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Houston, we have a problem: can satellite data bridge
the climate-related data gap?¹

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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.

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 ([Diwan and Amarayil Sreeraman 2023](#); [van Bommel, Rasche, and Spicer 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 et al. 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 (Dikau and Volz 2021; Durrani, Rosmin, and Volz 2020; Delgado 2023; Volz 2017). This includes investment decisions (NGFS 2019; ECB 2021b; BdE 2023; Bundesbank 2023), monetary policy tools (ECB 2021a), financial stability assessments through climate stress tests (Battiston et al. 2017; Acharya et al. 2023; European Central Bank 2022; Alogoskoufis et al. 2021), and the supervision of financial institutions (Kedward, Ryan-Collins, and Chenet 2023; Heynen 2022; ECB 2022).

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-preprocessing 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 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

¹Though, 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); EFRAG (2024).

²Ground-based data refers to data not collected remotely, e.g., by sensors or satellites.

³We 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.

⁴See for instance private sector initiatives like Planet Labs, DrivenData Labs, or GMV

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 (e.g., [Stigler and Lobell 2020](#); [Nagendra et al. 2022](#); [Nagendra, Narayanamurthy, and Moser 2022](#)).

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 skillsets, 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 et al. 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.

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The establishment of the Innovation Hub of the Bank of International Settlements in 2019 (BISIH) 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 finance⁸ 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

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

⁶To 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, [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 et al. 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](#)).

⁷For 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 ([Project Gaia](#)), while the Hong Kong Center has finalized [Project Genesis 1.0](#) and [2.0](#), 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.

⁸The BIS created the Innovation Network in 2021 ([BISIN](#)) to track technological trends and developments with relevance to the thematic areas of the BISIH.

digital measurement, reporting and verification (MRV) systems, for instance ([BISIN 2023](#)).

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 strategies. 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 macro-prudential 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 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 et al. \(2023\)](#), 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:

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

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.

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

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.

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

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, Carbó, José Manuel, and Marqués, J Manuel 2023).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 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 model-

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

ing 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 (Hengl et al. 2018; Georganos and Kalogirou 2022; Kopczewska and Ćwiakowski 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 (Georganos et al. 2021). 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 et al. 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 Ratio 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.

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 et al. \(2005\)](#), [Ghosh et al. \(2009\)](#), [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 ([Sutton et al. 2007](#); [Chen and Nordhaus 2011](#)), 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 NO₂ pollution for nowcasting industrial production (e.g., [Bricongne, Meunier, and Pical 2021](#); [Jiang et al. 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 NO₂ 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 NO₂ pollution followed lockdown policies. Related to this, [Franke et al. \(2009\)](#) and [de 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 [Tysiac, Strelets, and Tuszyńska \(2022\)](#).

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 et al. \(2018\)](#) 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 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 to 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, Carbó, José Manuel, and Marqués, J Manuel 2023](#)). 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 et al. 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

Table 1. List of databases used for data collection

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	

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.

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, Ng, and Jordan 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 C1. 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

¹⁰Figure C1 in the Appendix displays the relevant metrics and training times for model versions ranging from one to ten topics.

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 C1 in the Appendix), we assess the topics based on the relevance metric¹¹. 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 C2 through C6.

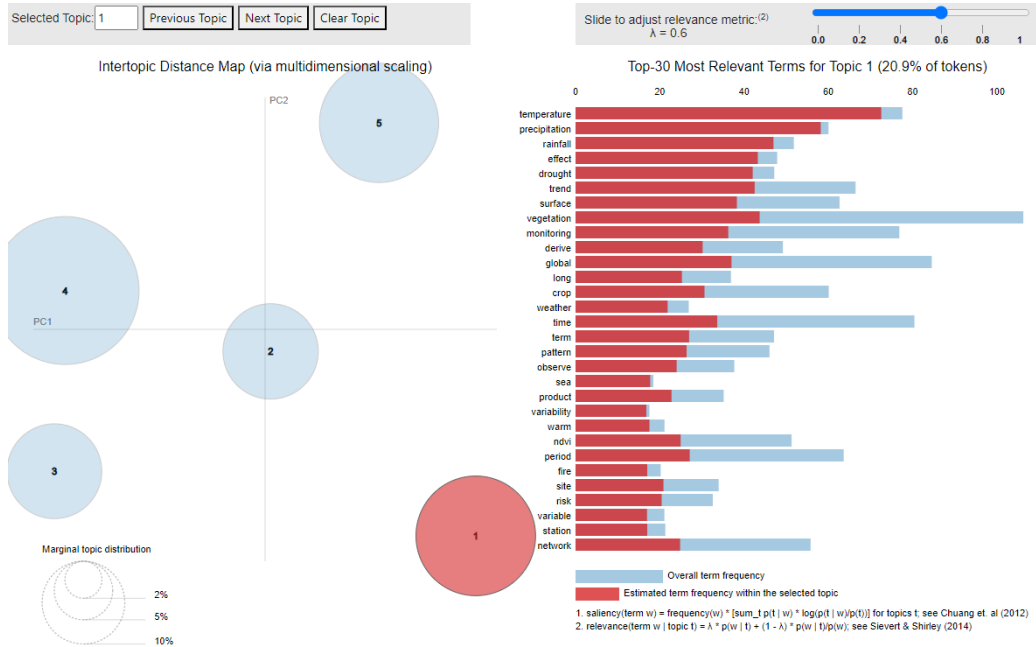


Figure 1. Intertopic distance map, and Top30 most relevant terms for Topic1.

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) and (TSVCM 2021). This assessment is a critical step in the design

¹¹Using $\lambda = 0.6$ and the PyLDAvis Python library proposed by Sievert and Shirley (2014)

and implementation of financial mechanisms that aim to reduce carbon footprints.

On another note, the emphasis on ecosystem health as the main indicator in nature finance (see, for instance, [TNFD 2023](#); [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](#)).

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

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

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., [DrivenData-Labs \(2023\)](#)) 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.

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Appendix 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 $N \times D$ 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, $\sum_{k=1}^K \theta_{k,d} = 1$. 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):

$$P(n|d) = \sum_{k=1}^K P(n|k) \cdot P(k|d) = \sum_{k=1}^K \beta_{n,k} \cdot \theta_{k,d} \quad (\text{A1})$$

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, Ng, and Jordan 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

¹³We 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.

¹⁴While 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.

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 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.

Appendix B. Clusters 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:

$$\lambda \log(\beta_{k,t}) + (1 - \lambda) \log\left(\frac{\beta_{k,t}}{p_t}\right), \quad (\text{B1})$$

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*.

Appendix C. Figures and Tables

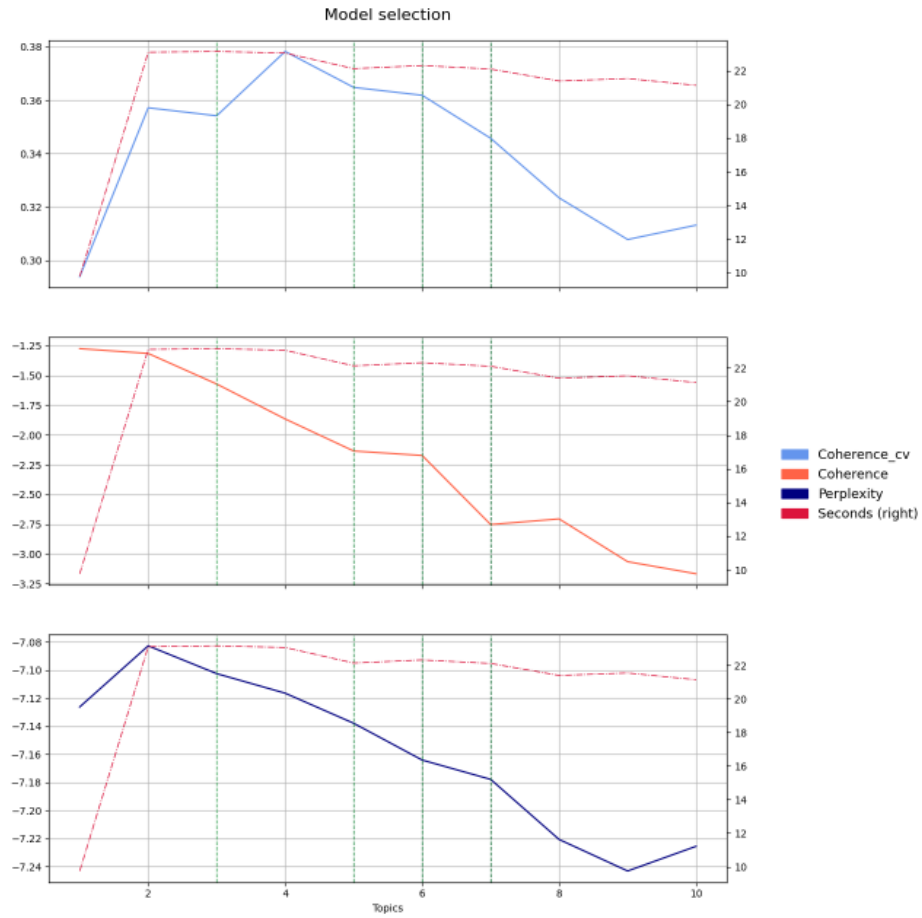


Figure C1. LDA model selection metrics

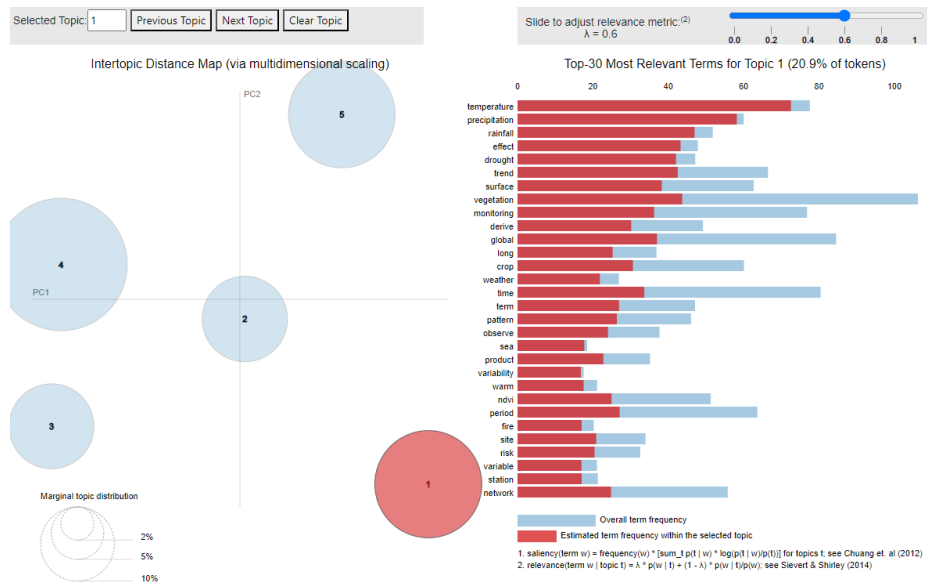


Figure C2. Intertopic distance map, and Top30 most relevant terms for Topic1.

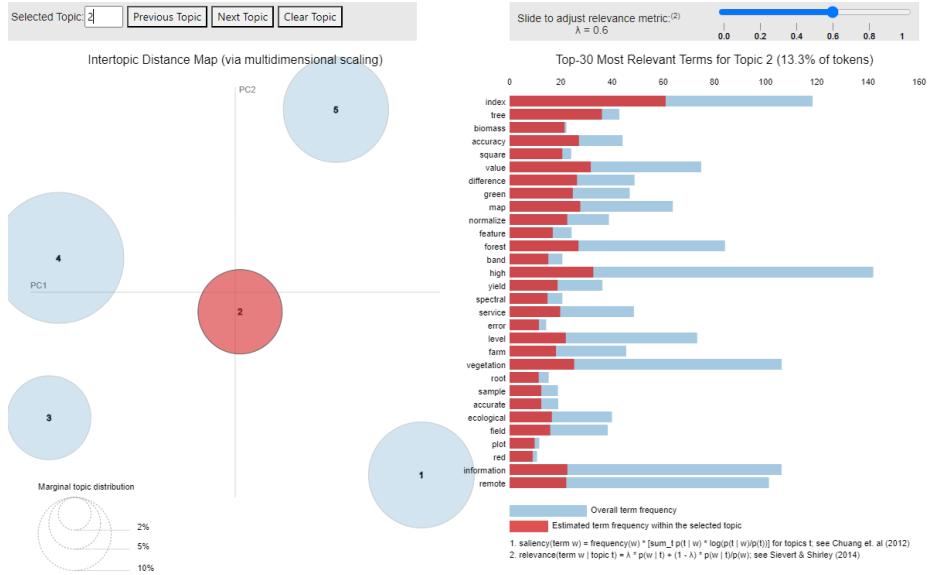


Figure C3. Intertopic distance map, and Top30 most relevant terms for Topic2.

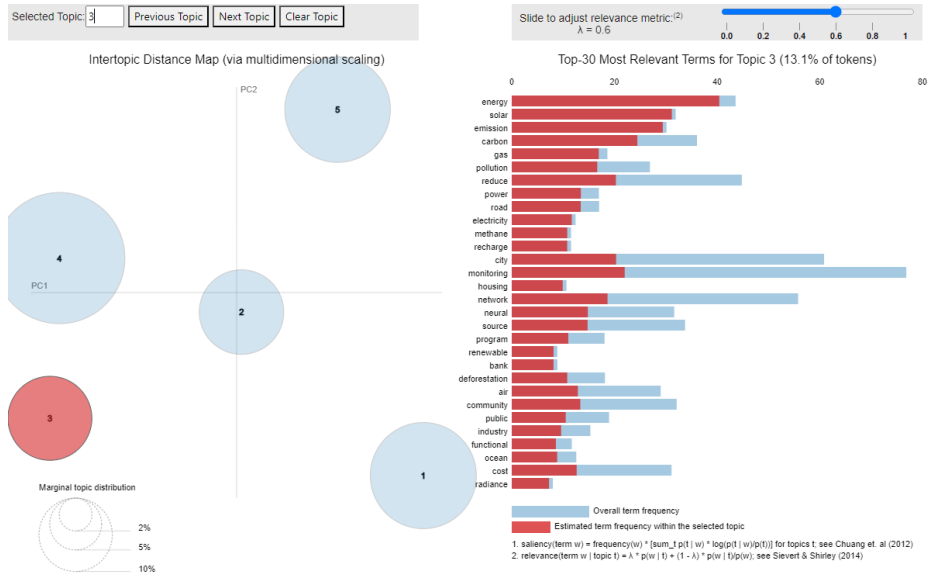


Figure C4. Intertopic distance map, and Top30 most relevant terms for Topic3.

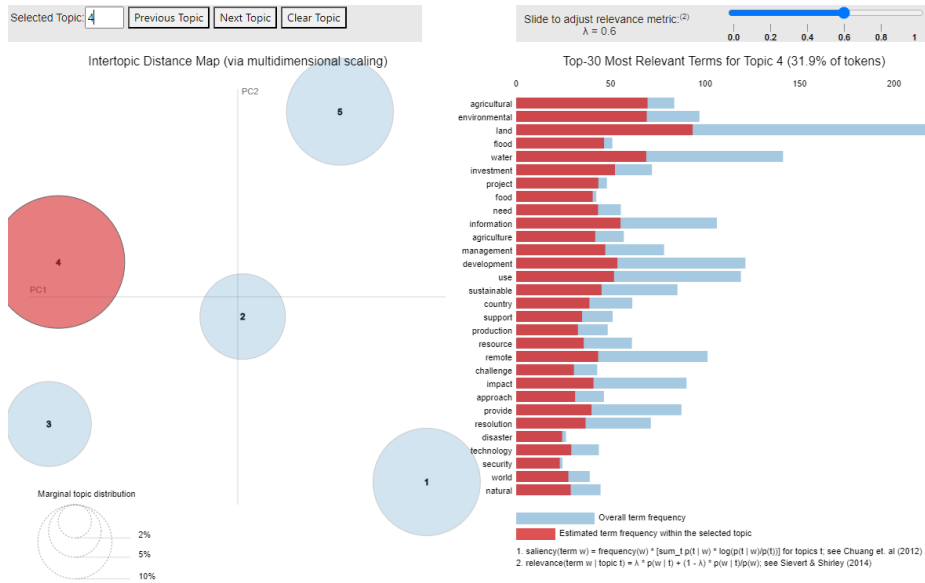


Figure C5. Intertopic distance map, and Top30 most relevant terms for Topic4.

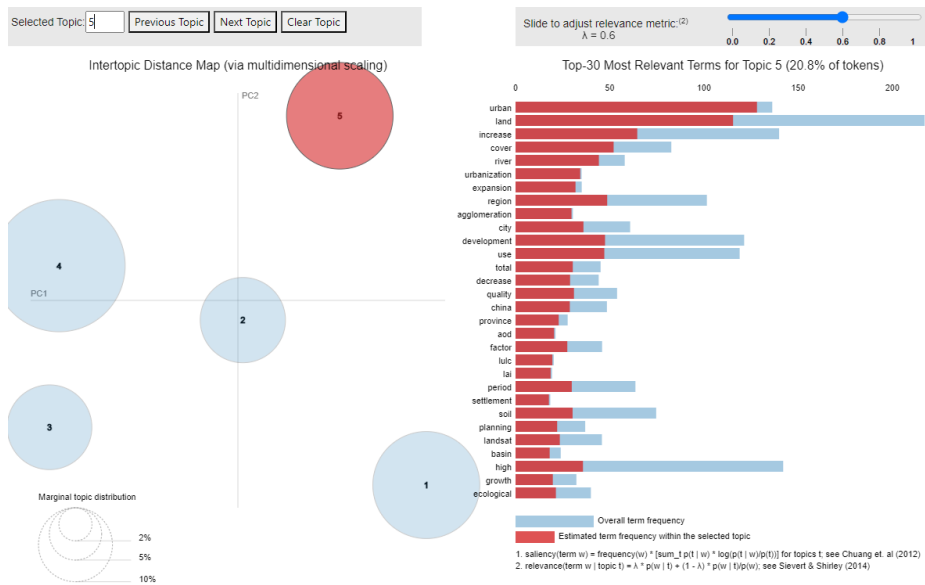


Figure C6. Intertopic distance map, and Top30 most relevant terms for Topic5.

Table C1. Probabilities of tokens per topic

Topic	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

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

Andres Alonso, Jose Manuel Carbo, **Emily Kormanyos**, Elena Triebkorn
Deutsche Bundesbank and Banco de España

IFC Workshop on “Addressing Climate
Change Data Needs: The Global Debate
and Central Banks' Contribution”



Agenda



The role of technology in bridging climate-related data gaps



Satellite data for green finance: Is this time different?



Use cases: ML-supported literature review



Outlook and conclusions

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Page 2

Motivation

The role of technology in bridging climate data gaps

Increasing focus on climate-related and sustainable finance data

- Central banks have **data needs** which they should close with **collaborative efforts** using **novel, unstructured** data sources (IFC, NGFS)
- Current efforts include:
 - **ECB** statistical indicators
 - **G20** data gaps initiative
 - **BIS** Innovation Hub (BISIH) and Network (BISIN):
 - Project Gaia, Project Viridis

Regulatory landscape

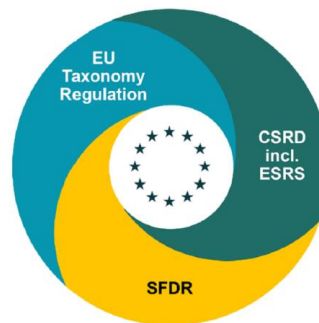
- New **directives** and **regulatory requirements** to improve data landscape:
 - ESAP – ESEF
 - CSRD, TCFD, TNFD, ...
- But **timeframe** and **extent** of (full) coverage until data availability is **not clear**

In the meantime, bridging technology is required

- **Technological innovation:**
 - as **bridge technology** until official data becomes available and/or
 - to **augment** / extend official data **when** it becomes available
- One of several promising candidates is geospatial data (esp. **Earth Observation** (EO) systems)



Taskforce on Nature-related
Financial Disclosures



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Motivation & project overview

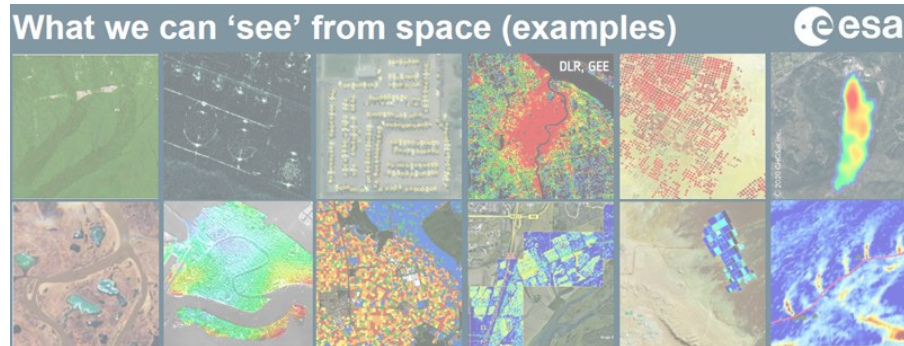
Why do we need to take (another) look at satellite data?

Situation

- Satellite data **available**, mostly **freely accessible**
- Already used in the **Global South**
 - E.g., Mexico, Egypt
- Limited use in the **Global North** due to availability of high-quality, granular, and timely **official statistics**

What we do

- Raise and help answer the question:
 - Is **sustainable finance a new frontier** for satellite data?
- Systematic literature review, topic modeling
 - Identify **where satellite data is successful** (e.g., insurance sector, agriculture, ...)
 - Identify **a gap in the literature** using satellite data for sustainable finance



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Successful use of EO data

Specific examples and future potential for green finance

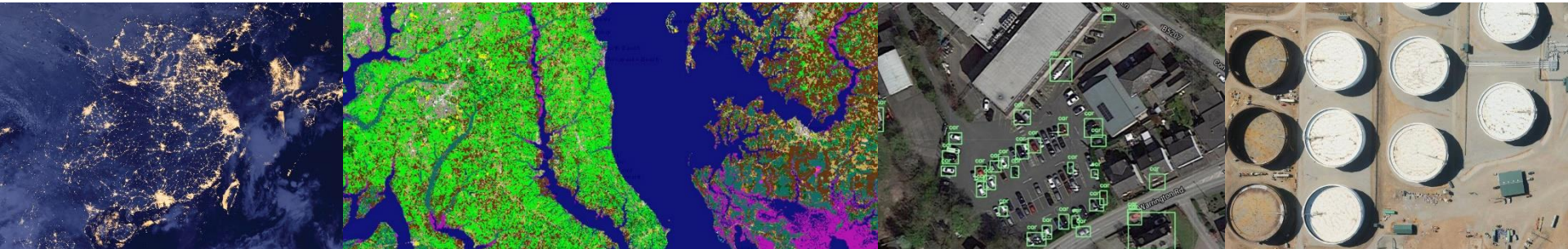
➤ **Two primary areas** of successful application:

- Development economics (tracking/estimating economic growth in Global South economies)
- Capital markets (esp. commodity and equity trading)

➤ **High potential of EO data** for predictive analytics in climate finance

➤ Specific examples:

- **Nighttime lights** to proxy economic activity
- Monitor urbanization patterns, infrastructure development, and land use changes (land use and land cover = **LULC**)
- **NO₂** pollution → environmental impact of economic activity
- **Oil storage facility** monitoring → commodities trading
- Retail **parking lots** → consumer spending
- Insurance markets: agricultural risk management



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Page 5

Satellite data in sustainable finance

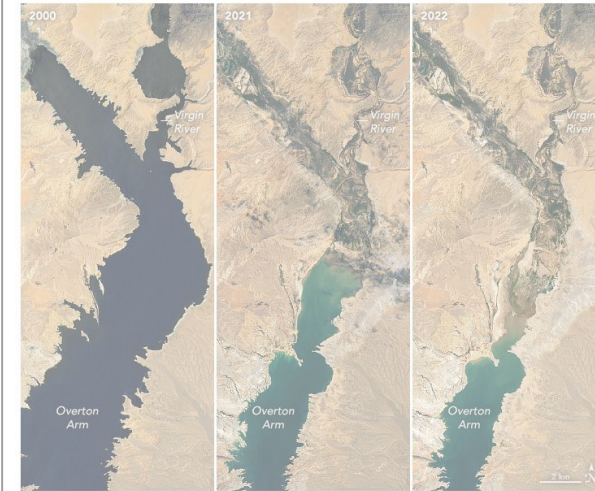
Our value proposition and contribution

Our proposition

- **Varying effects** of climate change within continents, countries, cities:
 - Transition and physical risks are **not evenly** distributed
 - **Climate finance is spatial**
 - Traditional data and models tend to **aggregate too broadly** over heterogeneously affected areas
- Satellite data can:
 - **address** these shortcomings of traditional data in the Global South and Global North
 - **enhance** the granularity (resolution) of traditional data & official statistics

But barriers to the success of satellite data remain

- Working with satellite data can be **difficult**:
 - Raster mapping
 - Link to official statistics?
 - Technological barriers (software usage, coding)
- We illustrate **typical challenges** and how to address them:
 - Econometrics
 - Parametrization (obtaining a series / variable from EO data)



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Systematic literature review aided by ML

Uncover clusters in the literature to derive use cases

Where has satellite data (not) seen success?

- While satellite data has seen success in **some domains**, it remains underused in others
- Conduct **large-scale literature** search
- Build topic model (**LDA**) to find **thematic clusters**
 - where EO data is used successfully vs.
 - where future efforts can use it to aid the green transition and inform central banks, official statistics, and academia

Approach to systematic literature review

- We use the **Publish or Perish** software for systematic literature search
- **Keyword combinations** for search queries based on domain expertise
- **Filter** search results to obtain final sample of relevant papers

List of databases used for data collection

Table 1

Databases selected on Harzing's *Publish or Perish* (open-source)

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	

Source: Alonso, Carbo, Kormanyos, Triebelskorn (2024), *Houston, we have a problem: Can satellite data bridge the climate-related data gap?*, Deutsche Bundesbank and Banco de Espana. Table 1, p. 16.

Finding optimal clusters

Iterative, human-in-the-loop process reveals thematic clusters in LDA topics

Topic model development

➤ Challenges:

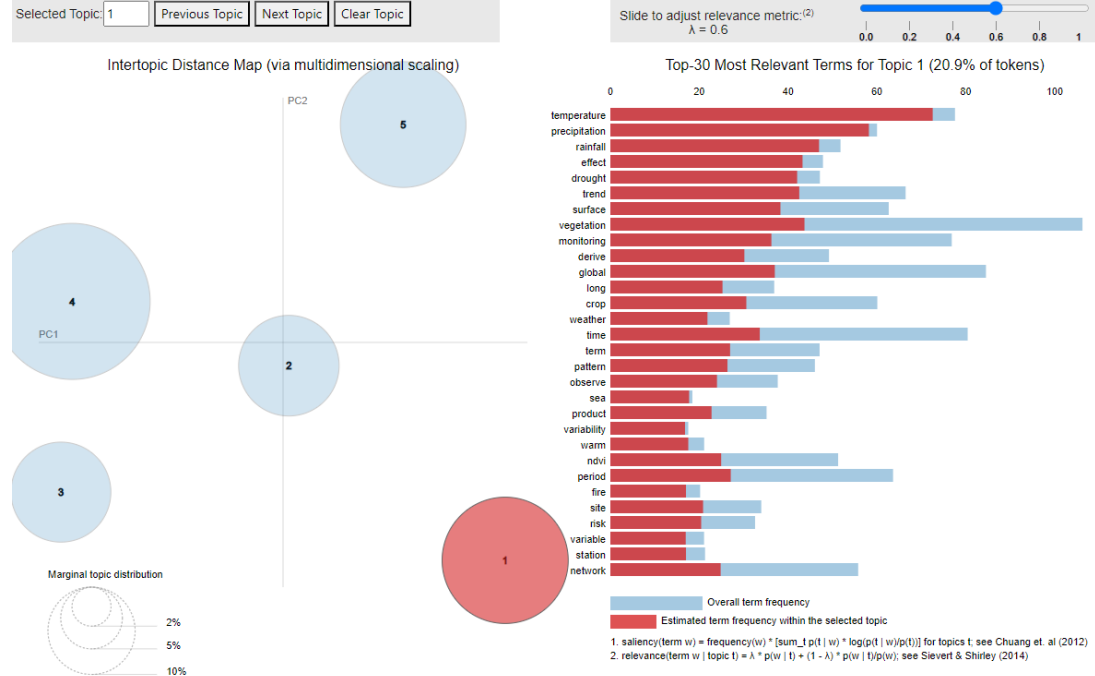
- Optimal number of topics
- Balance statistical metrics with costs

➤ Interpretable topic labeling based on **token analysis** and **relevance** metrics

➤ Iterative process:

- **Fine-tune** topics using **intertopic distance** maps and domain knowledge on **practical implications** for green finance

Intertopic distance map: topic 1 (physical risk)



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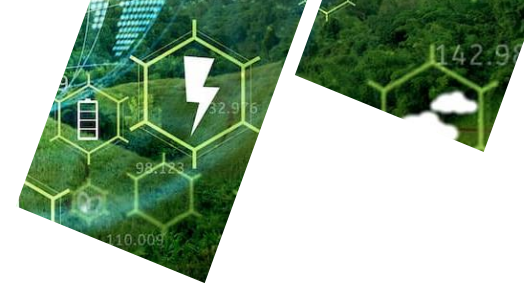
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Topic modeling results

Five distinct topics show current proliferation of EO data in the literature

LDA results					
Ten most frequent tokens, including each token's probability, per topic					
Topic →	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 environment	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	0.007 management	0.007 city
10	0.007 monitoring	0.008 green	0.005 pollution	0.006 flood	0.007 high
Topic label	Physical risk	Deforestation	Energy and emissions	Agricultural risk	Land use and land cover
Source: Alonso, Carbo, Kormanyos, Triebkorn (2024), <i>Houston, we have a problem: Can satellite data bridge the climate-related data gap?</i> , Deutsche Bundesbank and Banco de Espana. Table A1, p. 30.					

Conclusion and way forward



NOVEL DATA FOR CENTRAL BANKS

- Promising option to **bridge** climate-related **data gaps** of central banks
- EO data has **demonstrated usefulness** in diverse economic areas



POTENTIAL AND LIMITATIONS

- Core thematic areas where EO data can **support green finance**: physical risk, deforestation, energy and emissions, agricultural risk, and land use and land cover
- Despite **challenges** (accessibility and comparability), EO data has **high quality**, **auditability**, and **transparency**, positioning it as a **viable asset** to green finance



NEXT STEPS AND COLLABORATIVE EFFORTS

- EO data should be **integrated** with other data sources and technologies (e.g., ML/AI) to **maximize its potential**
- **Collaborative efforts** are needed to monitor developments and foster experimentation (e.g., BISIN, NGFS)
- **Next step**: derive **helpful, novel use cases** for EO data in sustainable finance for central banks and other FI

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Page 10

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Page 11



Appendix

Satellite data specificities

Gaining and understanding on EO data for green finance and beyond

Understanding satellite data

- **Satellite types:**
 - Communication, earth observation, navigation, astronomical satellites
 - Focus primarily on earth observation satellites for environmental monitoring and geographic mapping
- **Instruments and sensors:**
 - Multiple instruments with multiple sensors each
 - Sensors detect light in certain spectral bands
 - Different levels of spatial resolution for each sensor
 - One pixel corresponds to a certain geographic area
- **Passive vs. Active sensors:**
 - Passive sensors collect radiated photons from earth or sun
 - Active sensors send signals to earth and measure reflections, useful for penetrating clouds and capturing night images

Utilizing satellite data

- **Data applications:**
 - Measures various earth features like temperature, terrain, pollutants
 - Forms different types of images and videos, from natural color to false-color
- **Metrics and indices:**
 - Examples include NDVI, NBR, NDWI → ecosystem impact, wildfires, water scarcity
- **Economic relevance:**
 - Satellite data offers real-time, global coverage for tracking environmental health, land use, and deforestation rates
- **Challenges:**
 - Data access, cleaning, and pre-processing are significant hurdles
 - Econometric modeling required for interpreting raw data
 - Challenges to economic materiality in sustainable finance applications

Econometric modeling

- **Spatial dependency and autocorrelation:**
 - Proximity of geo-locations leads to spatial (auto-)correlation, violating independence assumptions in econometric models
- **Spatial heterogeneity:**
 - Relationships between predictor and outcome variables vary spatially
 - Requires different estimates for different regions
 - Spatial weights Address both spatial dependency and heterogeneity
 - Deriving weights can be challenging and increase model complexity
- **In addition to classical issues:**
 - Endogeneity
 - Sparsity
 - Missingness

ML and AI algorithms can handle nonlinearity, spatial heterogeneity, and clustering issues

Local Projections (Jordà, 2005, 2023) are suited to estimate responses to climate shocks

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Understanding satellite data

Color bands and sustainability metrics

Understanding satellite color bands

- Landsat collects 8 color bands:
 - B1 captures deep blue and violet light, useful for identifying aerosol particles
 - B2 captures blue light to differentiate water bodies
 - B3 captures green light, essential for assessing vegetation health
 - B4 captures red light, helpful in identifying plant types
 - B5 captures near-infrared light, indicating plant health and density
 - B6 captures shortwave infrared light (SWIR 1), useful for soil and vegetation moisture differentiation
 - B7 captures shortwave infrared light (SWIR 2), mapping geological features and vegetation
 - B8 captures panchromatic light, offering detailed landscape imagery

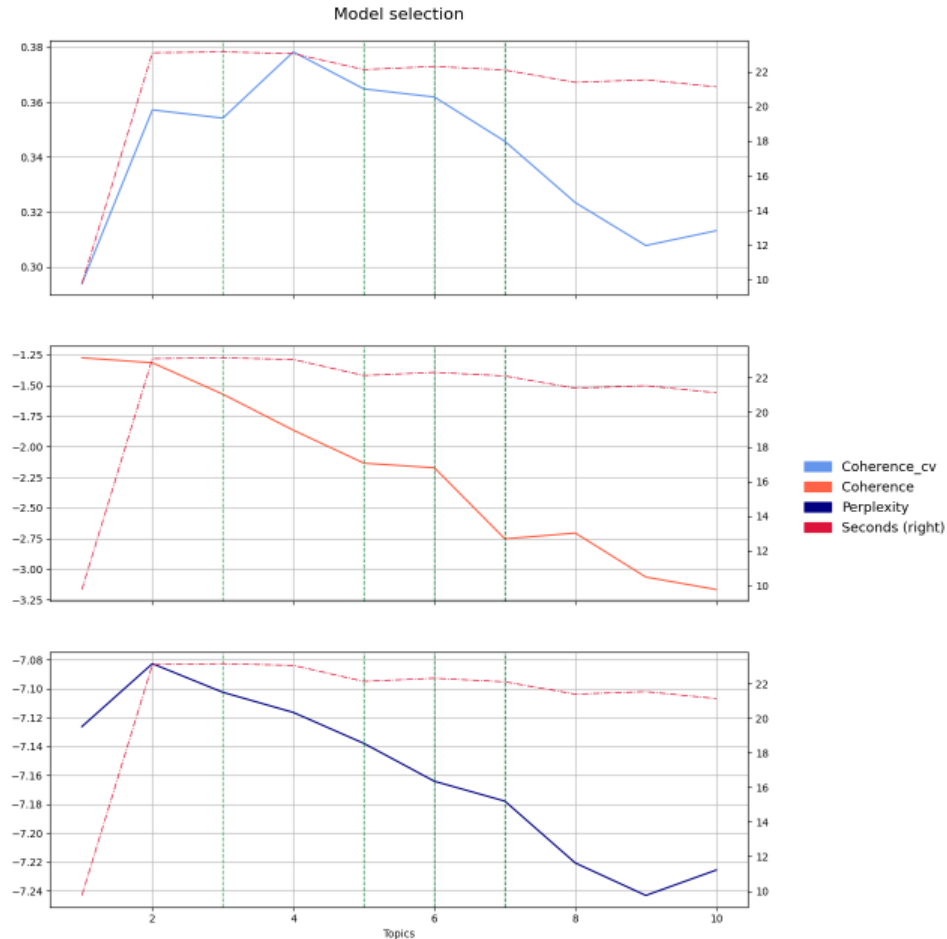


Examples of metrics derived from EO data

- NDVI (Normalized Difference Vegetation Index):
 - Measures vegetation health by contrasting near-infrared and red light
 - Useful for monitoring vegetation over time, including pre- and post-fire conditions
- NBR (Normalized Burn Ratio):
 - Specifically designed for identifying burned areas and estimating burn severity
 - Lower values indicate higher burn severity, aiding in fire impact analysis
- NDWI (Normalized Difference Water Index):
 - Optimized for water body detection by highlighting liquid water absorption and reflectance
 - Effective in delineating open water features and monitoring changes in water content of leaves

Topic model selection

LDA metrics



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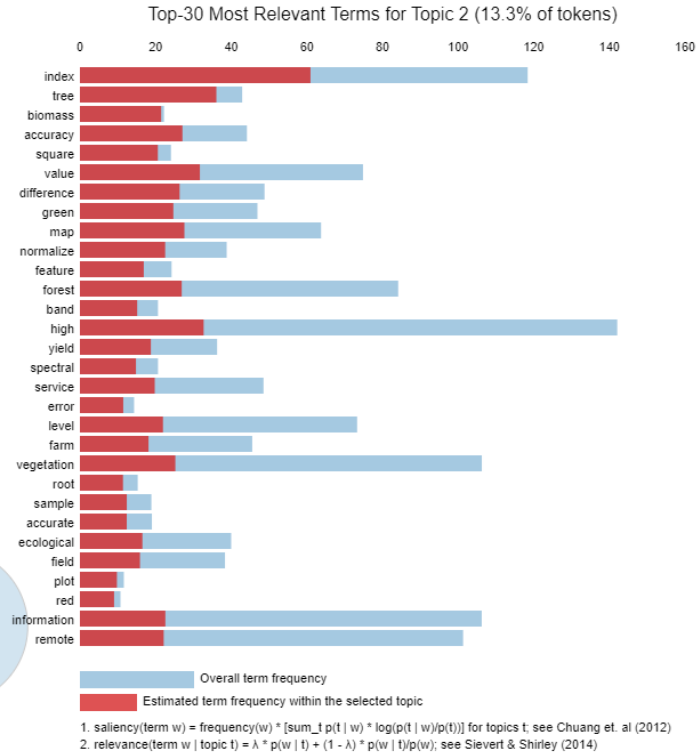
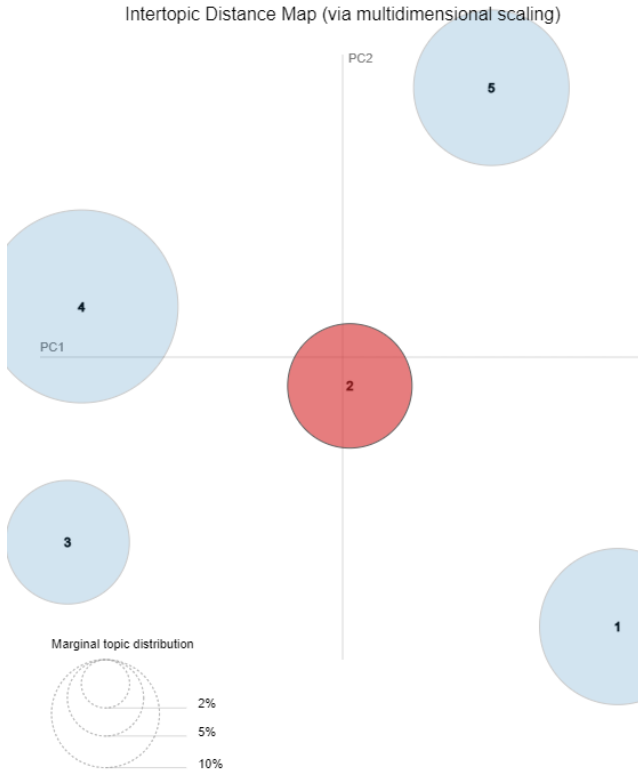
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Topic model development – intertopic distance

Topic 2: deforestation

Selected Topic:

Slide to adjust relevance metric:⁽²⁾
 $\lambda = 0.6$



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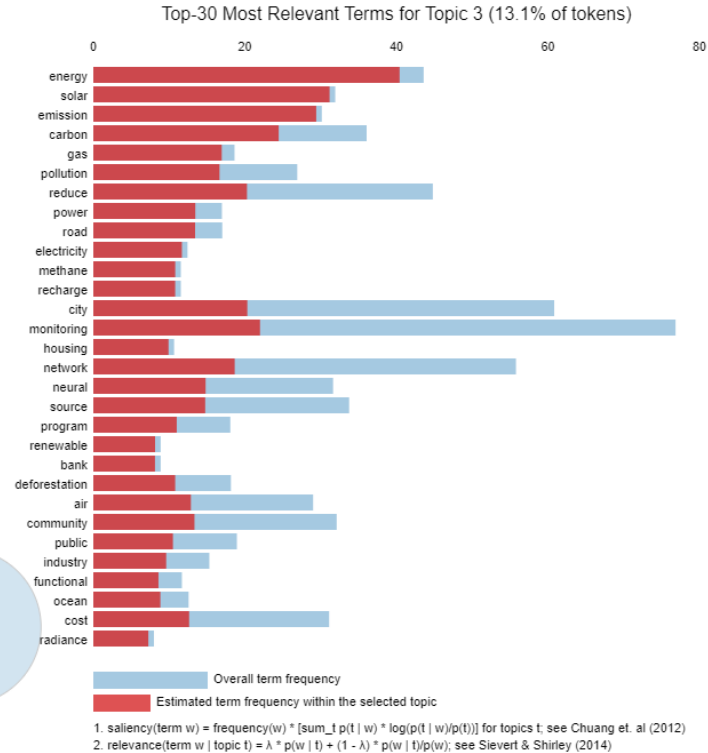
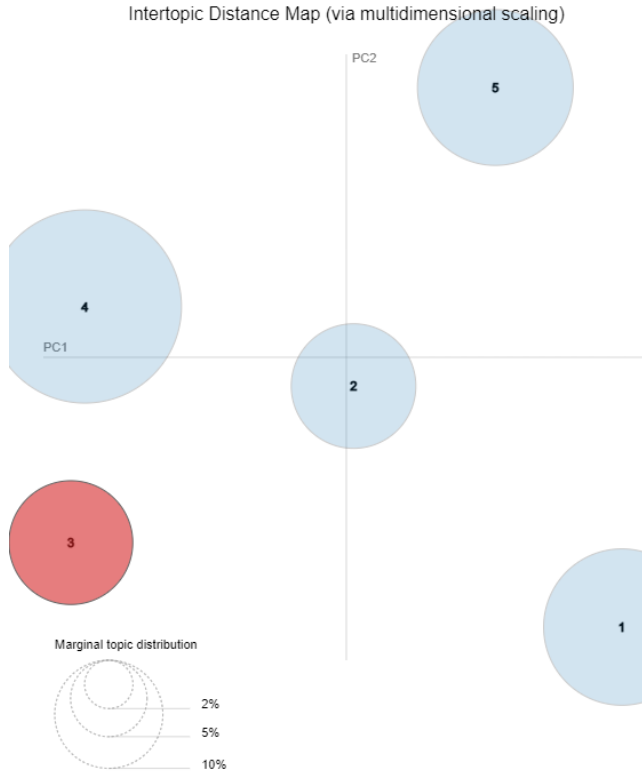
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Topic model development – intertopic distance

Topic 3: energy and emissions

Selected Topic: Previous Topic Next Topic Clear Topic

Slide to adjust relevance metric:⁽²⁾
 $\lambda = 0.6$

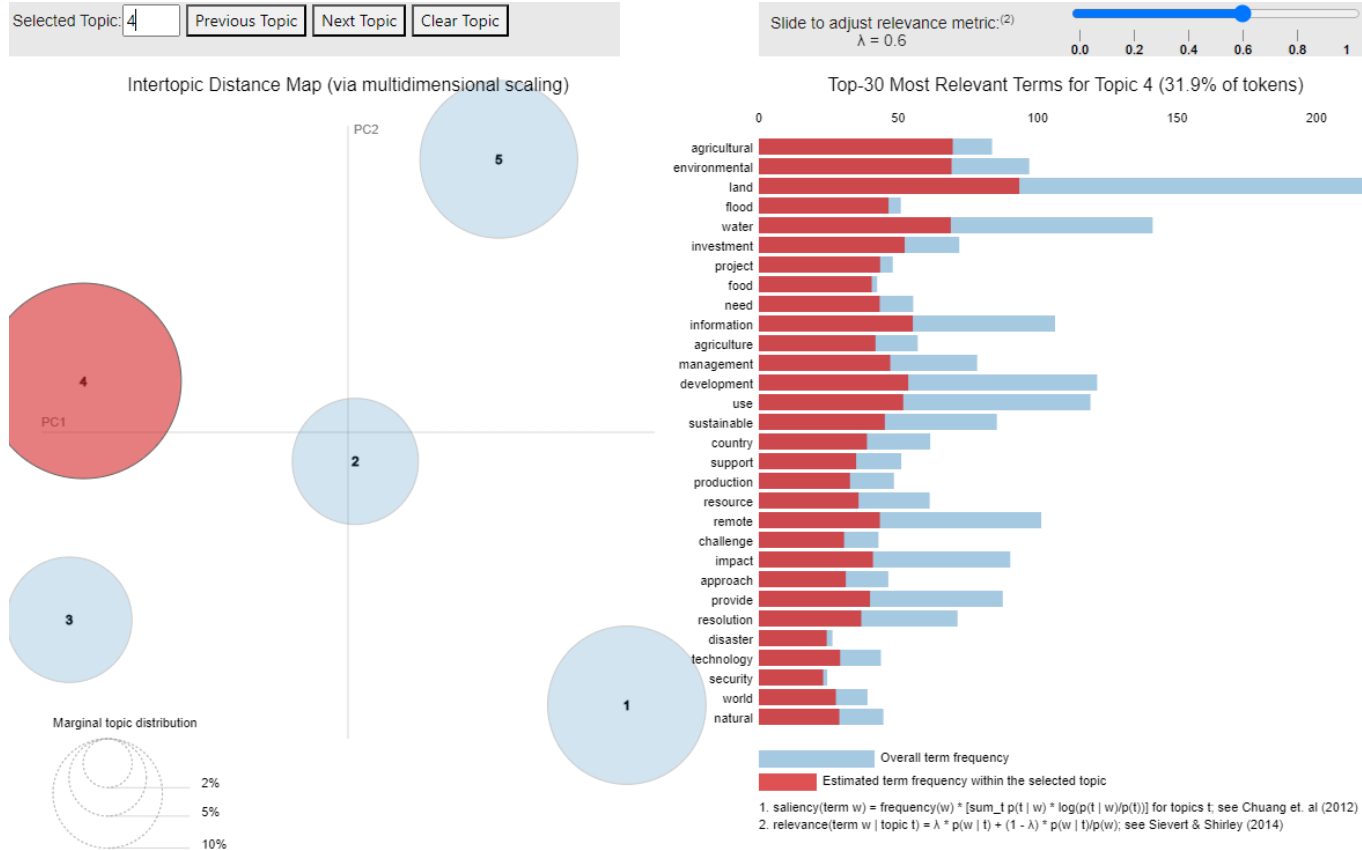


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Topic model development – intertopic distance

Topic 4: agricultural risk

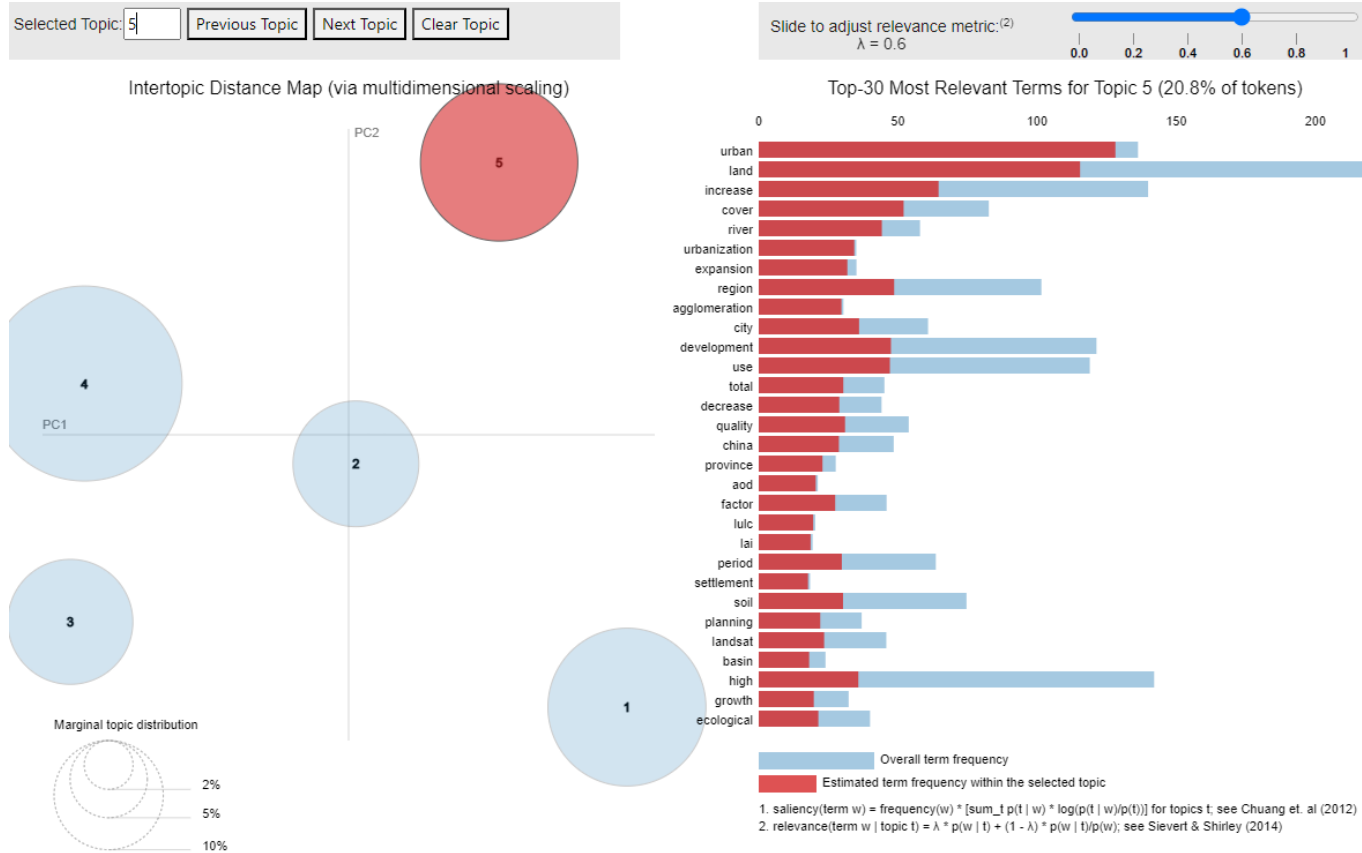


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Topic model development – intertopic distance

Topic 5: land use and land cover (LULC)



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