might be seen, therefore, as a challenge in itself for official statistical offices which require climate-related data to be fully transparent, and comparable (NGFS, 2022).

3.2 Econometric modeling

Recent advances in the rapidly growing literature on remote sensing and EO systems offer a plethora of solutions for spatial analysis. However, it is crucial to recognize that for quantitative analysis, we must first translate the spectral band data collected by satellites into meaningful metrics. This process involves several steps, as outlined in the boxes "Understanding Satellite Color Bands and Building Metrics" and "From Parametrization to Environmental Metrics and Economic Materiality."

Quantitative modeling has been significantly aided by the widespread availability and use of machine learning (ML) and artificial intelligence (AI) algorithms, such as neural networks, which are uniquely equipped to handle prevalent issues in (climate) finance, such as non-linearity, heterogeneity, and clustering issues (Alonso-Robisco, Bas, Carbo, de Juan, and Marques, 2024).[9] The Local Projections Method constitutes an alternative econometric approach to obtain the impulse response to shocks (Jordà, 2005). This method can enable a solid policy discussion of climate

9 Such as, e.g., in the development of the geographical random forest (Georganos et al., 2021; Georganos and Kalogirou, 2022; Hengl, Nussbaum, Wright, Heuvelink, and Gräler, 2018; Santos, Graw, and Bonilla, 2019).

change, as it utilizes the same language as applied economics in the context of estimating the dynamic causal effects of policy interventions (Jordà, 2023). Such interventions would traditionally refer to new fiscal policies (Jordà, Schularick, and Taylor, 2020), but can now also be adapted to climate events such as natural disasters or temperature anomalies (Dieppe, Kilic Celik, and Okou, 2020; Nie, Regelink, and Wang, 2023).

Notably, two satellite data-specific characteristics tend to cause econometric modeling challenges which need to be addressed: spatially interdependent data and spatially heterogeneous estimators. A multidisciplinary, growing stream of the scientific literature deals with addressing these issues in order to obtain consistent and unbiased spatial estimates (Georganos and Kalogirou, 2022; Hengl et al., 2018; Kopczewska and □wiakowski, 2021). In the following, we briefly outline these two issues of spatial data:

1. **Spatial dependency and autocorrelation:** Violating the basic assumption of independence (which tends to be required by the usual econometric models), geolocations in close proximity to one another are unlikely to be independent from one another. For instance, two neighboring areas of a forest are likely to be exposed to similar, if not the same, environmental stressors captured by satellite images. Therefore, models which fail to correct for spatial dependence and (auto-)correlation can produce biased estimates.
2. **Spatial heterogeneity or spatial non-stationarity:** the relation between predictor and outcome variables in spatial settings tend to vary spatially, i.e., different estimates are required for different areas or locations [@georganos2021geographical]. For instance, the relationship between precipitation and flood risks differs for adjacent urban neighborhoods depending on their distance from bodies of water, building quality, or their proximity to disaster relief services.

Spatial weights matrices help address both of these major issues by incorporating the geographical structure of the data into the econometric model (Anselin, 2022). However, deriving appropriate weights can be challenging, as the choice of weighting scheme relies on assumptions and increases model complexity. Though, approaches that address both spatial autocorrelation and spatial heterogeneity simultaneously, however, tend to increase computational complexity and cost beyond the computational capacities of regular machines (Ahn, Ryu, and Lee, 2020).

Beyond these two major concerns specific to geospatial data, analyses leveraging satellite data can additionally suffer from statistical issues analogous to those of non-spatial models. For instance, endogeneity is common in spatial analyses, and including spatially endogenous variables further complicates the modeling process (Brady and Irwin, 2011). Additionally, satellite data is also prone to suffering from sparsity and missingness. Importantly, these gaps tend to be non-random, i.e., systematically informative, and thereby impact results (see, e.g., Khan, He, Porikli, and Bennamoun, 2017).

3.3 Limitations for bridging the climate data gap

As pointed out by the NGFS "*Final Report on Bridging Data Gaps*" (NGFS, 2022), gaps in climate-related data encompass three dimensions: availability (e.g., coverage, granularity, and accessibility), reliability (e.g., quality, auditability, and transparency) and comparability. Despite the tremendous potential of satellite data for (sustainable) economics and finance, some key limitations remain, which can affect their capacity for bridging these data gaps:

1. **Temporal consistency:** Some environmentally relevant datasets might have poor temporal consistency due to missingness. This issue tends to compound over time, affects coverage and through this impacts availability, which in turn makes long-term environmental monitoring more challenging.
2. **Accuracy:** The precision of readily available spatial datasets varies significantly, which affects their reliability. There are two main categories of spatial datasets: vector files and raster files. Vector files consist of geometric shapes used to represent man-made delineations such as country boundaries or biodiversity protected areas. Raster files, on the other hand, are composed of grid cells (or pixels), each assigned a specific value to represent information like flood risk or forest loss. Discrepancies between these datasets, particularly in terms of boundary definitions, are not uncommon and often necessitate costly ground truth validation to ensure data accuracy. This situation suggests a possible impact on accessibility due to cost barriers, and affects reliability due to potential errors and the need for external validation. Additionally, merging datasets involves aligning spatial scales (e.g.: geocoding economic data), while maintaining the integrity over time, which is by itself challenging (e.g.: an asset's area may change over time from being non-protected to protected). This impacts auditability and adds layers of complexity in ensuring data reliability. Finally, identification of the region of interest (RoI) might therefore be a challenge in itself. This underscores a significant issue affecting both reliability and comparability due to ambiguous data interpretations.
3. **Spatial resolution:** Almost all publicly available raster datasets tend to have low spatial resolution (above 500 square meters), limiting the relevancy of the tasks which could be applied to (e.g.: deforestation and land degradations usually require finer resolution). This underscores a significant issue affecting both reliability and comparability due to ambiguous data interpretations. Data interdependence: newly available datasets often draw observational points from different datasets, with the possibility of compounding previous errors.
4. **Relevancy:** Parametrization of information makes it technically difficult to quantify variables of some economically relevant topics (e.g.: Normalized Difference Vegetation or NDVI and Normalized Burn Ration or NBR are usually applied in to study the impact of wildfires, though depending on the time of the year, type of vegetation and atmospheric conditions one metric might be better than the other.); therefore several studies tend to be biased towards the most technically feasible metrics. This can lead to issues in comparability when different studies or datasets use different parameters or indices based on their technical feasibility rather than their applicability.

From Parametrization to Environmental Metrics and Economic Materiality

Analyzing the Economic Impact of a Wildfire (Galicia, 14/10/2017)

Computing the impact on local firms and collateral can provide a tangible measure of economic materiality. However, this process is challenging due to the need for high-resolution data and accurate economic modeling that can translate environmental damage into financial terms

Parametrization and Region of Interest (RoI) Identification:

- Satellite choice is key: Landsat's finer resolution (30 meters per pixel) is balanced against its 16-day revisit time, while MODIS offers broader coverage with daily updates at a coarser 250-500 meters per pixel resolution, impacting the detail and timeliness of data.
- RoI alignment is critical: Landsat's swath of 185 km might not match the ROI exactly, leading to data gaps, Particularly in areas outside the direct pass. A defined RoI like a 20 km radius can provide a focused view but may miss some impacts outside this range. Techniques like data interpolation, using overlapping satellite passes, or integrating data from multiple satellites could help mitigate these gaps.
- Preprocessing complexities: Switching between Landsat and MODIS can present challenges, particularly in cloud-prone regions like Galicia. While manual cloud masking is necessary for certain satellites, automatic cloud masking by others like

MODIS is available, but the resulting cloud-free data sample is not daily and may compromise data frequency.

Environmental Metrics:

- Selecting the right metrics like NDVI and NBR is essential for quantifying fire damage and vegetation health. It is also important to understand historical values of those metrics in the RoI, and expected variations. A 10% or 20% change could be way to big or small. A threshold must be chosen based on the normal variability and ecological characteristics of the region, factoring in seasonal variations.
- Additional indices like EVI or SAVI could provide deeper insights in specific scenarios, such as regions with high biomass or varying soil reflectance, enabling a tailored approach to environmental impact assessment.

Economic Materiality:

- The economic impact analysis is not only about the direct damages such as property loss, but also indirect effects like supply chain interruptions, affected collateral in loans, and tourism downturns. This analysis requires an integration of fire damage data with local economic metrics.
- Specifically, it is vital to evaluate spatial dependence. This dependence often reflects the physical spread of the fire. The physical spread of a fire can differently affect adjacent sectors such as agriculture, collateral securities and tourism.
- Addressing spatial dependency involves employing spatial econometric models that can dissect and quantify these intertwined impacts. Techniques like spatial autoregressive models (SAR) or spatial error models (SEM) could be employed to correct for spatial autocorrelation in the data, ensuring that the estimated economic impacts accurately reflect the localized nature of the fire's damage.
- Collaboration with local authorities ensures that findings are grounded in reality

4 Literature review: satellite data in economics and finance

Satellite data has emerged as a powerful tool in some specific domains of economic and financial research, offering novel insights and harnessing different methodologies across various domains. In others, however, it remains underexploited. This literature review aims to segment and categorize those streams of the scientific literature which have successfully used satellite data. Generally, the successful application of satellite data tends to sit in two primary areas: (i) development economics, for tracking economic growth in developing countries or tumultuous times, such as the Covid-19 pandemic; and (ii) capital markets, e.g., in commodities trading (including estimating oil reserves) as well as equity trading. An illustrative example of such applications can be retail expenditure forecasting using satellite imagery in commercial areas such as parking lots.

First and foremost, satellite data has proven invaluable in monitoring and understanding economic growth in developing regions. Studies such as Ebener, Murray, Tandon, and Elvidge (2005), Ghosh, Anderson, Powell, Sutton, and Elvidge (2009), Henderson, Storeygard, and Weil (2012), and Pinkovskiy and Sala-i-Martin (2016) have utilized nighttime lights data as a proxy for economic activity, demonstrating its efficacy in capturing changes in GDP and economic development over time. Moreover, the use of high-resolution satellite imagery has facilitated the assessment of urbanization patterns, infrastructure development, and land use changes, offering nuanced insights into regional economic progress.

The nascent literature has also identified limits to satellite data. Specifically, it is noted that this data source tends to lose its informative power for advanced economies generally situated in the Global North (Chen and Nordhaus, 2011; Sutton, Elvidge, Ghosh, et al., 2007), as when a country grows, night-time luminosity tends to de-correlate from production and consumption metrics. This induced a move towards hitherto less frequently used types of remotely sensed data, such as NO_2 pollution for nowcasting industrial production (e.g., Bricongne, Meunier, and Pical, 2021; Jiang, He, Cui, Zhou, and Kong, 2020; Zhou, Zhou, and Ge, 2018). Since this substream of the literature suggests a direction of causality in which economic activity drives pollution, this link can also be used to detect large economic recessions that lead to a drop in NO_2 pollution. Castellanos and Boersma (2012) study the reduction in pollution in Europe during the global financial crisis of 2008. Similarly, Russell, Valin, and Cohen (2012) offer similar insights for the US, as do Du and Xie (2017) for China. More recently, Tobías et al. (2020) use pollution data to assess the impact of the lockdowns during the Covid-19 pandemic in Europe, and Le et al. (2020) and Beyer, Franco-Bedoya, Sebastian, and Galdo, Virgilio (2021) provide analogous findings for China and India, respectively.

For Global South economies, previous studies such as Kerimray et al. (2020) and Keola and Hayakawa (2021) document that changes in NO_2 pollution followed lockdown policies. Related to this, Franke et al. (2009) and Ruyter de Wildt, Eskes, and Boersma (2012) use satellite imagery to track shipping lanes and study world trade patterns.

Satellite data has also influenced capital markets, for instance in the field of commodities trading, by offering insights into supply chains, market trends, and natural resources availability. As an example, satellite imagery has been used to monitor oil storage facilities and track tanker movements, providing crucial information for assessing global oil supply and demand dynamics, as well as oil spill detection (Tysi□c, Strelets, and Tuszy□ska, 2022).

Moreover, the literature on consumer spending estimation has been revolutionized by satellite imagery: Feng and Fay (2022) and Kang, Stice-Lawrence, and Wong (2021), for instance, use satellite images of retail parking lots to estimate consumer spending. By counting cars in the lots, the researchers were able to accurately predict store-level sales, demonstrating the potential of satellite data in retail analytics and economic forecasting. This, in turn, gives rise to an application in equity trading where international retail company revenues can be estimated ahead of quarterly earnings announcements for market timing strategies. Notwithstanding, Katona, Painter, Patatoukas, and Zeng (2018) suggest that access to this source of alternative data might have had an impact on information asymmetry among market participants without enhancing price discovery.

In the field of green finance, insurance markets are a prominent example of the pioneer usage of satellite data. In particular, this type of data has led to promising results in agricultural risk management through its potential to reduce monitoring costs and alleviate moral hazard as well as adverse selection issues (Nagendra, Narayanamurthy, Moser, Hartmann, et al., 2022). Exploiting satellite data, insurers can efficiently price complex weather index insurance policies, protecting small farmers against crop damage (De Leeuw et al., 2014). Hedging the risk of weather shocks, they can also increase their agricultural productivity (Enenkel et al., 2019), which enables ethical decision-making in agricultural insurance claim settlement. The latter is crucial from a social perspective, as beneficiaries of these claims tend do be “poor and powerless”, as Nagendra, Narayanamurthy, and Moser (2022) put it.

Finally, as predictive analytics are increasingly being recognized as pivotal tools for climate finance, with applications reaching beyond insurance markets and catastrophe management (Alonso-Robisco, Bas, et al., 2024). As detailed by Ofodile et al. (2024), addressing the hurdles associated with data quality, model uncertainty, regulatory complexities, and the integration of climate-related factors in financial decision-making processes requires interdisciplinary collaboration and ongoing technological and financial innovation. This encompasses a wide range of techniques and information sources including novel climate models and satellite imagery.

In the context of the previous literature on satellite data for finance and economics, our proposition is as follows: While the data source is not new and has seen some success in specific domains, it remains under-utilized in others. We will subsequently analyze systematically whether the substream of the literature concerned with green finance can benefit from novel studies using satellite data. To this end, we briefly introduce Latent Dirichlet Allocation (LDA) in Section 5. The LDA model helps us uncover thematic clusters in a comprehensive dataset of scholarly papers on sustainable finance which already use satellite data. The use cases *not* uncovered by our analysis can inform us where future efforts of central banks, statisticians, and scholars may be targeted to effectively aid the green transition.

5 Topic modeling: satellite data in green finance

5.1 Latent Dirichlet Allocation (LDA)

As pointed out above, we rely on the LDA algorithm for the topic modeling task (Blei, Ng, and Jordan, 2003). In selecting the most suitable methodology for topic modeling within this study, the choice of LDA over alternatives like BERTopic or Topic2vec is underpinned by several key considerations. For instance, while BERTopic (Grootendorst, 2022) and Topic2vec (Niu, Dai, Zhang, and Chen, 2015) exhibit commendable performance in capturing semantic relationships and contextual understanding, the choice of LDA is rooted in its interpretability, scalability, and established track record in topic modeling (Jelodar et al., 2019). LDA, a generative probabilistic model, allows for a clear interpretation of topics as probability distributions over words, enabling a more straightforward comprehension of underlying themes within textual data. Additionally, LDA's computational efficiency and scalability make it well-suited for handling large corpora, offering a pragmatic advantage in processing substantial volumes of text data commonly encountered in empirical studies. Moreover, the widespread use and extensive literature on LDA provide a robust foundation for comparison, evaluation, and benchmarking against prior research, enhancing the reliability and interpretability of the findings derived from the topic modeling exercise within this study.

The key practical advantage of LDA is that it allows to treat documents like a mixture of different topics, while topics are presented as a mixture of words. Furthermore, no label of the documents is required. This makes it highly flexible and applicable to a wide range of domains and datasets, which fits the reality observed in climate finance studies, since different topics can partially overlap within a document. Interestingly, LDA is based on a generative probabilistic model, learning the topic-word distributions and the document-topic proportions from the data. Last but not least, LDA is easily scalable, as it handles large-scale datasets efficiently, which makes it valuable to fulfill our task at hand.

The procedure for extracting the topics consists of a variety of steps required for training, tuning, and applying the resulting LDA model to the corpus, as an unsupervised learning technique. We include a detailed description of this process in the Appendix, Section A.

5.2 Data collection

To conduct a systematic literature review, we use Harzing's Publish or Perish, a free application which enables large-scale literature searches. The user interface resembles Google Scholar and similar applications, and thereby allows searching by authors, years, journals, titles, and keyword combinations. The application also enables searches of various databases, among them Google Scholar, CrossRef, Pubmed, and others.

For the literature review, we use Google Scholar, CrossRef, OpenAlex, Semantic Scholar, and Scopus. Based on domain expertise, we decide on a list of keywords for our search. All combinations of these keywords, including mandatory mentions within titles and/or abstracts of the found papers as well as optional mentions, are considered. This means that, for instance, we use both "satellite data" and "climate finance" as well as satellite data climate finance separately as a combination of search terms.

The resulting total number of search word combinations is 112. We search each of the aforementioned databases (Google Scholar, CrossRef, OpenAlex, Semantic Scholar, and Scopus) for each of these terms. Within each search, we choose a maximum number of papers to be returned of 200. There are important differences between the matching paper results returned by each database: First, Google Scholar has taken precautions against automated data extraction so that we needed to limit the number of maximum returned papers in order to prevent our IPs being blocked. Second, Scopus only returns papers which fit the search well enough instead of returning all papers in decreasing order of "fittingness", which differs from the other platforms. Third, the scopes and information retrieval systems of all databases differ, as is made evident by the fact that the returned lists of papers do not overlap fully. The latter is one main reason why we use four databases, namely, to limit the results being influenced (or biased) by a single database's characteristics, and in turn maximize the number of results.

Due to these differences, the initial and final samples of papers do not consist of equal shares from each database. To obtain our final sample of papers relevant to our research question, we take several filtering steps. Table 1 illustrates the sample decomposition before and after filtering and across databases.

Database	Initial sample	Unique-observation sample
CrossRef	22,400	5,016
Semantic Scholar	22,400	4,842
OpenAlex	20,700	3,748
Scopus	3,681	1,822
Google Scholar	2,419	1,799
Total	71,600	17,227
Final sample after filtering		226

Table 1: List of databases used for data collection

The first step after collecting all papers is to remove duplicates. This step changes the sample from the initial sample to the unique-observation sample (i.e., sample without duplicates). Subsequently, we remove results with empty author information, results which author information contains only non-Roman letters, are published in appropriate media, and whose abstracts contain (i) satellite- or remote sensing-specific terminology as well as (ii) finance- or economics-specific terminology. The last filtering step is the most restrictive and ensures we only consider adequate papers for our analysis. During this work, we also add any papers which we come across "manually" and deem fitting for our purposes. The resulting final number of papers is 226. With this final sample, we conduct the NLP analyses described in the following sections.

5.3 Uncovering thematic areas

There are two main challenges when it comes to clustering topics in a corpus of texts. First, there is no one-size-fits-all approach to finding the optimal number of topics, i.e., the process always includes some trial and error. To aid the parameter selection process, the literature suggests several metrics, such as the perplexity (Blei et al., 2003) and coherence scores (Röder, Both, and Hinneburg, 2015). Increasing the number of topics usually improves these statistical measures during topic modeling. Simultaneously, however, a higher number of topics is associated with higher computational cost during training. In our case, we decide to estimate an LDA model with five topics, informed by the rate of perplexity change following Zhao et al. (2015).[10)]

A further challenge is selecting a number of topics which not only "make sense" to the ML algorithm, but also to humans. To ensure a human-interpretable labeling of the resulting topics, we conduct a qualitative review with human expert judgment, in which we verify that the words associated with each topic align roughly with the experts' domain knowledge of the established climate finance literature. Upon estimating the LDA model, we label the topics using a two-step approach: firstly, we examine the tokens with the highest probability for each topic, as detailed in Table 2. Then, a more thorough analysis of the clusters (see more details in the Appendix, Section B) allows us to identify the following set of topics: Topic 1 as *Physical risk*, Topic 2 as *Deforestation*, Topic 3 as *Energy and emissions*, Topic 4 as *Agricultural risk*, and Topic 5 as *Land use and land cover*.

For illustrative purposes, we outline the iterative, human-in-the-loop process of how we arrive at our final number and demarcation of topics. After reviewing the most frequent terms for each topic (see Table 2 in the Appendix), we assess the topics based on the relevance metric [11)]. For instance, Figure 1 displays the intertopic distance map, which we use to fine-tune the topic selection of our LDA model. The visualization presented in this map is indicative of topic differentiation, i.e., a wider distance corresponds to a stricter differentiation. The term-relevance chart, which shows the importance and the relevance metric of single terms for the selected topic, can be seen on the right-hand side of Figure 1. For Topic 1, we find significant emphasis on terms such as "weather", "temperature", "rainfall", and "drought". This emphasis enables a distinction of Topic 1 from the other topics, underscoring its semantic concentration on the impacts of extreme weather events and acute or chronic physical risks. Consequently, we categorize this topic as *Physical risk*. A similar methodology is applied to the remaining topics, with term-relevance charts analogous to Figure 1 provided in Figures 3 through 7.

Uncovering one topic can inform the labeling of others due to their interconnected nature. This interconnectedness enable us to address their practical implications in the field of green finance, where each of our topics aligns with emerging financial products in the field. For example, weather forecasting (Topic 1: Physical risk) is crucial for renewable energy trading (Ghoddusi, Creamer, and Rafizadeh, 2019), which is closely linked to the discussions in Topic 3 (Energy and emissions). In addition, as highlighted by Topic 3, assessing carbon emissions over the value chain is essential for creating effective carbon tax policies and facilitating carbon offset trading in secondary markets, (Borowski, 2021; TSVCM, 2021). This assessment is a critical step in the design and implementation of financial mechanisms that aim to reduce carbon footprints.

10 Figure 2 in the Appendix displays the relevant metrics and training times for model versions ranging from one to ten topics.
11 Using $\lambda = 0.6$ and the PyLDAvis Python library proposed by Sievert and Shirley (2014)

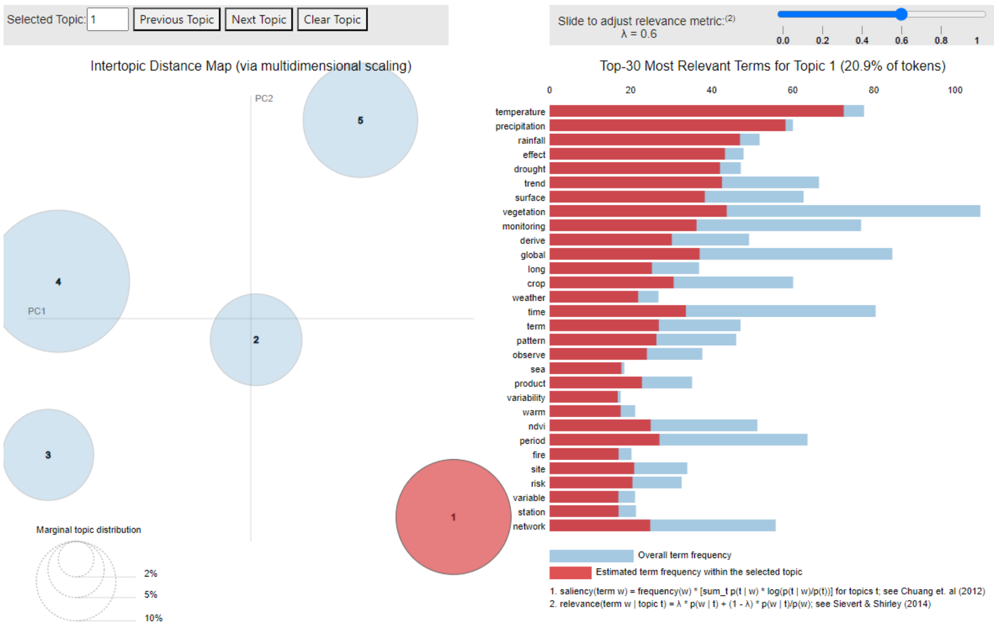

Figure 1: Intertopic distance map, and Top30 most relevant terms for Topic1.

On another note, the emphasis on ecosystem health as the main indicator in nature finance Schimanski et al. (2023), aligns with the research focus of Topic 2 (Deforestation) and Topic 5 (Land use and land cover). Their practical implication is exemplified by the partnership of World Bank and ESA, which leverages satellite data to monitor deforestation activities in the Peruvian Amazon. Insights from this collaboration could potentially help developing green finance products, like Sustainability-Linked Bonds (ESA, 2023), or enabling the verification of commitments in blue bonds (Thompson, 2022).[12)]

Lastly, our results support the application of satellite data to better assess agricultural risk (Topic 4). This is particularly relevant for a just transition where small farmers must adapt to current changes in climate. The importance of this facet is underscored by, for instance, the joint venture between IFAD and ESA (IFAD, 2023) and the Catalogue of Geospatial Tools and Applications for Climate Investments of IFAD (2022).

6 Conclusion and policy discussion

International central banks have identified the need to bridge climate-related data gaps to enable green finance to scale up. This need comes at a time where pressures on financial institutions are increasing along three major dimensions: Calls for increased voluntary and mandatory disclosure and regulation (e.g., the launch of EU Taxonomy, CSRD, and SFDR); the need to address "double materiality", which recognizes not only the financial materiality to companies arising from climate risks and opportunities but also the materiality for society and the environment arising from the companies' operations, which in turn can result in financial risks (Gourdel et al., 2022), and the growing importance for central banks around the topic of the "environment" (WWF, 2023), and biodiversity (NGFS, 2023).

12 Water resources, including rivers, oceans, floods, etc., occur in Topics 1, 4, and 5 of our LDA model.

A potential candidate to assist covering climate-related data gaps as defined by [NGFS (2022) is satellite data. This data source comprises spatio-temporal information retrieved from satellites and sensors that orbit the Earth. EO systems might potentially open bottlenecks in several operational problems by increasing the widespread availability of climate-related data, adding new layers of information (geo-location) to currently available data, and/or enhancing the reliability of self-reported data from corporates. However, they also faced important challenges and decisions that need to be addressed in order to use this information. We point out potential limitations of satellite data in addressing climate data gaps: availability (e.g., coverage, granularity, accessibility), reliability (e.g., quality, auditability, transparency), and comparability (due to the absence of a unified reporting standard). While EO systems can enhance data availability, accessibility remains limited, with barriers such as proprietary databases and high costs for newcomers needing to process raw data.

On the other hand, satellite data boasts impressive advantages, such as general high quality, auditability, and transparency, positioning it as a viable candidate to improve digital measurement and reporting systems especially in the field of green finance. However, the fact that parametrization needs to be undertaken individually by each user and use case, complicates the comparability of results based on spatial analysis.

We have already seen the use of this information in several cases. In emerging countries, information such as night-time luminosity has proven valuable for fore- and nowcasting indicators such as GDP growth and beyond. Similarly, in times of turmoil such as the COVID-19 pandemic, satellite imagery was useful to track urban mobility and estimate the effect of fiscal subsidies to boost economic activity locally. Within the financial literature, remote sensing has been used to estimate oil reserves, count cars in parking lots to estimate consumer spending at large retailers, and assist investors in market-timing strategies for such retailers' stocks. In the domain of green finance use cases, satellite data has been somewhat established in the insurance sector. However, we propose that today, there are more urgent thematic areas where researchers are researchers could harness this novel and largely free data source to solve a variety of problems.

In order to provide a more systematic analysis of the potential of this data for sustainable finance we use a semi-automated review of the scientific literature on the application of EO systems for green finance. To this end, we collect a corpus of scientific studies and, using NLP techniques (LDA), we uncover five application domains where researchers are exploring the value of EO systems. In particular, we find that (1) physical risk materialization (including both acute and chronic risk), (2) deforestation, (3) energy and emissions, (4) agricultural risk, and (5) land use and land cover, are core areas where satellite data might enable new green financial products and markets, such as sustainability linked bonds or blue bonds, nature finance, or voluntary carbon markets. Our results are echoed by innovative private sector players (e.g., DrivenDataLabs, 2023), who offer services based on artificial intelligence and new data types from EO systems in different business areas, such as natural resource management, disaster resilience, biodiversity conservation, energy efficiency, or upstream services.

We conclude by stating that satellite data shall not be an isolated area of research to fill in climate data gaps. It can work together with improved observational data, leveraging new technologies like machine learning or landscape audio. Used in this fashion, it can enable and new layers of information, and thereby boost new insights from ground-based data. Overall, although EO systems in green finance are still emerging, their potential has piqued the interest of central banks, as a potential public good, prompting exploration and collaboration on international platforms like the NGFS or BISIH to experiment, monitor, and track new developments.

References

Acharya, V. V., Berner, R., Engle, R., Jung, H., Stroebel, J., Zeng, X., and Zhao, Y. (2023). Climate stress testing. *Annual Review of Financial Economics*, *15*, 291–326.

Ahn, S., Ryu, D.-W., and Lee, S. (2020). A machine learning-based approach for spatial estimation using the spatial features of coordinate information. *ISPRS International Journal of Geo-Information*, *9*(10), 587.

Alogoskoufis, S., Dunz, N., Emambakhsh, T., Hennig, T., Kaijser, M., Kouratzoglou, C., … Salleo, C. (2021). Occasional paper series-ECB economy-wide climate stress test-no 281/september 2021. *ECB: European Central Bank*.

Alonso-Robisco, A., Bas, J., Carbo, J. M., de Juan, A., and Marques, J. M. (2024). Where and how machine learning plays a role in climate finance research. *Journal of Sustainable Finance & Investment*, 1–42.

Alonso-Robisco, A., Manuel Carbo, J., Kormanyos, E., and Triebskorn, E. (2024). Houston, we have a problem: Can satellite information bridge the climate-related data gap? *Documentos Ocasionales/Banco de España, 2428*.

Anselin, L. (2022). Spatial econometrics. *Handbook of Spatial Analysis in the Social Sciences*, 101–122.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., and Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change*, *7*(4), 283–288.

BdE. (2023). *Climate-related aspects of the banco de españa's non-monetary policy portfolios. March 2023*. Banco de España. https://doi.org/10.53479/29827

Beyer, R. C., Franco-Bedoya, Sebastian, and Galdo, Virgilio. (2021). Examining the economic impact of COVID-19 in india through daily electricity consumption and nighttime light intensity. *World Development*, *140*, 105287.

Beyer, R. C., Hu, Y., and Yao, J. (2022). *Measuring quarterly economic growth from outer space*. International Monetary Fund.

BISIN. (2023). *Summary of the workshop on the role of technology in green finance*. BIS Innovation Hub.

Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, *55*(4), 77–84.

Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research*, *3*(Jan), 993–1022.

Bommel, K. van, Rasche, A., and Spicer, A. (2023). From values to value: The commensuration of sustainability reporting and the crowding out of morality. *Organization & Environment*, *36*(1), 179–206.

Borowski, P. F. (2021). Digitization, digital twins, blockchain, and industry 4.0 as elements of management process in enterprises in the energy sector. *Energies*, *14*(7), 1885.

Brady, M., and Irwin, E. (2011). Accounting for spatial effects in economic models of land use: Recent developments and challenges ahead. *Environmental and Resource Economics*, *48*, 487–509.

Bricongne, J. C., Meunier, B., and Pical, T. (2021). *Can satellite data on air pollution predict industrial production?*

Bundesbank. (2023). *Climate-related disclosures by the deutsche bundesbank*. Deutsche Bundesbank.

Castellanos, P., and Boersma, K. F. (2012). Reductions in nitrogen oxides over europe driven by environmental policy and economic recession. *Scientific Reports*, *2*(1), 265.

Chen, X., and Nordhaus, W. D. (2011). Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences*, *108*(21), 8589–8594.

De Leeuw, J., Vrieling, A., Shee, A., Atzberger, C., Hadgu, K. M., Biradar, C. M., … Turvey, C. (2014). The potential and uptake of remote sensing in insurance: A review. *Remote Sensing*, *6*(11), 10888–10912.

Delgado, M. (2023). *The role of central banks in sustainable finance*. Retrieved from https://www.bde.es/f/webbde/GAP/Secciones/SalaPrensa/IntervencionesPublicas/Subgobernador/Arc/Fic/IIPP-2023-02-06-delgado-en.pdf

Dieppe, A., Kilic Celik, S., and Okou, C. I. F. (2020). Implications of major adverse events on productivity. *Available at SSRN 3699683*.

Dikau, S., and Volz, U. (2021). Central bank mandates, sustainability objectives and the promotion of green finance. *Ecological Economics*, *184*, 107022.

Diwan, H., and Amarayil Sreeraman, B. (2023). From financial reporting to ESG reporting: A bibliometric analysis of the evolution in corporate sustainability disclosures. *Environment, Development and Sustainability*, 1–37.

DrivenDataLabs. (2023). *Open data using AI for climate action*. Retrieved from https://drivendata.co/blog/ai-for-climate-action-data

Du, Y., and Xie, Z. (2017). Global financial crisis making a v-shaped fluctuation in NO2 pollution over the yangtze river delta. *Journal of Meteorological Research*, *31*(2), 438–447.

Durrani, A., Rosmin, M., and Volz, U. (2020). The role of central banks in scaling up sustainable finance–what do monetary authorities in the asia-pacific region think? *Journal of Sustainable Finance & Investment*, *10*(2), 92–112.

Ebener, S., Murray, C., Tandon, A., and Elvidge, C. C. (2005). From wealth to health: Modelling the distribution of income per capita at the sub-national level using night-time light imagery. *International Journal of Health Geographics*, *4*(1), 1–17.

ECB. (2021a). *ECB presents action plan to include climate change considerations in its monetary policy strategy*. Retrieved from https://www.ecb.europa.eu/press/pr/date/2021/html/ecb.pr210708_1~f104919225.en.html

ECB. (2021b). *Eurosystem agrees on common stance for climate change-related sustainable investments in non-monetary policy portfolios*. Retrieved from https://www.ecb.europa.eu/press/pr/date/2021/html/ecb.pr210204_1~a720bc4f03.en.html

ECB. (2022). *Supervisory assessment of institutions' climaterelated and environmental risks disclosures*.

ECB. (2023). *ECB publishes new climate-related statistical indicators to narrow climate data gap*. Retrieved from https://www.ecb.europa.eu/press/pr/date/2023/html/ecb.pr230124~c83dbef220.en.html

EFRAG. (2024). *EFRAG's public consultation on two exposure drafts on sustainability reporting for SMEs*. Retrieved from https://www.efrag.org/News/Public-479/EFRAGs-public-consultation%20-on-two-Exposure-Drafts-on-sustainability-r

Elderson, F. (2023). *Making finance fit for paris: Achieving "negative splits"*. Retrieved from https://www.ecb.europa.eu/press/key/date/2023/html/ecb.sp231114~5bf50e8b7a.en.html

Enenkel, M., Osgood, D., Anderson, M., Powell, B., McCarty, J., Neigh, C., et al.others. (2019). Exploiting the convergence of evidence in satellite data for advanced weather index insurance design. *Weather, Climate, and Society*, *11*(1), 65–93.

ESA. (2020). *Newcomers earth observation guide*. Retrieved from https://business.esa.int/newcomers-earth-observation-guide#:~:text=The%20swath%20of%20an%20instrument,the%20swath%20of%20the%20instrument.

ESA. (2023). *Satellite data and sustainability-linked bonds: Monitoring land use in peruvian amazon*.

European Central Bank. (2022). 2022 climate risk stress test.

Feng, C., and Fay, S. (2022). An empirical investigation of forward-looking retailer performance using parking lot traffic data derived from satellite imagery. *Journal of Retailing*, *98*(4), 633–646.

Ferreira, C., Rozumek, D. L., Singh, R., and Suntheim, F. (2021). *Strengthening the climate information architecture*. International Monetary Fund Washington, DC.

Franke, K., Richter, A., Bovensmann, H., Eyring, V., Jöckel, P., Hoor, P., and Burrows, J. P. (2009). Ship emitted NO 2 in the indian ocean: Comparison of model results with satellite data. *Atmospheric Chemistry and Physics*, *9*(19), 7289–7301.

Georganos, S., Grippa, T., Niang Gadiaga, A., Linard, C., Lennert, M., Vanhuysse, S., … Kalogirou, S. (2021). Geographical random forests: A spatial extension of the random forest algorithm to address spatial heterogeneity in remote sensing and population modelling. *Geocarto International*, *36*(2), 121–136.

Georganos, S., and Kalogirou, S. (2022). A forest of forests: A spatially weighted and computationally efficient formulation of geographical random forests. *ISPRS International Journal of Geo-Information*, *11*(9), 471.

Ghoddusi, H., Creamer, G. G., and Rafizadeh, N. (2019). Machine learning in energy economics and finance: A review. *Energy Economics*, *81*, 709–727.

Ghosh, T., Anderson, S., Powell, R. L., Sutton, P. C., and Elvidge, C. D. (2009). Estimation of mexico's informal economy and remittances using nighttime imagery. *Remote Sensing*, *1*(3), 418–444.

Giannarakis, G., Sitokonstantinou, V., Lorilla, R. S., and Kontoes, C. (2022). Towards assessing agricultural land suitability with causal machine learning. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 1442–1452.

Giglio, S., Kuchler, T., Stroebel, J., and Zeng, X. (2023). *Biodiversity risk*. National Bureau of Economic Research.

Gourdel, R., Monasterolo, I., Dunz, N., Mazzocchetti, A., and Parisi, L. (2022). *The double materiality of climate physical and transition risks in the euro area*.

Gratcheva, E. M., Gurhy, B., Emery, T., Wang, D., Oganes, L., Linzie, J. K., … Rink, R. (2021). *A new dawn*.

Grootendorst, M. (2022). BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *arXiv Preprint arXiv:2203.05794*.

Henderson, J. V., Storeygard, A., and Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, *102*(2), 994–1028.

Hengl, T., Nussbaum, M., Wright, M. N., Heuvelink, G. B., and Gräler, B. (2018). Random forest as a generic framework for predictive modeling of spatial and spatio-temporal variables. *PeerJ*, *6*, e5518.

Heynen, P. (2022). The ECB going green: Impact on the interrelationship between monetary policy and banking supervision? *Maastricht Journal of European and Comparative Law*, *29*(6), 667–684.

Hofmann, T. (2001). Unsupervised learning by probabilistic latent semantic analysis. *Machine Learning*, *42*(1), 177–196.

IFAD. (2022). *Catalogue of geospatial tools and applications for climate investments*. Food; Agriculture Organization of the United Nations.

IFAD. (2023). *Spatial technology creates opportunities for vulnerable small-scale food producers as IFAD and ESA join forces*. Retrieved from https://www.ifad.org/en/web/latest/-/ifad-and-esa-join-forces-to-help-vulnerable-small-scale-food-producers

IFC. (2021). Sustainable finance data for central banks. *IFC Report*.

IFC. (2023). Post-pandemic landscape for central bank statistics. *IFC Bulletins*.

IFRS. (2024). *General sustainability-related disclosures*. Retrieved from https://www.ifrs.org/projects/completed-projects/2023/general-sustainability-related-disclosures/

Iglesias-Suarez, F., Gentine, P., Solino-Fernandez, B., Beucler, T., Pritchard, M., Runge, J., and Eyring, V. (2024). Causally-informed deep learning to improve climate models and projections. *Journal of Geophysical Research: Atmospheres*, *129*(4), e2023JD039202.

Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y., and Zhao, L. (2019). Latent dirichlet allocation (LDA) and topic modeling: Models, applications, a survey. *Multimedia Tools and Applications*, *78*, 15169–15211.

Jiang, L., He, S., Cui, Y., Zhou, H., and Kong, H. (2020). Effects of the socio-economic influencing factors on SO2 pollution in chinese cities: A spatial econometric analysis based on satellite observed data. *Journal of Environmental Management*, *268*, 110667.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, *95*(1), 161–182.

Jordà, Ò. (2023). Local projections for applied economics. *Annual Review of Economics*, *15*, 607–631.

Jordà, Ò., Schularick, M., and Taylor, A. M. (2020). The effects of quasi-random monetary experiments. *Journal of Monetary Economics*, *112*, 22–40.

Kang, J. K., Stice-Lawrence, L., and Wong, Y. T. F. (2021). The firm next door: Using satellite images to study local information advantage. *Journal of Accounting Research*, *59*(2), 713–750.

Katona, Z., Painter, M., Patatoukas, P. N., and Zeng, J. J. (2018). On the capital market consequences of big data: Evidence from outer space. *9th Miami Behavioral Finance Conference*.

Kedward, K., Ryan-Collins, J., and Chenet, H. (2023). Biodiversity loss and climate change interactions: Financial stability implications for central banks and financial supervisors. *Climate Policy*, *23*(6), 763–781.

Keola, S., and Hayakawa, K. (2021). Do lockdown policies reduce economic and social activities? Evidence from NO2 emissions. *The Developing Economies*, *59*(2), 178–205.

Kerimray, A., Baimatova, N., Ibragimova, O. P., Bukenov, B., Kenessov, B., Plotitsyn, P., and Karaca, F. (2020). Assessing air quality changes in large cities during COVID-19 lockdowns: The impacts of traffic-free urban conditions in almaty, kazakhstan. *Science of the Total Environment*, *730*, 139179.

Khan, S. H., He, X., Porikli, F., and Bennamoun, M. (2017). Forest change detection in incomplete satellite images with deep neural networks. *IEEE Transactions on Geoscience and Remote Sensing*, *55*(9), 5407–5423.

Kopczewska, K., and □wiakowski, P. (2021). Spatio-temporal stability of housing submarkets. Tracking spatial location of clusters of geographically weighted regression estimates of price determinants. *Land Use Policy*, *103*, 105292.

Le, T., Wang, Y., Liu, L., Yang, J., Yung, Y. L., Li, G., and Seinfeld, J. H. (2020). Unexpected air pollution with marked emission reductions during the COVID-19 outbreak in china. *Science*, *369*(6504), 702–706.

Nagendra, N. P., Narayanamurthy, G., and Moser, R. (2022). Satellite big data analytics for ethical decision making in farmer's insurance claim settlement: Minimization of type-i and type-II errors. *Annals of Operations Research*, 1–22.

Nagendra, N. P., Narayanamurthy, G., Moser, R., Hartmann, E., and Sengupta, T. (2022). Technology assessment using satellite big data analytics for india's agri-insurance sector. *IEEE Transactions on Engineering Management*, *70*(3), 1099–1113.

NGFS. (2019). *A call for action climate change as a source of financial risk: First comprehensive report*. Network for Greening the Financial System.

NGFS. (2022). *Final report on bridging data gaps*.

NGFS. (2023). *Nature-related financial risks: A conceptual framework to guide action by central banks and supervisors*. Network for Greening the Financial System.

Nie, O., Regelink, M., and Wang, D. (2023). *Banking sector risk in the aftermath of climate change and environmental-related natural disasters*.

Niu, L., Dai, X., Zhang, J., and Chen, J. (2015). Topic2Vec: Learning distributed representations of topics. *2015 International Conference on Asian Language Processing (IALP)*, 193–196. IEEE.

Ofodile, O. C., Oyewole, A. T., Ugochukwu, C. E., Addy, W. A., Adeoye, O. B., and Okoye, C. C. (2024). Predictive analytics in climate finance: Assessing risks and opportunities for investors. *GSC Advanced Research and Reviews*, *18*(2), 423–433.

Pinkovskiy, M., and Sala-i-Martin, X. (2016). Lights, camera… income! Illuminating the national accounts-household surveys debate. *The Quarterly Journal of Economics*, *131*(2), 579–631.

Rangel-Gonzalez, E., and Llamosas-Rosas, I. (2019). An alternative method to measure non-registered economic activity in mexico using satellite nightlights. *Presentation Given at the 7th International Monetary Fund Statistical Forum, November*, *14*.

Röder, M., Both, A., and Hinneburg, A. (2015). Exploring the space of topic coherence measures. *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining*, 399–408.

Russell, A., Valin, L., and Cohen, R. (2012). Trends in OMI NO 2 observations over the united states: Effects of emission control technology and the economic recession. *Atmospheric Chemistry and Physics*, *12*(24), 12197–12209.

Ruyter de Wildt, M. de, Eskes, H., and Boersma, K. F. (2012). The global economic cycle and satellite-derived NO2 trends over shipping lanes. *Geophysical Research Letters*, *39*(1).

Santos, F., Graw, V., and Bonilla, S. (2019). A geographically weighted random forest approach for evaluate forest change drivers in the northern ecuadorian amazon. *PLoS One*, *14*(12), e0226224.

Schimanski, T., Senni, C. C., Gostlow, G., Ni, J., Yu, T., and Leippold, M. (2023). Exploring nature: Datasets and models for analyzing nature-related disclosures. *arXiv Preprint arXiv:2312.17337*.

Sievert, C., and Shirley, K. (2014). LDAvis: A method for visualizing and interpreting topics. *Proceedings of the Workshop on Interactive Language Learning, Visualization, and Interfaces*, 63–70.

Singhania, M., and Saini, N. (2023). Institutional framework of ESG disclosures: Comparative analysis of developed and developing countries. *Journal of Sustainable Finance & Investment*, *13*(1), 516–559.

Stigler, M. M., and Lobell, D. (2020). *Suitability of index insurance: New insights from satellite data*.

Sutton, P. C., Elvidge, C. D., Ghosh, T., et al. (2007). Estimation of gross domestic product at sub-national scales using nighttime satellite imagery. *International Journal of Ecological Economics & Statistics*, *8*(S07), 5–21.

Thompson, B. S. (2022). Blue bonds for marine conservation and a sustainable ocean economy: Status, trends, and insights from green bonds. *Marine Policy*, *144*, 105219.

TNFD. (2023). *Recommendations of the taskforce on nature-related financial disclosures*.

Tobías, A., Carnerero, C., Reche, C., Massagué, J., Via, M., Minguillón, M. C., … Querol, X. (2020). Changes in air quality during the lockdown in barcelona (spain) one month into the SARS-CoV-2 epidemic. *Science of the Total Environment*, *726*, 138540.

TSVCM. (2021). *Roadmap for strengthening market integrity*. Taskforce on Sacling Voluntary Carbon Markets.

Tysi□c, P., Strelets, T., and Tuszy□ska, W. (2022). The application of satellite image analysis in oil spill detection. *Applied Sciences*, *12*(8), 4016.

Volz, U. (2017). *On the role of central banks in enhancing green finance*.

WWF. (2023). *Geospatial ESG: The emerging application of geospatial data for gaining "environmental" insights on the asset, corporate and sovereign level*. WWF, World Bank Group, Global Canopy.

Zhao, W., Chen, J. J., Perkins, R., Liu, Z., Ge, W., Ding, Y., and Zou, W. (2015). A heuristic approach to determine an appropriate number of topics in topic modeling. *BMC Bioinformatics*, *16*, 1–10. Springer.

Zhou, Z., Zhou, Y., and Ge, X. (2018). Nitrogen oxide emission, economic growth and urbanization in china: A spatial econometric analysis. *IOP Conference Series: Materials Science and Engineering*, *301*, 012126. IOP Publishing.

A LDA: Topic modeling

A necessary first step in topic modeling is processing the corpus of documents by tokenizing each document into a collection of their individual words where order is unimportant (i.e.: each document is treated as a "bag of words"). Then, stopwords that have no topic context (such as "and", "of", "the"), are removed, as well as common terms that are highly repeated in the corpus, which we identify because they appear in more than half of the documents, or rare terms for which we set a threshold of being in less than two documents. We deem that both categories of terms contain little meaning to contribute to a relevant topic.[13] Remaining words in a document are lemmatized to generate the words' root, and accurately capture unique terms usage.[14] For simplicity, we keep our analysis to single word tokens as we find that it allows us to easily label the topics at the final stage.

Once the corpus is preprocessed, we count with D documents that together contain N unique tokens that we can represent by an N x D matrix W with entries $w_{n,d}$, which in turn are the number of occurrences of token n in document d. Thus, the total number of tokens in document d is $N_d = \sum_{n=0}^{N} w_{n,d}$. The LDA model consists of two matrices, $\beta_{N\times K}$ and $\theta_{K\times D}$, where K is the total number of topics. For topic k, the vector β_k contains the N token weights, which act as the probabilities $P(n|k)$ that the token n contribute to a document's bag of words, conditional on the topic k contributing to the document. That is, $P(n|k) = \beta_k$, i.e.: the weight of token n in topic k. Therefore, $\sum_{n=1}^{N} \beta_{n,k} = 1$. For document d, the vector θ_d contains the K topic weights – which act as the probability $P(k|d)$ that topic k appears in the document. Thus, $P(k|d) = \theta_{k,d}$, i.e.: the weight of topic k in document d. Similarly, $\sum_{n=1}^{N} \theta_{k,d} = 1$. When these probabilities are significant, we may say that a topic k is relevant in document d. Finally, this setting allows us to decompose the probability of a token n occurring in a document d in the following equation (Hofmann, 2001):

$$P(n|d) = \sum_{k=1}^{K} P(n|k) \cdot P(k|d) = \sum_{k=1}^{K} \beta_{n,k} \cdot \theta_{n,d} \qquad (1)$$

Topic modeling involves reducing the dimensions of these matrices to end up with the same number of rows (documents) but a restricted number of columns which represent the topics. To this purpose LDA assumes a particular Dirichlet distribution that can be used to produce probability vectors β_k and θ_d, that allow an assumption to be made about how topics are distributed across tokens and documents. Using two external inputs, α and β, as Dirichlet priors, we can determine the generative process in the LDA (Blei, 2012; Blei et al., 2003). α determines θ_d or per-document topic distribution, and the β parameter determines β_k or per-topic token distribution.

The LDA posteriors are a result of the trade-off between two inherently conflicting goals. Firstly, that only a relatively small number of topics are expected in a well-written document, and secondly that only high probability should be assigned to a small number of tokens that belong to highly

13 We decide not to include bi-grams or tri-grams in this process as we deem that common candidates like "climate change" or "green bonds" would fall under the definition of common terms when split into two. Therefore, we do not expect to change our results. Though, further research could be carried out to perform this robustness check.
14 While stemming consists on the removal of suffixes without considering the context or the actual meaning of the word, which can sometimes lead to the generation of non-interpretable words, lemmatization is the process of grouping together different forms of the same word, allowing to work with immediately interpretable tokens.

informative topics. The trade-off exists because if we assign, for instance, a single topic to a single document, thus succeeding at the first goal, the second goal becomes difficult to achieve because all tokens in the document must have a relatively high probability of belonging to that topic. The estimation of the LDA model requires a Bayesian updating from its initial semi-random allocation of topics to tokens and documents, to converge to a probabilistic distribution of topics across documents. Technically, the process will be completed when we find matrices $\beta_{N \times K}$ and $\theta_{K \times D}$ that most likely have produced the observed data W. In our case, the Gensim implementation in Python, based on a Bayesian approach, finds the best configuration of the model automatically as well as several settings related to numerical efficiency (Hofmann, 2001). In order not to stop at a local optimum we use a high enough number of iterations, in particular we needed 40,000 passes to reach a stable solution.

B Cluster analysis

Reviewing the top terms for each topic provides us with an initial understanding into their potential labels. However, this approach does not remove all uncertainty in assigning sufficiently different and sensible topics: some tokens, such as "vegetation" in topics 1 and 2 and "land" in topics 4 and 5, can be prevalent across multiple topics. Hence, we further scrutinize the top terms using the relevance metric, which prioritizes terms based on their significance within a topic relative to their presence in other topics. The relevance metric is defined as follows: for a given term t, its relevance to topic k is defined as follows:

$$\lambda \log(\beta_{k,t}) + (1 - \lambda) \log(\frac{\beta_{k,t}}{p_t}), \tag{2}$$

where $\beta_{k,t}$ is the probability of term t in topic k, p_t is the marginal probability of term t across all topics, and λ is a parameter that balances term frequency within a specific topic against its frequency across all topics. By applying this metric, we identify the following set of topics: Topic 1 as *Physical risk*, Topic 2 as *Deforestation*, Topic 3 as *Energy and emissions*, Topic 4 as *Agricultural risk*, and Topic 5 as *Land use and land cover*.

C Figures and Tables

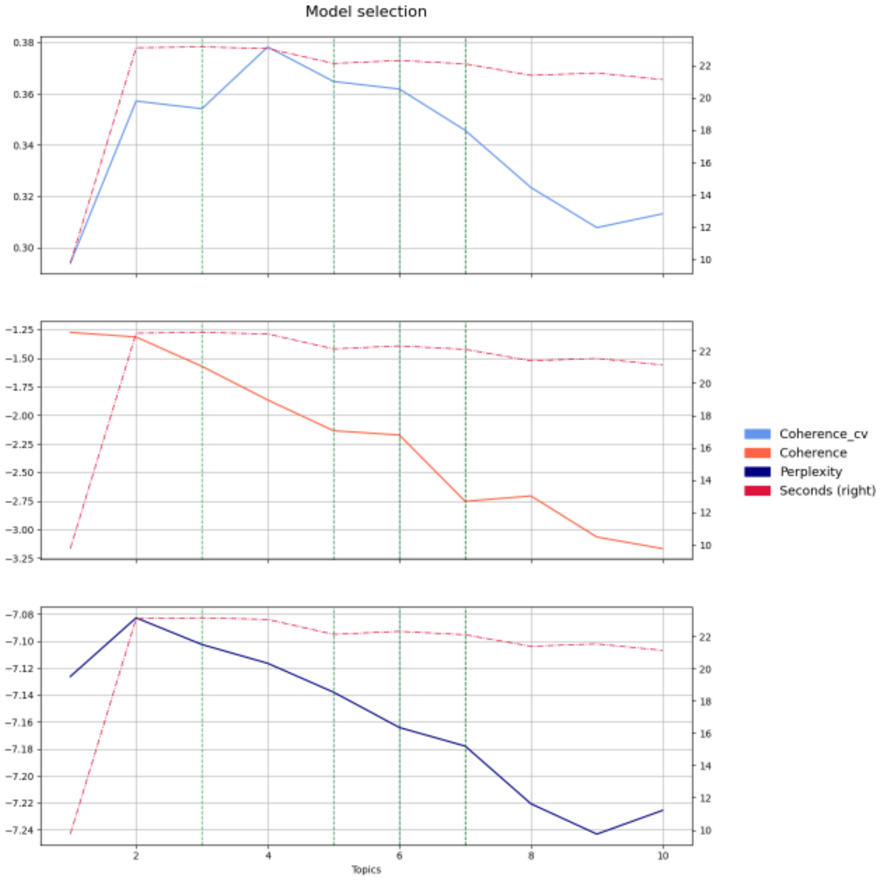

Figure 2: LDA model selection metrics

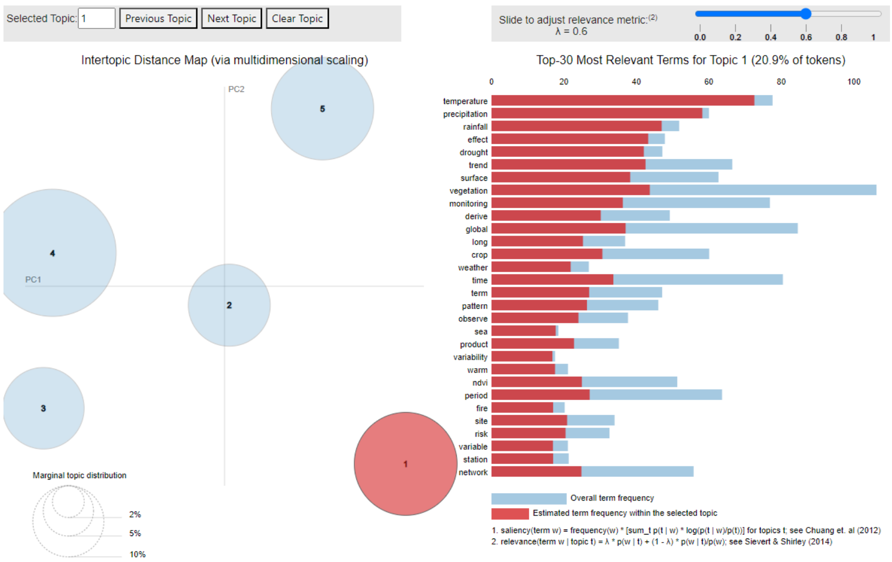

Figure 3: Intertopic distance map, and Top30 most relevant terms for Topic1.

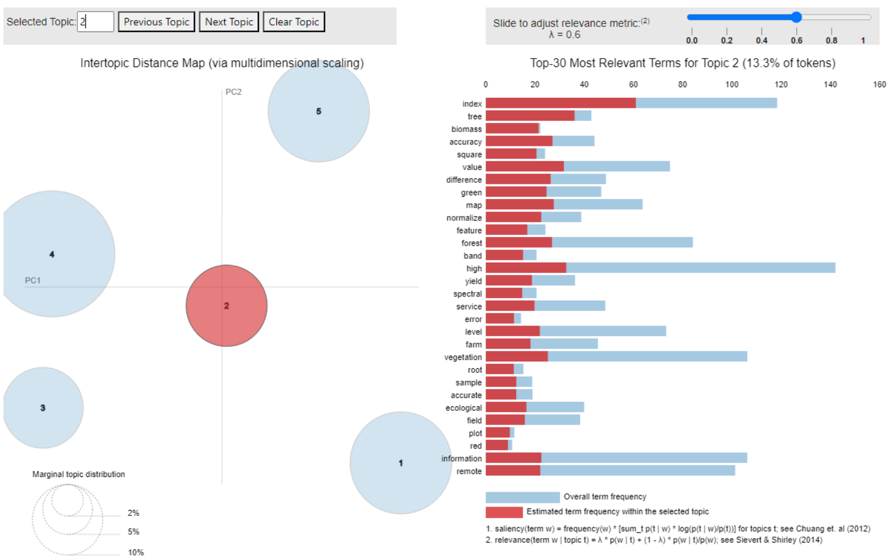

Figure 4: Intertopic distance map, and Top30 most relevant terms for Topic2.

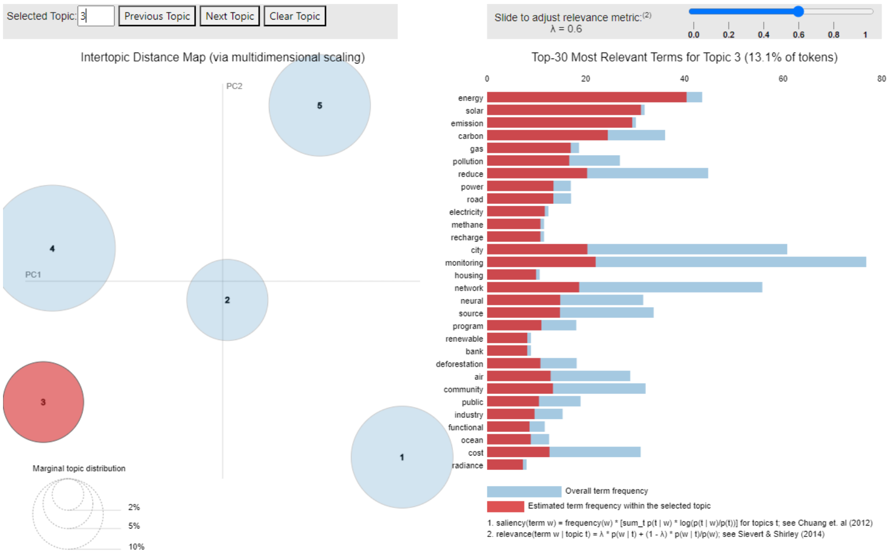

Figure 5: Intertopic distance map, and Top30 most relevant terms for Topic3.

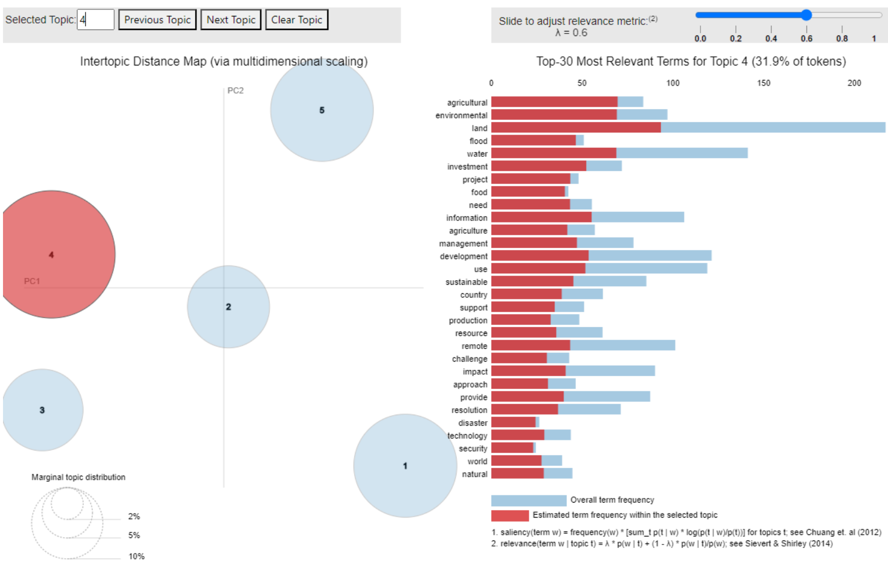

Figure 6: Intertopic distance map, and Top30 most relevant terms for Topic4.

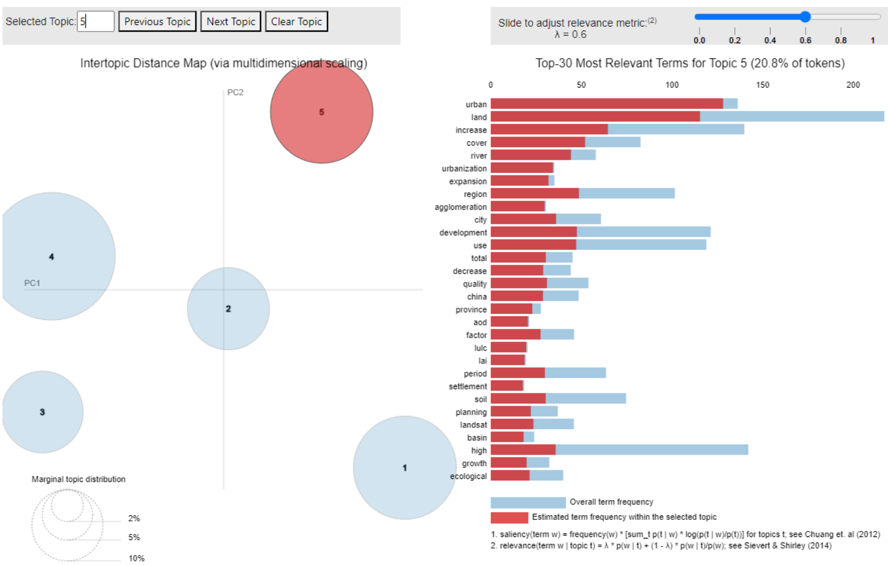

Figure 7: Intertopic distance map, and Top30 most relevant terms for Topic5.

Table 2: Probabilities of tokens per topic

Topic → / Term no. ↓	(1)		(2)		(3)		(4)		(5)	
1	0.015	temperature	0.020	index	0.013	energy	0.012	land	0.026	urban
2	0.012	precipitation	0.012	tree	0.010	solar	0.009	agricultural	0.024	land
3	0.010	rainfall	0.010	high	0.010	emission	0.009	environmental	0.013	increase
4	0.009	vegetation	0.010	value	0.008	carbon	0.009	water	0.011	cover
5	0.009	effect	0.009	map	0.007	monitoring	0.007	information	0.010	region
6	0.009	trend	0.009	accuracy	0.007	city	0.007	development	0.010	development
7	0.009	drought	0.009	forest	0.007	reduce	0.007	investment	0.010	use
8	0.009	surface	0.008	difference	0.006	network	0.007	use	0.009	river
9	0.008	global	0.008	vegetation	0.005	gas	0.067	management	0.007	city
10	0.007	monitoring	0.008	green	0.005	pollution	0.006	flood	0.007	high
Label	**Physical risk**		**Deforestation**		**Energy and emissions**		**Agricultural risk**		**Land Use and Land Cover**	