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To cite this article: Francis I Barre *et al* 2025 *Environ. Res. Lett.* **20** 094045

ENVIRONMENTAL RESEARCH
LETTERS

OPEN ACCESS

RECEIVED
16 May 2025

REVISED
29 July 2025

ACCEPTED FOR PUBLICATION
6 August 2025

PUBLISHED
19 August 2025

LETTER

High resolution GDP modelling for climate risk assessments with an application to coastal flooding in Norway

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Keywords: climate adaptation, natural hazards, value added, input output analysis, coastal flooding, hypothetical extraction method

Supplementary material for this article is available online

Abstract

An important prerequisite for accurately characterizing economic exposure from climate change at the national scale is a spatial inventory of economic activity and value creation. Current options for such inventories are limited, being either spatially precise but economically bounded sector-specific or owner-specific datasets, or gridded gross domestic product (GDP) products with coarse spatial resolution and inadequate sectoral resolution. To address these limitations, we develop a map of national GDP with high spatial and sectoral resolution. We stress this with meter-scale flood hazard maps to characterize GDP at risk from flooding. We further couple this to a macroeconomic input–output analysis to use the new sectoral resolution to estimate the scope of indirect economic exposure to flood at a national scale.

1. Introduction

The risk of impacts from extreme events comes from the combination of three factors: hazard, exposure, and vulnerability [1]. Modelling of the first, characterization of natural hazards, has seen formidable improvements in resolution, precision and coverage, thanks to technology improvements in remote sensing and machine learning techniques [2–4].

To understand the impacts of hazards, it is crucial to match it with an accurate understanding of the second of these factors, exposure, and, in particular, a better knowledge of the location of the populations and activities that are exposed to these hazards. Yet, work to understand economic exposure to potential hazards has not kept pace with advancements in hazard modelling.

The exposure of economies to sea level rise and coastal flooding is one area where exposure models lag behind progress in hazard modelling. Even a small to moderate degree of sea level rise, plausible under current greenhouse gas emissions trajectories, could increase the frequency and severity of coastal flooding by several orders of magnitude over the present day [5]. Understanding and modelling the exposure of coastal communities to flooding is crucial for promoting efficient prevention and adaptation measures [6].

Current attempts to characterize economic exposure to flooding are limited in important ways. Often assessments are limited in spatial resolution. Measuring economic activity at a fine spatial scale is necessary for making a meaningful comparison to flood forecasts which generally have meter-level resolution. In cases where analysts have been able to obtain fine scale activity data, these studies have been limited in comprehensiveness and sectoral resolution. Ideally a picture of exposure would be (a) measured at fine spatial scale (meters), (b) comprehensive of a national economy—meaning it accounts for all sectors and regions across the full spectrum of economic activity—and (c) differentiating economic sectors. This would allow linking exposure scenarios to economic tools for modelling cascading, recovery, and other dynamic effects.

Existing work characterizing flood risk has used exposure models with either fine spatial resolution, or economic comprehensiveness, but not both. Prior studies use either gridded gross domestic product (GDP) [7–10] or asset data [11] to evaluate risks in economic terms, from the local to the global scale. Gridded GDP models disaggregate national or regional GDP statistics on a raster grid using spatial proxies such as nighttime lights and gridded population data [12–15]. Yet the nighttime-lights based gridded GDP approach, even when augmented with additional data like population data [12, 16, 17], cannot deliver either building-level spatial resolution or any sectoral information. Additionally, the use of nighttime lights as a spatial disaggregation proxy suffers from known biases: it is saturation limited in urban cores, is unrealistically homogenous, and has irregular correlation with value added [18–20]. Another stream of research has employed asset-level data with good spatial precision to conduct sector-specific risk assessments for private asset owners, insurers, or sectors such as critical energy infrastructure [21], key transport infrastructure [22–24], building stock [25], healthcare and schools [26] or cultural sites [27]. These studies are usually topical, looking at the impact of natural hazards on one sector, or disruptions due to affected infrastructure. Such sector-specific or owner-bounded studies can be accurate yet are individually too idiosyncratic and collectively too incomplete to be compiled into a complete model of a national economy.

Accurately characterizing exposure to hazards both comprehensive across the entire economy and disaggregated by sector is essential for developing realistic scenarios that can be analyzed using macroeconomic models to capture how localized shocks can propagate through supply chains. Such second order dynamics can be very important: The cascading effects from natural hazards on the broader economy can be equal to or more severe than the direct effects [28]. To account for such effects, models representing linkages in the economy have been used in risk assessments, mainly input–output analysis (IOA) [29] and computable general equilibrium (CGE) [30]. Studies on flooding using such models have been conducted using exposure data with sectoral resolution, such as county-level employment [21], land use maps [21, 31–34], or capital stock composition [35]. However, these datasets lack the fine spatial scale necessary for direct comparison with flood hazards.

In summary, a new type of economic exposure data is needed to obtain both the high geographic resolution necessary for assessing specifically localized hazards and provide comprehensiveness and sectoral resolution. A promising approach in the most recent works is to use geolocated business registries to assess the share of each sector exposed to an event [36]. Building on this approach, this paper introduces a point-level economic dataset that is consistent with both regional and national statistics, offering high geographic and sectoral resolution for exposure assessments.

We present a bottom-up approach to characterize economic activity, disaggregating national GDP to point level, through its main component gross value added (GVA). This method provides improved sectoral resolution, improved spatial resolution, and comprehensiveness across all sectors. We demonstrate the approach by evaluating economic exposure to coastal flooding in Norway. National GVA is disaggregated to the point level using the public business register and other data, and this model of today's economy is stressed with coastal flood maps under a range of scenarios. Indirect exposure is then estimated using an input–output based approach, the hypothetical extraction method (HEM), to obtain an upper bound estimate of the scope of indirect impacts propagating through intersectoral linkages. We test different coastal flooding levels, (1) the extreme still water levels (e.g. the 1-in-20-year event) for today's climate and used in Norwegian planning law and (2) with AR6-based projected sea-level rise for 2100 in the high emissions scenario SSP3–7.0 added to the extreme still water levels [37]. The aim is to identify which sectors are currently at risk of coastal flooding, and to which extent, and to assess how much adaptation will be required due to climate change. We discuss the new opportunities created by the new spatial GDP modelling approach as well as its limitations.

2. Methods

National GVA at basic prices is disaggregated to point level using the business register of Norway, with NACE level 4 sectoral resolution. The economic model is then overlaid with coastal flooding maps, for different RPs, and including sea level rise under a high-emission scenario, SSP3–7.0, to assess direct exposure to the different flooding events. Indirect exposure is then calculated using the HEM of IOA to quantify interlinkages between the exposed sectors and the rest of the economy. All values were converted from NOK to € using the 2021 exchange rate (the year the latest production account statistics at regional level were published) for clarity to the international reader [38].

2.1. Economic map

The goal is to model the Norwegian economy at point level, disaggregating both value added and employment from national statistics (reported at regional and sectoral level) to the organization level. The decision to model GVA instead of GDP at the point level is based on two key factors: value added more accurately reflects an organization's economic activity by excluding taxes and subsidies, and it aligns with detailed regional and sectoral statistics, which typically report value added rather than GDP.

To disaggregate national GVA to point level, the initial step consists in determining the location of the Norwegian economy, sector by sector, using varying data sources. The main data source used for disaggregating national GVA and employment is the Norwegian public business register, Brønnøysundregistrene, which was geocoded using Nominatim [39], an OpenStreetMap tool, and mapbox geocoding for remaining addresses [40]. The register, which is updated weekly, reports data for all Norwegian entities including their sector of activity (NACE level 4), their address, employment, as well as accounting reports. The main strength of the register is that it tracks not only headquarters but all locations where economic activity takes place. For most economic sectors, the location therefore corresponds precisely to the physical location of value creation, though this approach fails to precisely locate value creation when it is spread over a larger area (e.g. agriculture, transportation). The business register does not include offshore activities. To cover the offshore facilities from the oil and gas sector, a crucial sector to the Norwegian economy, the OGIM dataset is used [41].

Proxy variables are used to measure the relative economic importance of separate entities within an economic sector. In the business register, 23.4% of organizations report their number of employees, whereas 28.3% report revenue. The weight for each point is calculated as the average of the normalized number of employees (relative to the total number of employees in the country) and the normalized revenue (relative to the sum of all companies' revenue). The variables are normalized to eliminate units and ensure they carry equal weight in the analysis. When only one variable is reported, it is chosen as the weight.

To deal with the organizations that report neither revenue nor number of employees (63.4% of them), several methods were tested. Considering that reporting obligations only apply to large organizations [42], and that 68.2% of companies in Norway have no full-time contracted employees [43], it is assumed that the large majority of organizations without a weight are of small economic importance. Based on testing several distribution methods during a calibration phase (which is further detailed in the calibration section) we opted to set the default weight as the lowest quartile of weights within the same administrative boundary and sector. Finally, for offshore oil and gas, total hydrocarbon output is used as a proxy.

The GVA, reported at the sectoral and regional level from the national statistics, is then distributed to point level using proxy weights. The disaggregation follows equation (1), where r is a given region, s a given sector, $P_{r,s}$ the collection of all points within that region and sector, and w the weight of a given point,

$$\forall p \in P_{r,s}, gva_p = \frac{GVA_{r,s} \cdot w_p}{\Sigma_{q \in P_{r,s}} w_q}. \quad (1)$$

Employment reported at the sectoral and municipal levels is disaggregated in the same fashion.

2.2. Assessing direct exposure

The point-level map of GVA and employment obtained in the prior step extent is stressed using a suite of flood scenarios from the Norwegian Water Resources and Energy Directorate [44]. These scenarios cover coastal flood scenarios for three return periods (RPs): 20, 200 and 1000 years, and are inclusive of projected sea level rise. Sea level in 2100 corresponds to the top of the likely range in the SSP3-7.0 climate change scenario. This scenario is meant as a high end of carbon emissions, when no mitigation policies are taken [45]. Using the upper end of this high-emission scenario therefore provides extremes for coastal flooding, not to be taken for predictions of coastal flooding in the next century. The relevant national authority, the Norwegian Directorate for Civil Protection, recommends the use of this high-end scenario for coastal planning [46]. Evaluating the exposure of today's economy to a future flood risk is not meant as an attempt to model the future economic impact of these floods, in which case a point-level approach is not suited. The goal is to evaluate how much adaptation must happen, given that areas which are not considered at risk today (even under highly unlikely 1000 year RP floods) will likely be frequently flooded in 2100 (in the 20 year RP floods). This model allows us to identify these areas which may become vulnerable either in a medium/long term future with climate change, but also on a shorter time scale would low probability/high impact tipping points happen (such as collapsing ice sheets). The scenarios are defined as following:

Characterizing value creation within the flooded areas in each scenario gives an estimation of flood exposure of different sectors and administrative boundaries, for different flood events, and for more extreme floods, such as those expected in 2100 under SSP 7–2.0, as summarized in table 1.

To compare how the results differ using a point-level model rather than a gridded one, the exposure to each flood is also calculated using gridded GDP as the exposure data [16]. The gridded GDP values are scaled to match total value added in Norway in 2021. Then, for each grid cell, exposed value added is calculated by multiplying value added of each grid cell

Table 1. The different coastal flooding scenarios.

Sea-level year \ Return period	20	200	1000
Present	P.frequent	P.rare	P.extreme
2100 (SSP 3–7.0)	F.frequent	F.rare	F.extreme

by the share of flooded land compared to total land within the grid cell.

2.3. Indirect exposure

Indirect effects from a disaster can occur both through forward linkages, because of disruptions in supply, and backward linkages, because of decreased demand. Studying indirect effects therefore requires an overview of traded goods and services between economic actors or the sectors they represent. At national level, this is captured by the input–output tables in the national accounts. Here we employ the HEM to estimate indirect exposure to coastal flooding. As HEM is computed using the Leontief model, where production is driven by demand, it only assesses backward linkages. This method was chosen as it is widely used, simple and transparent, and provides a clear upper bound estimate of indirect exposure. HEM consists of removing a sector from the economy and analyzing the consequences for other sectors. It has been used for measuring how economic sectors influence each other [47, 48], environmental footprint analysis [49–51], and disaster studies [52, 53]. The HEM evaluates exposure by establishing a simple counterfactual: the economy without the presence of the extracted activity(s). Comparing the actual to this counterfactual shows the pattern and magnitude of linkages between flooded companies and other economic sectors.

This approach evaluates the instantaneous exposure and does not consider any dynamic (time-varying) effects such as the post-shock recovery dynamics. Leontief production functions are linear—a reduction in any input causes a linear reduction in total output. Dynamic models use other production functions which can better capture substitutions or recovery processes such as reconstruction activity [54]. Despite these limitations, this model can give a first order estimate of indirect exposure during flooding events. Leontief production functions are established for identifying indirect exposure. They map the linkages between affected sectors and the rest of the economy, regardless of whether these linkages would ultimately result in decreased output if the event occurred.

Using the input output analysis framework, the total production in the economy x can be calculated from the final demand y and the Leontief matrix $L = (I-A)^{-1}$ such that $x = L \cdot y$. Value added T in each sector is given is proportional to the sector's output x, where θ is the value added per unit of output in each sector, or $T = \theta\hat{x}$, where $\hat{x}$ is the diagonal matrix formed from the elements of the vector x. The HEM consists in removing one or multiple sectors from the economy, calculating the new total output, and comparing it to the initial output, to study the linkages between the extracted sector(s) and the rest of the economy [55]. This is equivalent to the following equation:

$$x^o = x - x^* = Ly - L^* y^* \tag{2}$$

where the superscripts ^{o} represents the extracted economy and * the remaining economy.

The direct exposure to flooding (organization facility located in a flood zone for the different events) gives a share α_k of value added for each sector k which is exposed to the flood, where $0 \leqslant \alpha_k \leqslant 1$. To determine the value chain exposure to these flooded companies, each row j of the requirement matrix A is downscaled by the share α_j of directly exposed companies, as shown in equation (3). A more thorough explanation of equation (3) can be found in the SI,

$$\forall k, j,\ a^*_{jk} = \left(1 - \alpha_j\right) \cdot a_{jk}. \tag{3}$$

This approach is an extension from Dietzenbacher and Lahr by simultaneously applying partial extraction to all exposed sectors, whereas their analysis considers one sector at a time [53]. Another key distinction is that they keep the diagonal coefficient in the A matrix untouched, whereas we reduce it by α. Both approaches reflect different objectives. Dietzenbacher and Lahr study the effect of a 10% decrease in output for a given sector. Here, the 10% would correspond to directly exposed companies within the sector, which are to be extracted. The decrease in output should therefore exceed 10%, because other companies within the same sector trade with those exposed. One can also notice that, in the case where only one sector is fully extracted, i.e. $\alpha_k = 1$ and $\alpha_j = 0 \forall j \neq k$, then equation (3) is equivalent to case 2c of Miller and Lahr, column 2 as presented in an elaboration by Hertwich and colleagues, thus ensuring coherence with the existing HEM framework [47, 56].

Similarly, the extracted companies cannot provide final products to consumers, such as households and government. The final demand vector y is modified as shown in equation (4),

$$\forall k,\ y^*_k = (1 - \alpha_k) \cdot y_k. \tag{4}$$

Using modified A^* and y^*, we can calculate extracted output and extracted value added,

$$x^o = x - (I - A^*)^{-1} y^* \tag{5}$$

$$T^o = \theta\widehat{x^o}. \tag{6}$$

In this study we focus on the F.rare flooding scenario to evaluate indirect exposure. It should be noted that the 200 year flood map does not represent a single event. The 200 year flood map shows instead, for each point along the coast, the extent of a flood that would happen on average every 200 years, the 200 year floods would unlikely happen at the same time on the entire coast. When evaluating the indirect effects for all companies flooded by the 200 years floods, it is a higher bound of indirect exposure. The original sectoral resolution from the direct exposure assessment (NACE level 4, differentiating 613 sectors) is aggregated to match the 62 sectors from the national IO table.

Data on sectoral and regional value added, employment, and intersectoral linkages in the form of a national input–output table were sourced from the national statistical agency SSB [57–59]. The GVA and employment were spatialized using firm-level data with address and primary sector of activity (NACE level 4 code) sourced from the public business register Brønnøysundregistrene [60].

3. Results

3.1. Measuring sectoral value added at high geographic resolution

The sectoral distribution of the Norwegian economy reveals significant heterogeneity in where and how value added is created. As expected, total GVA is closely correlated with population density (figure 1). We evaluate the results in terms of GVA per sector (see also discussion), the main component of GDP. GDP is a national statistic and differs from GVA by the inclusion of product taxes such as VAT or sales tax, and subsidies [61]. The spatial distribution of value added varies meaningfully by sector. GVA in agriculture and fishing is largely distributed in the countryside and shows high output in some fjords due to aquaculture. Output from the Mining and Quarrying sector is concentrated in offshore facilities and cities closely associated with oil and gas industry activities. The Energy and Utilities sectors show high output cells throughout the country. The Business Services, Public Administration, Trade and Transportation, Construction and Manufacturing sectors are concentrated in dense urban centers, similarly to total value added. This diversity underscores the utility of adding sectoral detail to the economic inventory.

3.2. Assessing direct economic exposure to floods by sector

The economic exposure to costal storm surges shows that, in today's economy, i.e. without adaptation or growth, the Business Services and Public Administration sectors have the highest absolute exposure to F.extreme floods, at 3.3 and 4.1 billion EUR respectively. This amount is relatively small compared to their total output, respectively 3.8% and 5.1%. In the Agriculture and Fishing sector, organizations that constitute approximately 15% of the sector's GVA are exposed to that event, mainly due to coastal aquaculture. The exposure of the Norwegian economy results from overlaying the economic model with coastal flooding maps in various scenarios (figure 2(b)). Direct exposure (i.e. annual total value creation) to the different events varies from 0.75 billion EUR (0.2% of total value added in Norway) in P.frequent to 12.6 billion EUR (3.7% of domestic GVA) in F.extreme; see figures 2(c) and (d) for details. Economic exposure is significantly higher when using gridded rather than point-level value added, and with lower difference between flooding scenarios. In terms of employment, exposure varies from approximately 8200–107 000 employees under the range of scenarios, corresponding to 0.3%–3.8% of employed people in the country. It is important to notice that employment exposure is higher than value added exposure in relative terms.

The results reveal that sectors vary widely in their flood risk exposure. In terms of geographic distribution of exposure, in most scenarios the largest cities have the greatest absolute exposure of value creation at risk. Midsize coastal towns (e.g. Tromsø, Ålesund) stand out with very high exposure relative to their size. When ranked by the percentage of value added at risk, islands and coastal towns emerge as the most exposed.

A critical result is that the exposure of the Norwegian economy to floods we expect to see every 20 years in 2100 is modelled to be 3–4 times higher than the exposure to the 1000 year flood today. This result highlights the need for drastic adaptation and climate preparedness. Only a relatively small change in sea-level rise can have a dramatic incidence on exposure of human activities to storm surges.

3.3. Estimating cascading indirect exposure to flooding hazards

Indirect exposure calculated using IOA based the HEM approach to quantify interlinkages between the exposed sectors and the rest of the economy. The HEM establishes a counterfactual national economy with portions removed ('extracted') and assumes no changes to production recipes or inventory buffer. As discussed in the discussion and methods, this is a simple approach to assessing indirect exposure, which is in some ways an upper bound as it assumes no response to the shock, and in other ways potentially an underestimate as it ignores aspects of societal and economic interdependence which are not captured in financial flows linking sectors. The HEM exposes how risk could propagate along supply chains in case of a natural disaster. To highlight potential cascading effects of a hazard, we considered the extent of the F.rare flood. When evaluating the indirect effects for

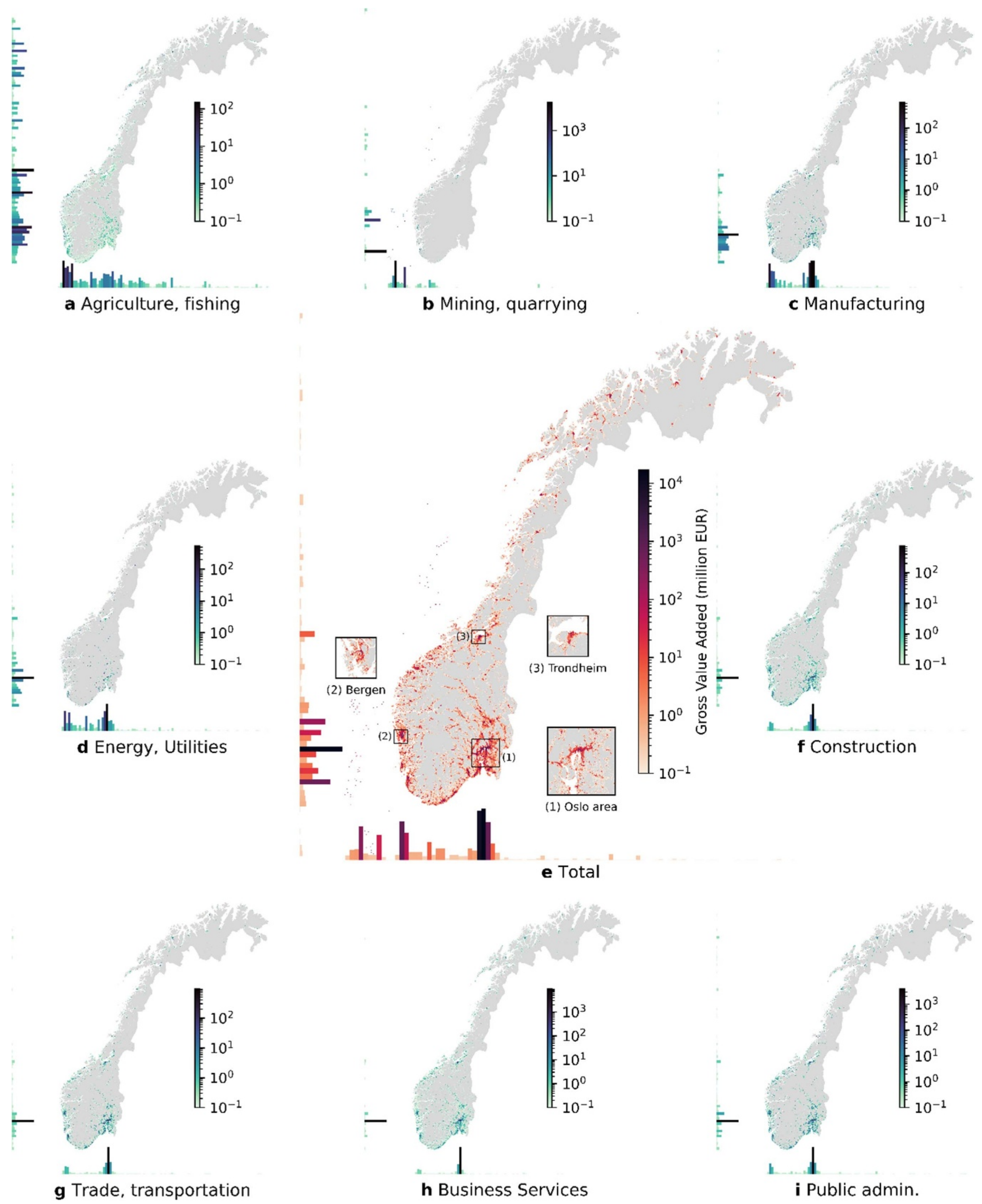

Figure 1. Gross value added (million EUR) distribution, gridded for display with 5 km grid, with major cities insets (1 km resolution), also showing latitude and longitude value added distribution. The maps show gross value added over all sectors (in the center) and eight sectors on the sides (aggregated from the underlying 615 sectors in the model). The intensity of total GVA and GVA from services follows urbanization patterns. GVA in agriculture widely distributed and GVA from the Quarrying and the Energy sectors are highly concentrated. Activities on the island of Svalbard are not shown. For sector definitions and high-resolution maps see the SI.).

all companies flooded by the 200 years floods at once, we are looking at a higher bound of indirect exposure to 200 year floods (see methods).

Using the map of the present-day economy, 7.3 billion EUR in value creation is directly exposed to this hazard. Considering trade linkages, the HEM assessment indicates that inclusive of these supply chains, approximately twice more value added (13.8 billion EUR) is exposed to this risk.

The distribution of direct vs. indirect exposure is uneven across sectors (figure 3). An interesting example is the Mining and Quarrying sector, an important economic sector in Norway because of oil

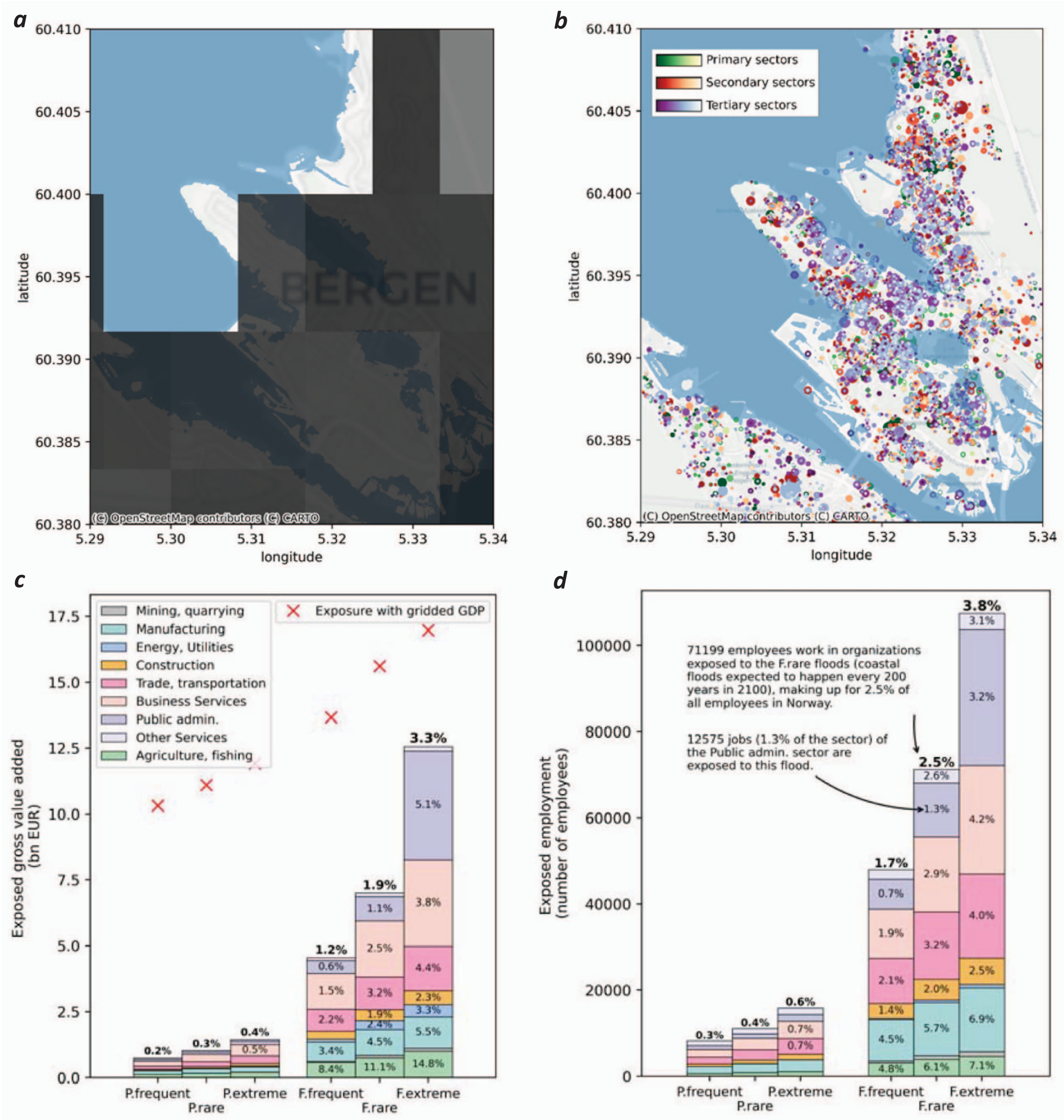

Figure 2. (a) and (b), Maps of value added in city of Bergen for the F.extreme flood. Value added is shown using (a) gridded GDP data from Kummu *et al* [16],which fails to finely capture exposure to this flood event (b) value added at point level with sectoral resolution, value added is represented by marker size and sector by color. To communicate flood exposure to local stakeholders, an online visualization tool is available on https://apps.sustainability.nilu.no/activitymap-no/. (c) and (d), Exposure of aggregated sectors to the different flooding scenarios for (c) gross value added, (d) employment. The sectoral aggregation is detailed in the SI. The red crosses show value added exposure using gridded data from Kummu *et al* [16].

and gas production. Most of the GVA in that sector is offshore and is therefore not considered at risk of coastal flooding. However, because the oil & gas sector depends on suppliers from other sectors, the indirect exposure is large, around 800 million EUR. On the other side of the spectrum, 97% of the exposure in Human health and social work activities ('Health and Social' in figure 3) is direct exposure. This can partly be explained by the fact that the sector's consumers are households and government, the sector is less dependent on interindustry demand. Sectors such as Manufacturing or Business Services show large indirect exposure due to the importance of sectoral linkages for these activities.

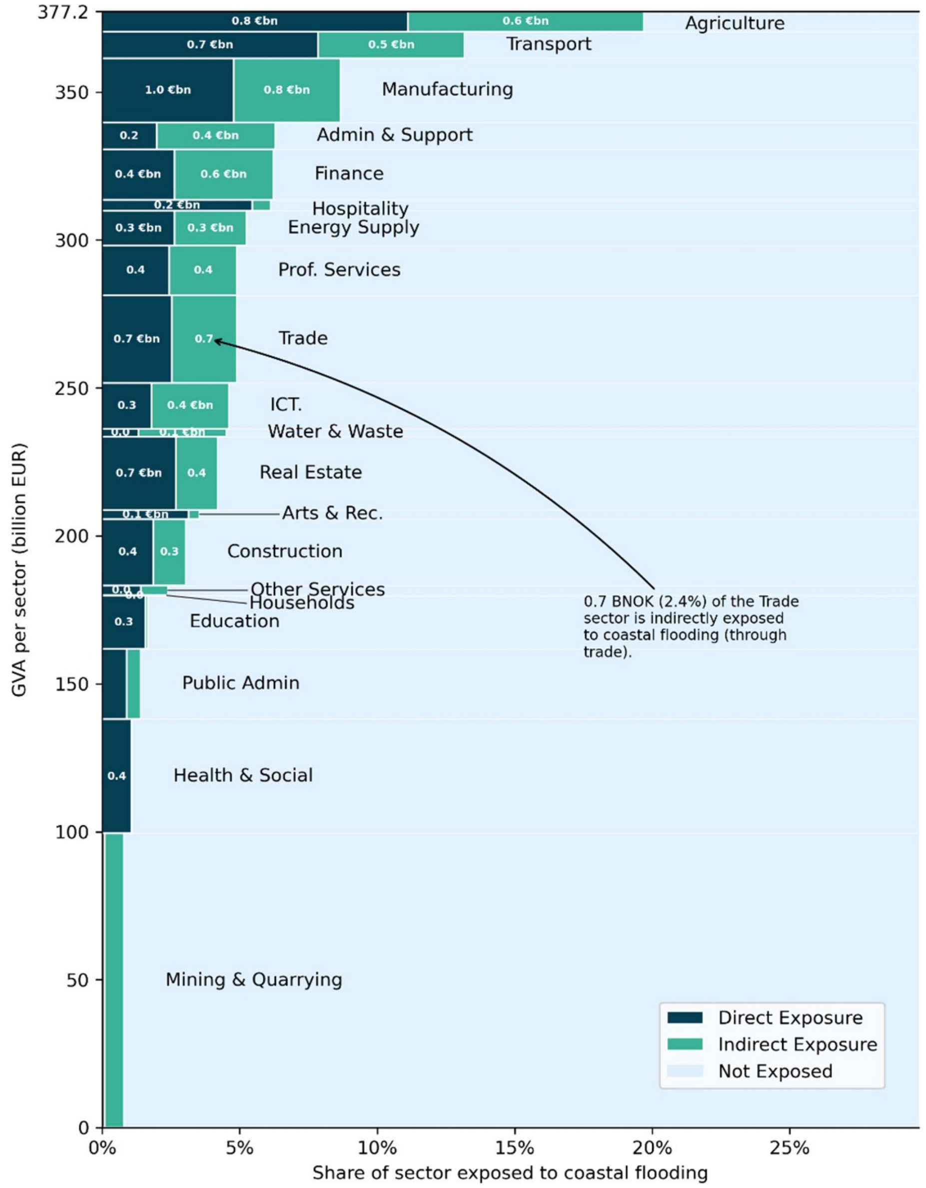

Figure 3. Direct and indirect exposure of NACE level 1 sectors under the flood scenario F.rare. Dark blue and green boxes represent direct and indirect exposure respectively for each sector. The vertical axis shows total value added in the sector and the horizontal axis represents the share of value added exposed in the flood scenario.

4. Discussion

The characterization of the economy to the point-level allows for a detailed analysis of the economic exposure to coastal flooding. In comparison, using a gridded economic model not only fails to capture sectoral patterns but also seems to lead to an overestimation of exposure. This approach also shows less difference in exposure between flood scenarios. A possible explanation is that many companies are in locations considered safe today, but which could become vulnerable in the future. The gridded exposure does not account for the uneven distribution of the economy within each cell, and assumptions must be made as to how the economy is affected in relation to the affected area. For example, if a cell is 50% flooded, it is often assumed that 50% of its GDP is affected. But businesses may be unevenly distributed into more or less flood-prone areas, leading to a misestimation of the true risk. The point-level model can identify where economic activity is concentrated, leading to potentially more precise and/or accurate estimates of flood exposure.

In this study we limit ourselves to characterizing direct and indirect exposure, not estimating damage or impact. The two are distinct concepts. Linking them requires further analysis, such as developing damage functions that relate flood height to GDP loss. Designing a damage function is challenging as it varies depending on the activity type and the extent of the flood [62]. These functions should be able to encompass the fact that sectors are unevenly affected by flooding. Whereas some service industries could continue to function with flooded premises, thanks to remote work, other sectors are less amenable to telecommuting. This would provide valuable insights into how exposure translates into economic losses, but it would also increase the uncertainty of the results. This is due to the lack of empirical data on damage curves, which are usually designed for linking depth and stock damage [63], have limited sectoral resolution and require additional transformation to measure flow damage [31]. Time considerations, i.e. the duration of business interruption and the speed of recovery, as well as potential substitutions between sectors and regions and increased economic activity from reconstruction would also have to be considered to model damage whether than exposure.

When working to estimate damage, mapping annual value creation provides only a partial picture. The model of direct and indirect exposure presented here assesses the extent of flows at risk at the moment of disaster but does not comment on sensitivity, adjustment dynamics, or damage to infrastructure and stocks underpinning flows. We have focused on spatially mapping the flows of annual value creation but have not further decomposed this into how that value is created though unique mixes of inventory, physical, intellectual and human capital ('people, things, and ideas'). In this study we have attempted to provide a reasonable estimation of where value is created, localizing it at the first instance at the firm, but one could argue that value creation also happens in other locations, such as the house of a remote worker. In addition to using business registry data, another potential approach to constrain workplace locations (as distinct from place of residence or commute) could be to draw on dynamic mobile phone data [64]. It is challenging to model value creation and risk exposure at fine spatial scale. To illustrate, consider whether the value of a farm is created on the field or in the barn, or whether the value of a ferry is created at its port of origin, of destination, or along the route? How may a disruption in one place jeopardize production in another place, e.g. transport and commuting disruptions? In this study, only organizations directly in the flood zone have been considered exposed. The omission of distal threats to value creation creates a systematic underestimate of true exposure to the hazard.

Three other large sources of uncertainties are how well the available proxy data is correlated with value added and employment, the quality of the business register itself, and the reliance on data available to tax authorities. Concerning the first point, revenue or number of employees and value added are not necessarily proportional. A retailer which sells a large amount of goods with a very little margin typically has high revenue and low value added, compared to a manufacturing company, where value added represents a larger share of the revenue. Similarly for employment: an automated industry will display higher than average value added per employee. In our model, economic variables are distributed using revenue and employment within a county and sector. The model thus implicitly assumes homogeneous technology, productivity and structure within a sector and county, but allows for different sectors to have different relationships between employment, revenue and value added (and for the same sector but in different counties to also have different productive structures).

Regarding the coastal flood mapping, the projections do not consider changes in storm surges themselves, only changes in sea level rise. This factor is however considered less significant compared to the mean sea-level rise. Additionally, wave dynamics are excluded from the analysis, which could leave to higher exposure for a given RP. The study is also limited to a single emission scenario and the 83rd percentile of the model spread, representing the upper end of the likely range. The spread in the projections is large, especially when considering low-likelihood high-impact events such as ice sheet collapse.

The main limitation of the high-resolution economic model is that it is harder to upscale than previous approaches such as Gridded GDP. It is dependent on a public business registry as input data. In the EU these are becoming available thanks to the European Data Act [65]. Similar data are available for other countries, such as Italy [66] or Denmark [67]. These can be augmented or superseded by other data sources either in total or on a sector-by-sector basis, as this study has done for the oil and gas infrastructure. The method can also be expanded to generate time series data by utilizing the business register over several years.

There is a need for tailored risk assessments that go beyond local hazard mapping to include also local-scale economic interconnections. Instead of using a national input–output table as done in this study, indirect exposure modelling can be improved by the use of subnational input–output tables, which have been successfully used to improve the accuracy of economic loss assessments from local events [23, 32]. At an even finer level, agent-based modelling was used to model supply chains at firm-level [68, 69]. Unfortunately, such approaches require additional information on firm level trade which is rarely available.

An economic analysis of employment and GVA exposure to flood events cannot replace an assessment of potential social consequences. Our results indicate that some public sectors (e.g. education, health) are less exposed than private sectors (e.g. business services, manufacturing). However, due to their critical societal roles, their disruption could have socioeconomic consequences which are not accounted for. This is a fundamental limitation of input–output and CGE based methods which document only the economic flows—sales and purchases—knitting together sectors, but do not document other aspects of sectoral interdependence.

In conclusion, a spatially and sectorally-resolved picture of the location of production and value creation is a fundamental knowledge need for many research and business cases. These include effectively navigating climate, disaster, or conflict risk; assessing supply chain vulnerability; assessing how tax revenue and jobs stand at risk from climate or other events; constructing plausible climate 'damage functions' relating temperature rise to productivity loss for integrated assessment modelling; evaluating policies; and performing cost/benefit analysis. Nearly all environmental, sustainability, and economic analyses rely at some point on a spatial inventory of economic activity as a core input to other modelling work.

Data availability statement

The data cannot be made publicly available upon publication due to legal restrictions preventing unrestricted public distribution. The data that support the findings of this study are available upon reasonable request from the authors.

The code for the model is available on Zenodo at https://zenodo.org/records/15774432.

Acknowledgment

The authors acknowledge funding from the Research Council of Norway through the RISKRES Project, Grant Nr. 342609. They also thank Marceau Cormery for proofreading the manuscript and Miguel Las Heras Hernandez for valuable advice regarding figure design.

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